

Punitive Attitudes in the United Kingdom and Uruguay: A Big Data Analysis

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A thesis submitted for the degree of
Doctor of Philosophy

Cardiff University
February 2025

Para mamá, papá, tata, y lala

Acknowledgements

For several years, I have been governed by a tendency to quantify - the following thesis is proof of this. After 4 years and two months, a global pandemic, several emotional ups and downs, a countless number of pints, more than 10 split Gs, and at least 50 new grey hairs, I have reached the end of this process. I often heard how tiring the process could be, how emotionally draining, the love-hate relationship formed with the project, etc. For many years, I was convinced that I would be the exception to all these problems. I wasn't.

However, if I've made it this far, it was with the help of many people. First of all, I want to thank my supervisors, Matt Williams and Nico Trajtenberg. They both pulled out all the stops to support me and get me here. Nico, believe it or not, was a constant source of support in discovering, thinking, re-interpreting, refining, and polishing each of the theoretical and methodological findings that emerged. He also invited me to my first kebab in Cardiff - happy, happy days. Matt not only poured all his experience and knowledge into each of his comments but also opened the doors to a host of new opportunities that have enhanced me as a professional and academic outside the strict scope of my thesis. It is impossible to explain how grateful I am to them.

Of course, I must also thank (and how much) my funders. I don't think it is necessary to elaborate too much on the importance of having resources to carry out any scientific endeavour. To the Agencia Nacional de Investigacion e Innovacion del Uruguay (ANII), thank you very much for the trust placed in me.

I now need to focus on those personal links that are indispensable to survive the years of shipwreck that a PhD entails. First of all, to my father, who, even in his later years, never ceased to encourage me to stay in Cardiff and finish my studies, being a guarantee and an infinite security. Secondly, to my mother, who had to put up with those regressions to my teenage years, the odd call at random hours, my broken communications, among so many other things. To my tata, an example of almost everything, but particularly of love for science and knowledge. To my lala, who at ninety-something years old learned to use WhatsApp to remind me that I can finish this (and bathe in emojis). To Clara, who more than once shared my frustrations and lifted me up. And finally, to my friends. On the one hand, those who became a virtual pillar of my day-to-day life, especially Agus and Santi, Los Muchachitos and El Haduken. On the other hand, to those new friends who filled my Welsh life: Chris, Lauren, Xela, Alvaro, Lara, Joe, Bella, Charlie, and Luigi.

Abstract

Punishment is a universal practice across all human societies, playing a central role in maintaining social order and shaping cultural norms. Previous research has linked citizens' punitive attitudes to the legitimacy of the political system, the implementation of ineffective criminal policy, and the prevalence of vigilante justice.

Research on punitive attitudes has relied on data from public opinion surveys. While this approach offers the advantage of statistical representativeness, it typically provides a static snapshot, failing to capture the dynamic, real-time shifts in public opinion. Surveys also focus on individuals in isolation, making it difficult to account for the communication networks, exchanges, and discussions that shape these attitudes. Additionally, they are often susceptible to social desirability bias, where respondents may tailor their answers to align with what they believe is expected by the interviewer or their community.

Using more than 100,000 crime-related tweets from the media and political system in Uruguay and the United Kingdom, alongside around 1.5 million citizen responses to both types of communications in 2022, this thesis explores the potential of social media data to develop and analyse alternative measurements of public attitudes toward punishment, advancing both methodological and theoretical innovation within Computational Criminology. It employs Natural Language Processing techniques, such as Topic Modelling, to analyse the main topics related to crime news and political communications on social media. Additionally, it uses Transformers Models to infer punitive attitudes from user-generated textual data and applies generalised linear models to compare the key determinants and consequences of these attitudes between the UK and Uruguay.

The research argues that the expression of punitive attitudes occupies a relevant place in the discussion of crime and punishment on social media. It further observes that both the characteristics of news stories and user profiles influence the shaping of these attitudes, highlighting convergences and divergences between this new form of measurement and conventional strategies. Finally, the study emphasises that these communications are highly dynamic, fluctuating over time in response to specific crimes that act as triggers, and often covary with the crime-related perspectives expressed by the political system.

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0. Introduction

On Monday, 29 November, in Montevideo, Uruguay, 18-year-old Lucas Zanolli vanished after leaving to meet a prospective buyer from Facebook Marketplace to sell his car. His sudden disappearance did not go unnoticed by his family, who, alongside filing a police report, mobilised on social media to publicise his search, aiming to gain widespread support. The family's efforts quickly went viral, catching the attention of the press, which soon launched its own investigations and reports, turning the case into a matter of national concern. Tragically, on Tuesday, 30 November, Lucas Zanolli was found dead by police (Subrayado 2021a). The public's reaction was immediate and pronounced. All major media outlets extensively covered the story. Across social media, calls for a demonstration outside the Palacio Legislativo (Uruguay's legislative seat) were circulated, echoing messages of outrage, sorrow, and demands for justice, with many asserting that such tragedies should 'never happen again' (Subrayado 2021c) in a country where crime and insecurity are pressing public concerns (Latinobarómetro 2020; LAPOP 2021). The Ministry of the Interior responded to the press with statements of shock and indignation, promising that the perpetrator 'will be punished to the fullest extent of the law' (Subrayado 2021b).

As part of this thesis, a data collection from Twitter conducted one month after the incident in 2022 identified 515 tweets mentioning 'Lucas Zanolli' between 30 November 2021, when he was found dead, and 8 December. These tweets garnered approximately 7,682 responses, including replies and quotes. On the night of 1 December, 'Lucas' emerged as the top trending topic alongside 'DEATH PENALTY,' with the latter accumulating 5,902 tweets. This fact is especially notable given that Uruguay abolished the death penalty in 1907.

Among the most retweeted tweets, some examples are:

It's outrageous to read this, the boy was 18 years old, the illusion of selling the car and being able to buy a better one, these scum have no heart and don't deserve anything, victims of a society my ass, sanitary rifle.

Until we apply doses of bullets, this is not over.

In a related context, a tragic case that mobilised public opinion in the UK occurred in 2018, when 16-year-old Aaron Campbell abducted, raped, and murdered 6-year-old Alesha MacPhail on the Isle of Bute in Scotland (Stubley 2019). Due to the case's exceptional nature and extreme violence, it provoked a significant public reaction. Particularly relevant to this thesis is the discussion on social media regarding

statements made by Campbell's defence, which described the minimum 27-year sentence as "excessive and a miscarriage of justice" (Binding 2019). Responses to news items reflecting these statements were collected and analysed, with approximately 2,000 replies or quotes, around 25% of which were classified as punitive (see the methodological chapter for the classification technique). In response to these public statements from the defence, many members of the public engaged in discussions about appropriate punishment, with some expressing support for harsher penalties, including extra-legal measures such as the death penalty. Again, this is in the context of a country that has abolished the death penalty and whose last execution was in 1964. Some notorious examples are:

He should get the death penalty! If it was my daughter I would have killed him my self!

Castration with a blunt object then slowly torture him to death would be a fair punishment 😡 Look 🙄 what he did 😡

Before the advent of social media, such discussions were largely confined to intimate settings—among family members watching television, with colleagues at the pub—and occasionally extended to communication with publishers as some individuals sought to share their views publicly. In some instances, organisations of varying types and formality levels would mobilise to support one stance or another. Today, however, individuals can express their immediate reactions and emotions in real-time from virtually anywhere using mobile devices, generating largely unexplored effects regarding punishment and justice.

Punishment is a universal practice observed across all human societies (Miethe and Lu 2005). Its historical ubiquity and the cultural embedding of legal notions of crime and punishment often obscure the intricate social mechanisms underpinning fundamental questions: What constitutes a crime? How should it be punished? What degree of punishment is appropriate? What emotions are acceptable in response? Who holds the authority to punish, and for what purposes? (Garland 1990). The public often perceives these questions as self-evident, their complexity hidden by the routine nature of punishment. However, as the previous examples suggest, such questions resurface in public discourse when triggered by the right conditions.

The study of punishment extends beyond the analysis of crime and its control, providing essential insights into the construction of social order and the cultural norms and values that sustain societal life, as highlighted by the Durkheimian tradition (Garland 1990; Garland 2001). Durkheim argued that punishment is not merely a response to criminal behaviour but fulfils a critical social function by

reinforcing cohesion and affirming collective values. When society condemns deviant behaviour, it symbolically reasserts the boundary between acceptable and unacceptable conduct, strengthening its members' shared moral beliefs and values.

In this sense, punishment operates as a social ritual, reminding community members of the norms that underpin their collective existence. Garland (1990; 2001) elaborates on this perspective, emphasising that within the Durkheimian framework, punishment is fundamentally an expression of societal outrage aimed at preserving the cultural fabric of society. This process extends beyond penalising individual offenders to reaffirming the moral standards necessary for social solidarity. Viewed through this lens, punishment serves a dual role: addressing specific behaviours that threaten social order while reinforcing the values that sustain it, making it a powerful mechanism for social control and integration.

For their part, citizens' views on the punishment of offenders, particularly their preference for more severe punishments, have been shown to have a significant impact on the functioning of the justice system. Enns (2014) develops a measure of public support for punitive policies in the United States and analyses its relationship with incarceration rates, finding that public opinion has consistently driven criminal justice outcomes, with a more punitive public opinion leading to stricter sentencing and increased incarceration rates. Similarly, Jennings et al. (2017) examine “penal populism” in Britain, exploring how public attitudes respond to changes in crime rates and how these attitudes impact incarceration and sentencing policies. Their analysis shows that rising crime rates lead to increased public demand for punitive measures, which then translates into higher incarceration rates.

These kinds of policies that rely on extensive use of imprisonment and lengthened sentences may not only fail to reduce crime but can also lead to several unintended negative consequences, including increased recidivism, human rights concerns, and substantial economic costs (Cullen et al. 2011; Liu et al. 2018; Loeffler and Nagin 2022). Cullen et al. (2011) argue that imprisonment does not effectively reduce recidivism and may even have a criminogenic effect, meaning that it could increase the likelihood of reoffending. Their analysis, grounded in a review of empirical research, suggests that the prison environment often exposes individuals to criminal networks, strains family connections, and fosters stigma, all of which may contribute to higher recidivism rates. Liu et al. (2018) focus on the economic costs associated with incarceration. Using data on bail and pretrial detention practices, they reveal how the high economic burden of detention affects not only detainees but also society at large. Similarly, Loeffler and Nagin (2022) assess the impact of incarceration on recidivism. Their findings reinforce that incarceration generally has a limited effect on

reducing reoffending and can, under certain conditions, exacerbate it, especially in settings lacking rehabilitative support.

The effects of punitive attitudes extend beyond legal frameworks, influencing citizens' acceptance of extra-legal justice methods, such as vigilantism. Nivette (2016) examines this phenomenon in Latin America, where public support for violent vigilantism is often linked to dissatisfaction with formal justice institutions. Her study reveals that individuals with strong punitive attitudes are more likely to endorse vigilantism. In the Global North, Van Damme and Pauwels (2012) explore a similar relationship in Belgium, analysing how punitiveness directly influences support for vigilantism. Their study of Belgian university students reveals that punitive attitudes mediate low procedural fairness in the justice system and support for vigilantism. Through structural equation modelling, they find that individuals with punitive views are more inclined to support vigilantism, particularly when perceiving the justice system as too lenient or ineffective.

However, despite the significance of studying punitive attitudes, the existing literature has notable limitations. Most research has been conducted in the Global North, particularly in the United States, with only a recent shift towards exploring the Global South. These studies predominantly rely on survey analysis and, in some cases, in-depth interviews, which are typically cross-sectional in nature. Such methods often provide a static snapshot that fails to account for the dynamic and real-time fluctuations in public opinion over weeks or months (Williams et al. 2020). Surveys focus on individuals in isolation, often overlooking the broader networks of communication, exchange, and discussion that shape attitudes (Edelmann et al. 2020). Furthermore, using surveys to address sensitive or controversial topics is susceptible to social desirability bias, where respondents may modify their answers to align with perceived expectations from the interviewer or their community (Stephens-Davidowitz 2018).

Furthermore, the rise and proliferation of digital technologies, especially in the realm of Information and Communication, have profoundly reshaped human experience, giving rise to what scholars have termed the Digital Society (Stratton et al. 2017; Dufva and Dufva 2019; Levin and Mamlok 2021; Sundberg 2024). Web 2.0 and social networks have profoundly transformed interpersonal communication, creating a new public arena or "digital agora" that significantly impacts political discourse and social activism. As van Dijck and Poell (2013) argue, social media platforms operate on a unique "social media logic" characterised by programmability, connectivity, popularity, and datafication. This logic mediates user interactions and reshapes institutional practices by blending mass media dynamics with the participatory nature

of social platforms. Edwards et al. (2013) highlight how these technologies generate new, naturally occurring data sources, allowing researchers to analyse social processes in real time, which was previously unattainable with traditional methods. Furthermore, the interactive features of platforms such as Facebook and Twitter, as demonstrated by Kalsnes et al. (2017), provide affordances for political engagement, enabling citizens to interact with political figures and bypass traditional media gatekeepers.

The implications extend to activism, as Powell et al. (2018) illustrate through the case of #JillMeagher, showing how collective meaning-making and social mobilisation emerge around crime events on social media. Noland (2017) emphasizes the role of "slacktivism," where online actions such as sharing and commenting, though often criticised as low-effort, can nonetheless foster broader participation in social causes. Carlomagno et al. (2022) examine the determinants of social media engagement in political contexts, revealing that competitive candidates and media visibility significantly drive interactions, underscoring the platform's role in amplifying public and political discourse.

The public relevance of the Lucas Zanolli case emerged and unfolded on social media, demonstrating how critical discussions about crime, law and order, and particularly punishment, have been reshaped by profound digital transformations. Despite this, the understanding of the dynamics within these conversations remains limited. What proportion of crime-related discussions focus on the punishment of offenders? To what extent do these discussions reflect explicitly punitive attitudes? Who expresses these attitudes, and what events or factors trigger them? How do these discussions evolve over time, and how do they correspond to findings from survey data? These are pressing questions that, so far, remain unanswered. The case of Alesha MacPhail illustrates how social media enables ordinary citizens to voice their opinions on punishment, potentially influencing judicial outcomes. Digital platforms enable the public to participate in discussions that were previously dominated by the judiciary, law enforcement, and political figures. This thesis aims to investigate the utility of social media data, specifically Twitter data, in developing alternative measurements of public attitudes towards punishment. The project will push forward methodological and theoretical innovation, building on the work in Computational Criminology (Williams and Burnap 2016; Williams et al. 2017) to address these questions comparatively between Uruguay and the United Kingdom.

Cross-cultural research provides a valuable opportunity to empirically evaluate whether explanations and predictors of punitive attitudes, originally developed in contexts such as the United States and Europe, apply to societies in low- and middle-

income regions that feature distinct social structures, institutional frameworks, cultural norms, and more importantly crime, violence, and victimisation rates (Stamatel 2009; Trajtenberg 2017; van Dijk et al. 2022). The UK represents an example of a Global North country that follows the trends associated with it. Long-term crime has shown a significant decline since the mid-1990s, particularly in violent and property crimes. The homicide rate in the population was 0.93 per 100,000 inhabitants (ONS 2024). However, it is worth pointing out that recent years have seen increases in specific categories such as sexual assaults, consumer fraud, and certain types of violent crime, with violence with injury rising by 49% in the year ending June 2024 and knife-enabled crimes increasing by 4%, returning to pre-pandemic levels.

Public attitudes have mirrored these trends, with concern about crime peaking in the early 1990s before steadily declining, reflecting a general alignment with decreasing overall crime rates (Tiratelli 2024). Previous studies have shown a connection between the punitive attitudes of British citizens and “real-crime” figures to a higher degree than their US counterparts (Jennings et al. 2017; Enns et al. 2022; Tiratelli 2024). Therefore, this emerging growth in both crime and public concern about crime raises questions about how it might affect punitive attitudes. Additionally, there is, to some extent, evidence of increasing support for vigilante justice in the United Kingdom, particularly on Social Media (Tippett 2022) and from some far-right movements (Ralph-Morrow 2019).

For its part, Uruguay serves as an example of a country from the Global South, with significant differences compared to the British case, making it a relevant point of comparison. Unlike the UK, Uruguay has experienced a substantial increase in crime over the past three decades, particularly in violent crimes such as homicides, robberies, and domestic violence. The homicide rate reached 11.2 per 100,000 inhabitants in 2022, almost double the global average and among the highest in South America, behind only Venezuela, Brazil, and Colombia (Rojido et al. 2023; Ministerio del Interior 2024). Public perception reflects this reality, with 52.3% of the population considering Uruguay an unsafe or very unsafe country, and 30% expressing constant fear of victimisation (Latinobarómetro 2023). Uruguayan society has consistently shown strong support for more punitive measures, including harsher sentencing and stricter criminal justice policies (Vigna et al. 2019). Additionally, there is evidence of increasing support for vigilantism and community justice initiatives, reflecting a different societal response to crime compared to that in the UK (Borraz et al. 2012; Rossi et al. 2017). Moreover, one of the complexities of a study based on social networks in the Global South is the differences in access that still exist regarding access to Information and Communication Technologies (Robinson et al. 2020b).

However, Uruguay has been a pioneer regarding universal access policies in the region, with penetration levels similar to those in Europe (Robinson et al. 2020a). The country, therefore, provides an excellent opportunity for comparative study.

The thesis is organised as follows. The next chapter begins by exploring foundational concepts of punishment, punitiveness, and punitive attitudes, establishing a theoretical framework for understanding how societies perceive and respond to crime. It emphasises how attitudes towards punishment are deeply rooted in social norms, emotional responses, and moral judgments, setting the stage for analysing how these views are shaped and expressed in contemporary contexts. The following chapter shifts focus to the emergence of the Digital Society, examining how technological affordances have fundamentally transformed the construction of social relations. It examines how digital spaces, particularly social media, have influenced public discourse on crime and punishment. This shift has enabled new ways for individuals to engage with, discuss, and influence societal perceptions, providing a deeper understanding of how the digital environment mediates and amplifies attitudes towards punitive measures and justice. Chapter 3 outlines the methodological strategy employed to address the research questions, covering foundational ontological and epistemological assumptions, research design, case selection rationale, data collection procedures, and the Machine Learning approaches used to construct the dependent variable. This is followed by the techniques for data analysis. The subsequent three chapters present the analysis undertaken to answer each research question. Chapter 4 provides a descriptive and exploratory analysis of the collected texts through Topic Modelling, Sentiment Analysis, and Emotional Analysis. Chapter 5 examines the determinants of punitive attitudes using a range of linear models. Chapter 6 investigates the temporal variation in punitive attitudes, their correlates, and potential impacts on political communications on Twitter. The thesis concludes by discussing these analyses, including limitations and implications.

1. Punishment, punitiveness, and punitive attitudes

1.1. Punishment

One of the primary challenges the Social Sciences face in addressing the punitiveness topic is defining the concept of punishment and contextualising it within social systems. While the idea of punishment as a response to deviance seems intuitive, given its historical and cross-cultural ubiquity (Garland 1990; Miethe and Lu 2005), understanding the attitudes surrounding it requires a deeper exploration of its definition and foundations.

While perspectives on punishment vary widely, certain scholars provide foundational insights that help frame this complex concept. Duff (2001, p. xiv-xv) describes *punishment* as: "something intended to be burdensome or painful, imposed on a (supposed) offender for a (supposed) offence by someone with (supposedly) the authority to do so". This definition captures the inherent intent of punishment to cause discomfort and its reliance on authority, elements central to penal theory. Meanwhile, Miethe and Lu (2005) expand on this by defining punishment as a cross-cultural practice that takes the form of social control involving negative sanctions imposed by formal or informal authorities on those who violate social norms. Binder (2002) adds further nuance, conceptualising punishment as an institution supported by the authority of the system it represents, stressing that punishment is not simply a transaction between an offender and a figure of authority; rather, it is an act that engages the entire social system. Three key features recur in the literature regarding punishment:

- 1) It is a practice present across societies and operates at various levels of social life;
- 2) It necessarily involves some form of loss or suffering;
- 3) An authority administers it in response to a breach of norms.

While these broad definitions provide a comprehensive understanding of punishment, the wide range of situations encompassed by the concept requires a more focused approach when doing empirical research (Hamilton 2014). Garland (1990) narrows his analysis of punishment to the legal process, defining it as the legal procedure by which violators of criminal law are condemned and sanctioned. This approach, which focuses on the penal system, has dominated contemporary analyses of punishment.

Brooks (2021) outlines four essential characteristics of punishment within this narrow legal framework:

- 1) Punishment must be for breaking the law.
- 2) Punishment must be imposed on a person.
- 3) Punishment must be intentionally administered by an authority within a legal system.
- 4) Punishment must involve a loss.

This project partially analyses punitive attitudes within this narrow definition, focusing on punishment for breaking the law. However, it also considers support for harsher, extra-legal measures—such as vigilante justice or extrajudicial actions—as expressions of punitive attitudes. These elements are particularly relevant in the Latin American context (Nivette 2016), where support for vigilantism is widespread, especially in a context of low state presence, with Uruguay not being the exception (Borraz et al. 2012; Rossi et al. 2017). Additionally, there is, to some extent, evidence of their support in the United Kingdom, particularly on Social Media (Tippett 2022) and from some far-right movements (Ralph-Morrow 2019). Since the expression of this type of preference (for severe punishment of offenders, even outside the legal system) encompasses the definition adopted in this thesis for the concept of punitive attitudes (see the next section), this expansion of the concept developed by Brooks is maintained.

1.2. Punitiveness

This research focuses on the issue of punitiveness, specifically analysing punitive attitudes. Although studies on this topic have proliferated in Criminology and the Social Sciences, there remains considerable debate over the definition of the phenomenon and its determinants (Matthews 2005; Hamilton 2014; Adriaenssen and Aertsen 2015; Aizpurúa 2015; Maguire and Johnson 2015). This ongoing disagreement stems, in part, from the fact that the concept of punitiveness has been applied to various interconnected phenomena across different levels of analysis.

Tonry (2007, p.7), recognising these complexities, develops one of the most comprehensive definitions of the term that helps frame the theoretical and empirical challenges, providing a starting point for further development: "a mix of attitudes, enactments, motivations, policies, practices, and ways of thinking that taken together express greater intolerance of deviance and deviants, and greater support for harsher policies and severe punishments." This definition encapsulates the multiplicity of elements considered in punitiveness studies.

Much of the confusion surrounding the concept of punitiveness can be attributed to its application at different levels. Kury and Ferdinand (2008) identify four distinct levels or forms in which punitiveness is exercised. *Legal punitiveness* refers to the

penal law itself, while *juridical punitiveness* pertains to the actions of the criminal legal system through its actors and institutions, focusing on how strictly they apply the law within their discretionary power. *Operational punitiveness* encompasses the attitudes of individuals who operate within the penal system, such as the police and prison staff, but do not make legal decisions. Finally, *local punitiveness* addresses the attitudes and actions of citizens in their daily lives concerning the punishment of offenders. This research specifically focuses on the latter level—local punitiveness, referred to as punitive attitudes. Thus, punitiveness can be understood as a general concept that applies at various levels, associated with the sanctioning of harsher measures on offenders, while punitive attitudes refer specifically to individual attitudes that show a preference for this type of punishment.

1.3. Punitive Attitudes

While some of the confusion surrounding the concept of punitiveness stems from its application at different levels of analysis, narrowing the focus to the micro-level—specifically, people's attitudes towards punishment—does not entirely resolve the issue. Even when excluding definitions that attribute punitiveness to entities other than individuals, ambiguity remains in the concept's definition, with varying interpretations across the literature. Although criminologists have shown great interest in exploring the causes and consequences of punitive attitudes, less attention has been devoted to thoroughly discussing their measurement and definition, with some notable exceptions (De Keijser et al. 2002; Aizpurúa 2015; Maguire and Johnson 2015; Armbrorst 2017; Trajtenberg et al. 2024).

As a starting point, this research adopts an initial definition proposed by Aguilar-Jurado (2018) in his literature review: punitive attitudes can be understood as the mental disposition of citizens regarding the punishment that offenders deserve. A preference for more severe punishments, particularly those that lean towards excess, would indicate a more punitive attitude. This definition is sufficiently general and straightforward to serve as a foundation for further exploration. Despite ongoing debates in the literature, there is some consensus: punitive attitudes are properties of individuals, reflect a specific state of mind—which will be further elaborated below—and are concerned with the punishment of offenders who break the law, with more punitive individuals expected to favour harsher penalties.

However, two key issues arise from this initial definition: those related to the characteristics of attitudes and those concerning the content of these attitudes. First, it is crucial to clarify the nature of punitiveness. If punitiveness is understood as an attitude, a thorough understanding of the characteristics and properties of attitudes is

necessary. Second, the content of these attitudes must be elaborated, explicitly identifying what elements constitute support for harsher punishments.

A literature review reveals that different terms have been used to describe the phenomenon of individual punitiveness. While the concept of "attitude" has been predominant (Roberts and Indermaur 2007; Unnever and Cullen 2009; Unnever and Cullen 2010; Falco and Martin 2012; Aizpurúa 2015; Armbrorst 2017; Silver and Silver 2017; Aguilar-Jurado 2018; Intravia 2019), other terms such as "punitive sentiment" (Ramirez 2013; Stewart et al. 2018), "punitive view" (Brown and Socia 2017), and "punitive preference/support" (Baker et al. 2015) have also been used. These various terms suggest different mental states, each with distinct properties, making it crucial to specify what is meant. This research will refer to punitive *attitudes*, a concept that will be further developed below.

Additionally, it is noted that the content of these mental states differs. Adriaenssen and Aertsen (2015) synthesise these contents into four:

- 1) Goals of punishment: This includes the justification and role of punishment. Commonly retributive, incapacitatory or deterrent objectives are considered to be more punitive than rehabilitative or restorative objectives.
- 2) Forms of penal sanctions: This includes support or rejection of specific types of application of justice, such as the death penalty or community-based sanctions.
- 3) The intensity of the penal sanction: This includes support for longer measures, harsher sentences, worse prison conditions, and so forth.
- 4) Sentencing policies: This refers to the application of policies that limit options toward either greater or lesser severity (e.g. three-strikes laws).

It is worth asking to what extent all these elements are part of the concept of punitive attitudes. It is also necessary to ask to what extent these elements are distinguishable.

1.3.1. Attitudes definition

The concept of attitude has played a central role in the development of cognitive and social psychology (Haddock and Maio 2004; Riemer et al. 2014) and has been adopted by other disciplines within the social sciences (Voas 2014; Albarracin and Shavitt 2018). Analysing and understanding attitudes from a social perspective can help bridge the gap between individual mental states, behaviour, and the broader understanding of social phenomena. However, the concept has not been without controversy, particularly concerning how attitudes are formed (Cunningham and

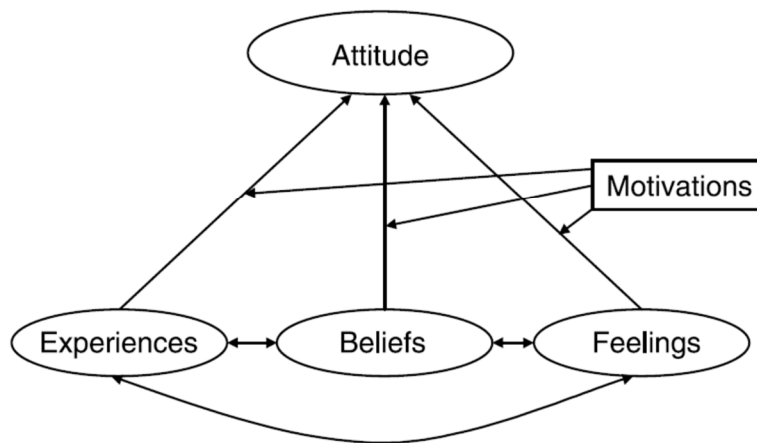
Zelazo 2007; Schwarz 2007; Riemer et al. 2014) and their relationship to behaviours (Ajzen and Fishbein 2005).

At the core of the concept, and commonly agreed upon in the literature, is the idea that attitudes represent a person's evaluation of an object along a continuum from good to bad. This object can be a material item, a person, an action, or an abstract idea (Bohner and Dickel 2011; Albarracin and Shavitt 2018). Attitudes are seen as a universal property of individuals, though their form and influence on behaviour may vary across cultures (Riemer et al. 2014).

Beyond this basic agreement, the literature explores various properties of attitudes, including a debate on the nature of attitudes as a mental state. Some scholars view attitudes as stable entities stored in memory, while others argue they are temporary judgments constructed around the objects of interest based on the information available at the time (Schwarz 2007; Bohner and Dickel 2011). Similarly, a closely related discussion revolves around the type of evaluative response: implicit (System 1) and explicit (System 2) (Whitfield and Jordan 2009; Kahneman 2011) – or integrated (Cunningham and Zelazo 2007). Roughly, implicit responses can be considered to occur relatively automatically, representing an immediate or instinctive predisposition toward an object when motivation or resources for a more complex evaluation are lacking, akin to Kahneman's System 1 thinking. Explicit evaluation occurs when an individual has the motivation and resources to thoroughly assess the stimulus in question, reflecting the slower, more deliberate processing of System 2. Usually, these two evaluative processes are considered components of attitudes. The two types of information processing help explain inconsistencies between measurement strategies, individual ambivalences, and discrepancies between attitudes and behaviour (Shoda et al. 2014).

Another central aspect of attitude research is understanding the factors that contribute to their formation, as well as their components. The function-structure attitudinal model (Maio et al. 2004), portrayed in Figure 1, synthesises three key mental states that interact to shape the evaluation of a given object: experiences, beliefs, and feelings. The influence of these elements on attitudes can vary depending on the object of evaluation and the individual's motivation. Importantly, these components do not operate in isolation but interact dynamically (Dalege et al. 2016), influencing implicit and explicit attitudes, which can affect behaviour across different contexts – Borsboom et al. (2021) provide a deep discussion on the different alternatives around how multiple psychological objects interact to create specific attributes.

Figure 1 Function - structure model of attitudes



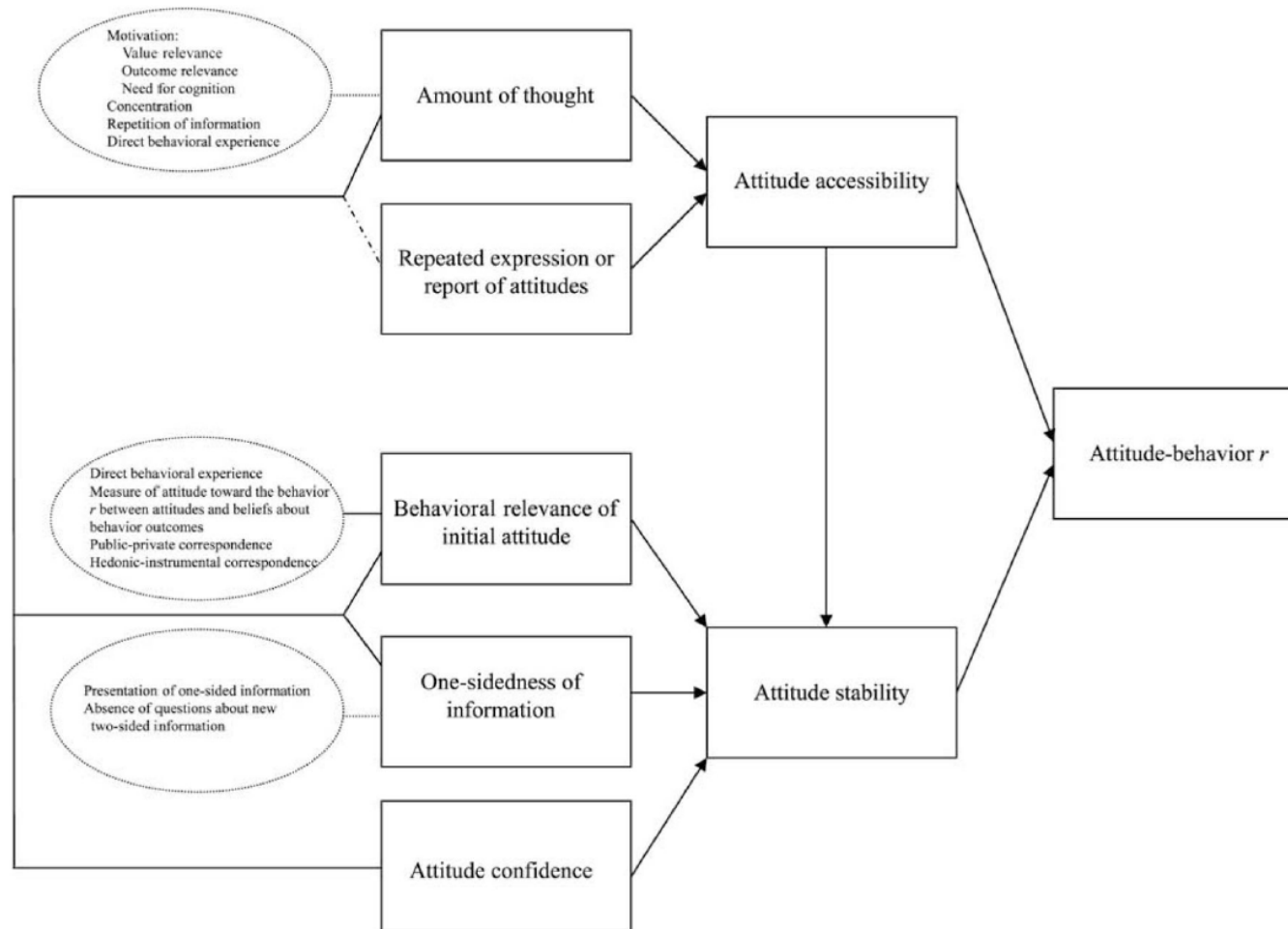
Source: Maio et al. 2004, p.11

Bringing together the central elements of the discussion and applying them to the specific issue of punitive attitudes, these attitudes can be understood as individual properties that reflect the evaluation of the various aspects of punishment. This evaluation depends on the motivation to activate different types of information processing—explicit or implicit—and the interaction results of the various mental states synthesised in the function-structure model. Higher levels of punitive attitudes correspond to greater approval of punishment, with the specific components of punishment to be examined later in this chapter.

Another critical discussion for this thesis concerns the interaction between attitudes and behaviours, mainly since the punitive attitudes will be inferred from the expression of favourable opinions about punishing criminal offenders on social media—a specific behaviour. The relationship between behaviour and attitudes is a central topic in psychology and has been widely discussed (Ajzen and Fishbein 2005; Bechler et al. 2021), with various attitude characteristics (Glasman and Albarracín 2006) and contextual factors (Guagnano et al. 1995; Hogg and Terry 1999) influencing this relationship. Attitudes that are easily recalled (accessibility) and remain consistent over time (stability) are more likely to guide behaviour. Direct experience with an attitude object enhances both accessibility and stability. Furthermore, the amount of thought invested in forming an attitude and its relevance to behaviour strengthens the attitude-behaviour link, making well-considered and relevant attitudes stronger predictors of behaviour. Additionally, attitudes formed from one-

sided information and held with high confidence tend to be more stable and, therefore, more likely to influence behaviour (Glasman and Albarracín 2006). This complex relationship between properties is illustrated in Figure 2.

Figure 2 Processes involved in the prediction of behaviour from attitudes.



Variables in boxes represent factors that influence attitude-behaviour correspondence; variables in ovals denote the various indicants of those factors in our meta-analysis. Source: (Glasman and Albarracín 2006, p.42).

Moreover, the characteristics of the context significantly influence the likelihood that attitudes will translate into behaviour. These contextual factors include the availability of resources, social norms, and external pressures, such as rewards or penalties, all of which can determine whether the behaviour occurs and shape the specific nature of that behaviour. (Guagnano et al. 1995; Hogg and Terry 1999; Schwarz 2007).

Finally, the relationship between attitudes, attitude valence, and behaviour is non-linear, with more pronounced changes occurring near neutral categories, while stabilisation occurs between moderate and high values within the negative or positive categories (Bechler et al. 2021). These considerations will be addressed during the operationalisation of punitive attitudes. Punitive attitudes in this thesis will be operationalised by automatically detecting text indicating support for more severe measures. This strategy requires a prior behaviour: posting on Twitter. This behaviour involves the interaction of actors' desires, beliefs, and opportunities (Hedstrom 2005), where various attitudes are being activated, so it is important to consider the subtleties of analysing attitudes and their interaction with behaviours.

1.3.2. The 'punitive' side

So far, the thesis has identified the type of mental state under analysis - attitudes - and explored its specific properties. It is now necessary to examine the other side of the concept, specifically the content of punitive attitudes.

As previously noted, Adriaenssen and Aertsen (2015) identify four types of content or objects commonly associated with punitive attitudes in the literature: goals of punishment, forms of penal sanctions, the intensity of the penal sanction, and sentencing policies. This thesis focuses on the intensity of punishment as the most relevant dimension of punitive attitudes and argues against including the other types of content. Next, arguments are developed to justify this exclusion and demonstrate why the intensity of punishment is the most appropriate focus for this research.

The first question corresponds to the role that each of these components would play. One strategy for this is based on set theory and the notions of necessary conditions – the ones that must be present for the presence of the concept to be identified - and sufficient conditions - conditions that by themselves ensure the presence of the concept (Goertz 2006). While Adriaenssen and Aertsen (2015) identify these components or dimensions, they do not specify their relationship to the overall concept. The first element that stands out from the literature review is the prominence of the idea of punitiveness as the severity of punishment. Most empirical studies incorporate elements related to it (Aguilar-Jurado 2018), in some cases exclusively and in other cases incorporating other dimensions as well. This ubiquity in the

literature would seem to suggest that the intensity or severity of the punishment is a necessary condition for the concept. Additionally, if the object of the attitude is punishment, understood as suffering, the intensity of suffering is an explicit property of the object that follows logically from it.

The goals or justifications of punishment are often incorporated into the definition and measurement of punitive attitudes (Coleman 1990; Mackey and Courtright 2000; Colémont et al. 2011; Falco and Martin 2012). Justifications rooted in retribution, incapacitation, or deterrence are generally viewed as more punitive than those based on rehabilitation or restorative justice. However, another body of research distinguishes these elements, suggesting that the justifications or objectives of punishment may influence punitive attitudes—understood as support for harsher punishments—while representing a separate construct (Oswald et al. 2002; Payne et al. 2004; Gerber and Jackson 2013; Pickett and Baker 2014; Maguire and Johnson 2015; Armbrorst 2017). Some challenges arise when incorporating goals or justifications for punishment into punitive attitudes. Firstly, the relationship between punishment goals and other dimensions of punitive attitudes is complex. For instance, retributive goals do not necessarily lead to harsher punishments, as they can be moderated by proportionality considerations (Matthews 2005; Hoskins 2020). This correlation - or rather its absence - with the severity or intensity dimension previously identified as necessary implies that the only possible relationship between both dimensions if we were to consider goals as part of the concept, is given by the union of both dimensions: punitive attitudes should entail an increase in the intensity of punishment and furthermore justification based on retributive, incapacitatory, or deterrent objectives. This suggests a possible avenue for conceptualising the concept. However, it is not clear in the literature how and why these goals should be a necessary condition without justifying their possible correlation with intensity or failing to prove that these elements load on the same latent factor. Secondly, individuals often hold multiple, sometimes conflicting, punishment goals simultaneously (Gromet and Darley 2009), and these goals can be highly adaptable (Twardawski et al. 2020). Moreover, there are frequent inconsistencies between the reasons individuals give for punishment and the types of punishment they ultimately support (Carlsmith 2008). These factors make it challenging to classify individuals along a punitive gradient based on these interpretations, leading to measurement problems when creating a summary variable for punitive attitudes that incorporates these goals (Maguire and Johnson 2015; Armbrorst 2017). Additionally, this assumes that for any given penalty, there is a specific set of goals possible, depending on the type of goals being considered. Assuming the presence of retributive, deterrent,

incapacitatory, and rehabilitative goals, this would mean at least 15 possible combinations that would have to be identified in their punitive condition and potentially their degree. Finally, it is worth asking what happens when punitive and non-punitive goals coexist in the same person. For these reasons, it seems best to separate the punishment goals construct from the punitive attitudes construct. The former can be understood as part of the determinants influencing the latter.

Different forms of criminal punishment and sentencing policies are relevant primarily because they reflect the intensity of punishment rather than being of intrinsic interest in measuring punitive attitudes. This argument follows from the definition of punishment as a form of suffering. Under this definition, the various possible applications or strategies are ultimately reduced to the application of suffering, becoming equivalent in their outcome and groupable along a continuum of intensity. Survey questionnaires often include assessments of these elements—such as the death penalty, a commonly used indicator—because they represent varying levels of punishment severity. This thesis argues that while these elements are important, they should be considered in measurement, specifically in terms of how they reflect differing degrees of intensity or harshness in punishment.

Building on the definition of attitudes and the specific characteristics of the object of study, punitive attitudes can be understood as evaluative attitudes concerning the severity of punishment that should be imposed on criminals. Any attitude favouring increasing the costs or consequences of crime for offenders is considered an expression of a punitive attitude. This definition also includes opposition to reducing the costs of crime when proposed, such as having an antagonistic stance toward a law that decreases prison sentences for certain crimes. Finally, a favourable opinion for more severe punishments will be considered a necessary and sufficient condition to indicate the presence of punitive attitudes.

1.4. The determinants of punitive attitudes

Having clarified the concept of 'punitive attitudes' used in this thesis, the following section focuses on the scientific literature concerning their determinants. Studying these determinants is important for two reasons: first, it helps contextualise the analysis of punitive attitudes online by identifying factors that could influence measurement. Additionally, since this thesis aims to model such attitudes, the literature review will provide essential guidance for the analysis.

The section will be structured according to the logic of the function-structure model (Maio et al. 2004) of attitudes, incorporating the contextual elements of the ABC model (Guagnano et al. 1995). At each step, the focus will be on precisely identifying

the type of phenomenon being discussed and the causal mechanisms (Hedstrom 2005; Hedström and Bearman 2009; Elster 2015) that link determinants to punitiveness.

1.4.1. Feelings or Emotions

Emotions are integral to understanding human behaviour and the formation of attitudes, yet they are challenging to define. Elster (2015) highlights five key characteristics that define emotions: they involve physiological arousal (such as changes in blood pressure or respiration), are expressed through psychological manifestations (like bodily postures or voice pitch), generate action tendencies, focus on an intentional object, and carry a valence along the pain/pleasure spectrum. For the purposes of this thesis, the terms “feelings” and “emotions” will be used interchangeably. These emotional responses are particularly relevant in the context of crime and punishment, as both direct and vicarious experiences often provoke strong emotional reactions (Garland 1990; Gale and Coupe 2005; Carvalho and Chamberlen 2012; Mastroiocco and Minale 2018; Turner et al. 2021). Such emotions not only shape perceptions of justice but also influence attitudes toward punishment, as evidenced by studies highlighting their mediating effect on punitive attitudes (Treadway et al. 2014; Freling et al. 2020). This interplay between emotional reactions and punitive attitudes highlights the importance of examining how emotional responses to crime shape broader societal perspectives on justice.

Three types of emotions have been predominantly included in studies of punitive attitudes: fear of crime, anger at crime, and empathy. Fear of crime is one of the most common emotional responses studied in the context of punitive attitudes. A key challenge in analysing this response lies in distinguishing between its emotional and cognitive components (Armbrorst 2017; Rader 2017). While the cognitive component relates to beliefs about perceived risk, the emotional component primarily reflects the state of discomfort arising from worrying about victimisation. Although these elements are interrelated, the strength of their correlation can vary among individuals. Various studies have incorporated fear of crime as a factor, positing that punitive responses may stem from a desire to alleviate this concern (Chiricos et al. 2004; King and Maruna 2009; Spiranovic et al. 2012; Armbrorst 2017; Intravia 2019). However, the results across studies have been inconsistent, with some studies showing a positive and significant relationship (Chiricos et al. 2004; Armbrorst 2017; Intravia 2019), others showing mixed results (King and Maruna 2009; Kury and Winterdyk 2013), and others finding no relationship at all (Kleck and Jackson 2017).

Similarly, several studies have identified anger toward crime as a robust predictor of punitive attitudes (Gault and Sabini 2000; Johnson 2009; Hartnagel and Templeton 2012; Bastian et al. 2013; Côté-Lussier 2016; Kort-Butler and Ray 2019). Côté-Lussier & David (2023) understand anger at crime as a state of moral outrage arising from the individual's perception of a moral norm being violated. At a more general level, they understand anger as an action-oriented emotion that arises when an event or situation is perceived to violate one's interests, for example, through deception or injustice. This type of emotion tends to motivate aggressive and hostile behaviour that can act as an incentive to produce punitive attitudes.

Another line of research has examined the relationship between empathy and punitive attitudes (Courtright et al. 2005; Lovegrove 2013; Decety and Yoder 2016). Unnever and Cullen (2009) explore this connection by defining empathy as the ability to experience another individual's emotions as one's own. This capacity for empathy may extend to offenders, increasing the likelihood that individuals will contextualise the criminal act, recognise the offender's potential for guilt or remorse, and feel compassion for the suffering associated with punishment. However, this capacity for empathy can vary depending on the type of crime, leading the same individual to hold punitive attitudes in some cases and more lenient ones in others. A similar and inverse mechanism would also operate on the victim, where the higher the levels of empathy, the greater the punitiveness (Hanslmaier and Baier 2015; Johnson et al. 2020).

1.4.2. Beliefs

A diverse set of beliefs has been employed to explain individuals' punitive attitudes. Central among these are beliefs related to the incidence of crime and the functioning of the penal system. Individuals who perceive crime as increasing or believe the risk of victimisation is high—regardless of actual statistics—tend to exhibit stronger punitive attitudes (Roberts and Indermaur 2007; Spiranovic et al. 2012; Pickett and Baker 2014; Adriaenssen and Aertsen 2015; Armbrorst 2017; Aguilar-Jurado 2018). The explanatory mechanisms vary: this perception may be linked to fear or anxiety (see above) or the belief that the punishment system needs to be "calibrated", adjusting the severity of penalties or enforcement practices to provide adequate deterrence. It may also relate to other beliefs or attitudes, for example, toward younger generations, as suggested by the moral decline model (Tyler and Boeckmann 1997; Unnever and Cullen 2010) – see below.

Similarly, more accurate knowledge about the criminal justice system is associated with lower levels of punitiveness (Falco and Martin 2012; Mitchell and Roberts 2012;

García España 2013; Adriaenssen and Aertsen 2015; Aguilar-Jurado 2018; Kääriäinen 2019). This relationship emerges because individuals often hold inaccurate beliefs about the system, perceiving it to be more lenient than it actually is, which fuels unrealistic demands for harsher punishment. When individuals are presented with factual information about how the system operates and the policies in place, most studies find a decrease in their punitive attitudes (Mitchell and Roberts 2012; Stalans 2013).

Information about the offender can also influence attitudes toward punishment. This effect is particularly evident in vignette studies, where respondents are presented with information about a specific crime and asked to determine the appropriate penalty (Campregher and Jeglic 2016; Socia et al. 2019; Kruis et al. 2023). When asked to recommend penalties for a crime, individuals typically form an image of the crime and the offender, which shapes their judgment of the severity of punishment. Often, this image is exaggerated in terms of violence and dangerousness, so when individuals are provided with accurate information, their punitive response may change (Stalans 2013).

One of the most extensively studied characteristics of offenders is their age. Aizpurúa (2015) identified that punitive attitudes and punitive attitudes toward minors represent distinct constructs. Generally, findings suggest that as the offender's age increases, so does the punitiveness (Cassidy and Rydberg 2020; Sparks 2021; Schutten et al. 2022; Kruis et al. 2023). This correlation is often explained by the notion that younger individuals are perceived as less psychologically developed and, consequently, less responsible for their actions, influencing attribution styles (see below). However, some studies have not found such a correlation (Doherty et al. 2022).

Vignette studies, particularly those focusing on sex crimes, often incorporate the sex of the offender as a key characteristic (Socia et al. 2019; Cassidy and Rydberg 2020; Kruis et al. 2023). Male perpetrators generally receive harsher punishments in these hypothetical scenarios, as they are perceived as more dangerous and harmful. This perception may stem from traditional gender roles and societal expectations, which often portray men as more aggressive and capable of committing serious crimes (Socia et al. 2019). Supporting this, Butcher et al. (2017) analysed administrative data and found that approximately 30% of the gender differences in sentencing could not be explained by other offender or offence characteristics—a finding echoed by Spohn (2013). However, studies examining other types of crimes (Doherty et al. 2022; Burkhardt et al. 2023; Kuettel 2023) do not show an association between the

offender's gender and punitive attitudes, suggesting that this correlation may be specific to the type of offence.

The offender's race has also been considered in several studies. In many cases, the correlation between punitive attitudes and race is attributed to respondents' racial attitudes, which will be explored later when discussing the interaction between punitive attitudes and other attitudes. However, in some instances, this correlation is explained by other beliefs about the offender. Evidence from various studies suggests that Black perpetrators tend to receive harsher sentences in vignette studies (Applegate et al. 1994; Metcalfe et al. 2015; Johnson and King 2017; Peffley et al. 2017; Ramirez 2021), often in interaction with other offenders or offence characteristics. Nonetheless, these findings are not without contention (Doherty et al. 2022; Burkhardt et al. 2023; Kuettel 2023). The mechanisms underlying this bias mirror those related to gender, where Black individuals are perceived as more dangerous and violent. However, Peffley et al. (2017) identify two causal mechanisms that might produce opposite effects for Black offenders, potentially explaining some divergent results in studies that incorporate this variable. The study distinguishes between two primary types of racial attributions: dispositional (blaming Black individuals' behaviour, such as a perceived tendency toward violence) and systemic (blaming discrimination by police and courts). Those who hold dispositional attributions are more likely to support harsh punishments, while those who recognise systemic discrimination tend to be less supportive of punitive measures.

Similar studies have examined ethnicity as an independent variable (Esqueda et al. 2008; Costelloe et al. 2021; West et al. 2021), revealing some evidence of stronger punitive attitudes against ethnic minorities, particularly Latinos in the US. However, the results remain inconsistent (Alvarez and Miller 2017). Deep-seated stereotypes, perceived cultural and economic threats, and the justification of biases through legal or social status have been hypothesised to drive this relationship. Additionally, these studies have identified an association between the immigration status of the offender and punitive attitudes, with a tendency to advocate for harsher penalties for non-citizens.

An important factor that has been studied in the context of jury sentencing (Roberts 2008; Roberts and Sanchez 2015) but has received relatively little attention in the analysis of punitive attitudes is the offender's criminal history (Feather and Souter 2002; Roberts et al. 2008; Roberts and Hough 2011; Spiranovic et al. 2012; Hester et al. 2018). The correlation between criminal history and punitiveness is often explained by perceptions of the offender's dangerousness and potential for rehabilitation, providing incapacitating reasons for harsher penalties. Additionally, recidivism is

typically viewed as evidence of the system's failure to rehabilitate the offender, which may influence the severity of the sentence both for incapacitatory reasons and potentially with the intention of effectively rehabilitating or deterring. Finally, there are also retributive motives for this increased punishment, based on the simple understanding that it is possible to measure the moral character of the offender according to the number of previous offences, and under the notion that “bad guys” require more severe treatment. (Roberts 2008). Public response to specific offenses has emerged as one of the most significant predictors of punitive attitudes when included in the analysis (Cullen et al. 2000; Sanderson et al. 2000; Sööt 2013; Tajalli et al. 2013; Aizpurúa and Fernández 2016; Michel 2016; Vigna et al. 2019; Wozniak et al. 2022). While it may seem intuitive that more severe offences lead to harsher punitive attitudes, the underlying causal mechanism remains unclear. This pattern aligns with a retributive approach, where more severe punishment corresponds to greater harm caused, which is generally consistent with the principles of criminal law. However, the nature of the offence can also indicate the offender's dangerousness, potential for rehabilitation, or even moral character (Vasiljevic and Viki 2013; Wozniak et al. 2022).

As noted in the above explanations, much of the impact of an offender's characteristics on punitive attitudes appears to be mediated by two key beliefs: the offender's perceived dangerousness (Sanderson et al. 2000; Payne et al. 2004; King and Roberts 2017; Rozmann and Walsh 2018; Socia et al. 2019; Kruis et al. 2023) and the offender's potential for rehabilitation or redeemability (Maruna and King 2009; Rogers and Ferguson 2011; Burton et al. 2020; Wozniak et al. 2022). Other offender characteristics have also been manipulated, although to a lesser extent (Edens et al. 2013; Tam et al. 2013; Vasiljevic and Viki 2013; Johnson and King 2017; Wozniak et al. 2022). These include moral character, with offenders perceived as “lazy” or “immoral” often judged more harshly (Tam et al. 2013; Wozniak et al. 2022), attributions of psychopathy, particularly in severe cases like capital murder, have been linked to greater support for punitive measures (Edens et al. 2013). Additionally, physical attractiveness or beauty has been shown to influence perceptions of offenders, with more attractive offenders often eliciting less punitive attitudes, highlighting the role of implicit biases in public judgment (Tam et al. 2013; Wozniak et al. 2022)

Information about the offender and the offence committed also interacts with attribution styles, another element frequently evaluated in studies on punitiveness (Grasmick and McGILL 1994; Cochran et al. 2003; King and Maruna 2009; Falco and Martin 2012). Attributional style refers to how individuals interpret the reasons behind an offender's actions. One of the most common distinctions in the literature is

between dispositional and situational attributions (Pickett and Baker 2014). Dispositional attributions explain the offence due to the offender's inherent characteristics, while situational attributions focus on the offender's environment and circumstances. These attribution styles significantly influence punitive attitudes, as situational attributions tend to reduce the perceived responsibility of the offender and the perceived effectiveness of punishment in preventing future crimes.

The third yet unmentioned component of crime, the victim, has also been incorporated in several vignette studies to analyse its effect on punitive attitudes (Hanslmaier and Baier 2015; Socia et al. 2019; Horstman et al. 2021; Kruis et al. 2023). In general, it is younger and female victims who arouse more punitive attitudes, although this may be a product of the overabundance of vignette studies for sexual offences. The mechanism that would explain this relationship is the helplessness and lack of responsibility of the victim in the incident. Hanslmaier and Baier (2015) also consider victim sympathy, depending on whether the victim has a criminal record, noting that this characteristic can also affect citizens' attitudes.

Trust in the judicial and penal systems has been a significant focus in studies on punitive attitudes, with most findings indicating a negative relationship between trust and punitiveness (Unnever and Cullen 2010; Brookman and Wiener 2017; Singer et al. 2020). Distrust in these institutions can foster punitive attitudes by reflecting a lack of confidence in their ability to protect citizens effectively from crime. When individuals perceive the judicial system as overly lenient or believe that judges are too sympathetic toward offenders, they may view it as failing to deliver justice, leading to demands for harsher punishments to compensate (Cochran and Piquero 2011). Similarly, research on trust in the police has found evidence of a negative relationship with punitiveness (Roberts and Indermaur 2007; Fortete and Cesano 2009; Van Kesteren 2009). The underlying hypothesis suggests that low levels of trust in the police lead to higher punitiveness, as individuals may believe harsher punishments are necessary to compensate for the perceived lack of deterrent power (Sööt 2013). Additionally, the literature has examined other forms of trust, including interpersonal trust (Tyler and Boeckmann 1997; Soss et al. 2003) and trust in government (Unnever and Cullen 2010; Ramirez 2013; Lobos Irrazabal 2021). Sööt (2013) identifies four mechanisms through which high levels of interpersonal trust may decrease punitive attitudes: fostering beliefs in rehabilitation, attributing crime to environmental factors, reducing the desire to inflict suffering, and recognising the potential societal value of individuals, which leads to a preference for more lenient and restorative forms of justice. Meanwhile, the relationship between trust in the political system and punitiveness shows mixed results (Ramirez 2013). Increased distrust could lead to

greater support for harsh treatment, as it raises doubts about the government's effectiveness in ensuring public safety. However, it can also reduce punitive attitudes if the public resists granting more power to the executive branch, fearing potential abuses of authority. Conversely, higher trust could correlate with support for harsher punishments, as individuals may feel more confident in the government's authority to enforce laws.

Earlier, the analysis distinguished between the goals of punishment and punitive attitudes. Previous studies commonly consider punitiveness associated with retributive, incapacitatory or deterrent objectives, while the opposite is true for rehabilitative or restorative objectives (Adriaenssen and Aertsen 2015). However, some studies find positive or non-significant correlations between support for more severe punishments and support for rehabilitative measures (Mascini and Houtman 2006; Unnever et al. 2010). Gromet and Darley (2009) observe, in a set of experiments with university students, that multiple goals of punishment can coexist in an individual's assessment of punishment for a given offence. Oswald et al. (2002) analyse the relationship between the goals of punishment and punitiveness, observing higher punitive attitudes in those who hold retributive and deterrent goals. This relationship can be mediated by the importance given to the different parties involved (offender, victim or society).

Additionally, the literature has incorporated beliefs not directly related to crime into the analysis of punitive attitudes. These beliefs can influence the evaluation of punishment either directly or by affecting other emotions, beliefs, or desires. Different studies have analysed the influence of beliefs regarding personal and contextual economic situations on punitive attitudes, with mixed results (Costelloe et al. 2009; King and Maruna 2009; Lehmann and Pickett 2017; Singer et al. 2020; Singer et al. 2020). For instance, King and Maruna (2009) and Costelloe et al. (2009) included satisfaction with personal economic situation in their studies, suggesting that changes in an individual's economic status can alter their stance on punishment for retributive reasons, as economic hardship may increase victimisation costs. Additionally, challenging economic circumstances within a society might drive potential offenders toward criminal activity, thus heightening the perceived need for deterrence. Other scholars, such as Wacquant (2010), offer a different explanation, arguing that harsher penalties may alleviate the anxiety generated by economic uncertainty in Western societies. However, Lehmann and Pickett (2017) and Singer et al. (2020) reported that economic insecurity can sometimes reduce punitiveness, as individuals facing hardship may empathise with offenders or prioritise social welfare over harsher penalties. For example, Singer et al. (2020) found that personal

economic insecurity led to lower punitive attitudes in some cases, possibly due to concerns about the disproportionate impact of punitive policies on economically disadvantaged groups.

Religiosity has been incorporated into various analyses of punitive attitudes (Roberts and Indermaur 2007; King and Maruna 2009; Unnever and Cullen 2010; Falco and Martin 2012; Pickett and Baker 2014; Brown and Socia 2017; Singer et al. 2020). Religiosity is expected to influence individuals' broader interpretation of the world, including their views on crime and punishment. However, the direction of this relationship depends on the specific content of each individual's belief. A compassionate image of God may promote less punitive attitudes, while religious doctrines based on rigid rules may foster more punitive perspectives by amplifying the symbolic harm of the offence within a retributive framework of punishment. Additionally, the intensity of belief interacts with its content, further complicating the relationship. As a result, empirical research in this area has yielded inconsistent findings.

How individuals interpret their context plays a significant role in shaping punitive attitudes. Singer (2020) found that greater trust in one's neighbourhood correlates with lower punitive attitudes. Additionally, beliefs about the moral context and social change in the immediate environment have been studied as determinants of punitive attitudes (Tyler and Boeckmann 1997; Maruna and King 2009; Unnever et al. 2010). For example, the belief that society is in "moral decline" may lead some individuals to view punishment positively for its expressive capacity to reinforce social order, a perspective that may also be linked to attitudes toward social or generational change (Tyler and Boeckmann 1997)¹.

1.4.3. Experiences

Arguably, the most frequently studied individual experience related to punitiveness is victimisation. The prevailing hypothesis suggests that experiencing victimisation may influence beliefs about the risk of crime and generate emotions such as anxiety, fear, or anger, potentially leading to higher levels of punitiveness (King and Maruna 2009; Unnever and Cullen 2010; Falco and Martin 2012; Pickett and Baker 2014; Armbrorst

¹ It is important to acknowledge that several relevant factors, such as political stance, have not yet been discussed. While these elements encompass beliefs, they also involve emotions and experiences, making it more appropriate to consider them as attitudes related to, but distinct from, punitive attitudes.

2017; Intravia 2019; Singer et al. 2020; Visconti 2020; Ventura et al. 2024). However, the results are inconsistent, with many studies finding non-significant relationships (Maruna and King 2009; Falco and Martin 2012; Singer et al. 2020).

However, given that direct experiences with crime are relatively limited for most citizens (especially in the Global North), researchers have turned their attention to other potential sources of information that might shape perceptions of crime and punitive attitudes. Kort-Butler and Habecker (2018) propose a model emphasising three main factors: media exposure, personal experiences, and personal networks. Several studies have examined the role of media exposure in shaping punitive attitudes (Roberts and Indermaur 2007; Spiranovic et al. 2012; Pickett and Baker 2014; Intravia 2019). The way individuals interact with traditional press outlets and, more recently, with social media platforms like Facebook and Twitter significantly influences the information they receive, shaping their beliefs and feelings about crime. Roberts and Indermaur (2007) highlight that exposure to mass media often leads to distorted beliefs about crime, exaggerating perceived risks and fostering punitive responses. Their analysis reveals a positive and significant correlation between commercial television viewing and punitive attitudes. Spiranovic et al. (2012) report similar findings, while Pickett and Baker (2014) do not find significant effects. Intravia (2019) expands the focus in a more recent study to include traditional media, news consumption on the internet, and social media use. This study concludes that consuming crime-related content on social media is associated with increased punitive attitudes.

To a lesser extent, some studies have explored the impact of personal networks' experiences with crime and the penal system on punitive attitudes (Johnson 2009; Davila et al. 2011; Kleck and Jackson 2017; Kort-Butler and Habecker 2018; Lehmann et al. 2020; Singer et al. 2020). Johnson (2009) includes having incarcerated friends or close relatives as an independent variable, finding a negative and significant effect on punitive attitudes, a result replicated by Davila et al. (2011). In contrast, the direct effect of vicarious victimisation appears to be non-significant (Kleck and Jackson 2017; Lehmann et al. 2020), although it may indirectly influence punitiveness through increased fear of crime (Singer et al. 2020).

1.4.4. Attitudes

This thesis focuses on the punitive attitudes of citizens. It is important to note, however, that attitudes do not exist in the minds of individuals disconnected from each other (Stalans 2013; Albarracin and Shavitt 2018). Attitudes are interconnected within a broader cognitive framework (Elster 2015; Teng et al. 2015), where central

values (Blankenship et al. 2015) and perceived consequences (Lavine et al. 1997) serve as the connecting elements. Studies on punitiveness have sought to understand how various attitudes are related to punitiveness. The following section reviews the antecedents of punitive attitudes that may be considered attitudes in their own right.

An attitude commonly included in studies on punitiveness concerns political attitudes, particularly where individuals position themselves on the left (liberal)–right (conservative) spectrum (Chiricos et al. 2004; Roberts and Indermaur 2007; Costelloe et al. 2009; King and Maruna 2009; Unnever et al. 2010; Falco and Martin 2012; Gerber and Jackson 2013; Pickett and Baker 2014; Adriaenssen and Aertsen 2015; Aguilar-Jurado 2018; Singer et al. 2020; Laterzo 2024). Individuals' political ideology is expected to influence their worldview and attitudes towards punishment. While the literature shows some variation, higher punitive attitudes are generally observed among those with right-wing or conservative political views. Gerber and Jackson (2016) trace several mechanisms that may explain the association between political ideology and punitive attitudes. Their findings suggest that individuals with conservative and authoritarian attitudes tend to view the world in a decadent light, perceive others as dangerous, and place a high value on preserving the status quo or restoring a perceived past social order. These tendencies give rise to punitive attitudes because punishment is seen as a tool for maintaining respect for order and social cohesion. Additionally, conservatives are more likely to attribute crime to personal characteristics rather than environmental conditions, further reinforcing punitive views.

Racism and attitudes toward ethnic or racial minorities have been considered focal antecedents of punitive attitudes. Racial or ethnic prejudice often leads individuals to form mental images of these groups characterised by negative traits. Such prejudices can foster the belief that minorities are responsible for societal crime problems, which, in turn, fuels the perception that these groups do not deserve respect or empathy. This lack of empathy can result in support for harsher penalties (Unnever and Cullen 2010). Brown and Socia (2017) extend this model by incorporating animosity toward poverty alongside racial prejudice, finding that both forms of animosity contribute to higher levels of punitive attitudes.

Silver and Silver (2017) integrate the moral foundations theory, linking punitive attitudes to societal preferences for individualism or social cohesion (Di Santo et al. 2022). The underlying hypothesis suggests that individuals who prefer cohesive societies, emphasising moral foundations such as authority, loyalty, and purity, perceive crime as violating the collective group or societal order. This perception intensifies punitive attitudes, as individuals prioritising these binding foundations

seek to protect group norms and maintain social cohesion (Garland 1990; Garland 2001). Meanwhile, in individualistic societies, the focus shifts to personal well-being and rights. This emphasis results in less punitiveness, as these individuals tend to advocate for fairness and rehabilitation for offenders and victims rather than seeking punishment solely for disrupting societal order.

1.4.5. Socio-demographics

Most studies include socio-demographic variables, either as direct factors of interest or as control variables. These variables describe individual characteristics that, when serving as explanations, must be linked to underlying causal mechanisms involving their mental states. These mechanisms have been explicitly tested in some instances, while in others, the connection remains more speculative or less clearly defined.

The gender of respondents, typically measured by sex, has been included in most studies on punitive attitudes. However, findings are inconsistent, with some studies identifying significant effects in different directions, while others report no significant relationship (Adriaenssen and Aertsen 2015; Aguilar-Jurado 2018). Several factors may account for gender differences in punitive attitudes. Research on gender disparities in attitudes towards probation and punitiveness (Gault and Sabini 2000; Dodd 2018) suggests that variations in risk exposure between men and women could lead to different emotional responses to crime. Additionally, gender effects may be mediated by various other variables, such as authoritarianism, religiosity, and racial prejudice, often difficult to control in non-experimental studies (Stack 2000).

Similarly, age has also been incorporated into most studies (Adriaenssen and Aertsen 2015; Aguilar-Jurado 2018). While the results are inconsistent, several studies have found significant relationships between punitiveness and age (Chiricos et al. 2004; Payne et al. 2004; Hanslmaier and Baier 2015; Silver and Silver 2017), meanwhile others have not found any relationship after controlling for third variables (Hogan et al. 2005; Roberts and Indermaur 2007; Costelloe et al. 2009; Johnson 2009; Spiranovic et al. 2012; Gerber and Jackson 2016; Brown and Socia 2017). Most of these studies have incorporated age as a control variable without elaborating on the causal mechanism. This type of procedure assumes that age is only connected to punitive attitudes due to its effect on third variables. Armbrorst (2017) found moderating effects of age on the relationship between fear of crime and punitive attitudes.

Among socio-demographic variables, educational level stands out as consistently associated with punitive attitudes (Aguilar-Jurado 2018). Generally, studies have found that higher education levels correlate with lower punitiveness (Roberts and Indermaur 2007; Maruna and King 2009; Unnever et al. 2010; Spiranovic et al. 2012;

Singer et al. 2020). Most causal mechanisms hypothesised to explain this relationship are based on the idea that one or more third variables mediate the relationship. Aguilar-Jurado (2018) emphasises the role of education in enhancing knowledge about crime and the reliability of information sources. Additionally, education often correlates with socio-economic status, which may influence an individual's risk exposure or fear of crime. Some studies have also examined the impact of specific fields of study. For example, O'Connor et al. (2011) find that criminology students exhibit significantly less punitive attitudes than students from other fields. Similarly, Costelloe et al. (2018) compare social science students with other undergraduates and observe that the former are less punitive.

Race and ethnicity have been critical variables in various studies on punitive attitudes (Chiricos et al. 2004; Johnson 2008; Maruna and King 2009; Pickett and Baker 2014; Singer et al. 2020). Although results vary, significant relationships often reveal higher levels of punitiveness among the white population. For instance, Johnson (2008) finds that in the United States, punitive attitudes differ between the white and non-Hispanic Black populations. White individuals' greater punitiveness is often linked to racial animosity and a desire to uphold the status quo, while Black individuals' less punitive attitudes may stem from their belief that the justice system is biased against them (see above). Aguilar-Jurado (2018) suggests that race may correlate with other factors, such as economic status, which could explain these variations.

Economic status, typically measured through income, has been included as a control variable in several studies on punitive attitudes (Costelloe et al. 2009; Maruna and King 2009; Spiranovic et al. 2012; Adriaenssen and Aertsen 2015; Silver and Silver 2017; Aguilar-Jurado 2018). However, the findings generally show no significant effects when controlled for third variables such as education or fear of crime (Spiranovic et al. 2012).

To a lesser extent, other studies have incorporated marital status (Costelloe et al. 2009), geographic region (particularly in the United States North-South divide) (Chiricos et al. 2004; Unnever and Cullen 2010; Brown and Socia 2017) and social class (Roberts and Indermaur 2007).

1.5. Summary

Chapter 1 examines the foundational concepts of punishment, punitiveness, and punitive attitudes, laying the groundwork for understanding citizens' responses to crime and deviance. This thesis defines punishment based on the following characteristics: it is imposed on an individual, it entails a loss, and it is carried out for breaking the law. Although the literature tends to emphasise that it should be carried

out by the competent institution, in democratic systems this means the justice system, this thesis understands as punitive attitude also those expressions of desire to punish offenders outside the justice system. Punitiveness is framed as a multifaceted concept that encompasses individual attitudes, state policies, and societal practices advocating harsher responses to crime. Among these, the thesis focuses on punitive attitudes—individual dispositions favouring severe penalties for offenders. These attitudes are shaped by a complex interplay of emotions, beliefs, and experiences, reflecting deeper societal values and cognitive processes. Punitive attitudes are defined as evaluative mental states centred on the intensity of punishment. Personal preferences for harsher punishments indicate greater punitive attitudes.

The chapter further explores the determinants of punitive attitudes, highlighting the roles of emotions, such as anger and fear of crime, alongside beliefs about crime trends, offender characteristics, and trust in justice institutions. Media consumption is shown to amplify punitive attitudes by shaping perceptions of crime. Political ideology, racial prejudice, and moral values further shape how individuals perceive and respond to crime, underscoring the deep connections between attitudes toward punishment and broader societal dynamics. This discussion sets the stage for the thesis's investigation of how digital spaces, particularly social media, reshape discussions on crime and punishment in Uruguay and the UK, providing new insights into contemporary punitive attitudes.

2. Digital Society, digital trace data, media and crime

This thesis aims to examine citizens' punitive attitudes within the highly specific setting of social media, with a particular focus on Twitter. This objective requires a thorough understanding of the broader implications of digitally mediated communications in what will be referred to in this study as a Digital Society. This chapter will explore the implications of social life within the context of advanced digitalisation, particularly as they pertain to social media studies, focusing on analysing crime and punishment in social media contexts.

2.1. Digital Society

Technological change in societies affects how individuals live and relate to each other (McLuhan 2011; Innes et al. 2021). With the beginning of the new millennium, the technological change that has arguably most influenced social life is the expansion and development of Information and Communication Technologies (ICTs), in particular, personal computers, mobile devices, and the Internet (Dufva and Dufva 2019; Levin and Mamlok 2021).

Sundberg (2024) refers to the process of digitalisation as one in which different areas of social life are restructured around digital communications and media infrastructures. Dufva and Dufva (2019) distinguish three concepts. The 'digital' is explicitly based on the technology associated with binary systems, which allows computer systems to be built around them that can be programmed and reprogrammed without the need to modify the physical medium or hardware, as a central feature of technological change. 'Digitisation' is the process of transforming various previously analogue human processes and activities into digital technologies. Ultimately, 'digitality' refers to the impact that these technologies and their corresponding changes have had on social life.

Levin and Mamlok (2021) argue that the emergence of this new digital society involves potentialities that have radically modified the ontological reality of individuals and what it means to be a human living in society. This transformation means the social reality now occurs in a hybrid space between the digital and the analogical. The authors highlight three key transformations shaping digital society. First, they describe the growing difficulty of distinguishing between reality and virtuality, suggesting that these concepts are increasingly intertwined in modern life, challenging dualist perspectives. Second, they note the blurring of boundaries between humans, nature, and artefacts, driven by advances in biotechnology that increasingly link humans to artificial systems. Finally, they discuss the shift from information scarcity to

abundance, emphasising how the sheer volume of available data distinguishes the digital era from earlier societal structures.

Stratton et al (2017) take the definition of Digital Society directly into the field of criminology, arguing for a greater connection between this field of study and the different disciplines that have analysed societal and technological change. The authors emphasise the emergence of Web 2.0 from the 2000s onwards, where the Internet - in contrast to Web 1.0 - is no longer exclusively a tool for receiving information, but also allows for user communication and creativity, giving rise to the 'social web'. This change represents a new space for communication and socialisation between individuals. The next point of transformation comes with the emergence of mobile devices, sharpening this hybridisation of social life while at the same time increasing the amount of individual information collected. These technological developments carry significant implications for criminology, as they create new arenas for studying criminal behaviour, victimisation, and justice responses. This ongoing evolution necessitates an expansion of criminological analysis to encompass techno-social practices, positioning crime as increasingly embedded within digital and social contexts rather than being confined to an offline phenomenon.

2.2. Social Media

2.2.1. A definition in the context of a Digital Society

As Stratton et al. (2017) point out, one of the most critical societal transformations occurs with the emergence of Web 2.0 and, specifically, social media (Edwards et al. 2013; Jiang et al. 2021; Vahed et al. 2024), which is also the medium used for data collection in this research. Alhabash and Ma (2017) distinguish social networking sites as a subdomain of social media. The latter can be defined as any form of computer-mediated communication where individuals present themselves through a personalised online profile and generate or share content with other users (Whiting and Williams 2013; Carr and Hayes 2015). The latter can be understood as a platform where 1) users have identifiable profiles created with information supplied by themselves, by other users, or by the system, 2) articulates information and communication between users that third-party users of the platform can view, 3) users can consume, produce, and interact with content, also generated by other users (Ellison and Boyd 2013). The difference is subtle, but it is defined by the communication from one to many, which, depending on the platform, may include friends, followers, forums, and other options, and by the consolidation of all these options within a specific platform (website or mobile application).

Social media offers a wide-reaching and powerful platform that supports the growth and strengthening of political, economic, and social activities. They facilitate the formation of new types of diverse communities, innovative methods for expressing opinions, and new frameworks for activism (Roth-Cohen and Rashi 2024). However, these digital spaces are not 'passive' spaces where individuals meet; instead, the content users receive is heavily mediated by algorithms generated by the platforms based on user data to maintain and capitalise on engagement. Data processing algorithms act as significant "instruments of perception," subtly shaping which social issues receive collective attention and which are overlooked, heavily influencing social order (Amoore and Piotukh 2015; Innes et al. 2021). Additionally, communication and communities formed on social networking sites can affect social reality and public opinion (Bail et al. 2018; Trottier 2020; Williams et al. 2020; Roth-Cohen and Rashi 2024).

However, these potentialities in communication between users are not without risks. Sundberg (2024), building on the analyses of Beck and Giddens, identifies three key characteristics of the digital risk society. First, it is a society with layered risks, meaning that many solutions to problems brought about by digitalisation involve new risks. These include challenges such as algorithmic biases, unequal access to benefits, cascading errors, and difficulties in understanding and learning from failures. Secondly, Sundberg emphasises the potential for dehumanisation and the exacerbation of digital divides. Dehumanisation occurs as tasks traditionally performed by humans are increasingly delegated to machines and algorithms, which operate with opaque inner functions. This shift has been linked to the erosion of individual autonomy and the reduction of people to mere "users" within digital systems. The digital divide highlights unequal access to technological benefits, disproportionately affecting marginalised groups and intensifying existing societal inequities. Vulnerable populations, such as those at risk of social exclusion, often lack the resources to engage effectively with digital systems, leaving them disadvantaged in areas such as healthcare and education. Thirdly, the emergence of global communication platforms in the private sphere represents a profound redistribution of power among the state, the market, and civil society. This shift is characterised by the concentration of technological and economic power in the hands of a few corporations, often referred to as an "authoritarian technocracy." These entities influence governance and surveillance, challenging traditional democratic mechanisms and raising concerns about privacy, transparency, and accountability in a digitalised world.

2.2.2. Why do people use social media?

Before interpreting any user behaviour on social media or making inferences about the social reality stemming from this behaviour, it is necessary to understand the characteristics of the platforms, their affordances and restrictions, and why and for what purpose individuals use them. The uses and gratifications theory is the most commonly used communication approach to understanding this phenomenon (Whiting and Williams 2013; Alhabash and Ma 2017; Brailovskaia et al. 2020).

The basis of the uses and gratifications theory is quite simple: individuals use means that satisfy their needs and cause gratification (Weaver Lariscy et al. 2011). Alhabash and Ma (2017) highlight five assumptions of the theory based on the literature: 1) Audience members are active, goal-driven consumers of media; 2) individuals use media to fulfil specific needs; 3) different media sources compete with other similar-oriented media; 4) media users are conscious of their interests and motivations, holding certain expectations that guide their media choices; and 5) media users are the ones best equipped to evaluate the quality of media. The theory is not without its critics, in particular, due to its lack of clarity regarding the definition of uses, needs, and gratification; its individualistic approach; and the assumption of user awareness (Ruggiero 2000; Dunne et al. 2010; Alhabash and Ma 2017). Beyond these limitations, the theory has been used extensively in the literature (Dolan et al. 2016; Ng and Zhao 2020; Ng and Zhao 2020; Pelletier et al. 2020; Kim et al. 2021b) and allows an approach to understanding the motivations of users when expressing themselves on the networks, a point that will be fundamental when conceptualising punitive communications on Twitter.

The number of uses and gratifications found for social media varies between studies. Whiting and Williams (2013), in one of the most cited studies, identified ten uses and gratifications that explain why individuals engage with social media. These include *social interaction*, where users seek to connect and communicate with family, friends, and acquaintances. *Information seeking*, as individuals turn to social media for news, events, and educational content. Many users also use social media *to pass the time* or for entertainment, as a tool for *relaxation*, providing an escape from stress or the monotony of daily life. Additionally, it allows users to *express their opinions* through posts, comments, or other forms of engagement. The *communicatory utility* of social media facilitates conversations by giving users topics to discuss, while its *convenience utility* offers an accessible platform that can be used anytime and anywhere. Social media also serves as a medium for *information sharing*, where users share personal updates and content. Lastly, it serves as a tool for surveillance, allowing users to monitor and stay informed about the activities of others.

This set of uses may vary in intensity (Whiting and Williams 2013) and may depend on the particular platform and its potentialities and limitations (Alhabash and Ma 2017; Pelletier et al. 2020). Given that this research is conducted on Twitter (currently X), it is worthwhile to dwell briefly on it – some more specific platform capabilities are developed in the methodological chapter. Twitter allows users to share short messages known as "tweets" of up to 280 characters. Launched in 2006, it became a popular means of communication for individuals and organisations, with over 330 million monthly active users in 2017. Its format emphasises brevity and real-time communication, encouraging users to share thoughts, ideas, and updates with their followers. In addition, users can follow other accounts to see their tweets in their timelines and use hashtags and mentions to participate in broader conversations on specific topics or with other users (Leis et al. 2019; Britannica 2023). Notably, in October 2022, the platform was bought by the Chief Executive Officer of Tesla and SpaceX, billionaire Elon Musk (Jia et al. 2023). This change of hands had effects both on user preference for the platform, given the mediatic and controversial component of Musk's personality (Safak and Sridhar 2022; Chang et al. 2023), and also directly on the platform, from the reinstatement of banned users (Rohlinger et al. 2023), to potential modifications to the nuts and bolts of the technology (e.g. in terms of engagement algorithms) (Barrie 2022).

Based on the Uses and Gratifications studies on social media (Whiting and Williams 2013; Marshall et al. 2020; Pelletier et al. 2020; Spiliotopoulos and Oakley 2020; Tarullo 2020), Twitter is used primarily for consuming real-time information and engaging in discussions related to public affairs, particularly politics and current events. Twitter allows users to express opinions on public matters, often focusing on intellectual discourse rather than personal updates, distinguishing it from other platforms like Facebook or Instagram. Unlike these platforms, which tend to emphasise social connection or visual content, Twitter is more text-centric and favoured for professional networking, information-seeking, and public debate participation.

In this sense, the choice of Twitter for studying punitive attitudes follows a logic related to the specific uses that users make of the platform, in addition to the accumulated literature on the subject and certain methodological advantages associated with data access during the pre-Musk era (discussed in the methodological chapter).

2.3. Media and Crime: continuities and disruptions in the digital society

This thesis primarily examines citizens' reactions to crime-related communications from news outlets and political actors on Twitter. Therefore, it is necessary to briefly review how these topics have been addressed in the existing literature, particularly within the context of a digital society and social media. For both press and political communications, this section begins by briefly reviewing how these issues have traditionally been addressed in the criminological literature, followed by an exploration of the changes that have occurred in the context of the digital society. The chapter concludes by incorporating the limited evidence specifically related to the study of citizen attitudes toward the punishment of offenders on social media.

2.3.1. News Media

The portrayal of crime by the press has long been a significant concern within the criminological literature (Gerbner 1973; Gerbner and Gross 1976; Erickson 1991; Gerbner 1998; Greer 2005; Dowler et al. 2006; Grosholz and Kubrin 2007). This body of literature can be divided into three dominant themes: the content of press communications about crime, the public's consumption of this content and its potential effects on opinions and attitudes, and the production of crime-related content by media companies and communicators (Greer 2009). Central to this thesis are the issues of content and its effects on the audience. Meanwhile, the news production processes can provide context and enhance the understanding of these two aspects. These points are logically interconnected, based on the underlying idea that news content shapes consumers' interpretations of reality (Gerbner 1998; Garland 2000; Näsi et al. 2021), thereby indirectly influencing the functioning of democratic societies where public opinion plays a crucial role.

In terms of the content, most research on media portrayals of crime has consistently highlighted significant distortions between "media pictures" of crime and the "real-world" picture derived from official statistics (Greer 2009). Media representations often exaggerate the levels and risks of severe interpersonal crimes and favour individualistic explanations over structural causes, thus shaping public perception in ways that may not align with empirical evidence (Weitzer and Kubrin 2004; Doyle 2006; Grosholz and Kubrin 2007). Moreover, media portrayals frequently emphasise individual offenders while neglecting broader societal influences on crime, contributing to a narrative that supports punitive criminal justice responses (Reiner 2003; Chagnon 2015). This isolation of incidents from their social contexts presents crime as episodic, leading audiences to interpret such events as random and

universally threatening, which in turn inflates public fear and erodes trust in the criminal justice system as a protective mechanism (Altheide 1997; Greer and Reiner 2012; Kort-Butler 2023). Furthermore, media sources have been criticised for their selective framing, whereby certain types of crime are overrepresented and in ways that perpetuate stereotypes about offenders, especially racial and ethnic minorities, and victimhood (Grosholz and Kubrin 2007). Broadly speaking, the literature appears to agree on certain features of crime reporting that exhibit cross-cultural characteristics and are also consistent over time. Marsh (1991) summarises these in four points: the press tends to over-represent violent crime, this over-representation is unrelated to crime figures, there is an overestimation of the effectiveness of the justice system and the police, and finally, the press fails to give an adequate account of the chances of victimisation, how to prevent crime, or to explain it.

Much of the literature on the effects of consuming crime news (and media violence in general) can be divided into two main themes: the criminogenic effects that such content consumption may generate—where exposure to violence may incentivise criminal behaviour—and the impact on perceptions of crime and its prevalence in society, mostly concerning fear of crime (Gerbner and Gross 1976; Doyle 2006; Greer 2009). This thesis focuses on the latter, specifically on the effects of media consumption on citizens' attitudes towards crime and crime control.

The news media play a significant role in shaping public perceptions of crime, often amplifying and distorting the reality of criminal activity (Reiner 2003; Greer 2009). Media overrepresentation of crime may produce in the audience the perception that crime is more pervasive and threatening than it is, resulting in heightened fear and support for harsh criminal justice responses (Gerbner and Gross 1976; Chiricos et al. 2000; Silva and Guedes 2023). Additionally, the overrepresentation of marginalised groups as offenders and the sensationalism surrounding certain crimes contribute to biased perceptions, reinforcing stereotypes and social divides. However, media influence on crime perceptions is not straightforward and is mediated by various social and psychological factors. The two-step flow model (Choi 2015) emphasises that media content is filtered through opinion leaders who interpret and disseminate information within social networks and then reinterpreted by the final consumer, highlighting the interplay between media messages and individual predispositions (Boda and Szabó 2011). This model suggests that the audience is not a passive recipient of media content; personal characteristics and social context shape how individuals understand and react to crime news.

Finally, the production of crime news is shaped by a complex interplay of selection, processing, and prioritisation of events, influenced by journalists, editors, working

conditions, and news sources (Greer 2009). Powerful criminal justice institutions, such as the police and the justice system, play a crucial role in this process because they consistently provide reliable and reportable crime data. As a result, these institutions have "privileged access" to the media, allowing their perspectives and information to be more easily publicised than those of less powerful or less newsworthy sources (Chermak 1994; Doyle 2006).

Not all events are deemed "newsworthy," and crime news are selected based on criteria known as "news values," which favour events that are sensational, deviant, or disrupt social expectations (Grosholz and Kubrin 2007). These news values ensure that only a fraction of criminal events is reported, often prioritising those with heightened emotional appeal or sensational qualities. This focus on deviance and disruption is particularly characteristic of crime news across different media types and formats, which vary in their approaches and styles.

The nature of crime news production has evolved with the rise of new media. The rise of Web 2.0 allows for greater public participation in creating and sharing news as social media users adopt "gatewatching" roles, actively selecting and curating content across multiple platforms (Stratton et al. 2017; Vicario et al. 2017). The portability and ubiquity of digital technologies have increased the public's exposure to crime news, contributing to what some scholars term "digital spectatorship," which may amplify punitive attitudes. Moreover, social media's instantaneous and interactive nature makes it possible for anyone to record, produce, and share crime content without traditional journalistic standards, thus shaping public perceptions and sometimes even influencing ongoing legal processes (McGregor 2017).

This shift toward digital media has significant implications for audiences who access and interact with crime news. Social media platforms such as Facebook, Twitter, and Instagram are central to how audiences consume news, altering their habits and journalistic routines (Hase et al. 2023). News outlets now adapt their production to align with the "platform logic" of social media, characterised by algorithmic curation, interactivity, and visuality, which differ from traditional mass media logic (van Dijck and Poell 2013; Kort-Butler 2023). For example, Twitter's chronological and highly interactive structure promotes short, real-time updates and visual content, fostering a "continuous, breaking news" logic favouring rapid dissemination over in-depth analysis (Hase et al., 2023). Algorithmic curation, in particular, plays a pivotal role by prioritising content that aligns with user preferences and engagement patterns, often amplifying sensationalist and mainstream content over in-depth or niche reporting (Dujeancourt and Garz 2023).

Digital media also facilitate cross-media landscapes where audiences can selectively engage with topics and information that align with their interests or reinforce their existing beliefs. Unlike the more passive consumption associated with television, online and social media platforms offer interactive and personalised news experiences, allowing users to craft and share their own narratives about crime (Näsi et al. 2021; Kort-Butler 2023). This active engagement is further incentivised by social capital gained through social media participation as users gain recognition and credibility within their networks (Altheide 2013; Phillips and Chagnon 2021).

Social media algorithms have fundamentally reshaped the production, consumption, and amplification of crime news, with profound implications for public discourse (Table 1). Newsworthiness is now heavily influenced by algorithmic preferences that prioritise engagement-driving elements such as conflict, controversy, drama, and shareability, pressuring news outlets to create content tailored to these metrics (Harcup and O'Neill 2017; Munger 2020; Lischka 2021). Li and Xie (2020) conducted an experimental study analysing user interactions with news posts containing visual elements, demonstrating that images and videos significantly enhance attention and engagement. Similarly, Berger and Milkman (2012) analysed viral online content through regression models, revealing that emotionally charged and sensationalist headlines are more likely to be shared. Dujancourt and Garz (2023) employed a difference-in-differences approach to investigate Twitter's transition to an algorithmic timeline, revealing a measurable increase in engagement with sensationalist topics compared to quality journalism. Lischka (2021) employed qualitative content analysis of social media posts and interviews with social media editors, illustrating how platforms like Facebook reward negative or conflict-driven narratives. These dynamics raise critical concerns about the societal implications, including the erosion of journalistic standards, increased public anxiety, and heightened polarisation in digital spaces.

Table 1 Traditional vs Social Media portrayals of crime

ASPECT	TRADITIONAL MEDIA	SOCIAL MEDIA
PORTRAYAL OF CRIME	Exaggerates severe interpersonal crimes and focuses on individual offenders over structural causes.	Sensationalism amplified by algorithmic curation, prioritising emotionally charged and conflict-driven narratives.
FRAMING	Frames crime as episodic, disconnected from social context, inflating public fear.	Interactive and real-time updates; users actively craft and share narratives, reinforcing their beliefs.

PRODUCTION	Dominated by "news values" such as deviance and sensationalism; relies on powerful institutions for information.	Public participation in news creation through "gatewatching"; platform logic emphasises shareability and engagement.
CONSUMPTION	Primarily passive, shaped by mass media narratives and filtered through opinion leaders.	Highly interactive; algorithms personalise content based on user preferences, fostering selective exposure.
EFFECTS ON PUBLIC PERCEPTION	Inflates perception of crime prevalence, heightening fear and support for punitive responses.	Sensationalism drives higher engagement at the cost of quality journalism.
NEWSWORTHINESS CRITERIA	Focuses on emotional appeal, deviance, and disruption; limited selection of events reported.	Algorithm-driven prioritisation of engaging content, such as conflict or drama, and format, such as video and images.
IMPACT ON JOURNALISM	Emphasises professional standards and editorial oversight; relies on traditional gatekeeping mechanisms.	Decline in journalistic standards; pressure to conform to platform metrics for visibility.

Similarly, the analysis of discourses emerging from the political system follows a logic akin to that of the press and news media and can be divided into three areas: the content of political discourse (Oliver 2002; Marion et al. 2009; Pantazis and Pemberton 2012; Fondevila and Navarrete 2013), its production and how it can be explained (Pratt and Miao 2022; Hamilton 2023), and its interaction with public opinion and the media, both as an effect and a cause (Boda et al. 2015; Shi et al. 2020; Karstedt and Endtricht 2022).

Research has shown that, much like the press, political discourses often exaggerate the crime problem by employing emotionally charged narratives centred around fear, victimisation, and security. Drake and Henley (2014) demonstrate, through qualitative analyses of British political speeches and policy documents, how such narratives frame victims as deserving of rights and protection while casting offenders as morally culpable, dangerous, and "other." This framing justifies punitive policies that prioritise retribution over systemic reform. Similarly, Boda et al. (2015) use content analysis to examine political and media discourses from the Hungarian case, finding that penal populism transcends ideological divides, with politicians from diverse parties aligning their rhetoric with public fears to maintain electoral appeal. Their coding of communication materials quantifies the prevalence of narratives emphasising punitive solutions over rehabilitative or structural approaches. Hamilton (2023), drawing on case studies of far-right populist movements across Europe, highlights

how crime-related narratives are intertwined with broader themes such as immigration and social exclusion, exploiting public anxieties to justify exclusionary and punitive policies.

One of the most widely used approaches to explain the emergence and recent consolidation of this type of discourse comes from the framework of penal populism or punitive populism. Politicians capitalise on public fears, anxieties, and perceived insecurities to gain support for punitive policies (Pratt 2007). This framework emphasises the use of emotionally resonant narratives that frame crime as a pervasive threat requiring immediate and forceful responses, often prioritising punishment over rehabilitation or prevention (Drake and Henley 2014; Boda et al. 2015). The political system would not be driven by empirical evidence or long-term policy planning but by a desire to reflect and amplify public sentiment, creating an "us versus them" dynamic that appeals to voters' sense of moral order and justice (Garland 2001; Drake and Henley 2014; Hamilton 2023). Penal populism helps explain why political leaders focus on high-profile or sensational cases, using them to construct broader narratives that suggest leniency within the justice system and a need for stronger law enforcement (Simon 2007). Such discourses serve political purposes by constructing crime as a moral crisis and positioning politicians as defenders of public safety, earning electoral support (Marion et al. 2009).

Regarding the causes and consequences of the political discourses around crime, the relationship between public opinion, political discourse, and crime is complex and contested, with debates surrounding the origins and effects of punitive narratives. One perspective suggests that political discourse is primarily reactive, with politicians shaping their rhetoric in response to what they perceive as public desires for harsher crime policies (Drake and Henley 2014). However, other scholars argue that political discourse can proactively shape public opinion, using agenda-setting and framing techniques to guide how citizens understand and interpret crime and justice issues (Beckett 1999; Boda et al. 2015; Karstedt and Endtricht 2022). Additionally, there is a growing recognition of more intricate feedback loops between public opinion, political discourse, and media coverage. These mutually reinforcing relationships create a dynamic where public perceptions of crime influence political rhetoric, which in turn shapes media representations and vice versa, with all three being further influenced by the actual functioning of the justice system and crime trends (Simon 2007; Shi et al. 2020).

Just as the emergence of the digital society and Web 2.0 has affected how news is produced, distributed, and consumed, it has also brought new possibilities for political communication. Social media platforms enable politicians to bypass

traditional media filters, providing them with a space to craft messages, respond to issues in real-time, and foster a sense of direct connection with voters. This immediacy of engagement enables politicians to react quickly to public sentiment and emerging issues, shaping their discourse based on immediate feedback and metrics such as likes, shares, and comments, which serve as indicators of public support and reaction (Margetts et al. 2015; McGregor 2020).

2.3.2. Public reactions to crime on social media

Although still emerging, some studies have explored citizens' reactions to crime—specifically what may be considered punitive attitudes—on social media through various approaches.

One of the studies closer to this thesis is by Ravid and Dror (2023). They argue that social media platforms like Twitter offer unique methodological opportunities to understand public sentiment around crime and to explore how ordinary people discuss and justify their views on criminal justice and punishment. The authors focus on four high-profile criminal cases in the United States, analysing tweets surrounding pivotal moments such as verdicts or sentencing decisions. These cases—Casey Anthony, Aaron Hernandez, Kimberly Potter, and Nikolas Cruz—were selected due to their media attention and the different procedural stages they represent, with two cases centred on trial verdicts and two on sentencing outcomes. They collected tweets using keyword-based searches, focusing on mentions of the perpetrators' names during key moments in the cases. The authors employ a text-as-data approach to analyse social media discourse regarding criminal punishment, combining two advanced natural language processing (NLP) methodologies. The first is Topic Modelling, an exploratory machine learning technique that uncovers hidden thematic structures in large text datasets, enabling researchers to impose order on vast collections of textual data and identify latent patterns beyond their initial assumptions. This technique is also used in the first empirical chapter of this thesis. The second method is text classification, where predefined categories are assigned to open-ended texts. For this task, the authors utilise GPT-3.5 to classify tweets based on their thematic content without requiring specific supervised training. They found that while much of the discussion centres on the innocence or guilt of the defendants, the authors demonstrate that social media also serve as a vehicle for expressing punitive attitudes and debating appropriate punishment. They further observe that most punitive online attitudes are grounded in retributive reasons, consistent with existing literature about citizens' opinions. Additionally, discussions around crime and punishment often include significant doses of anger, sometimes incorporating elements of hate, such as racist or misogynistic comments.

Other studies have also focused on high-profile crimes to analyse public reactions to them, while not specifically related to punitive attitudes or punishment in general (Milivojevic and McGovern 2014; McEnery et al. 2015; Williams and Burnap 2016; Innes et al. 2018; Powell et al. 2018). Overall, these studies highlight the potential of social media as a platform for public discourse on critical or traumatic events where users can reinterpret the information received from various media and form *ad hoc* communities, such as those dedicated to searching for missing persons or demanding specific responses from authorities. Additionally, social media enables the multiplication of voices transmitting content about these events, generating distinct networks and echo chambers. Moreover, the dynamic nature of social media means that discourses and communications, particularly those surrounding serious crimes, evolve over time as new information becomes available. Milivojevic and McGovern (2014) and Powell et al. (2018) examined public responses to the murder of Jill Meagher, highlighting how social media platforms became a space for collective grieving, meaning-making, and the mobilisation of outrage. They demonstrate that users utilise platforms to demand justice, reinforce community values, and criticise systemic failures, illustrating the role of social media in shaping collective responses to violent crimes. McEnery et al. (2015) analyse press and social media reactions to ideologically inspired murders, using corpus linguistics to show how public discourse online focused on constructing narratives of guilt and ideological extremism. Their findings emphasise how these narratives reinforce divisions and stereotypes, amplifying the polarisation of public opinion. Similarly, Williams and Burnap (2016) focus on cyber hate on social media in the aftermath of the Woolwich terror attack, employing supervised machine learning to analyse hate speech patterns. They reveal that high-profile crimes can trigger spikes in cyberhate, targeting specific ethnic or religious groups, and demonstrate the role of social media in both amplifying and combating such discourses. Innes et al. (2018) propose the "Ten Rs" framework to explain social reactions to high-profile events on social media, emphasising how platforms facilitate rapid responses, the reproduction of information, and the reinterpretation of narratives over time.

Several studies have explored the phenomenon of digital vigilantism, also known as "digilantism," where social media users mobilise to identify, shame, and punish individuals perceived to have committed social transgressions or crimes. The rapid spread of moral outrage characterises this informal justice-seeking and calls for retribution, often amplifying discriminatory and punitive attitudes. Galleguillos (2022) examines digital vigilantism as a model rooted in moral judgment and social

sanctioning, highlighting how platforms like Twitter and Facebook enable users to bypass traditional legal frameworks in favour of immediate punitive action.

One group of studies that has analysed citizen reactions to crime on social media has focused on the expression of fear of crime or safety. Prieto Curiel et al. (2020) examine how social media users express fear of crime, demonstrating that spikes in discussions about safety often follow high-profile crime events. Using geolocated tweets, the study reveals that fear-related discourse is frequently concentrated in specific urban areas, suggesting that the online expression of fear reflects localised concerns about crime and insecurity. Similarly, Chaparro et al. (2021) analyse Twitter data to quantify perceptions of security, comparing these with official crime statistics. Their findings indicate a weak correlation between actual crime rates and online expressions of fear, highlighting the influence of media coverage and public sentiment in shaping perceptions. Both studies underscore the potential of social media platforms to amplify fear of crime, as users share and interact with content that reinforces emotional reactions rather than objective risk assessments. This amplification of fear may also influence punitive attitudes, as heightened insecurity can lead to stronger support for retributive justice measures.

While some incipient studies have begun to address the problem of punitive attitudes online, the field remains understudied. The only study to date, based on the literature search conducted in this thesis, that addresses the problem directly is Ravid and Dror (2023). While the study represents an important advance in the field, it logically does not cover all potential areas of study regarding online punitive attitudes. First, the study employs unsupervised techniques that have not been specifically designed for classifying punitive attitudes. Secondly, the study focuses on four cases in the United States. It is, therefore, difficult to know both the specific effects of each case on the discussion and the particularities of the US cultural context. Third, the study does not leverage the temporal granularity of social media data to analyse variation in these attitudes, nor does it utilise the available metadata to estimate possible user-level determinants. Moreover, while other studies have addressed the problem indirectly, these weaknesses seem to recur. This thesis represents the first study of cross-cultural online punitive attitudes using supervised learning techniques specifically designed for the collection and quantification of these attitudes in social media. In addition, it is the first study to analyse the determinants of online punitive attitudes and their temporal variation.

2.4. Summary

Chapter 2 examines the impact of digitalisation on society, focusing on how social media reshapes discussions around crime and punishment. It introduces the concept of the Digital Society, where advances in Information and Communication Technologies (ICTs) have transformed human interactions, blending the boundaries between physical and digital realities. An abundance of data, algorithmic mediation, and the restructuring of social life around digital infrastructures characterise this hybridisation. Social media platforms, central to the Digital Society, play a pivotal role in reshaping public discourse. These platforms are not neutral spaces, but rather are mediated by algorithms that prioritise engagement and influence the visibility of content. This mediation shapes public perceptions, amplifying certain narratives while sidelining others. Social media offers affordances such as real-time communication, community-building, and public participation, which enhance its utility for expressing opinions and engaging in activism. However, it also brings risks, including algorithmic biases, digital divides, and the concentration of power in private corporations, which influence social dynamics and perceptions of justice.

The chapter also highlights the role of news media and political discourse in shaping public attitudes toward crime and punishment. Traditional media often exaggerates crime levels and emphasises sensationalist narratives, inflating public fear and reinforcing punitive attitudes. With the rise of digital media, these portrayals have become more interactive and personalised, amplifying sensationalist content through algorithmic curation. Emerging research on public reactions to crime on social media demonstrates its potential as a platform for expressing fear, outrage, and punitive attitudes. High-profile cases often trigger spikes in discourse, with users debating justice outcomes, expressing moral outrage, and even engaging in digital vigilantism. Despite its potential, the study of punitive attitudes on social media remains underdeveloped. Existing research has explored public sentiment surrounding specific cases, but it often lacks cross-cultural analysis or advanced techniques to quantify these attitudes. This thesis addresses these gaps by employing supervised learning methods to study the expression and determinants of punitive attitudes on Twitter, comparing the dynamics in Uruguay and the UK.

3. Methodology

3.1. Introduction

The previous sections introduced the main objectives guiding this thesis, defined the concept of punitive attitudes, summarised the most important effects and determinants found in the literature, and introduced the role of digital society and social media in studying crime and punishment. This section presents the methodology for analysing punitive attitudes on Twitter, comparing the UK and Uruguay in 2022. It begins with explaining the research's ontological and epistemological assumptions, followed by a description of the research design and questions. Next, the data collection strategy is outlined, followed by a discussion of the quantitative content analysis strategies used for descriptive and exploratory analysis, including topic modelling and sentiment analysis. The section also details the Machine Learning techniques applied for the automatic classification of punitive communications, which form the dependent variable for subsequent analysis. Finally, it introduces the statistical models used to analyse the determinants of punitive attitudes, including multilevel Generalised Linear Models (GLMs) for cross-sectional analysis at the tweet, individual, and news item levels, and AutoRegressive Integrated Moving Average with eXogenous inputs (ARIMAX) models for time series analysis of the fluctuations in punitive attitudes by country.

3.2. Post-positivism and critical realism

This thesis is grounded in a post-positivist social research philosophy, as outlined by Bachman and Schutt (2013). This perspective ontologically assumes the existence of an external reality governed by objective mechanisms akin to the positivist tradition. However, it acknowledges that access to this reality and knowledge production are inherently imperfect, constrained by the methods and strategies employed, which inevitably introduce some degree of partiality and bias. The inability to directly access the object of study highlights the importance of using diverse analytical strategies and achieving intersubjective agreement within the scientific community, emphasising transparency throughout the research process—from theoretical foundations to data analysis. Based on the post-positivist philosophy, this thesis assumes a critical perspective at the epistemological level but a realistic one at the ontological level. This posture, called Critical Realism, suggests that fallible subjective interpretations produce approximate knowledge of an assumed real external world because they are formed by the conceptual frameworks in which the researcher operates (Lawani 2021).

Based on the previous assumptions, this thesis advocates for a Critical Multiplism approach (Letourneau and Allen 1999). Given the imperfect knowledge that science can produce through research tools, using multiple approaches is not only unproblematic but desirable. This approach allows for the progressive delimitation of the problem and the identification of convergences from different perspectives. In the following section, this idea will be revisited in the discussion of the types of information used and the analysis strategies within the research design.

3.3. Research design, questions, and objectives

Following the goals of social research proposed by Jegede (2021), this thesis attempts to *describe* news media and political communications about crime in Uruguay and the UK in conjunction with citizen response to them, to *categorise* these communications, in particular those that can be considered punitive, to *correlate* citizens' online punitive attitudes with third variables of interest, and to *compare* these elements between the two selected countries. Although the thesis discusses potential explanations, it is not in a position to make causal inferences, given the limitations of the design. It is, therefore, a descriptive, categorical, correlational, and comparative project.

To answer the research questions and achieve the objectives, data were downloaded from Twitter for both countries in 2022. Punitive attitudes, the main variable of interest, were inferred through user communications in response to news or political tweets about crime. Human assistants first had to annotate these data to enable statistical analysis of this information. This interpretative process is central to the artificial intelligence training that allows the text to be translated into a dichotomous variable indicating the presence or absence of punitive opinions, which positively evaluate increased punishment. In this sense, although the thesis primarily employs quantitative strategies based on the numerical coding of the variables of interest, it also incorporates a qualitative thematic analysis component as a starting point. The details of this process are outlined in the following sections

The analysis strategy designed for answering the questions with the collected data follows the following steps (presented as ordered in the subsequent chapters of the thesis):

The first empirical chapter addresses research questions:

- 1) Can reliable and valid measures of punitive attitudes be created through user-generated text data collected from social media? If so, how prominent is the

discussion of punishment, particularly punitive attitudes, within the broader online public debate about crime?

- 2) What is the general context of the discussion on punitiveness? What is the public talking about when discussing crime on social media?

Quantitative textual data analysis, topic modelling, and sentiment and emotion analysis techniques are used to answer these questions. The details of these techniques are developed in the following sections of the chapter.

The second chapter elaborates on question 1), and addresses the question:

- 3) What are the determinants of punitive attitudes online? To what extent do these coincide with or differ from the determinants analysed using traditional methods?

It utilises the automatic classifiers developed within the framework of this thesis for both countries to obtain the dependent variable of interest. A series of independent variables is then collected based on textual data and metadata from Twitter, including data about the tweets, users, and news items or political communications, to model the determinants of punitive attitudes using multilevel GLMs.

The third chapter deals with the question:

- 4) What is the explanatory capacity of Twitter-based measures of punitiveness to understand cognate offline and online phenomena?

Time series models, particularly ARIMAX, are estimated to analyse how the variation in punitive attitudes covaries with other phenomena of interest, such as daily crimes, political communications, and different types of press communications.

3.4. Case selection

Even though the selection of cases is partly driven by practical considerations (the research is conducted at a British university, while the funding comes from Uruguay), the interpretation of the results follows a logic in which these countries are treated as representing specific characteristics of the global North and South. This is significant given the multiple macro-structural factors, such as crime and violence rates, political culture, social policy, economic development, and inequality, that can shape the formation and diffusion of punitive attitudes and punitive public policy (Lappi-Seppälä 2013; Sozzo 2022; Clegg et al. 2024).

Strictly in terms of crime, the United Kingdom has experienced a substantial decline since the 1990s, particularly in violent and property offences. The homicide rate stood

at 0.93 per 100,000 inhabitants (ONS 2024). In recent years, however, many of these declines have stabilised, reaching a plateau, and in some cases, even showing signs of reversal (ONS 2024; ONS 2025). The implications of these trends for punitive attitudes must therefore be considered with caution, especially given the influence that perceptions of worsening crime conditions or deteriorating moral values may exert on such attitudes (see section 1.4.2). Moreover, previous studies have demonstrated a stronger connection between British citizens' punitive attitudes and "real-crime" figures compared to their U.S. counterparts. This suggests that recent crime levels may have had a measurable effect on punitiveness (Jennings et al. 2017; Enns et al. 2022; Tiratelli 2024).

Beyond these considerations, time-series evidence indicates a sharp decline in punitive attitudes in the United Kingdom since the late 1990s (Jennings et al. 2017; Tiratelli 2024). More recently, however, between 2019 and the present, the trend has remained relatively stable, with around 65% of Britons believing that sentences for criminals are not harsh enough and only 12% considering them adequate (Kirk 2022b; YouGov 2025a). Attitudes toward the death penalty reveal further complexity: while 40% express support and 50% opposition in general terms, support rises when the question refers to specific offences. Britons are more likely than not to endorse the death penalty for the murder of a child, terrorist-related killings, or cases of multiple murder. These patterns underscore the nuances involved in measuring and interpreting punitiveness, since survey items on the topic are not necessarily equivalent (Trajtenberg and Ezquerro 2025).

Regarding feelings of safety, a representative survey conducted by Ipsos UK in 2022 (Home Office 2023) found that the majority of respondents felt safe in their local area: 78% strongly or somewhat agreed, while only 11% strongly or somewhat disagreed. Yet, when asked about the most significant problem in their area, crime and anti-social behaviour were most frequently cited, accounting for 48% of responses. By contrast, when asked about the most significant problems facing the country, only around 15% identified crime as the most significant problem (YouGov 2023b). Levels of institutional trust also reveal important patterns. In 2022, trust in government stood at 35%, with 49% expressing distrust and the remainder neutral. Trust in Parliament (where the political communications analysed in this thesis originate) stood at 34%, with 46% expressing distrust. By comparison, trust in the police was considerably higher, at 65% (23% expressing distrust), and confidence was even stronger in the courts and legal system, where 68% expressed trust and 18% distrust (ONS 2022). Despite relatively high levels of trust in key justice institutions, there is nonetheless some evidence of growing support for vigilante justice in the United Kingdom,

particularly on social media (Tippett 2022) and within specific far-right movements (Ralph-Morrow 2019).

In economic terms, the United Kingdom's GDP in 2022 was approximately 3.11 trillion dollars, representing a growth rate of 4.84%. GDP per capita (in 2015 dollars) stood at 47,682 dollars, reflecting an increase of 3.88%. Inequality, measured by the Gini index, was 32.4 in 2022. Poverty (without digging into the complexities of cross-national comparisons) was only 1% of the UK population in 2021, measured by the number of people living on less than 8.30 dollars per day. The share of the urban population residing in slums was 0.16%. The unemployment rate (for individuals aged 16 and over, seasonally adjusted) stood at 3.8%, while the economic activity and inactivity rates were 78.1% and 21.9%, respectively (World Bank 2025).

Turning to the functioning of the justice system, the United Kingdom has the highest incarceration rate in Western Europe (Jones and Lally 2025), with 135 prisoners per 100,000 inhabitants in 2022 (ICPR 2025). Additionally, England and Wales impose more life sentences than Germany, Russia, Italy, Poland, the Netherlands and Scandinavia combined (Vannier and Nellis 2023). Moreover, Average prison terms have lengthened in recent years, driven by legislative reforms that increased maximum penalties for certain offences (Jones and Lally 2025). Meanwhile, community sentences declined by more than 50% between 2012 and 2022, falling from 12.3% to 6.6% of all sentences (National Audit Office 2023). The minimum age of criminal responsibility, in England and Wales, is 10 years, meaning that a child from that age can be arrested and sent to court if they commit a criminal offence (Brown and Charles 2021). The Anglo-Saxon model of criminal justice has often been characterised as fostering a culture of retributive punishment, where sanctions are justified primarily by the offender's moral desert and the need to express societal condemnation (Monterosso 2009). A broader tendency toward individualism in legal and political culture underpins this tradition (Kornhauser 2015), in which personal responsibility and moral agency are emphasised over structural or social explanations of offending. Within this framework, punishment functions not merely as a tool of deterrence or incapacitation but as a symbolic reaffirmation of moral order, a public act that communicates shared values and boundaries (Garland 2001; Brown 2009).

Politically, the United Kingdom is classified as a full democracy, scoring 8.28 in the 2022 Democracy Index and ranking 18th globally (Economist Intelligence Unit 2023). Voter turnout in the 2019 General Election was 67.3%, with the Conservative Party securing 43.6% of the vote and 56% of parliamentary seats (House of Commons 2020). In terms of ideological self-placement, the largest category in 2022 was the "centre" at around 23%, followed by "slightly left-of-centre" and "slightly right-of-

centre,” each at approximately 14%. Smaller proportions identified as “strongly left” (around 10%) or “strongly right” (around 7%) (YouGov 2025b).

Finally, in a study that seeks to understand attitudes through the analysis of social media, it is essential to consider patterns of internet access and usage. According to the Office for National Statistics (ONS 2020) in 2020, 95% of adults in the United Kingdom were internet users, including 100% of those aged 16–34 and 99% of those aged 35–44. Data from the UK telecommunications regulator, Ofcom, indicates that the share of households without internet access fell from 11% in March 2020 to just 6% in March 2021, suggesting that the pandemic accelerated both internet penetration and the development of digital skills (Ofcom 2021). Concerning social media, and Twitter in particular, the UK had 16.7 million users in 2022 (Statista 2023). A YouGov survey (2023a) further reported that in July 2022, 49% of adults held a Twitter account, although 12% stated they used it once a month or less.

Uruguay, by contrast, exhibits levels of violence and crime more characteristic of the Global South. Unlike the United Kingdom, Uruguay has experienced a marked increase in crime over the past three decades, particularly in violent offences such as homicide, robbery, and domestic violence (Vigna et al. 2025). In 2022, the homicide rate reached 11.2 per 100,000 inhabitants, almost double the global average, around ten times higher than in the UK, and among the highest in South America, surpassed only by Venezuela, Brazil, and Colombia (Rojido et al. 2023; Ministerio del Interior 2024).

According to the 2022 wave of the World Values Survey conducted in Uruguay, 54.6% of respondents opposed the death penalty (categories 1–4 on a Likert scale where 1 indicates that the death penalty is “never justifiable” and 10 that it is “always justifiable”), while only 15.5% expressed support (categories 6–10) (World Values Survey Association 2022). Drawing on slightly older data, one of the most comprehensive national surveys on the topic found that in 2018, around 75% of Uruguayans supported a general increase in penalties for all crimes (Vigna et al. 2019).

These findings correspond with comparatively higher levels of insecurity in Uruguay than in the United Kingdom. In 2021, 43% of Uruguayans reported feeling “very unsafe” or “somewhat unsafe” in their own neighbourhood with regard to the risk of being assaulted or robbed (LAPOP 2023). Also, in contrast to the UK, the Uruguayan population has consistently identified crime and security as the country’s most important problem in recent years, reaching peaks of nearly 45% of respondents. This concern was only overtaken by the economy in 2020 (Latinobarómetro 2023). Patterns

of institutional trust in Uruguay, however, resemble those observed in the UK. According to LAPOP (2023), 44.7% of respondents reported low trust in government (levels 1–3 on a 7-point scale), while 42.5% expressed high trust (levels 5–7). For political parties, 49.3% indicated low trust compared with 29.6% expressing high trust. Although LAPOP does not provide specific data on trust in parliament, these figures for political parties offer a valid proxy. Trust in the police is somewhat higher, with 52% of the population reporting confidence (levels 5–7) compared to 28% expressing low trust (levels 1–3) in 2018/19. By contrast, trust in the judiciary remains relatively weak: only 33% of respondents stated that they had some or a great deal of faith in the judicial system to punish the perpetrator of a robbery or assault, while 67% reported having little or no faith.

Uruguay's GDP in 2022 was approximately 70.59 billion dollars, reflecting a growth rate of 4.49%, which is broadly similar to that of the United Kingdom. GDP per capita (in 2015 dollars), however, was much lower at 18,228, although it still represented a growth rate of 4.66%. Inequality, measured by the Gini index, was higher than in the UK at 40.6. The poverty headcount ratio at 8.30 dollars per day stood at 6.3% of the population, while 1.3% of the population lived in slums (World Bank 2025). Labour market indicators also reveal a less favourable picture: the unemployment rate was 7.9%, and the activity rate 62.7%, both significantly less advantageous than in the United Kingdom (INE 2023a).

Examining the functioning of the justice system, Uruguay and the United Kingdom display some striking similarities. In 2020, Uruguay's incarceration rate was 372 per 100,000 inhabitants, the highest in South America (Amnesty International USA 2021). In this respect, both countries rank at the top within their respective regions; however, Uruguay's concentration of prisoners is significantly higher. The country's incarceration rate has also been rising steadily for at least two decades (ICPR 2024). In other respects, however, the Uruguayan justice system is less punitive than its British counterpart. Uruguay abolished the death penalty in 1907, several decades before the United Kingdom, and its legislation does not provide for life imprisonment. The maximum custodial sentence is 30 years, extendable to 45. Moreover, the age of criminal responsibility is 18, substantially higher than in England and Wales. Uruguay's criminal justice tradition has historically reflected a more eclectic and, at times, liberal-guarantist orientation, strongly influenced by continental European codification, particularly from Italy and Spain. Yet since the mid-1990s, a "legislative fever" has driven the rapid proliferation of new offences and harsher penalties, often creating tensions with this liberal-democratic tradition (Aller 2010).

Politically, Uruguay is also classified as a full democracy, scoring 8.91 in the Economist's Democracy Index, ranking as the most democratic country in the Americas and 11th worldwide (Economist Intelligence Unit 2023). Voter turnout in the 2019 general election was 90.1%, in a context where voting is compulsory (Inter-Parliamentary Union 2019). Although the left-wing coalition Frente Amplio was the most-voted party in the first round, with 40.49% of the vote, Uruguay's electoral system requires a runoff if no candidate secures an absolute majority. In the second round, a coalition of centre-right parties (the National Party, the Colorado Party, Cabildo Abierto, and the Independent Party) prevailed with 50.79% of the vote, electing Luis Lacalle Pou of the National Party as president. In terms of ideological self-placement, data from 2018/19 show that 38% of Uruguayans located themselves on the right (positions 6–10 on a Likert scale where 1 indicates Left/liberal and 10 Right/conservative), 37% on the left, and 25% at the centre (LAPOP 2023).

One of the challenges of conducting social media-based research in the Global South lies in the persistent inequalities in access to Information and Communication Technologies (Robinson et al. 2020b). Uruguay, however, has been a regional pioneer in implementing universal access policies, achieving penetration levels comparable to those of European countries (Robinson et al. 2020a). This makes the country a particularly valuable case for comparative study. According to ITU data, in 2022, 91% of Uruguayan households had internet access, covering 94% of the population (International Telecommunication Union 2022). In the same year, Uruguay had approximately 575,900 Twitter users (Kemp 2022). Survey evidence further indicates that 26.3% of the population reported having a Twitter account, with 66.2% of these users accessing the platform at least once a week, while the remainder reported less frequent use (INE 2023b).

Taken together, these country profiles illustrate the potential of the UK and Uruguay as a productive comparative pairing. While each presents unique historical and institutional trajectories, they also exemplify broader patterns often associated with the global North and South. The United Kingdom, a wealthy Northern democracy with a declining crime rate, strong state institutions, and a retributive penal tradition, provides a context where punitive attitudes persist despite relatively favourable conditions of security and stability. Uruguay, by contrast, embodies a Southern setting where rising insecurity, inequality, and distrust in justice institutions coexist with a historically liberal legal framework, producing an environment in which demands for harsher punishment have grown more pressing.

This contrast enables the study of how punitive attitudes are shaped not only by immediate crime conditions but also by broader structural and cultural differences

between North and South. At the same time, both countries share important features, high levels of democratic consolidation, strong traditions of political participation, and widespread access to digital technologies, which make them particularly suitable for a comparative study of punitive attitudes expressed on social media. By bridging North–South contexts while holding certain institutional and technological preconditions constant, the UK and Uruguay together provide a specific vantage point to examine how global and regional forces intersect in the formation and diffusion of punitive attitudes.

3.5. New and Emerging Forms of Data

3.5.1. Advances and limitations in the measurement of punitive attitudes

The measurement of punitive attitudes has advanced significantly since the initial studies of the 1970s to the present day (Wood and Viki 2001; Aguilar-Jurado 2018). The first studies included only very general measures of attitudes toward sentencing and punishment, usually based on a single item and with minimal context (e.g., support for the death penalty or a general increase in sentences). Such studies may overestimate the punitive attitudes of individuals, as they do not provide information on other types of measures (such as rehabilitative measures) and do not consider the characteristics of the crime, the victim, or the offender (Stalans 2013).

Progressively, studies have become more sophisticated in their measurement strategies. First, some surveys included questions about specific cases using vignettes (case-scenario). These studies allow not only the control for crime characteristics but also their manipulation in experimental contexts (Campregher and Jeglic 2016; Jahnke 2018; Socia et al. 2019; Horstman et al. 2021). Other studies have used batteries of questions to strengthen the validity of the measures used through psychometric analysis strategies like exploratory and confirmatory factor analysis (Ortet-Fabregat and Pérez 1992; Mascini and Houtman 2006; Piquero et al. 2010; Ramirez 2013; Aizpurúa 2015; Maguire and Johnson 2015; Armbrorst 2017). Finally, qualitative strategies have been used to explore how factors like religion, media, and neighbourhood contexts shape punitive attitudes by analysing individual perceptions and cultural influences (Cook and Powell 2003; Boda and Szabó 2011; Leverentz 2011).

However, this methodological sophistication of previous studies is not without its limitations. Surveys and interviews typically provide a static snapshot that is insensitive to the dynamics of changing and real-time flows of citizens' opinions over

weeks and months (Williams et al. 2020). Another important aspect is that punitiveness surveys are focused on atomised individuals and hardly manage to capture existing networks of communication, exchange, and discussion (Edelmann et al. 2020). Additionally, using surveys to measure sensitive or controversial issues may be subject to social desirability bias, where respondents tailor their responses to what they perceive as expected by the interviewer or the community (Stephens-Davidowitz 2018). Finally, the use of the above techniques has been heavily based on cognitive components, overlooking the behavioural component that these attitudes may generate (Trajtenberg et al. 2024).

3.5.2. NEFDs Potential

As previously suggested, some of the limitations of surveys can be addressed by complementing them with the use of New and Emerging Forms of Data (NEFD)². NEFDs are multimedia data digitally recorded through various interactions between humans and machines (Radanliev and De Roure 2023). The expansion of the Internet for personal use and its application in various kinds of processes and objects led to an exponential growth of this type of data (Bail 2014; Edelmann et al. 2020).

A key advantage of NEFDs is their ability to capture the spontaneous and dynamic nature of public opinion. For example, social media discussions about high-profile criminal cases often unfold in real time, providing insights into how punitive attitudes evolve immediately following a court decision or media report (Ravid and Dror 2023). Similarly, digital trace data from online petitions, comment sections, or search engine queries can reveal behavioural dimensions of punitiveness, what people do when confronted with crime-related issues, rather than what they merely claim in a survey (Stephens-Davidowitz 2018; Edelmann et al. 2020).

NEFDs also allow researchers to examine large-scale interaction patterns that are difficult to detect through conventional survey instruments. Instead of isolating individuals, NEFDs highlight networks of communication, enabling analysis of how punitive discourses circulate, gain traction, or fragment across different communities (Bail 2014). This provides a valuable corrective to the “atomised individual” problem in survey research, by situating attitudes within broader social dynamics and contexts of influence.

² Many names have been used to refer to these new types of data, one of the most common being Big Data (Bail 2014). Additionally, the concepts of Digital Trace Data (Lazer et al. 2009), Social Media Data (Edwards et al. 2013), and Smart Data (Alsharif et al. 2020) have been used.

Furthermore, NEFDs facilitate longitudinal and real-time monitoring of attitudes, overcoming the static “snapshot” limitation of surveys. Digital traces enable the study of shifts in opinion before, during, and after critical events—such as terrorist attacks, changes in criminal law, or viral news stories, thus providing greater temporal sensitivity to the dynamics of punitiveness (Innes et al. 2018; Williams et al. 2020).

Importantly, NEFDs should not be viewed as a substitute for traditional methods but as a complementary resource. Integrating survey data with NEFDs can validate findings, triangulate results, and open new opportunities for mixed-methods approaches that combine breadth, depth, and contextual sensitivity (Edelmann et al. 2020; Hofman et al. 2021). At the same time, these potentials come with methodological and ethical challenges. Issues of representativeness are crucial: not all groups participate equally in online spaces, and digital traces may reflect the voices of younger, more technologically engaged populations (Tufekci 2014). Moreover, platform-specific dynamics (e.g., algorithms, moderation, bot activity) may distort observed patterns. Ethical concerns also arise around privacy, consent, and the responsible use of personal data, requiring careful methodological safeguards and transparency (Salganik 2019).

3.5.3. Twitter Data

Twitter allows users to share short messages known as “tweets” of up to 280 characters. Launched in 2006, it has become a popular means of communication for individuals and organisations, with over 330 million monthly active users in 2017. Its format emphasises brevity and real-time communication, encouraging users to share thoughts, ideas, and updates with their followers. In addition, users can follow other accounts to see their tweets in their timelines and use hashtags and mentions to participate in broader conversations on specific topics or with other users (Leis et al. 2019; Britannica 2023).

Until 2023, Twitter’s academic API offered several options for downloading information. In this regard, several alternatives were available for studying punitive attitudes. Four major non-exclusive types of strategies emerged from the literature review:

- Downloading data around events (e.g., Williams and Burnap 2016; Powell et al. 2018; Harb et al. 2020)
- Downloading data around topics (e.g., Kostakos 2018; Rodriguez et al. 2020; Hu and Kearney 2021)

- Downloading geo-localised data (e.g., Flores 2017; Ozalp et al. 2020; Williams et al. 2020)
- Downloading interactions around users (e.g., Garimella et al. 2016; Zijian and Kenneth 2021; Cullen and Williams 2022; Oliveira et al. 2022; Cullen and Williams 2023)

A common strategy in Twitter studies involves selecting a case of interest and downloading associated tweets, typically through keyword searches or, in some instances, using geo-location strategies. For example, Williams and Burnap (2016), in one of the early studies in Computational Criminology, collected data around the 2013 Woolwich (London) terrorist attack to analyse the emergence of cyber-hate directed at Black Minority Ethnic (BME) and religious groups. Similarly, Powell et al. (2018) used Twitter data to reconstruct the online narrative surrounding a case of violent crime in Australia, exploring the collective meaning-making practices that emerge in response to public crime events in a digital society. Harb et al. (2020) utilised Twitter to examine the emotional reactions to mass shooting incidents in the United States.

A similar and widespread strategy in studies conducted on Twitter involves collecting tweets around specific topics. Instead of framing the search around a specific event, the study tries to capture tweets referring to a subject by searching particular keywords (including hashtags). This strategy is often anchored in geo-referencing, although it is not necessarily so. Kostakos (2018), for example, performs a targeted download of all tweets in English linked to organised crime, terrorism, and the mafia through keywords for a month to understand their representations in social media. Rodriguez et al. (2020) downloaded data on the feminist movement #LasTesis, which has a strong presence in the media and commonly uses a specific set of hashtags that facilitate tracking to analyse the main topics around it. In addition, Hu and Kearney (2021) examine gender differences in the political debate occurring on social media by searching English tweets based on a validated set of words that capture political discussion.

Moreover, on many occasions, the research problem requires the geographical delimitation of the collection. Since Social Media is a collection of virtual platforms, this can bring certain complications. Twitter allows users to geolocate their tweets, making this information the most direct strategy. Williams et al. (2020), for example, collects geo-referenced tweets in London, which they then classify based on whether they express hate against ethnic or racial minorities. It then uses this information to analyse the correlation between the geo-localised presence of hate tweets and offline

hate crimes by geographic area. Flores (2017) uses self-reported users' geo-location (another option available to users) to collect information on opinions regarding the immigrant population in Arizona before and after the approval of a law limiting immigration access to the State. This case complements geo-referencing with the thematic search based on keywords. Ozalp et al. (2020) use various types of metadata (time zone, self-reporting, and user description analysis) to capture tweets originating from the UK in their study on anti-Semitism. Like Flores (2017), Ozalp et al. (2020) complement geo-referenced search with thematic search based on a selection of search keywords.

Finally, other studies have focused on capturing interactions between users. This strategy is prevalent in network studies (Himmelboim et al. 2016). Garimella et al. (2016), in their study of the incorporation of the tweet-quoting feature, conducted a case study on the quotes made to the tweets of US presidential candidates in 2015, aiming to understand what kind of conversation emerges from this new feature. Zijian and Kenneth (2021) followed a similar strategy for analysing responses to US President Donald Trump to understand user characteristics and possible information bubbles at the level of online political expression. Oliveira et al. (2022) performed one of the pieces that has more similarities with the data collection strategy followed in this thesis: aiming to understand the emotional response to news about COVID-19 on Twitter, the authors select a set of news outlets for which they download news related to COVID-19 and the users' responses to those. Finally, Williams and Cullen (2022, 2023) analyse hate tweets directed explicitly at players from the Wales and England football teams, examining patterns of abuse that often spike after key matches, particularly in the context of racial discrimination and public reactions to team performance.

Each of these strategies has advantages and disadvantages. Event-driven analysis has the virtue of collecting dense information on an event of interest. However, it suffers when gathering information on longer time series because of the very time-limited nature of the events. Data collection based on topics can be very relevant, but it requires specificity in the language used or more complex filtering techniques. This problem arises when the subject of interest uses words, phrases, or hashtags which overlap with other topics. This difficulty is relevant in studying reactions to crime, specifically punitive attitudes. Prieto Curiel et al. (2020) attempt to study the representation of crime on Twitter in Latin America by searching geolocated tweets based on keywords related to crime, violence, and justice. One of the conclusions observed in their study is that approximately 66% of these tweets are associated with crime, while the rest use the keywords figuratively (e.g., "I would kill for a beer right

now”). This fact implies a significant presence of "noise" in the data to be analysed. Additionally, the opposite may also be true. Some relevant information may be lost because specific reactions to crime do not include any keywords. For example, "throw away the key" is a clear indicator of punitive attitudes, yet it does not contain specific words linked to crime. The exact phrase could potentially be searched for, but a priori, it is not straightforward to know what kind of sentences would reflect such attitudes. Searching for specific words (like “key”) would involve collecting even more noise. Potentially, more sophisticated data filtering strategies could be developed, for example, by using supervised learning techniques to distinguish tweets of interest from those that are not, and then classifying punitive tweets (Chaparro et al. 2021). For its part, using geo-location strategies on its own involves the collection of large amounts of data - even by Big Data standards - when it comes to cross-country comparisons. Two problems emerge in this regard: the computational capacity to store and process this information and the detection of tweets that could be considered punitive for training an automatic classifier, which faces problems similar to those mentioned for topical analysis. This strategy would involve collecting large amounts of information unrelated to crime and punishment.

However, an alternative approach is to utilise interactions with crime-related news, the option chosen in this project, based on the fourth strategy mentioned earlier. Several arguments guide this decision. Firstly, exploring punitive attitudes entails activating and expressing opinions since attitudes represent states of mind. While conducting a survey or interview, this activation results from the researcher's question; online observation, on the other hand, requires an external stimulus. Kort-Butler and Habecker (2018) propose a model with three primary sources of information that influence emotions and attitudes towards crime, which could potentially function as triggers for the expression of punitive attitudes online: personal experiences, crime-related news, and the experiences of acquaintances. The experience that individuals have with crime tends to be somewhat limited, particularly in countries of the Global North where victimisation is lower. To represent this in terms of the countries analysed in this study, the United Kingdom reported 9.1 million offences in 2022 for a population of 67.33 million people, according to the latest victimisation survey (CSEW) ending in September 2022. Around 80% of adults were not victims of crime. Meanwhile, the latest victimisation survey, developed by the government in Uruguay, is from 2017 and shows a 24% chance of personal victimisation (INE 2017), slightly higher than in the UK. However, it is worth noting that the type of crime and the level of violence differ substantially: While Uruguay recorded 383 homicides in 2022, a rate of 10.8 homicides per 100,000 inhabitants (ONVC - MI

2023), the UK recorded 663 homicides, meaning a rate ten times lower, at 1.1 per 100,000 inhabitants (ONS 2023a).

These figures reflect that, even in contexts of relatively high violence, direct experience of crime is fairly infrequent. However, law and crime are central social order problems and tend to capture a significant portion of public debate and attention (Miethe and Lu 2005; Stalans 2013). For this reason, individuals must turn to other sources of information to form opinions and attitudes towards the issue (Baranauskas and Drakulich 2018; Kort-Butler and Habecker 2018). In this sense, news media continue to be a fundamental trigger for expressing users' attitudes and emotions about crime. Regarding the experiences of acquaintances, it is impossible to capture information about people close to the users that could affect the information received without using alternative sources of information or pre-selecting a sample.

An additional advantage of this strategy is geo-localisation, at least for the news portals. While this does not mean that the news will be exclusively of local origin or answered by users from the selected countries, it is expected to capture as many local events and their reactions as possible. These arguments lead this thesis to download crime-related news items from 40 media outlets, 20 in Uruguay and 20 in the UK, and then download user responses to them.

To complement the existing information on punitive attitudes, this study also includes an analysis of tweets related to crime posted by members of parliament (MPs) from Uruguay and the United Kingdom, along with the replies and quotes those tweets received. In democratic societies, the authority to impose such punitive measures is constrained by legal frameworks and exercised by the State, specifically through the actions of legislators and the executive branch. As a result, public demands for harsher measures or increased penalties often target these political actors. As a social media platform, Twitter plays a crucial role in this context by providing a space where citizens can directly voice their concerns and demands to their representatives. This makes it a valuable data source for understanding the dynamics of public opinion and how politicians engage with these sentiments. By analysing the interactions between politicians and users on Twitter—focusing on how MPs discuss crime and how the public reacts to it—this study aims to shed light on the nature of public demands for punitive measures. This approach can reveal how discussions about crime and punishment are shaped and contested in the public sphere, offering insights into the complex interplay between public opinion, political communication, and policy-making in crime control.

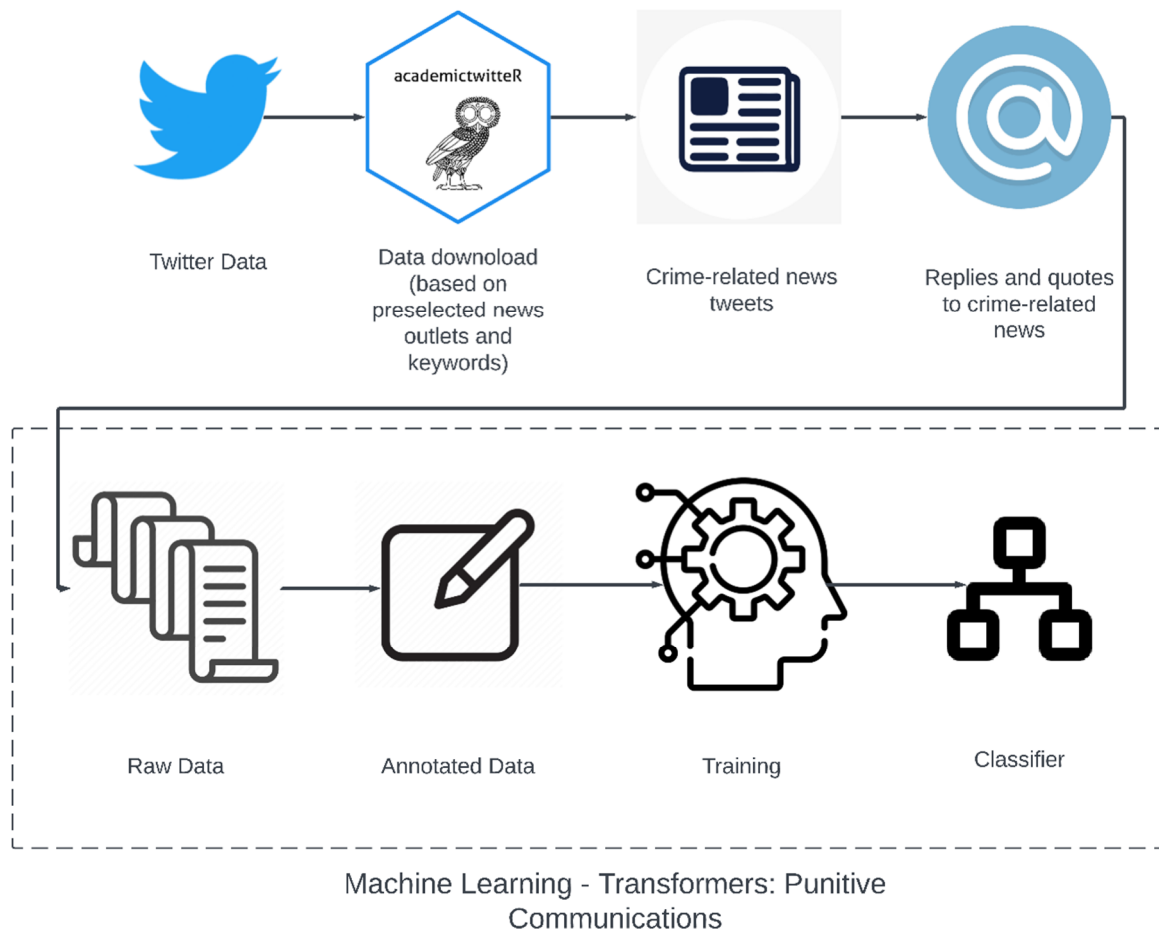
3.6. Data Collection

Twitter data has been widely used in social science research. The platform's ease of data access for researchers, compared to the limitations of other platforms (Blagus and Žitnik 2018; Antonakaki et al. 2021), along with its significance in news and political communication, has contributed to the proliferation of studies utilising Twitter (Jin et al. 2014; Himelboim et al. 2016; Flores 2017; Leis et al. 2019; Ozalp et al. 2020; Prieto Curiel et al. 2020; Williams et al. 2020; Hu and Kearney 2021). However, the termination of the academic API in 2023 following Elon Musk's acquisition of the platform, has made it extremely challenging to conduct academic research without incurring substantial costs³.

The following strategy was implemented to analyse reactions to crime in both countries, with each step detailed in the following subsections. First, a selection of the most important press outlets on Twitter was made based on secondary data regarding news consumption in both countries, combined with the metrics of each account. For these media outlets, all tweets related to crime news were downloaded using a set of selected keywords. Next, all user responses (replies and quotes) to these news items were collected. A sample of these responses was manually annotated as punitive or non-punitive based on a predefined set of rules (Appendix 1). This annotated set of tweets was then used to train a range of Machine Learning and Transformers models to detect punitive tweets automatically. After experimenting with different models, the one with the best performance was selected, and predictions were applied to classify the entire dataset of responses (see Figure 3). The same approach was applied to the Twitter accounts of political representatives in both countries.

³ <https://www.theverge.com/2023/5/31/23739084/twitter-elon-musk-api-policy-chilling-academic-research>

Figure 3 Data collection pipeline



For the news download, a sample of 20 news portals was selected for each country. Secondary information was gathered to identify each country's most influential news portals based on their reach (Montevideo Portal 2021; UNESCO 2021; Newman 2022; Majid 2023). Additionally, the analysis considered the frequency of publications, whether the outlets regularly covered crime news and the level of interaction they typically received. This information was manually verified by reviewing the timeline of each media account and examining the publicly available data associated with it. In the case of Uruguay, this process led to the inclusion of Leo Pedrouza⁴ (a journalist rather than a media outlet) due to the relatively low number of media outlets with significant reach and impact on Twitter.

⁴Leo Pedrouza is a Uruguayan journalist specialising in the presentation of police news, with a number of followers on Twitter similar to that of some smaller media outlets, and with great impact in terms of interactions. He is also part of two of the most important media outlets in Uruguay (Channel 4 and Channel 12). <https://x.com/leopedrouza?lang=en>

Table 2 UK News Sources

News Source	User	Followers
BBC News (UK.)	BBCNews	15090513
The Guardian	guardian	10895497
Sky News	SkyNews	8386716
The Independent	Independent	3628283
The Telegraph	Telegraph	3328749
Daily Mail Online	MailOnline	2821249
The Sun	TheSun	2065979
The Times and The Sunday Times	thetimes	1771013
The Mirror	DailyMirror	1386788
BBC Scotland News	BBCScotlandNews	607146
Liverpool Echo	LivEchonews	534157
Birmingham Live	birmingham_live	351991
Wales Online	WalesOnline	345981
BBC News NI	BBCNewsNI	336178
Daily Star	dailystar	234632
BBC South East	bbcsoutheast	230662
Evening Standard	EveningStandard	165954
BBC East Yorks and Lincs	looknorthBBC	87160

Table 3 Uruguay News Sources

News Source	User	Followers
Subrayado	Subrayado	871979
El Observador	ObservadorUY	825914
EL PAÍS	elpaisuy	823152
Montevideo Portal	portalmvd	604471
la diaria	ladiaria	402712
Telemundo	TelemundoUY	322411
Telenoche	TelenocheUy	261714
BÚSQUEDA	BUSQUEDAonline	153892
BÚSQUEDA	BUSQUEDAonline	153891
Diario La R	diariolaruy	126562
Sarandí 690	RadioSarandi690	85602
Canal 5 Noticias	5noticiasuy	59554
MVD Noticias	MVDNoticias	30375
Leonardo Pedrouza	LeoPedrouza	25733
Agencia UYPRESS	uypress	21668
VTV Noticias	vtvnoticiasuy	17001

Cronicas del Este	CronicasDelEste	16102
Informativo Carve	InformaCarve850	16049
LARED21	LaRed21	8438

All tweets containing at least one crime-related keyword or query (Appendix 2) from 2022 were downloaded for each account. The selection of keywords and crime types was informed by an initial exploratory analysis using Twitter, LexisNexis, and Media Cloud data. This process was iterative: data was downloaded from all sources, and the most relevant keywords were identified through analysis. Subsequently, a random sample of the collected data was qualitatively analysed to ensure that the selected keywords effectively captured information on various types of crime while minimising the collection of non-relevant information. Data was collected using Twitter's academic API between February and March 2023, facilitated through the statistical software R and the *academictwitteR* package (Barrie and Ho 2021).

Once these tweets were downloaded, for the download of public reactions, only those tweets made by the selected accounts were kept (eliminating retweets), and only those tweets that contained at least one reply or quote were sub-selected since those tweets without replies or quotes do not offer relevant information for downloading. This information allows the API to download all tweets responding to any previously collected tweets, as well as any tweets that quote them. To clarify what this means, the Twitter interface offers a reply option, which creates a new tweet that mentions the user or users who made the original tweet being responded to. Twitter assigns an identity to each conversation thread, making it possible to track the entire conversation and download each reply. A different interaction is the quote feature, where users can share a third party's tweet on their profile while adding a comment to the original message. In this scenario, the user comments on and attaches another user's tweet that they consider relevant (Garimella et al. 2016).

The same strategy was used to download crime-related tweets from MPs, along with their respective replies and quotes. The users are presented in the appendix (Appendix 3) for space reasons. The analysis also included the accounts of the parties with parliamentary representation and, in the case of Uruguay, the accounts of the president and vice president.

From an ethical standpoint, it is worth noting that the research was approved by Twitter, which granted access to the academic API. In this regard, only tweets made from public accounts with active users at the time of the data download were used. The possibility of this information being used in academic research was part of

Twitter's terms and conditions at the time the study was conducted, working as informed consent. Although this information is traceable (due to its public nature), no user information has been publicly disclosed, to allow users who so wish to exercise their right to be forgotten. This means that if a user decides to delete their account or the tweet, they cannot be traced using the information available in the thesis (Salganik 2019; Zhang et al. 2025). In Uruguay, data collection for crime-related news yielded 26,263 tweets from 20 news media sources after filtering, averaging 72.15 crime-related news items per day. By contrast, applying the same strategy to the United Kingdom produced 56,023 news items, averaging 153.91 per day. Based on these datasets, 334,827 responses to crime news in the UK were collected, originating from 153,655 unique users. Participation was strongly right-skewed: the vast majority of users responded only once (the mode and the median), while the most active 5% of users generated 37.27% of responses, and the least active 75% accounted for 31.68%. In Uruguay, 107,828 responses were collected from 22,431 unique users. The average participation per user was more than twice as high as in the UK (4.81 vs. 2.18). The most active 5% of users in Uruguay contributed 44.13% of the responses, while the least active 75% generated only 23.34%, reflecting a higher concentration of activity.

When analysing communications made by politicians on Twitter, specific considerations must be taken into account. A crucial factor is the number of retweets. In the United Kingdom, 25,278 tweets were collected (before filtering), of which 13,985 were retweets. In Uruguay, 3,544 tweets were collected, including 2,179 retweets. Retweets are significant as they reflect content to which followers are exposed. Still, they also raise methodological concerns, as extensive retweeting within the political system can artificially amplify the perceived importance of certain communications. For this reason, different analytical operations are required depending on the type of analysis, as specified in the relevant chapters.

After filtering, 791,840 responses to crime-related tweets from UK politicians were obtained from 212,905 unique users. The top 5% of most engaged users accounted for just over 38% of responses, while the least engaged 75% contributed around 29%. The average number of responses per day was 2,175, though several key peak dates were identified, with the maximum reaching nearly 30,000 responses. In Uruguay, 52,822 responses were collected from 13,727 users. The most engaged 5% accounted for just over 34% of responses, while the least engaged 75% produced 34.49%. The average number of responses per user was similar across countries (3.85 in Uruguay vs. 3.72 in the UK). The daily average was 191 responses, though peaks

were observed, with three days exceeding 2,000 responses (these peaks and their context are analysed in Chapter 4).

Now, these tweets are grouped into various structures, which are relevant for analysis in later chapters. While each chapter specifies the strategy used and the nesting of the data, this section provides an overview:

Chapter 4, the first empirical chapter, dedicated to topic modelling of the collected communications, uses the tweet itself as the unit of analysis for each of the aforementioned datasets: crime news in Uruguay and the United Kingdom, responses to crime news in Uruguay and the United Kingdom, political communications (parliamentary and executive) in Uruguay and the United Kingdom, and finally responses to political communications in Uruguay and the United Kingdom.

Chapter 5 analyses the determinants of punitive attitudes in responses to crime news in Uruguay and the United Kingdom. This is where this thesis makes the most use of the nested nature of the data. The analysis is carried out on three different levels: First, the determinants of a tweet being punitive are estimated. However, these tweets come from a specific user, who may have posted more than one tweet. For this reason, the determinants of a user being punitive are also analysed, taking the user as the unit of analysis. In turn, the tweet originates as a response to a crime news story, so the analysis also considers the ratio of punitive responses to the specific news story, with the news story then being the unit of analysis. These two levels are not grouped together (since not all users respond to all news stories).

Chapter 6 analyses the time series that arises from aggregating tweets per day. Three dependent variables are analysed: the punitive attitudes of Twitter users towards crime news, the number of responses to crime news, and the number of political communications related to crime. In each case, the unit of observation is the number of tweets per day (for the whole of 2022).

3.7. Analysis

3.7.1. Quantitative Analysis and Topic Modelling

The initial analysis of the tweet data employed traditional quantitative content analysis techniques, specifically word counts and bigrams. Word counts involve counting the frequency of each word in the collected tweets. Bigrams focus on identifying pairs of words that commonly occur together, like "crime prevention" or "justice reform". Topic modelling was employed to uncover the hidden semantic structure within the corpus of tweets by identifying groups of words that frequently

co-occur. These word groups, referred to as "topics," represent the dominant themes or concepts in the text (Blei et al. 2003; Blei 2012). The utility of topic modelling in the social sciences lies in its ability to code large volumes of text in an automated and inductive manner, requiring minimal human intervention. However, researchers must make key decisions, such as setting the model's hyperparameters and determining the number of topics to extract (Mohr and Bogdanov 2013). These characteristics make topic modelling particularly useful for initial exploratory data analysis of text, as it provides a way to quickly identify and categorise the main themes present in the data without relying on predefined labels. By revealing the structure of the text data, topic modelling offers an overview of the primary subjects being discussed. It advances the exploratory analysis of textual data, functioning similarly to cluster analysis in traditional survey data, and enables the detection of more complex relationships between words than those observed through methods like bigrams or trigrams. Additionally, it employs an inductive approach—emerging directly from the data—that complements the deductive strategy of defining topics through keywords or using supervised techniques.

Using topic modelling strategies for analysing interactions occurring on Twitter is nothing new in Computational Social Science and Computational Criminology. One of the most direct antecedents is the work by Berubé et al. (2020), where the authors collected tweets immediately after the 2017 terrorist attack in Manchester (UK) and applied topic modelling strategies - specifically Latent Dirichlet Allocation (LDA) - to understand the evolution over time of the social reaction to the event and its applicability for crisis management. Oliveira et al. (2022) used topic modelling strategies on COVID-19-related news that they will then relate to emotional responses to such news. Barberá et al. (2019) used topic modelling to analyse the relationship between the topics discussed by the political system, the press, and citizens on Twitter in the United States.

The primary method used for topic modelling was Biterm Topic Modelling (BTM) (Yan et al. 2013). BTM is a textual information clustering technique optimised for the analysis of short texts, where traditional strategies such as Latent Dirichlet Allocation (LDA) (Blei et al. 2003) are problematic due to sparse word co-occurrence data, limited context, and high variability, which result in poor topic coherence. BTM, which focuses on the co-occurrence of word pairs (biterms), is particularly well-suited for capturing patterns in short-text data, such as Twitter posts. This analysis was conducted in R using the BTM package. To ensure robustness, a secondary analysis was performed using a different topic modelling technique, designed as an alternative solution to challenges posed by short-text data: a collapsed Gibbs Sampling

algorithm for the Dirichlet Multinomial Mixture model (GSDMM) (Yin and Wang 2014). The results are congruent between the models.

A particular feature of these clustering techniques is that they require the prior definition of the number of clusters (or topics) to be created (k). k can be defined on theoretical grounds (e.g. the existence of a prior category definition that is expected to be found), or it can be induced from the data. For this purpose, several indicators can be used to define k . This second strategy was used for all cases. The ``stm`` (Roberts et al. 2019) and ``ldatuning`` (Nikita 2016) packages were used for this purpose.

These packages use traditional topic modelling techniques (LDA) to calculate the various indicators for the number of topics to be maintained, so they are not optimised for the specific methods used (BTM and GSDMM). However, it is used as an automated proxy for choosing a value of k , which can then be evaluated based on the results obtained once the models are estimated. Most of these indicators should be examined together as they have pros and cons when selecting the number of topics. The `stm` package returns four indicators: The Held-Out likelihood or Perplexity accounts for how well the model can predict unseen data. Semantic Coherence measures how semantically similar the top words in each topic are. It is commonly used as an indicator for selecting the number of topics and the quality of the model. Like traditional regression analysis, residuals are a general indicator of how well the data fits the model. The lower bound approximates the marginal likelihood of the data given the specific model. Higher values of the lower bound indicate that the model fits better. The ``ldatuning`` package also returns four indicators: CaoJuan2009 is based on the logarithm of the ratio of the probability of the data given the model to the probability of the data given a null model. Deveaud2014 is based on the difference between the topic coherence of the top n words in each topic and the average coherence of all word pairs in the corpus. Griffiths2004: This indicator is based on the perplexity of the model. Arun2010 is based on the point-wise mutual information (PMI) between the top n words in each topic. Arun2010 and CaoJuan2009 should be minimised, Deveaud2014 and Griffiths2004 should be maximised for a better fit.

As an additional robustness test, for both types of modelling strategy, BTM and GSDMM, two models with different k -values were estimated for each source and country. This operates as a second robustness check, accounting for possible topics that may have been hidden in the smaller clustering (Chuang et al. 2015). If the clustering works appropriately, the topics should be relatively stable, disaggregating previously shown information.

Different techniques were used to interpret the results. Firstly, the probability of each topic is reported. In addition, the phi values of the ten most important words per topic are also presented. In a BTM topic model, the phi values represent the topic-term distributions, where each element of the phi matrix corresponds to the probability of a specific term in the vocabulary being generated by a particular topic in the model. The LDAvis R package (Sievert and Shirley 2014) was also used to explore topic modelling results. The LDAvis's interactive visualisation tool consists of two main components: the topic display and the term display. The topic display is a scatterplot that shows the relationships between the topics in the model based on their similarity and the frequency of their occurrence in the corpus. The term display is a bar chart showing the most relevant terms for each topic based on their frequency and distinctiveness in the corpus. Finally, a sample of tweets classified under each topic was reviewed to refine the initial interpretations based on the various statistics extracted (Grimmer and Stewart 2013; Roberts et al. 2016). The selection process focused on tweets with a high classification certainty within each topic, using an indicator derived from the phi values of the words in the text. The number of tweets read was determined by theoretical saturation—i.e. when additional reading no longer yielded new or relevant information for interpreting the topic (Maier et al. 2021).

3.7.2. Sentiment/Emotion Analysis

Chapter One briefly presents the models of attitudes from psychology. These models tend to consider emotions – in a broad definition – as part of the components of attitudes, together with cognitive and experiential components. Moreover, the lack of attention to emotional components in studies of punitive attitudes has been criticised, and the potential to incorporate this type of analysis has been expressed as one of the advantages of Social Media Data strategies.

Both sentiment and emotion analysis have a long-standing tradition in linguistic text analysis, particularly within the field of Natural Language Processing (NLP). The rise of Web 2.0 and social media has drawn considerable interest from researchers seeking to apply these methods to study social life (Mäntylä et al. 2018). Sentiment analysis aims to assess the polarity of a text—whether it is positive, negative, or neutral—by interpreting the sentiment expressed within a document, sentence, or word. Emotion analysis seeks to provide a more detailed understanding of the specific emotions underlying the text, such as anger, sadness, or fear. Emotion analysis can be approached using two main models. Dimensional models represent emotions through three parameters: valence (the positivity or negativity of an emotion), arousal (the level of activation or intensity), and power (the degree of control or dominance). Categorical models, in contrast, differentiate between distinct emotions (Sailunaz and

Alhaji 2019; Nandwani and Verma 2021). One of the most widely used categorical models in NLP is Ekman's model (Ekman 1992), which identifies six basic emotions: anger, disgust, fear, joy, sadness, and surprise.

Techniques for classifying sentiment and emotions can generally be divided into two categories: those based on Machine Learning and those based on Lexicons. Machine Learning approaches typically employ supervised learning strategies to estimate sentiment or emotion by training models on human-annotated data. Lexicon-based approaches use predefined dictionaries or lexicons to determine the sentiment or emotion expressed in a text. This method involves creating a list of words or phrases with associated sentiment scores, often indicating positivity or negativity. The overall sentiment is calculated based on the accumulated sentiment or emotion scores by analysing the text and matching its words to entries in the lexicon (Sharma et al. 2020).

Several studies have used Twitter sentiment and emotion analysis techniques in computational social sciences. Menshikova and van Tubergen (2022) analysed for a panel of Twitter users in the United Kingdom, the effect of exposure to news media on the sentiments expressed regarding immigration using a lexicon-based approach. Harb et al. (2020) used Machine Learning (deep learning models) to perform emotion analysis in the context of mass violent events. Oliveira et al. (2022), after performing topic modelling of COVID-19 news items, also used Machine Learning (transformer-based) for emotion detection of user responses on Twitter.

This project employs both Machine Learning strategies based on transformer models and lexicon-based methods. While Transformer-based techniques are better at classifying discrete categories, the use of lexicons allows for the use of clearly interpretable valences. For this reason, Transformers are used for analysing the prevalence of feelings and emotions in Topic Modelling, while lexicon strategies are incorporated into multivariate models. These techniques are explained in greater depth in the following section.

3.7.3. Supervised Machine Learning for Text Classification

Machine Learning text classification techniques aim to assign a predefined category to a given text input. In this project, text classification is employed for the automated detection of punitive attitudes in naturally occurring communications on Twitter, thereby constructing the primary dependent variable of the study. Additionally, it's used to build other dependent variables from the Twitter metadata. "Machine Learning" refers to any algorithm that enables a computer to "learn" a specific task without being explicitly programmed for it. This learning process involves the computer optimising its classification performance by iteratively fitting a model to the

data and using a fit indicator to assess itself. The computer gains "experience" through this iterative process that improves its task accuracy. In this sense, all the tools used in this project for the automated classification of tweets, including Transformers, can be considered Machine Learning tools (Bi et al. 2019).

Additionally, it is possible to distinguish between traditional or shallow strategies and new natural language processing techniques based on deep learning and transformers (Gasparetto et al. 2022). Traditional algorithms rely on manually designed features, such as word frequencies or specific keywords, which need to be predefined by researchers. In contrast, deep learning models, including Transformers, automatically learn patterns from the raw text. These models utilise multiple layers to comprehend the context and complex relationships between words, making them more adept at capturing language nuances without requiring extensive manual feature selection.

3.7.3.1. Operationalisation

The objective of training the automatic classifier in this thesis is to develop what will subsequently serve as the dependent variable across the various chapters (with different transformations or emphases): the detection of punitive attitudes expressed in textual information from posts on the social media platform Twitter. Behind this objective and strategy lies a series of decisions that must be clarified and justified.

A binary definition of punitive attitudes is adopted, meaning that tweets are classified as either punitive or non-punitive, with no intermediate categories or gradations of intensity. This choice rests on both practical and conceptual grounds. Practically, it simplifies the process of creating an automated detector. Annotators need only determine the presence or absence of a punitive attitude, without distinguishing between levels of intensity. Conceptually, it also facilitates the task of defining potential indicators of intensity once punitive attitudes have been identified. This is particularly relevant given that most survey-based research in this field has not measured intensity directly but has instead relied on Likert scales to capture variation (Trajtenberg and Ezquerro 2025). In survey research, multiple questions on punitive attitudes are often treated as equivalent, with intensity inferred from the position on the scale. Such a structure does not exist in naturally occurring Twitter data, where intensity must instead be inferred from the specific content of posts. While some cases allow for clear distinctions (for instance, a demand for a 10-year prison term can be considered more punitive than a demand for a 5-year term), others are more ambiguous. Is a call for life imprisonment more or less punitive than a call for torture?

Moreover, although multi-class text classification and the construction of ordinal measures of punitiveness are technically feasible, they require a substantially larger annotated dataset, as each additional label demands sufficient representation for accurate identification (Li et al. 2018; Henning et al. 2022). This poses challenges in a context with limited resources and where the target category is highly imbalanced: in a manually annotated sample of collected tweets, only around 5% were identified as punitive. This means that increasing the number of categories of the dependent variable would involve collecting and annotating a greater number of tweets (multiplied by n , where n is the number of categories incorporated), which would significantly increase the time and monetary costs.

Finally, although the evidence remains limited, recent studies suggest that survey responses on punitiveness measured with Likert scales often behave practically like binary items, as respondents tend to gravitate towards the extremes of the scale (Yamamoto and Maeder 2019; Trajtenberg and Ezquerro 2025).

Taken together, these considerations, combined with the adequacy of a binary operationalisation for the purposes of this thesis, justify the decision to model punitive attitudes in binary terms. Subsequently, these data can be grouped together to analyse, for example, the determinants of punitive attitudes at the user level, the intensity of the punitive response in the news, or the temporal variation of punitive attitudes on the platform at the country level (chapters 5 and 6).

3.7.3.2. Data Annotation

Traditional Machine Learning and Transformer techniques were tested for the automatic classification of tweets. These techniques required the manual annotation of tweets, which the author of this thesis carried out as the lead annotator and three criminology MSc students from the University of Manchester were recruited specifically for this task. For the Uruguayan data, three graduates of the Sociology degree at the Faculty of Social Sciences of the University of the Republic of Uruguay were recruited.

Annotating tweets as punitive or non-punitive is a challenging task, with inherent margins of ambiguity. An annotation guide was developed to facilitate consistency among annotators (Appendix 1). The lead annotator conducted both general and individualised interviews with the other annotators, aiming to ensure a shared understanding of the annotation rules and to resolve specific doubts on a personalised basis. This process was intended to improve agreement among scorers and ensure the reliability of the annotations.

A punitive tweet was defined as any tweet that expressed support for the increased cost of crime by criminals. This includes support for the death penalty, harsh treatment, longer sentences, poor prison conditions, reduced rehabilitative measures, and deportation or expulsion from the country, among others.

Some examples (presented to the annotators in the guide):

- *"They need to bring back d*ath by firing squad"*
- *"Unconditional bail????????? Why are yall letting him roam free wtf"*
- *"Lowlife waste of oxygen, throw away the key"*
- *"@user let those damned devils rot in jail. And may the little Angel rest in peace"*
- *"@user @user Keep him in a small, dark, lice-ridden cell"*
- *"@user @user A pretty joke. 60 years would be fair."*
- *"@user So would the 2w guys not shot the driver if not B lock them up for life"*
- *"Set him on fire"*

Initially, the annotators iteratively annotated 2,100 tweets. Each annotator worked on the same tweets to determine inter-annotator agreement. The average Kappa score obtained was .74, which is considered moderate in terms of interrater reliability (McHugh 2012). Achieving that score involved an iterative process, where different text samples were annotated, problematic tweets were observed, and a final decision was made among all annotators in meetings led by the principal investigator. Once these results were obtained, the annotation task was parallelised, i.e., each annotator received a new set of 2000 tweets to classify, which they performed autonomously. After this, a total of 10,000 tweets were annotated. This database was used to train the Machine Learning and Transformers models. The final database is highly unbalanced, with only 5% of cases classified as "punitive".

3.7.3.3. *Shallow Machine Learning Techniques*

For a long time, shallow Machine Learning strategies were the central tool for text classification in various areas of NLP, specifically in the Social Sciences and Computational Criminology. Williams et al. (2020) employ Support Vector Machines (SVM) with Bag-of-Words feature extraction for classifying hate tweets, focusing on those targeting race (anti-Black/Middle Eastern) or religion (anti-Islam/Muslim). Ozalp et al. (2020) follow the same strategy for classifying antagonistic tweets against Jews and Jewish identity. Both studies achieve good accuracy, precision, and recall levels, with F-scores above .70. Chaparro et al. (2021) use two shallow machine learning strategies for their study on users' security perception in Bogotá. The first approach utilises word embeddings in conjunction with SVM to classify security-related tweets,

while the second employs multinomial naive Bayes for sentiment analysis. A summary of the available and commonly used algorithms can be found in Gasparetto et al. (2022).

The initial tests were carried out on the UK data, which provided the basis for estimating the model for the Uruguayan case. The following traditional Machine Learning models were tested in this project:

- KNN (Guo et al. 2003)
- Logistic Regression (Hosmer Jr et al. 2013)
- Decision Trees (Rokach and Maimon 2005)
- Random Forest (Rigatti 2017)
- Support Vector Machines (Noble 2006)
- XGBoost (Chen and Guestrin 2016)
- AdaBoost (Schapire 2013)

All these techniques require a training set and a validation set. In all cases, the split was 80%-20%, respectively. Additionally, these models require pre-processing of the textual information, a stage called "feature extraction". This stage involves translating the textual data into a numerical representation that Machine Learning algorithms can interpret. Traditionally, the Bag-of-Words (BoW) strategy has been used for this transformation. The BoW model creates a vocabulary of all the unique words in a text corpus. Then, each document in the corpus is represented as a vector that contains the number of times each word in the vocabulary appears in the document. Another commonly used technique is the development of word embeddings. Word embeddings enable the representation of words from a vocabulary in a lower-dimensional continuous vector space. These methods extract word profiles unsupervised by considering the contexts in which the words appear. Unlike bag-of-words models, word embedding techniques go beyond the limitations of individual words and capture both syntactic and semantic aspects (Enríquez et al. 2016).

Both vector representation strategies for classification were tested in this project. All analyses were performed in Python. For feature extraction using Bag of Words, the Scikit-Learn library was employed (Pedregosa et al. 2011). First, the documents were tokenised, eliminating user names, links, special characters, and stopwords. All words were lemmatised, following standard procedures. In order to reduce the dimensionality problems in the data, Latent Semantic Analysis (LSA) using truncated Singular Value Decomposition (SVD) was implemented over the Bag of Words representation (Kherwa and Bansal 2017). Working with the entire base, 2,000 components were maintained, accounting for 78.4% of the variance. In the exercises

with oversampling, 750 components were retained, accounting for 75.8% of the variance. The pre-processing stage ended with a training base of 7,996 rows and 2,000 columns for the case without undersampling and 1,892 rows and 750 columns for the case with undersampling.

Additionally, the imbalance between the class of interest and the majority class (5%-95%) can be an obstacle to the ability of these models to predict correctly. To overcome this obstacle, the models were tested with and without undersampling. Undersampling is a common technique (Mohammed et al. 2020) that involves reducing the majority class to fit a specific ratio. In this case, the 25%-75% split was tested.

The models were fitted to their hyperparameters in all cases through a cross-validated search on the training set (5-fold) (Berrar 2019). The adjustment indicator used was the F1 score (Goutte and Gaussier 2005). This process involved training 28 models (7 algorithms * 2 sampling strategies * 2 feature engineering strategies).

3.7.3.4. Transformers Models

The Transformers architecture (Vaswani et al. 2017) has quickly become dominant in Natural Language Processing, outperforming alternatives (Wolf et al. 2020; Gasparetto et al. 2022). This type of model captures long-range sequence features efficiently and allows their pre-training on large text corpora, a strategy that results in pre-trained models that can later be used in downstream tasks with significant performance gains, for example, in classification tasks (Wolf et al. 2020). In simpler terms, this means that it is possible to use pre-trained models with large amounts of text, which capture, to a large extent, the subtleties of the language on which they were trained, and then specify tasks on smaller datasets, as in this case, to capture punitive attitudes on Twitter. An in-depth explanation of the computational foundations of transformer models is beyond the scope of this space. A summary of the characteristics of this architecture and its advantages over previous deep learning models can be found in Soyalp et al. (2021).

The emergence and improved performance of these models over previous ones have also boosted their use in computational social sciences. Both Harb et al. (2020) and Oliveira et al. (2022) used transformer-based emotion analysis in their studies (reviewed above). Al-Garadi et al. (2022) used transformers to detect Intimate Partner Violence on Twitter. Moreover, Benítez-Andrades et al. (2022) did the same for detecting tweets about eating disorders. It should be noted that these papers test these models against other types of implementations, obtaining better results.

This revolution in natural language processing led to a series of publicly available pre-trained models that can be fine-tuned for specific tasks. Many of these models are hosted on the Hugging Face platform⁵ (Jain 2022). In this project, the Python "simpletransformers"⁶ library was used to pre-process and fine-tune transformer models to classify punitive tweets automatically. The 80-20 split between the training and testing sets was maintained, as with traditional Machine Learning models. Five pre-trained models were tested, each with between 3 and 5 epochs (Brownlee 2018). These models were tested with and without undersampling.

When evaluating the different classification strategies, various performance metrics were employed. As explained in section 3.7.3.1, the task of inferring punitiveness in posts was treated as a binary classification problem. In this type of task, four possible outcomes exist: True Positives (cases correctly classified as punitive), True Negatives (cases correctly classified as non-punitive), False Positives (non-punitive content incorrectly classified as punitive), and False Negatives (punitive content incorrectly classified as non-punitive). From these outcomes, a range of evaluation metrics can be derived to assess the model's predictive ability. In all cases, metric values range from 0 (poor performance) to 1 (perfect performance) (Baratloo et al. 2015; Hicks et al. 2022).

The metrics used were as follows:

1. Accuracy: The proportion of true positives and true negatives in all evaluated cases.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

2. Sensitivity: The ability of the classifier to determine positive cases correctly.

$$Sensitivity = \frac{TP}{TP + FN}$$

3. Specificity: the ability of the classifier to determine negative cases correctly.

$$Specificity = \frac{TN}{TN + FP}$$

4. Precision: the ratio between correctly classified samples and all samples assigned to that class.

⁵ <https://huggingface.co/>

⁶ <https://github.com/ThilinaRajapakse/SimpleTransformers>

$$Precision = \frac{\# \text{ samples correctly classified}}{\# \text{ samples assigned to class}} = \frac{TC}{TC + FC}$$

5. **F1 Score**: the harmonic mean of precision and sensitivity. Commonly used as a summary measure of overall model performance.

$$F1 = 2 \times \frac{precision \times sensitivity}{precision + sensitivity} = \frac{2 \times TP}{2 \times TP + FP + FN}$$

For the UK data, the best-performing model was bertweet-base, with an F1-score value of 0.772. For the Uruguayan data, the best-performing model was robertuito-base-deacc, with an F1-score value of 0.851.

The five models tested for the UK data were:

- distilbert-base-uncased (Sanh et al. 2019)
- bert-base-uncased (Devlin et al. 2018)
- roberta-base (Liu et al. 2019)
- elecetra-base-discriminator (Clark et al. 2020)
- bertweet-base (Nguyen et al. 2020)

The five models tested for the Uruguay data were:

- distilbert-base-multilingual-cased (Sanh et al. 2019)
- Twitter/twhin-bert-base (Zhang et al. 2021)
- dccuchile/bert-base-spanish-wwm-cased (Cañete et al. 2020)
- dccuchile/distilbert-base-spanish-uncased (Cañete et al. 2020)
- pysentimiento/robertuito-base-deacc (Pérez et al. 2022)

3.7.3.5. *Model Interpretability*

Although the model's predictive capacity demonstrates its usefulness for analysing online punitive attitudes, this approach is often considered a "black box."

Understanding which elements the model uses to make classifications is challenging, making its interpretation difficult. To address this, Local Interpretable Model-Agnostic Explanations (LIME) were employed to validate the chosen models, helping to "open the black box" (Ribeiro et al. 2016). LIME works by creating a simplified model that approximates the behaviour of the original model around a specific prediction. This simplified model is then used to explain why the original model made a particular prediction. Being model-agnostic, LIME can be applied to various Machine Learning models. This approach allows to assess whether the model's reasoning aligns with human-like logic when classifying data. This is important for two reasons: on the one

hand, it allows for testing the performance of the classifier in various scenarios and verifying that there are no words artificially associated with one class or another for any reason. On the other hand, it allows us to account for specific effects of the interaction between some terms that may be fundamental when interpreting the results. For example, the use of negatives that change the meaning of the sentence (e.g. ‘We should **not** increase penalties’).

Some examples are presented below:

Figure 4 Interpretability example 1

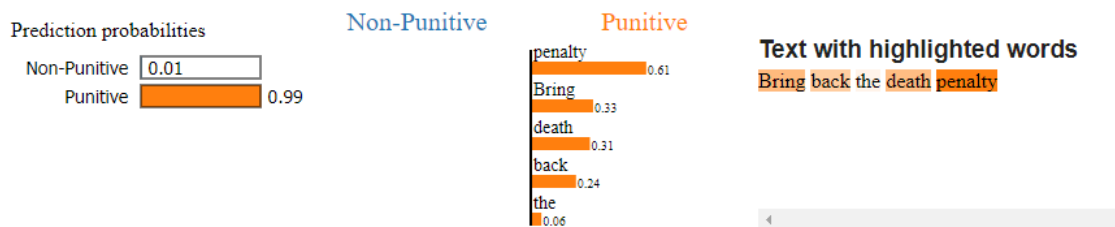
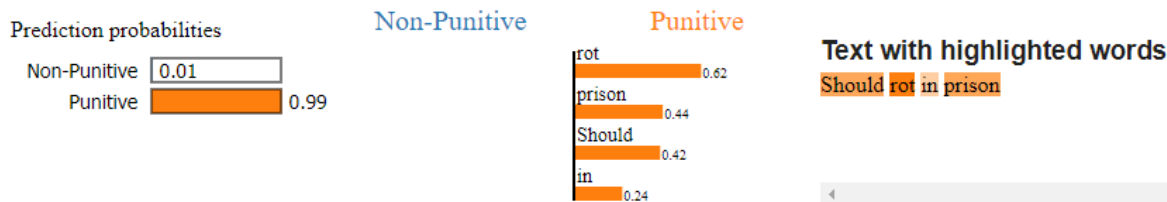


Figure 5 Interpretability example 2



3.7.4. Determinant Analysis

To address question three, regarding the determinants of punitive attitudes, a series of multivariate generalised linear models were estimated to capture the independent effects of user and tweet characteristics associated with the expression of punitive attitudes. The approach involved estimating different models that considered various possibilities for controlling for third variables, aiming to provide a comprehensive view that robustly identifies the predictors associated with the dependent variable of interest.

3.7.4.1. Logistic Regression

The simplest model involves analysing individual responses to crime-related news or political communications. In this scenario, the automatic classifier assigns binary values: 1 for punitive and 0 for non-punitive. This type of binary variable is typically modelled using logistic regression, a model specification optimised for such variables. Logistic regression addresses the limitations of using Ordinary Least Squares (OLS) with non-continuous variables and is easily interpretable through Odds Ratios (OR). This distinction influences the choice of the parametric model and the

underlying assumptions. However, after accounting for this difference, the analytical methods used in logistic regression align closely with the general principles of linear regression (Hosmer Jr et al. 2013; Chen and Chen 2021).

The logistic regression model employs the logistic transformation, which converts the linear combination of predictor variables into a probability value that ranges between 0 and 1. Specifically, this is achieved through the formula:

$$\pi(x) = \frac{e^{\beta_0 + \beta_1 x}}{1 + e^{\beta_0 + \beta_1 x}}$$

Where $\pi(x)$ represents the probability of an outcome (e.g., a punitive response) given a predictor x . The logistic transformation ensures that the model's predictions are confined within a valid probability range, making it suitable for binary outcomes. To linearise this relationship, the logit transformation is applied, which converts $\pi(x)$ into a log-odds scale:

$$g(x) = \ln \left[\frac{\pi(x)}{1 - \pi(x)} \right] = \beta_0 + \beta_1 x$$

This transformation allows logistic regression to use linear methods, making interpreting the relationship between x and the outcome easier, as it extends from $-\infty$ to ∞ like a linear regression model. Additionally, the conditional distribution of the outcome variable and the errors follows a binomial distribution.

Fitting a logistic regression model involves using maximum likelihood estimation (MLE) to determine the values of the parameters that best describe the relationship between the predictors and the outcome. MLE identifies the parameter estimates that maximise the likelihood of observing the given data. This process starts by constructing a likelihood function (The log-likelihood), which calculates the probability of the observed outcomes based on different parameter values. By differentiating the log-likelihood with respect to the parameters and solving the resulting equations iteratively, the model finds the parameter values that most closely align with the observed data. These estimates provide the best fit for the logistic regression model, enabling accurate predictions of binary outcomes. The models were estimated using base R's `stats` package (R Core Team 2023).

Given that the model estimates log odds, which are difficult to interpret, it is possible to exponentiate this result to obtain the Odds Ratios (OR), which represent the change in the odds of the event of interest occurring compared to not occurring, given a one-unit increase in the independent variable (presence vs. absence for dichotomous or dummy variables). This strategy is applied to analyse tweets and users in both

countries. In the case of tweets, this aggregates all available information to determine the likelihood that a given piece of content is punitive or not. In the case of individual users, every user who expressed at least one punitive tweet was considered a punitive individual.

3.7.4.2. *Negative Binomial count models*

Furthermore, following strategies used in other social media studies, count models are also used (Burnap and Williams 2015; Williams et al. 2020). These models no longer aim to calculate the probability or likelihood of the presence of an attribute but rather to count the number of times the event occurs within a specific time frame or observation period (Chen and Chen 2021). This thesis used these models to analyse the accumulation of punitive responses per news item or political communication. The count models add new information by capturing the frequency and intensity of punitive responses across news items or political communications. While the logistic regression model provides insights into the likelihood of an individual tweet or user being classified as punitive, the count model reveals patterns in how often these punitive responses occur concerning specific content. This allows for analysing which topics or events generate a higher volume of punitive reactions. It highlights not just the presence of punitive attitudes but their overall accumulation and impact within the social media discourse.

The most straightforward specification of these models involves applying Poisson models. The Poisson regression type of Generalised Linear Model (GLM) assumes the dependent variable follows a Poisson distribution, with the mean and variance being equal. The model uses a log link function to relate the expected count (mean) to a linear combination of predictor variables. The probability of observing a specific count y given the mean μ is defined by the formula (Zeileis et al. 2008):

$$f(y; \mu) = \frac{e^{-\mu} \mu^y}{y!}$$

In this model, the relationship between predictors and the response is expressed as:

$$\ln(y) = \beta_0 + \beta_1 x_1 + \dots + \beta_p x_p$$

Where μ is the expected count, and $\beta_0 + \beta_1 x_1 + \dots + \beta_p x_p$ are the regression coefficients. The model is estimated using MLE. A key challenge with Poisson models is overdispersion, where the observed variance exceeds the mean, which can result in underestimating standard errors and overly optimistic test statistics. This assumption can be tested statistically. Extensions like quasi-Poisson or negative binomial models can address overdispersion by relaxing the assumption that the variance equals the

mean. Overdispersion problems were addressed in this thesis using negative-binomial models. These models have an identical mean to that of the Poisson, with a variance expressed in the following formula:

$$\text{Var}(y) = \mu + \frac{\mu^2}{\theta}$$

Given that different news items receive different numbers of responses, thus affecting the potential occurrence of punitive cases, this was directly modelled through the offset of the model, which takes exposure into account and calculates the ratios (UCLA 2024). Offsets adjust for varying exposure levels or observation periods across different data points, ensuring that comparisons between counts are fair and meaningful. For instance, when analysing social media data, one news item may receive far more responses than another simply due to its reach or prominence. Using an offset allows the model to account for this variation by scaling the counts relative to the amount of exposure (e.g., total responses per news item). This enables the estimation of rates rather than raw counts, which provides a more accurate representation of how frequently punitive responses occur relative to the exposure level. This adjustment is crucial for ensuring that the results are not biased by differing levels of visibility or reach across observations.

3.7.4.3. *Multilevel Modelling*

Finally, multilevel models were employed as a third robustness test. These models account for the grouping of observations into higher-level units, which is relevant in this thesis at two levels: individuals who post multiple responses and news items that gather multiple responses. Traditional logistic regression does not account for this grouping, violating the assumption of independence of observations and errors. Failing to account for this correlation can lead to biased estimates and incorrect inferences (Chen and Chen 2021). Multilevel models enable the estimation of fixed effects while varying the intercept, based on clusters, thereby overcoming this limitation. This modelling approach is beneficial when patterns differ between groups; for instance, some users may be more consistently punitive in their responses, or specific news items may evoke stronger punitive reactions. By considering these differences, multilevel models add a layer of analysis, allowing the exploration of the overall likelihood of punitive responses and how this likelihood varies between individuals or types of content. This helps identify specific patterns that could be missed in simpler models.

To illustrate the need for these models, the Intraclass Correlation Coefficient (ICC) was used. The ICC is a key metric used to assess the extent of similarity or clustering within groups in a dataset. It measures the proportion of the total variance in the dependent variable that is attributable to differences between clusters, rather than differences within clusters. In the context of this thesis, the ICC helps to quantify how much of the variation in punitive responses is due to differences between individuals (users) or between news items rather than random variation or differences within each group.

$$ICC = \frac{\tau^2}{\tau^2 + \vartheta^2}$$

High ICC values indicate that a significant portion of the variation is due to these group-level differences, suggesting that responses are more similar within clusters (e.g., responses from the same user or related to the same news item) than between clusters. When the ICC is high, it indicates that using a multilevel model is appropriate, as it enables the inclusion of random effects that can account for variation between groups, resulting in more accurate and reliable estimates. High values were observed in all cases, suggesting the need for multilevel modelling.

3.7.5. Time Series Analysis

Finally, Auto Regressive Integrated Moving Average with eXogenous inputs (ARIMAX) models were used to answer question four regarding the effects and determinants of punitive attitudes over time. The ARIMAX model extends the Auto-Regressive Integrated Moving Average (ARIMA) framework by integrating exogenous variables that can influence the studied time series. The main idea behind ARIMA models is that a time series' past contains information that can help to explain its current value, and therefore, before endogenous explanatory variables are considered, it is first necessary to build a model that is based on the series' past (Vliegenthart 2014).

According to the ARIMA framework, a series can be described as a (p, I, q) process, with p autoregressive terms (AR), I orders of integration (number of times a series needs to be differenced before it is stationary), and q lagged moving-average terms (MA). The series must be stationary to model it in terms of its past values with AR and MA. A stationary time series is one whose statistical properties do not depend on the time at which the series is observed, with no predictable patterns in the long term. One way to make a non-stationary time series stationary is to compute the differences between consecutive observations. This is known as differencing, expressed by the I term (Hyndman and Athanasopoulos 2018). Once the series is stationary, it can be approximated by the following formula:

$$y_T = a_0 + \sum_{i=1}^p a_i * y_{t-i} + \sum_{i=1}^q b_i * \varepsilon_{t-i} + \varepsilon_t$$

The ultimate goal is to find a specification of the model that correctly models the series' past without leaving any information from this past unused. Unused information appears as autocorrelation in the residuals, indicating that the residual at a certain point is significantly correlated with residuals from previous values. In that case, the residuals are not mimicking white noise. This can be tested after the analysis using the Ljung-Box test. After obtaining a suitable specification of the univariate ARIMA model, the model can be expanded by adding exogenous, explanatory variables to the right-hand side of the equation. The residuals of the new model should still mimic white noise. Furthermore, as with the dependent variable, the independent variable should be stationary. Coefficients and standard errors of the independent variables show whether the effect of the independent variable on the dependent variable is significant, while the AIC and BIC indicate whether the model has improved compared to the univariate model.

4. What are we talking about when we talk about crime?

The objective of this first chapter is to summarise the different data sets collected, including crime-related news and user responses in the UK and Uruguay, as well as crime-related communications from political representatives' accounts and user responses in both countries. Three key questions guide the analysis: Firstly, to what extent does the discussion of punitiveness emerge inductively from the data? A central hypothesis of this thesis is that social media, specifically Twitter, serves as a vehicle for expressing punitive attitudes. While this information can be tracked and analysed deductively (as the strategy used to build the automatic classifier in subsequent chapters), examining the inductive emergence of this issue through unsupervised learning provides an alternative validation. Secondly, in what contexts does this discussion emerge? Although the thesis focuses on online punitive attitudes, understanding the other types of communications with which these expressions coexist is essential. These coexisting communications can explain variations in punitive attitudes and potentially result from such attitudes. Thirdly, what is the prominence of punitive discussions within the broader discourse? These last two questions cannot be addressed using supervised learning strategies alone, as the initial Topics discussed in the collected data remain unknown. Topic modelling is employed to answer these questions, and quantitative thematic analysis techniques, as well as sentiment and emotion analysis, complement it.

4.1. The portrait of crime news in Uruguay and the UK.

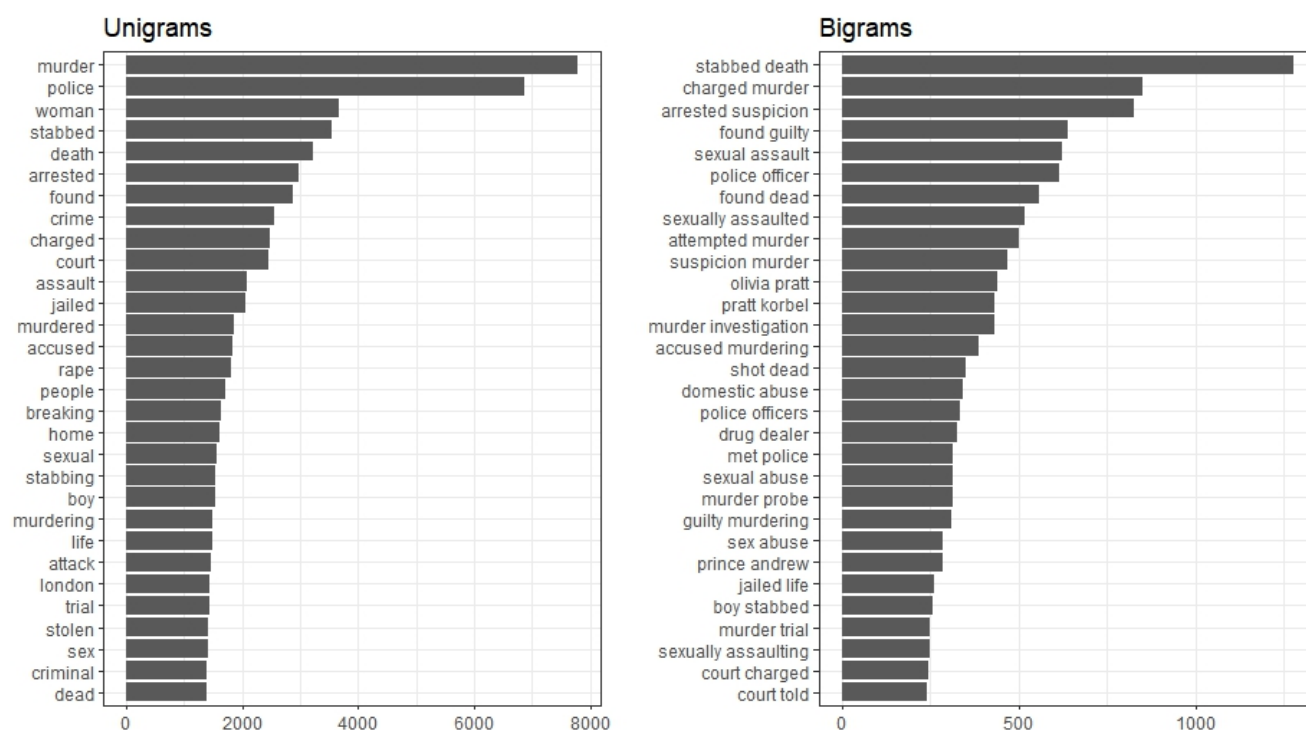
4.1.1. Descriptives

In Uruguay, the data collection yielded 26,263 tweets after filtering, averaging 72.15 crime-related news items daily. In contrast, the United Kingdom produced 56,023 news items, averaging 153.91 daily. To contextualise these figures, the Media Cloud tool (Roberts et al. 2021) captured the attention that the press in each country devoted to crime-related topics. Media Cloud measures attention as the ratio of news items containing specific keywords in any part of the news item to the total number of news items captured daily. For the United Kingdom, the keywords "crime" or "crimes" were used, while in Uruguay, the keywords "crimen," "crimenes," "delito," and "delitos" were employed. Due to data collection issues associated with Media Cloud during the first month of 2022, this month was omitted from the descriptive statistics. The analysis revealed that Uruguay had an average attention ratio of 0.7, compared to 0.5 in the United Kingdom. The attention ratio indicates the proportion of news items

mentioning the searched keywords out of the total number of news items collected by the tool. These figures demonstrate that the Uruguayan press consistently pays more attention to crime than the UK press. This finding aligns with public concern data from surveys (LAPOP 2023; ONS 2023b; YouGov 2023b) and the general prevalence of crime, particularly violent crime. However, this difference in media attention does not correspond proportionally to the actual difference in crime incidence between the two countries.

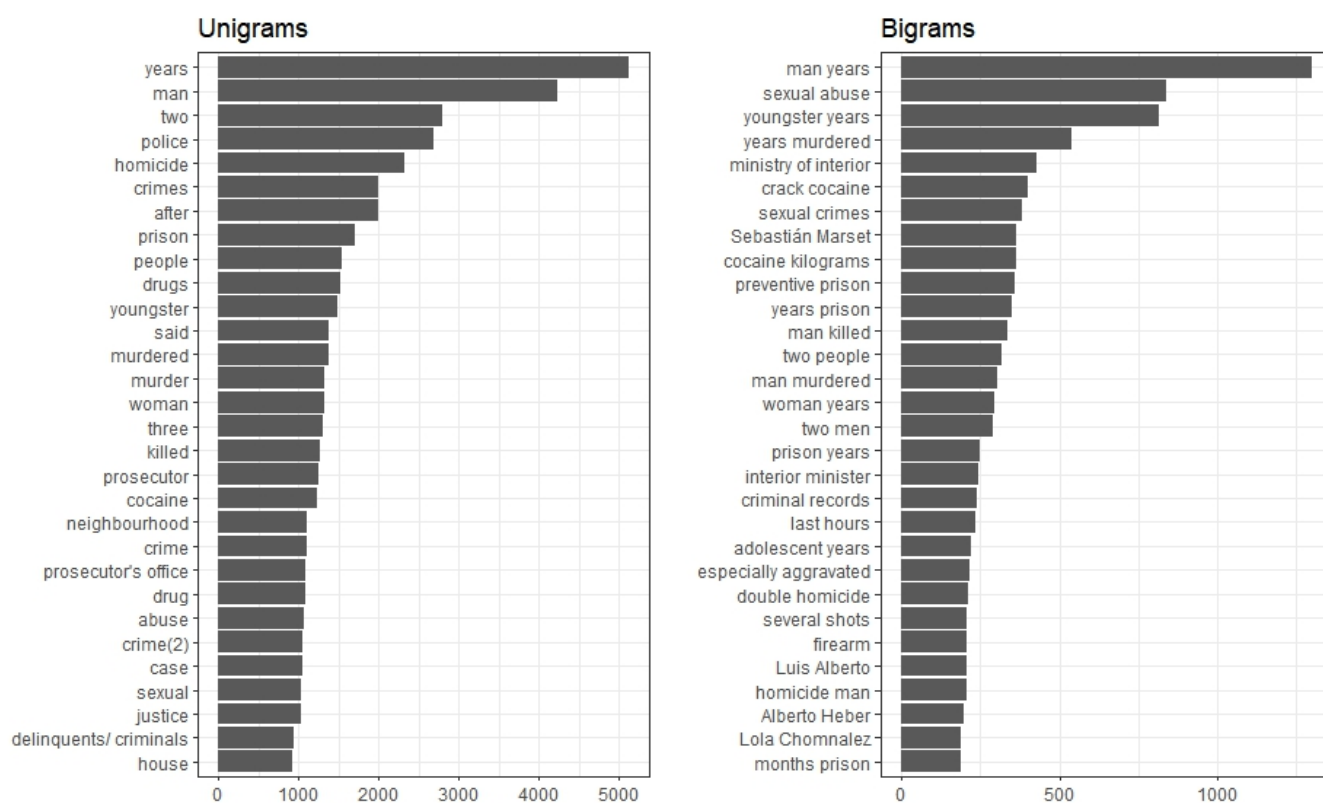
To further contextualise this information, the 30 most frequently mentioned words (unigrams) and the most frequently mentioned word pairs (bigrams) in both sets of news items are identified in Figures 6 and 7. Figure 6 illustrates that UK crime-related news titles predominantly focus on violent crimes and the immediate actions of law enforcement and the judicial system. Terms like "murder," "stabbed," and "rape" frequently appear, indicating a strong media emphasis on physical and sexual violence. This reflects public interest in the severity and immediacy of crimes, with detailed coverage of police actions and legal proceedings underscored by words such as "arrested," "charged," and "court." Additionally, an analysis of the bigrams reveals the prevalence of a specific high-profile case: the homicide of Olivia Pratt-Korbel. This highly publicised incident in 2022 involved the killing of a 9-year-old girl in Liverpool by a stray bullet during a conflict between criminal gangs (Smith 2022).

Figure 6 Top 30 unigrams and bigrams in crime-related news for UK



In contrast, Figure 7 shows that Uruguay's crime-related news titles emphasise crime's societal and institutional dimensions, highlighting long-term impacts and broader contexts. The frequent use of terms related to time, such as "years", "prison", and "years prison", suggests a focus on sentencing, incarceration, and the justice system's response to crime over time. Drug-related issues are prominently featured, with references to "cocaine" and "crack cocaine". Moreover, there is considerable coverage of government involvement in crime prevention and management, as seen in references to the "Ministry of Interior" and the name of the Minister at the time, "Luis Alberto (Heber)" and "Alberto Heber". These keywords reflect a media interest in how authorities handle crime and public safety. Similarly, as in the UK, a specific case stands out, the case of Lola Chomnalez, who disappeared and was found dead in 2014, a crime that was only solved in 2022 (La Diaria 2022). Both sets of media focus on serious crimes such as murder and sexual assault. The attention given to law enforcement actions and legal outcomes underscores a common narrative around crime prevention and resolution, reflecting shared priorities in maintaining social order.

Figure 7 Top 30 unigrams and bigrams in crime-related news for Uruguay



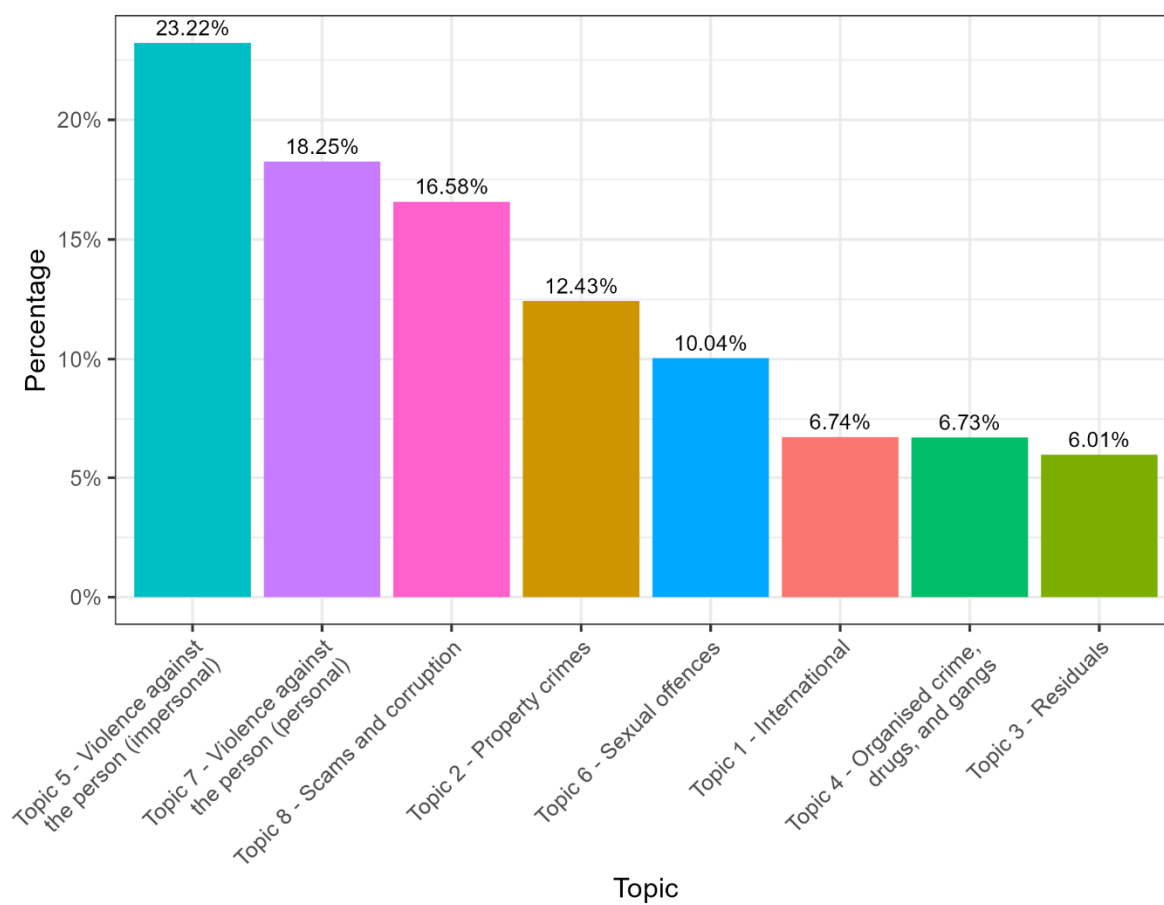
4.1.2. Topic Modelling

This study estimated a series of Topic Models to understand the main topics of discussion in the press of both countries on Twitter. The following sections present the main results of this analysis, categorised by country.

4.1.2.1. Topic Modelling – UK.

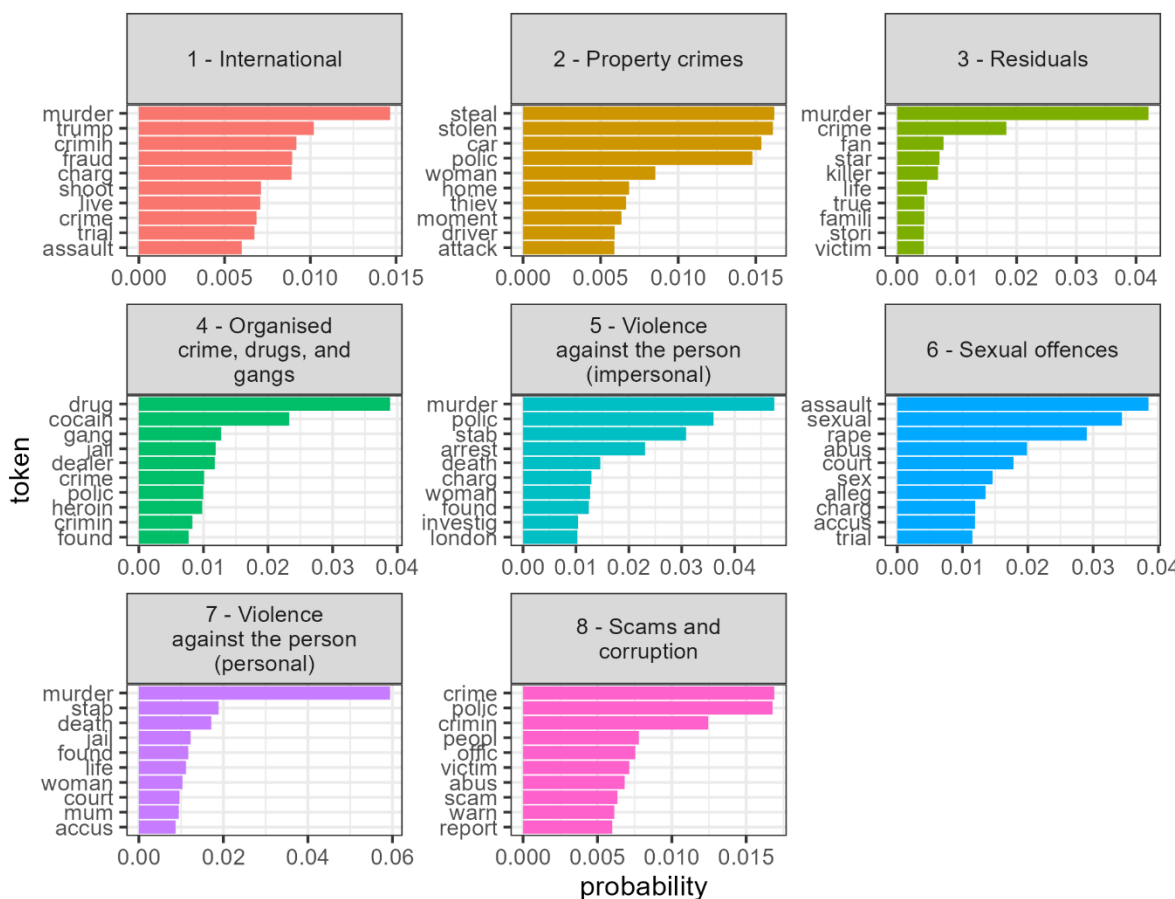
Figure 8 illustrates the topic proportions based on the classification of documents by their probability values. Figure 9 presents the ten words with the highest phi values per Topic to interpret the topics' content. In a Biterm Topic Model (BTM), the phi values represent the topic-term distributions. Each element of the phi matrix indicates the probability that a specific term in the vocabulary will be generated by a particular topic in the model. This information facilitates the interpretation of the topics' content. For clarity, the topics are tagged based on the interpretation of their content and colour-coded.

Figure 8 Topic proportion in crime-related news based on topic classification – UK.



N = 56,023

Figure 9 Top words by Topic based on phi values – UK.



Building on this information set, the following provides a brief description of each topic to offer a global understanding of the main topics discussed in the press for both countries. The presentation of the Topics follows the order of their classification proportions.

The topic modelling analysis of crime-related news items reveals that Topic 5 is the most prominent, accounting for 23.22% of the cases. This Topic focuses on crimes involving violence against persons, particularly highlighting offences such as murder, attempted murder, manslaughter, and wounding. Notably, it encompasses all mentions of the Olivia Pratt-Korbel case. Following closely, Topic 7 represents 18.25% of the news tweets and also pertains to severe interpersonal violence, as indicated by the highest phi value word in this Topic, “murder” (Figure 9). A deeper examination of the documents categorised under these topics reveals a nuanced distinction: Topic 5 generally addresses violent crimes of an "impersonal" nature, often involving attempted robberies or gang-related conflicts. In contrast, Topic 7 predominantly covers cases of intimate violence, especially those involving parents and children or

minors. Understanding this distinction is crucial for comprehending public reactions, as the nature and context of these offences differ significantly.

Topic 8, comprising 16.58% of the news stories, encompasses two main issues. Primarily, it covers various scam cases, especially those that arose during the COVID-19 pandemic, when many aspects of social life transitioned online, leaving less digitally literate individuals vulnerable. Additionally, it includes crimes of fraud or corruption linked to the political system, particularly irregularities surrounding COVID-19 loan fraud.

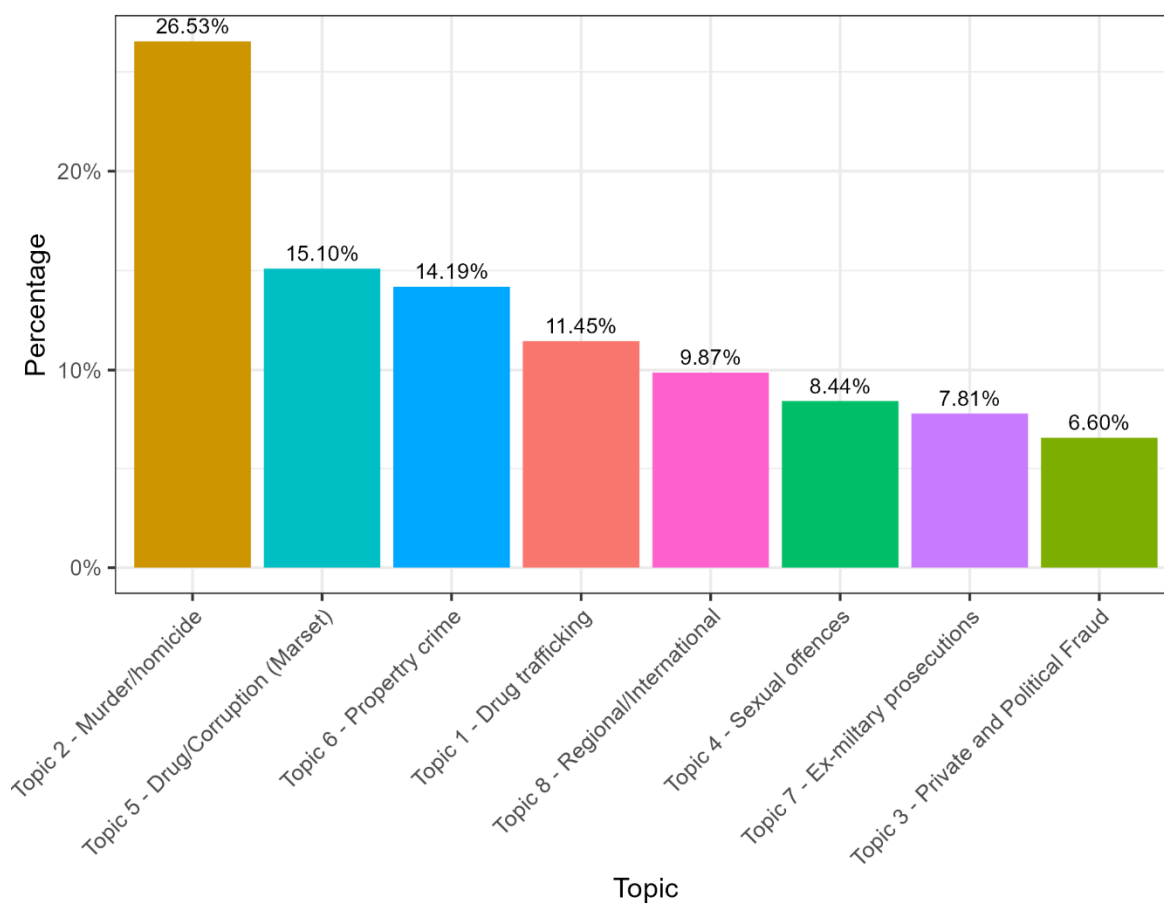
Topics 2, 6, and 4 have relatively more straightforward interpretations. Topic 2, which accounts for 12.43% of the news, pertains to minor non-violent property crimes such as burglaries and thefts. Topic 6, representing 10.04% of the news, is associated with sexual offences, with terms like assault, sexual, and rape being the most relevant. Topic 4, encompassing 6.73% of the news, relates to organised crime, mainly involving gangs engaged in drug trafficking. These stories typically report the prosecution of criminals and the seizure of large quantities of drugs or drug money.

Topic 1, covering 6.74% of the news, is somewhat ambiguous based on the keywords presented. However, analysing the classified documents reveals a strong presence of international news, particularly from the US, with many stories revolving around Donald Trump, the second most important word in this Topic. Finally, Topic 3, accounting for 6.01% of the news, captures residual cases that are not easily classifiable. It also includes topics that are outliers, focusing on TV programs or fiction rather than "real crime."

4.1.2.2. Topic Modelling – Uruguay

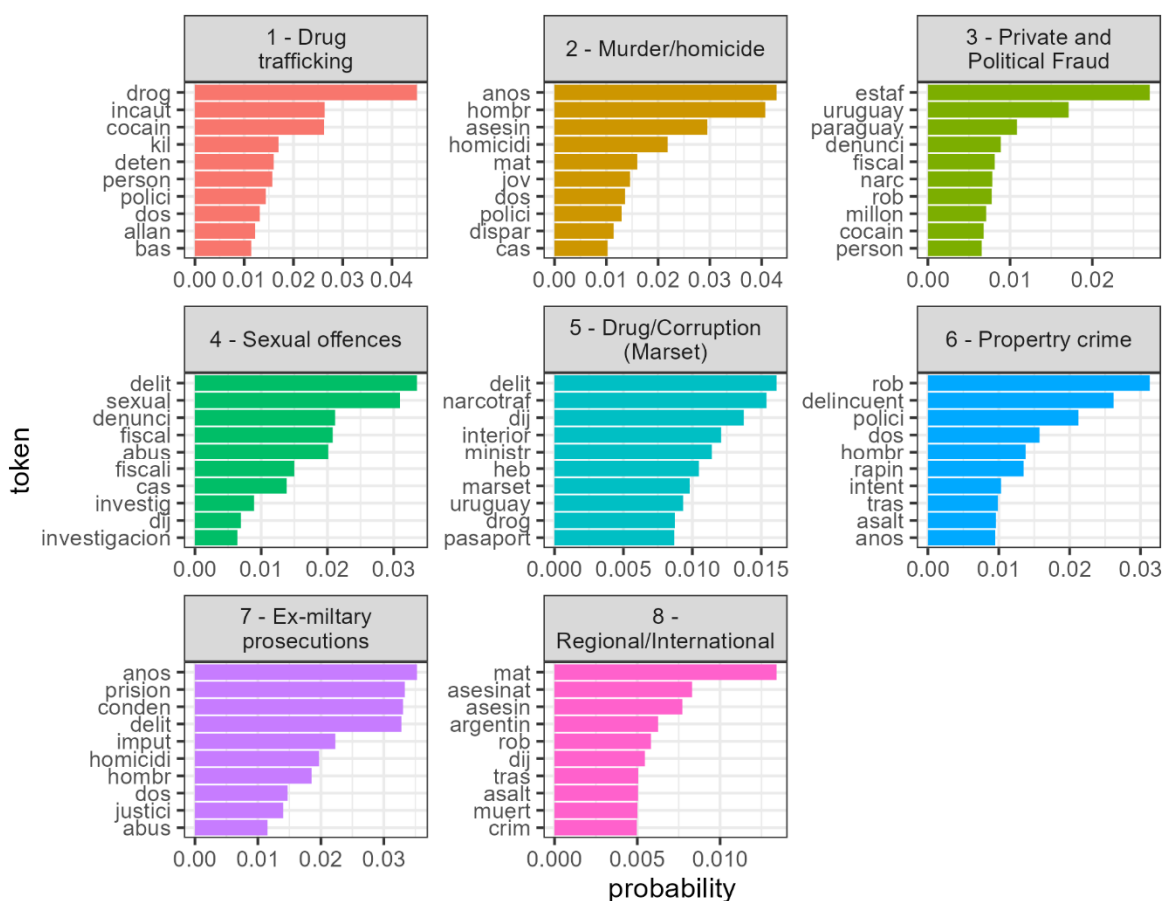
The analysis of the Uruguayan press followed the same process as that applied to the UK. Figure 10 shows the estimated topic proportions, while Figure 11 highlights the most important words for each Topic, based on the phi values.

Figure 10 Topic proportion for crime-related news based on topic classification - Uruguay



N = 26,263

Figure 11 Top words by Topic based on phi values - Uruguay



In Uruguay, the most important Topic (Topic 2) also relates to murders, constituting over one-fourth of the total cases. News stories frequently highlight two distinguishing features of violent crime in Uruguay compared to the UK. First, these reports often involve homicides emerging from gang conflicts, with many cases remaining unresolved and the victim's body being found. Second, there is a significantly higher prominence of firearms in these reports.

Topic 5, comprising 15.10% of the news, is associated with a high-profile case involving drug trafficking and political corruption. This Topic centres on the case of Sebastián Marset (El Pais 2022), a key figure in the Uruguayan media in 2022. Marset, allegedly a Uruguayan drug trafficker with connections to global organised crime, was arrested in Dubai in 2021 for entering the country with a false passport. In January 2022, thanks to the efforts of the Uruguayan consulate, Marset obtained a legitimate passport, which secured his release. This incident had significant political repercussions. The opposition criticised the decision, arguing that granting a passport

to a dangerous criminal allowed him freedom of movement. In contrast, the government contended that there were no active legal cases against Marset, which justified the issuance of the document. The case led to the resignation of political leaders and accusations of government corruption. In contrast, Topic 1, accounting for 11.45% of the news, also relates to drug trafficking but without any connection to the specific Marset case or political ties. This Topic encompasses news about police seizures of drugs, the closure of illegal sales centres, and similar events.

Topic 6 is mainly associated with property crime. Words such as robbery, mugging, and theft appear together, differentiated from homicide news. In Uruguay, the distinction between news on homicides and physical violence, particularly crimes against property, is more pronounced. While in the UK, cases of armed robbery (especially those involving knife crime) are often grouped with homicide news, the Uruguayan context differentiates these categories.

Topic 8, comprising 9.87% of the news, is less interpretable based solely on the keywords. The prominent mention of Argentina suggests that it involves international news, which is confirmed by analysing the documents with higher theta values for this Topic. Additionally, this Topic appears to encompass news related to the entertainment world, similar to the "residuals" category in the UK, where non "real crime" related topics are grouped together.

Topic 4 (8.44%) and Topic 3 (6.60%) result in relatively straightforward interpretations. Topic 4 relates to sexual offences, with "crime" and "sexual" as the first and second most important words, respectively. Topic 3 refers to fraud offences. Unlike the British case, these offences are also associated with money laundering, drug trafficking, and international corruption cases. Finally, Topic 7 is interesting, as it is context-specific. It primarily concerns news related to the prosecution of former military personnel during the military dictatorship. Although analysing the documents, some news items refer exclusively to the prosecution of criminals, especially for sexual offences, in general. The Topic seems to capture mainly this first group, which, although small, is relevant.

4.2. Reactions to crime news in Uruguay and the UK.

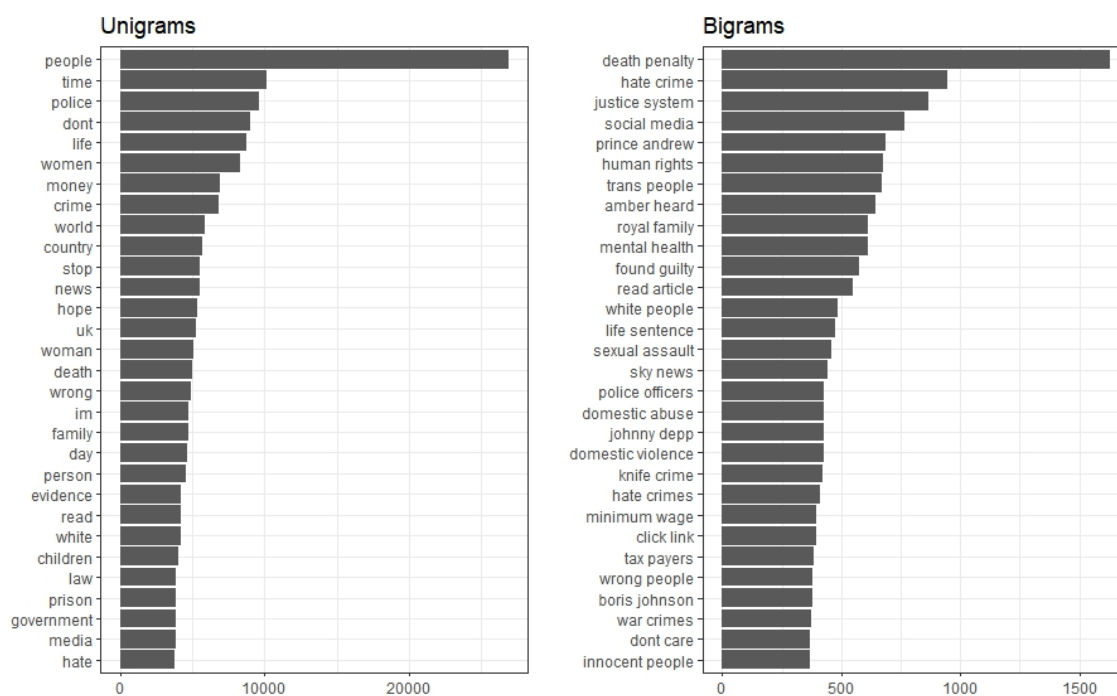
4.2.1. Descriptives

The analysis of the responses to the news items followed the same pipeline as the analysis of the news items. 334,827 responses to crime news in the UK were collected, originating from 153,655 unique users. The distribution of participation per user is strongly skewed to the right, with the vast majority of users responding only

once, making this the mode and the median. Additionally, the most active 5% of users generated 37.27% of the responses, while the least active 75% accounted for 31.68% of the interactions. In Uruguay, 107,828 responses were collected from 22,431 unique users. The ratio of participation per user in Uruguay is more than twice as high as in the UK (4.81 vs. 2.18). The most active 5% of users in Uruguay generated 44.13% of the responses, whereas the least active 75% of users produced 23.34%, accounting for a higher concentration too.

To contextualise this data, the UK had 16.7 million Twitter users in 2022 (Statista 2023). According to a YouGov survey (2023a), 49% of the population over 18 reported having a Twitter account in July 2022, but 12% reported using it once a month or less. In Uruguay, there were 575.9 thousand Twitter users in 2022 (Kemp 2022). Survey data indicate that 26.3% of the population had a Twitter account, with 66.2% accessing Twitter at least once a week, and the rest reported using it with less frequency (INE 2023b).

Figure 12 Top 30 unigrams and bigrams for the replies and quotes for crime-related news in the UK 2022



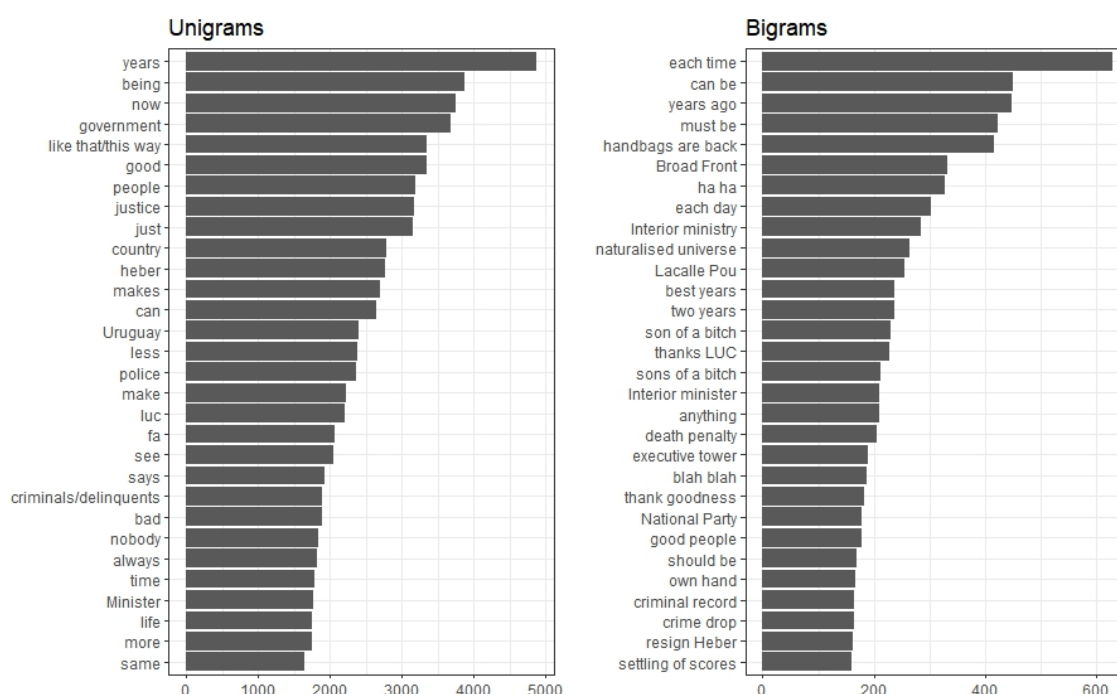
The unigrams and bigrams for the UK news replies and quotes are shown in Figure 12. One of the first elements that stands out in the analysis of the keywords for the UK is the prominence of the "death penalty" bigram at the top of the responses, mentioned more than 1500 times. While this information does not reveal the direction of the discussion (whether it is primarily for or against it), it indicates that users on social

media are actively debating the issue. The news media appear to catalyse public discussion on punishment. Similarly, "life sentence" also appears among the top 30 keywords, suggesting that various aspects of severe punishment are topics of interest in these responses.

The unigrams and bigrams analysis for Uruguay (Figure 13) requires some clarification:

- 'Lacalle Pou' is the president of Uruguay.
- 'LUC' stands for 'Ley de Urgente Consideración' (Law of Urgent Consideration), a set of measures implemented by the government at the beginning of its mandate, which includes certain modifications regarding criminal punishment.
- 'FA' is the acronym for the Frente Amplio (Broad Front), a centre-left opposition party.
- 'Handbags are back' is derived from a famous statement by the Minister of the Interior, implying that improved security policies have made it safe again to carry handbags without fear of theft.
- 'Naturalised Universe' refers to a specific user with high participation in the discussion, who signs his tweets with this phrase. While these communications were initially included to maintain the context, they are removed from the determinants analysis due to their impact as outliers.
- 'Executive Tower' refers to Uruguay's government headquarters.

Figure 13 Top 30 unigrams and bigrams for the replies and quotes for crime-related news in Uruguay 2022



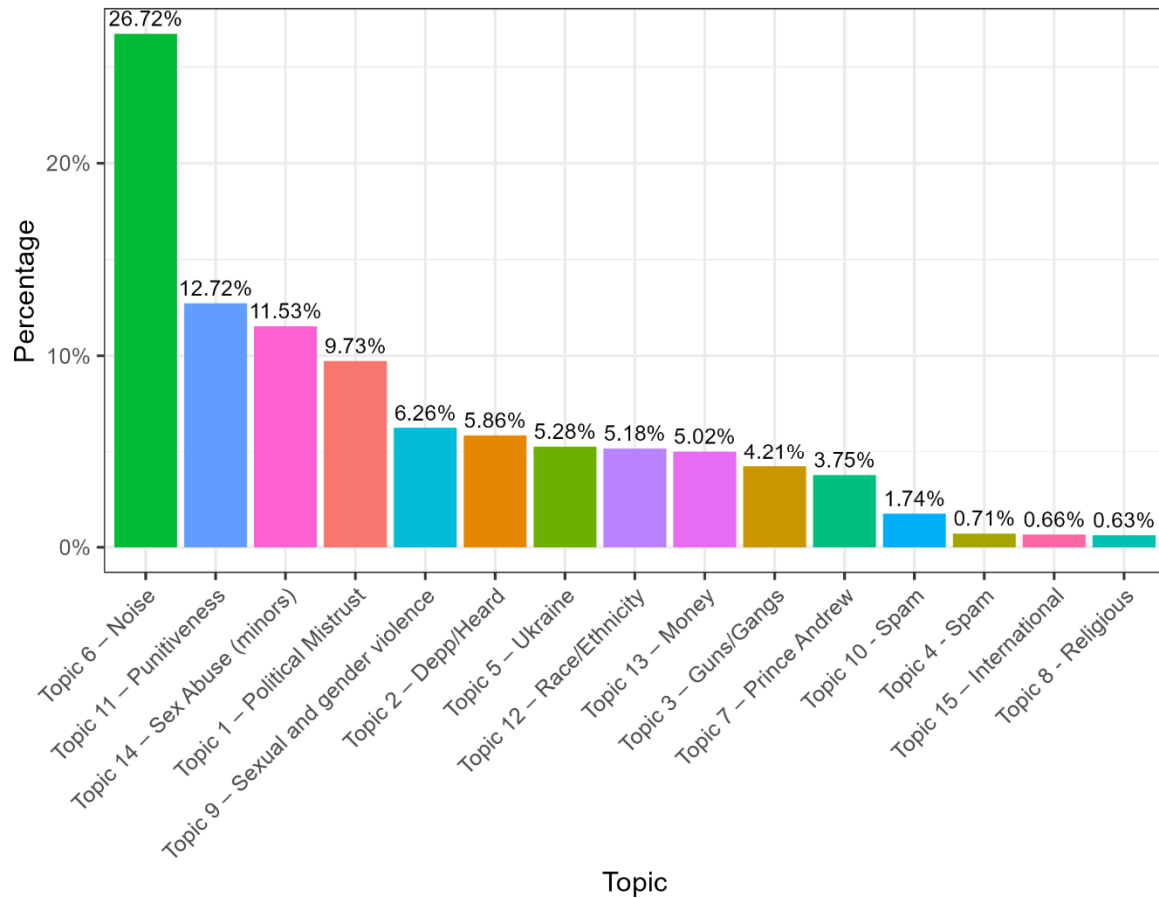
Several main bigrams are not particularly informative in the Uruguayan case, as they can be applied in different contexts. In the top 10, three are directly associated with the political discussion that seems to capture much of the conversation: "Frente Amplio", "Ministerio del Interior", and "Lacalle Pou". As in the UK, the bigram "pena muerte" (death penalty) appears, albeit in smaller proportions and with less importance. However, other bigrams are of interest regarding the reaction to crime. "Hijo puta" and "Hijos puta" appear in the top 30. It is the same insult in Spanish, whether in the plural or singular. This type of reaction - an emotive response through the insult - seems less relevant in the UK. Another relevant element that emerges in Uruguay is the concept of "mano propia" (associated with "justicia por mano propia" – vigilante justice).

4.2.2. Topic Modelling

The same topic modelling strategies were applied to cluster the textual material from news responses in the UK and Uruguay. In these cases, 15 topics were estimated, given the larger volume of information. Quantitative indicators and model interpretations suggest that this k-value yields the best results.

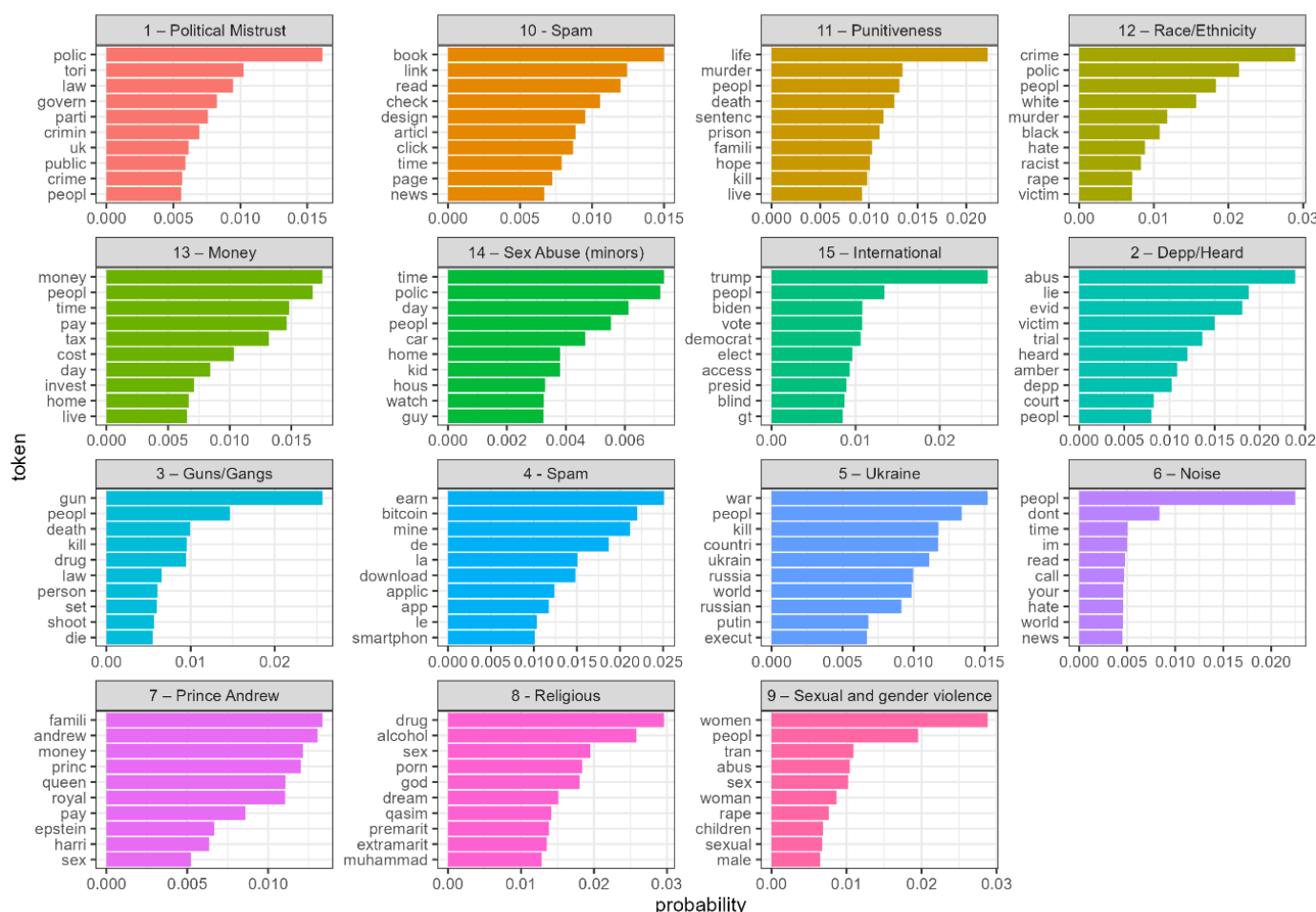
4.2.2.1. Topic Modelling – UK.

Figure 14 Topic proportion for the replies and quotes for crime-related tweets based on topic classification – UK.



N = 334,827

Figure 15 Top words by Topic based on phi values – UK.



The first point observed from the visual examination of the LDAvis (see methodology) output is the significant interrelation between the topics emerging from the replies. This result may arise because the answers are often shorter and depend on the context of the conversation, making it difficult to distinguish specific topics.

Following the classification order in Figure 14 for topic interpretation, Topic 6 stands out with a very high classification percentage (26.72%). The most important word is "people," the most frequently used word in the responses, as noted in the word count. Analysing the keywords and tweets with higher theta values does not provide much specific information. The topic modelling appears to capture common words throughout the entire set of replies and quotes on this Topic, somewhat gathering the "noise" or "background" with words commonly appearing in various tweets within different types of responses, rather than an actual meaningful theme. However, analysing the top 30 words according to their Phi values reveals words like "hate" and

"racist," indicating the importance of the discussion about discrimination on Twitter in response to crime news across many news items.

The next Topic, Topic 11 (12.72%), is particularly relevant to the issue of interest in this thesis. This Topic directly addresses punitive attitudes, encompassing requests for extended sentences, the death penalty, and demands for justice, largely based on retributive grounds—emphasising that the criminal should suffer parallel to the harm caused. Expressions of disgust and anger are also prevalent in this Topic, highlighting the emotional intensity surrounding discussions of punishment and justice.

Topic 14 (11.53%) is not easily interpretable at first glance. However, analysing the responses and the news they refer to suggests that it revolves around news about sexual abuse, particularly among minors. It is important to note that the punitive response to such crimes is concentrated in Topic 11, reflecting the strong retributive attitudes these crimes can trigger. Several topics, including Topic 14, discuss specific crimes with relevant keywords. However, the response to these crimes may be distributed across multiple topics. For instance, in discussions about sexual abuse, a broad punitive response might be classified under Topic 11. Concurrently, there may be a discussion about the specifics of the event, such as highlighting the offender's predatory attitude. Descriptions using keywords specific to sexual offences would be incorporated into Topic 14.

Topic 1 (9.73%) pertains to discussions about the government's crime control policy in 2022 and includes expressions of mistrust or lack of legitimacy in the political system. Although the Topic primarily criticises the current government, it also contains expressions of discontent against the whole political system and the opposition parties. This Topic indicates a broader scepticism and dissatisfaction with political leadership and crime control strategies. For its part, Topic 13 (5.02%) is closely related to Topic 1. It refers to discussions around economic resources and money in 3 ways: cases of fraud, corruption, and investment (or lousy investment) by the government.

Topic 9 (6.26%) focuses on discussions of sexual and gender violence. This Topic includes conversations around rape cases, hate crimes, and issues related to gender, particularly concerning the trans population. It highlights the social media discourse on these critical issues, reflecting concerns about sexual violence and discrimination based on gender identity. This topic is linked to Topic 7 (3.75%), which is directly associated with allegations of abuse against Prince Andrew and the repercussions for the royal family. It is important to note that case mentions appear in other instances linked to Topics 9 and 14.

Interestingly, Topic 2 (5.86%) refers to the discussion generated around one newsworthy event: the domestic violence trial between Johnny Depp and Amber Heard. Although a large part of the tweets classified in this Topic refer specifically to this event, given some of the keywords, other tweets are also classified in this Topic, referring to the follow-up of notoriety lawsuits, particularly in cases of sexual violence. Next, Topic 5 (5.28%) groups tweets about the war in Ukraine. This result occurs because, in some cases, the filters used to avoid collecting discussions about international war crimes were ineffective. It also occurs in other instances where users raise the issue due to the thematic proximity of the specific news item.

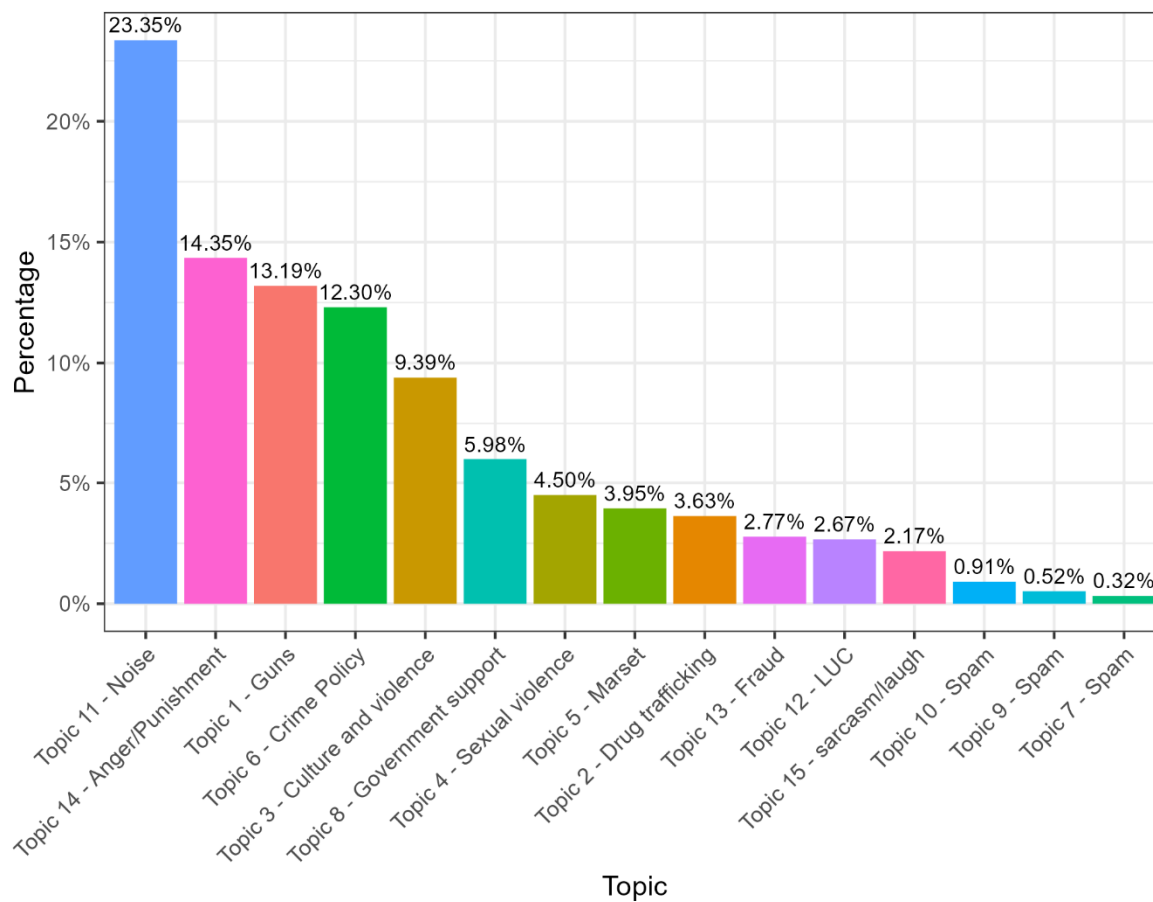
Topic 12 (5.18%) focuses on responses concerning the race or ethnicity of those involved in crime news. Analysis of tweets within this Topic reveals numerous comments that could be considered racist or xenophobic. Many users demand clarification and specification of the minority groups to which the criminals belong, often drawing correlations between crime and ethno-racial affiliation.

Topic 3 (4.21%) is the last meaningful Topic extracted from the modelling (having already discussed Topic 7). It accounts for the repercussions of crime with guns, drug dealing, and its link with criminal gangs. Then, Topics 10 (1.74%) and 4 (0.71%) appear to be spam (related to selling or promoting different kinds of products or content). Topics 8 (0.63%) and 15 (0.66%) are very small and should be interpreted cautiously. Topic 8 includes religious responses to crime. Many of them condemn the aggressor in religious terms, especially regarding drug or alcohol use. Topic 15 collects some international news, much of which is in languages other than English, where the filters did not work as expected.

4.2.2.2. Topic Modelling – Uruguay

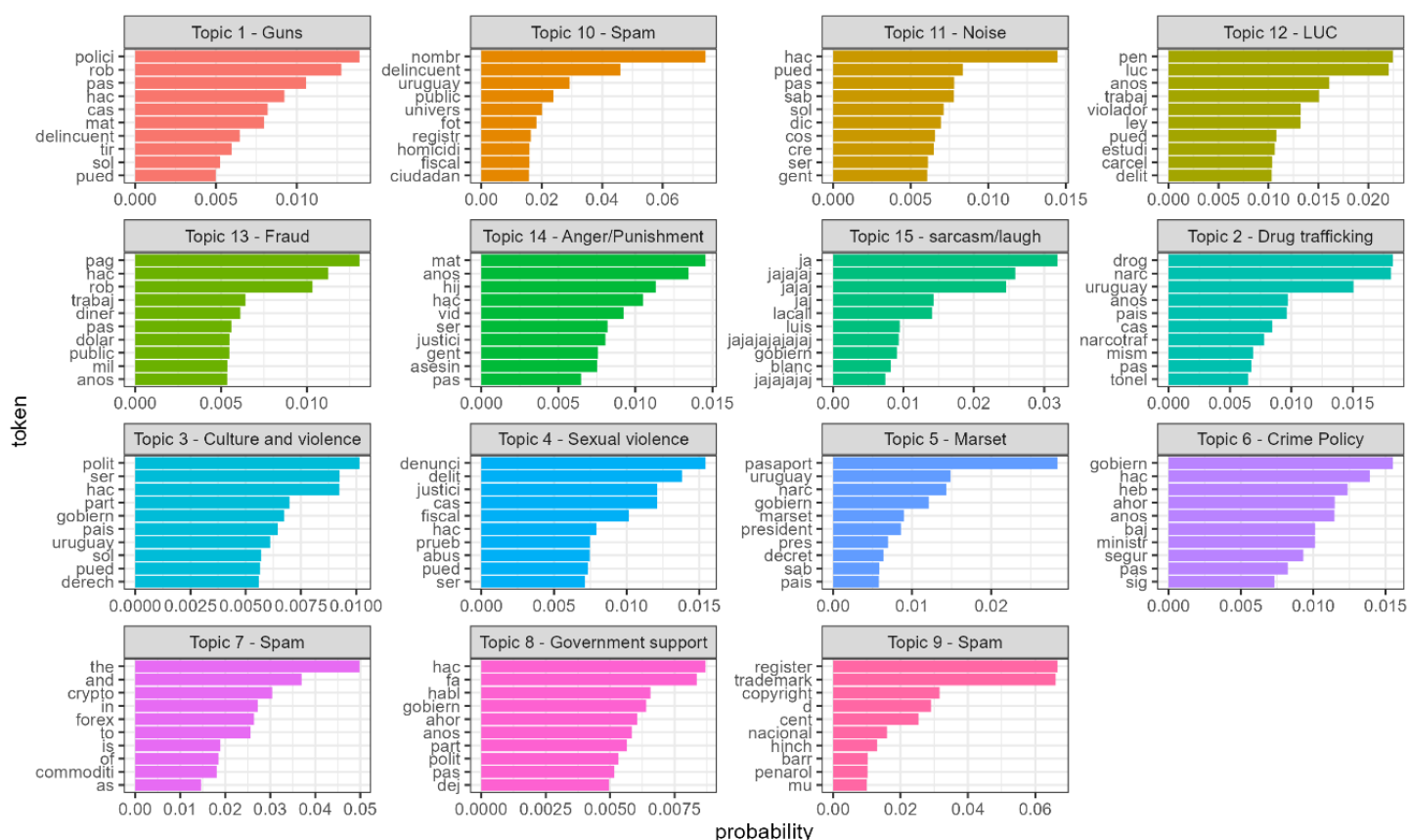
The following section presents the results of the topic modelling applied to responses to crime-related news in Uruguay. Figure 16 shows the topic proportions, while Figure 17 presents the top words for each Topic. Similar to observations in the UK, the interrelationship between topics in the responses is much higher than that observed for the news items.

Figure 16 Topic proportion for the replies and quotes for crime-related tweets based on topic classification – Uruguay.



N = 107,828

Figure 17 Top words by Topic based on phi values – Uruguay



The most significant Topic, based on the proportion of classified tweets, Topic 11 (23.35%), seems to comprise common words in the Spanish language that permeate general crime discussions. A quick analysis of these tweets reveals short, context-specific responses that are challenging to interpret without additional context from the broader conversation. Like a natural conversation, many replies lack informative content on their own. The consistent prominence of this Topic in the classification, with few exceptions, when analysed by date, also supports this observation.

The next Topic, Topic 14 (14.35%), seems to confirm initial intuitions about the characteristics of the public response in Uruguay. This Topic includes keywords such as several Spanish insults ("put", "mierd", "hdp"), along with "justice" and "prison". It reflects an emotional response of anger and indignation toward crime. This Topic captures most of the punitive responses collected in Uruguay. However, punitive tweets appear more diluted and mixed with these other types of replies compared to the British case.

In third place, Topic 1 (13.19%) seems to be associated with various comments on the use of firearms. Many of these comments only reproduce the content of the news item, especially in cases of violent outcomes for the criminal, for example, 'he nodded the bullet', in one case of a criminal shot by the police with a bullet to the head. Other news items use directly punitive concepts associated with the idea of eliminating criminals ('shoot him and throw him in the dump truck'). Finally, other comments use the idea of the presence of gunshots and firearms to describe the situation of insecurity.

Topic 6 (12.30%) primarily focuses on discussions about the crime control policies of both the current and previous governments. Security has been a central issue in political campaigns for years due to the constant increase in crime, particularly violent crime. Consequently, debates about the effectiveness of various governmental measures have proliferated on social media, reflecting widespread public concern about this critical issue. Similarly, Topic 8 (5.98%) also involves political discussion. This Topic mainly comprises support for the current centre-right government and criticism of the left. Although some comments may reverse this direction, the Topic is primarily characterised by this type of opinion.

Topic 4 (4.50%) is triggered by monitoring specific cases in the justice system, including the complaint, trial, and sentencing processes. It is particularly associated with the follow-up of cases involving sexual violence. Similarly, Topic 5 (3.95%) focuses on the monitoring of the Sebastian Marset case (explained above). The prominence of this case and its extensive news coverage have led to a discussion specific to this incident, encompassing significant criticism and counter-criticism of the government. This Topic is quite similar to Topic 2 (3.63%), which also addresses drug trafficking but in a more general context.

Topic 13 (2.77%) encompasses responses to crimes involving large-scale fraud, such as million-dollar scams and corruption cases, as well as government neglect or inoperativeness. Discussions often recall corruption cases from the previous government, particularly those involving the vice president, who resigned after being accused of misconduct in using corporate cards with public funds.

It is important to note that the smaller topics described next are unreliable in terms of their classification. The Topic modelling still identifies significant relationships between words, providing insight into public discussion. However, they have a considerable degree of error in terms of prediction. Despite its small size, Topic 12 (2.67%) is particularly interesting for studying punitive attitudes. This Topic requires contextualisation within the Uruguayan legal framework. With the new government

assuming office, which shifted leadership from a left-wing coalition to a right-wing coalition, a significant legal change occurred through the "Law of Urgent Consideration" (LUC). This law introduced numerous articles modifying regulations in various areas of social life, including education, the economy, and security. Regarding security and justice, it led to the punitive inflation of certain offences, specifically by limiting the possibilities of early release for sex offenders (Queirolo 2020). Topic 12 captures the defence of the LUC by advocating for increased penalties. Topic 15 (2.17%) appears to group responses characterised by "hahaha" (jajaja) or similar expressions, commonly used to respond sarcastically to specific events. Next, Topic 10 (0.91%) includes answers and quotes from a user who frequently shares news items – the same as that mentioned when analysing the bigrams. This user consistently includes their username in their shared information, creating a minor topic. Topics 9 (0.52%) and 7 (0.32%), are primarily spam (content or product promotion) that managed to evade the filters and data cleansing processes.

4.2.3. Sentiment and emotion analysis

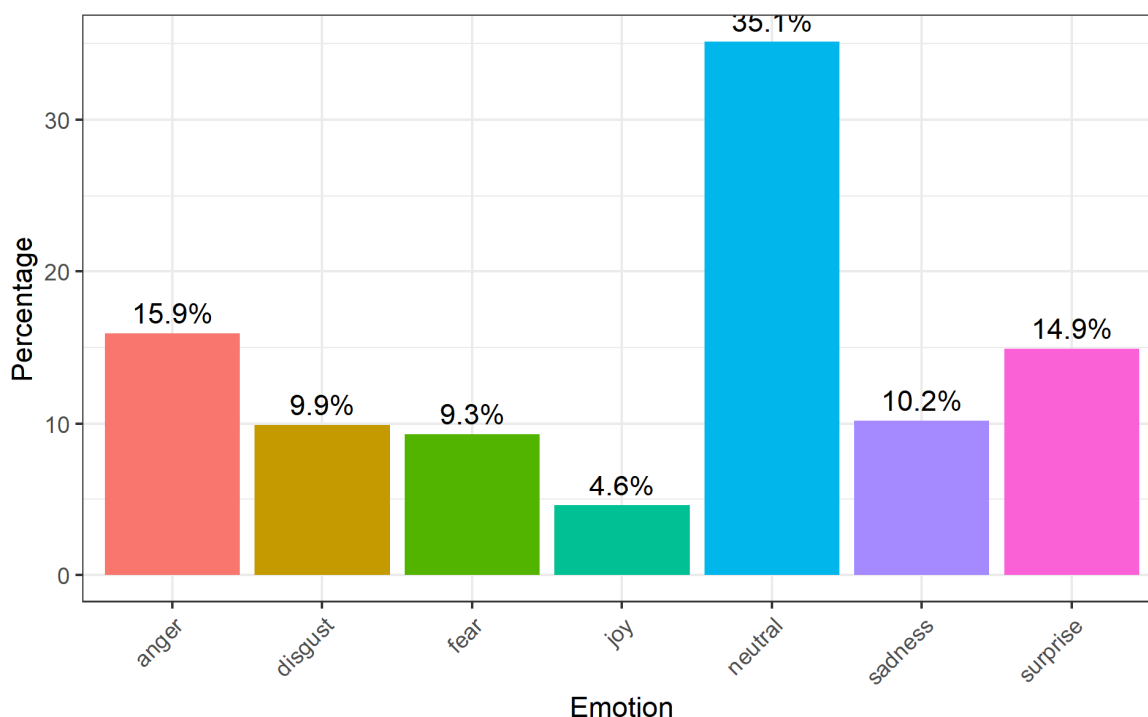
Additionally, this study employs sentiment and emotion analysis to complement the topic analysis and gather more information about the characteristics of public discussions surrounding crime. These techniques often complement topic modelling to refine the interpretation of large volumes of text (Fino et al. 2021; Mujahid et al. 2021; Qiao and Williams 2022; Yin et al. 2022). This study employs a similar strategy, particularly the approach used by Oliveira et al. (2022) in examining emotional responses to COVID-19-related news. Emotions are considered a constitutive part of attitudes (see theoretical chapter). However, they can be complex to measure using traditional methods, such as surveys (Mossholder et al. 1995; Ciuk et al. 2015). Employing sentiment and emotion analysis strategies within the context of public discussion can provide a deeper understanding of their role in forming punitive attitudes. The analysis uses pre-trained transformer models to classify emotions (Pérez et al. 2021; Hartmann 2022) and sentiments (Barbieri et al. 2020). Ekman's (1992) classification of six basic emotions is used for emotion analysis. Sentiments are categorised into three main types: positive, neutral, and negative.

4.2.3.1. General – UK.

As expected, given the type of news analysed, most responses (61.3%) are negative, 32% are neutral, and 6.7% are classified as positive. In terms of emotion, after discarding neutral cases—which can occur when the tweet expresses emotional neutrality, when there is ambiguity regarding the emotion communicated, or when there is a lack of information needed to infer it—the majority emotion is anger,

followed by surprise. Disgust, fear, and sadness have even proportions, each around 10%. Finally, joy is in the minority, with only 4.6%. Minor differences may occur between sentiment and emotion analysis values because each inference utilises different pre-trained models. Consequently, the sum of positive, negative, or neutral values may vary slightly between the two analyses.

Figure 18 Emotion distribution for the replies and quotes of crime-related news in the UK 2022



N = 334,827

4.2.3.2. By News topics – UK.

The analysis of each news Topic shown in Table 4 reveals minimal differences in the magnitude of sentiment and emotion. A detailed examination of the tweets with the most reactions within each news topic shows a general trend: tweets reporting the most severe incidents within each category receive the highest engagement. This trend could explain the minimal differences in sentiments and emotions, as the most severe crimes tend to elicit similar reactions. For instance, corruption cases that gather the most responses usually involve more severe economic implications or higher-ranking individuals in terms of power and resources. Similarly, property crime cases with the most defenceless victims (e.g., older people) and the most damage provoke the harshest reactions. These scenarios evoke predominantly negative responses, mirroring those expected for even more violent crimes (homicides or sexual abuse) since they do not allow room for other types of responses. These

classifiers do not provide polarity (intensity levels) of the sentiment or emotion classified, so it is impossible to determine if there is a difference in this sense with this data.

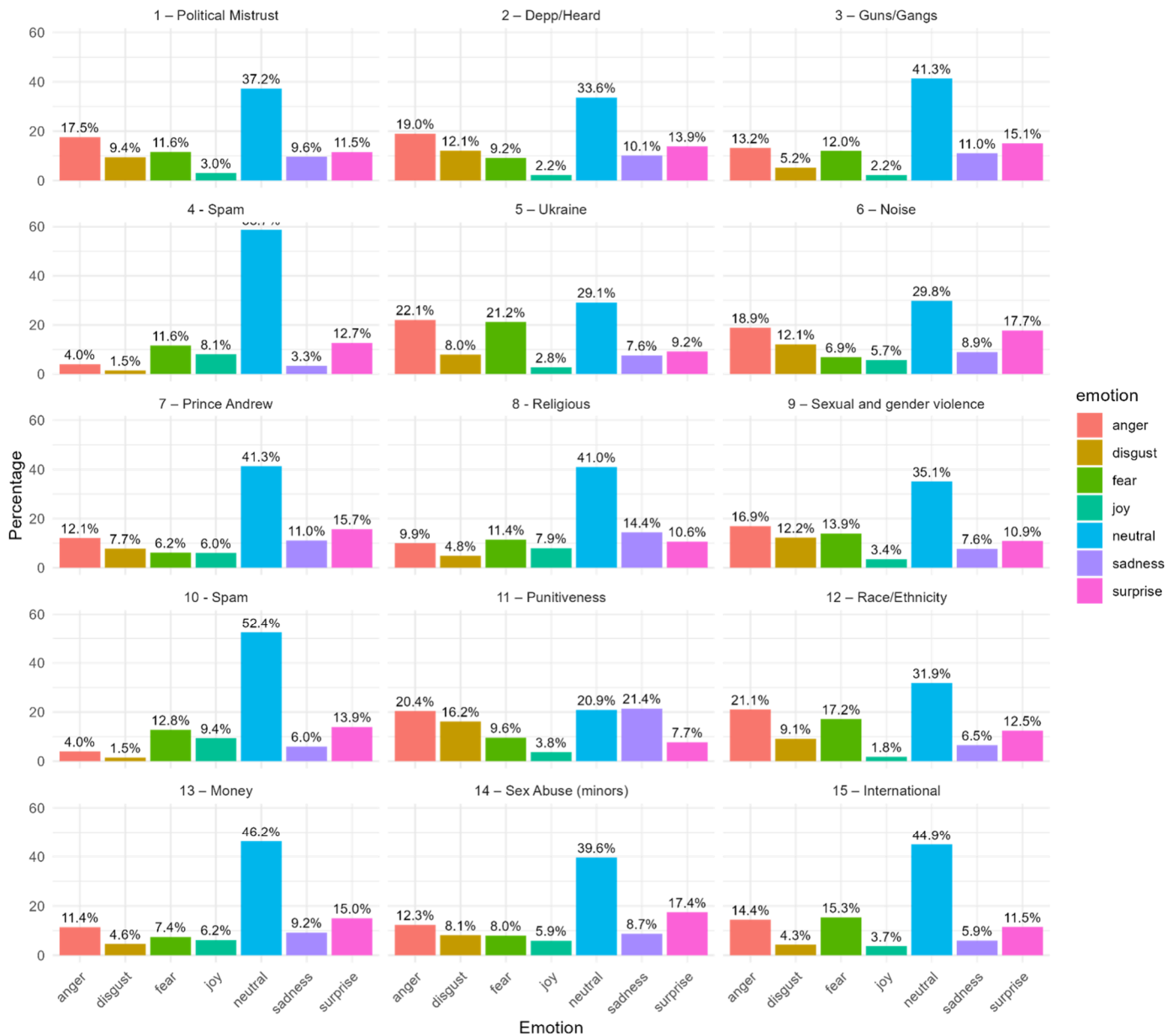
Table 4 Emotion distribution for the replies and quotes of crime-related news in the UK 2022 by news topic

News Topics	Anger	Disgust	Fear	Joy	Neutral	Sadness	Surprise
Topic 1 - International	17.9%	10.5%	10.0%	4.3%	34.0%	10.2%	13.1%
Topic 2 – property crimes	16.3%	9.5%	9.6%	4.7%	33.9%	10.5%	15.5%
Topic 3 - residuals	16.1%	10.5%	9.3%	5.0%	34.0%	11.0%	14.0%
Topic 4 – organised crime/gangs	17.4%	9.5%	10.4%	4.5%	33.6%	10.2%	14.3%
Topic 5 – Violence against the person (impersonal)	17.5%	9.8%	9.9%	4.5%	33.3%	11.1%	14.0%
Topic 6 – sexual offence	17.2%	10.2%	10.4%	4.4%	34.1%	10.6%	13.0%
Topic 7 - Violence against the person (personal)	17.0%	10.7%	11.3%	4.3%	33.6%	9.8%	13.3%
Topic 8 – scams and corruption	16.8%	11.6%	9.5%	4.5%	33.6%	10.2%	13.8%

4.2.3.3. By Replies topics – UK.

When analysing the emotions by Topic (Figure 19), Topic 6, which groups a set of general keywords, follows a distribution similar to the pattern observed for the entire dataset. Of particular interest for this thesis, Topic 11 shows lower levels of neutrality and a higher incidence of all negative emotions, particularly anger. Topics 14, 1, 9, and 2 also exhibit distributions similar to those of the entire dataset. However, Topic 5, related to the war in Ukraine, presents the highest levels of anger and fear. Topic 12, associated with discussions of race and ethnicity, also exhibits very high levels of anger and fear. Topic 3, focused on gun crime and gang violence, shows a similar emotional distribution to the total dataset, with a slight increase in the neutral category. The remaining topics account for very small proportions of the classification.

Figure 19 Emotion distribution for the replies and quotes of crime-related news in the UK 2022 by replies and quotes topic

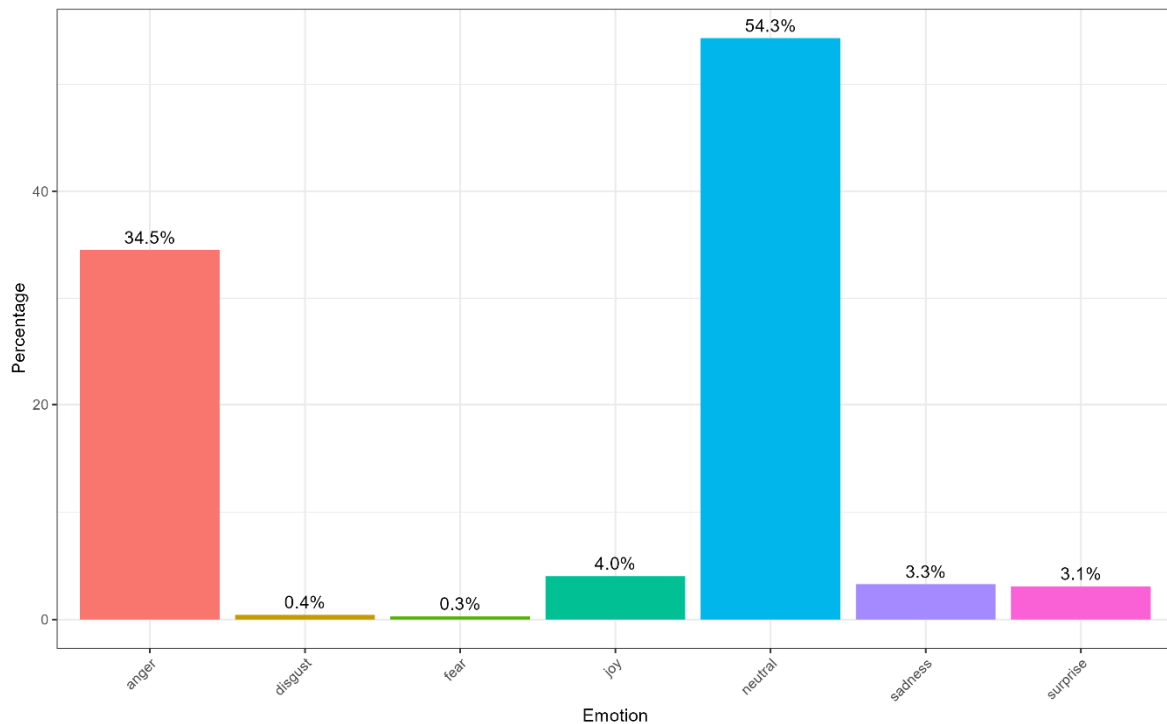


This initial interpretation of the topics reveals that the distribution of emotions in response to criminal news varies across discussion topics. Semantically connected reactions often imply a specific type of emotional response. The discussion on punishment, in particular, exhibits high levels of negative emotions, as illustrated in Figure 19 and occupies a significant percentage of the discourse on social media, as shown in Figure 14.

4.2.3.4. General – Uruguay

Following the same procedure for Uruguay, the distribution of responses according to the tweets' sentiment mirrors the response in the UK. Negative replies account for 61.0%, neutral for 31.3%, and positive for 7.7%. In terms of emotions, like in the UK, most tweets fall into the "neutral" category (Figure 20). However, in Uruguay, this category contains more than half of the classified tweets. Conversely, aside from "anger" (34.5%), the remaining categories exhibit a marginal distribution share.

Figure 20 Emotion distribution for the replies and quotes of crime-related news in Uruguay 2022



N = 107,828

4.2.3.5. By News topics – Uruguay

Regarding emotions associated with news topics, Table 5 presents a pattern similar to that observed in the UK. No significant differences appear in the proportions by type of news item, classified using Topic Modelling strategies. The same hypothesis about why this occurs remains.

Table 5 Emotion distribution for the replies and quotes of crime-related news in Uruguay 2022 by news topic

Topic News	Anger	Disgust	Fear	Joy	Neutral	Sadness	Surprise
Topic 1 – drug traffick	35.2%	0.6%	0.2%	3.4%	54.3%	3.2%	3.0%
Topic 2 - Murders	36.4%	0.6%	0.3%	3.3%	53.5%	3.2%	2.8%

Topic 3 - Fraud	36.3%	0.4%	0.4%	3.4%	53.4%	3.5%	2.6%
Topic 4 – Sexual offences	36.5%	0.3%	0.3%	3.4%	53.7%	3.1%	2.7%
Topic 5- Marset	36.4%	0.5%	0.4%	3.2%	53.3%	3.4%	2.8%
Topic 6 – property crime	38.6%	0.4%	0.2%	3.5%	51.0%	3.7%	2.5%
Topic 7 – ex-military prosecutions	36.9%	0.4%	0.2%	3.3%	53.1%	3.3%	2.8%
Topic 8 – Regional/International	36.6%	0.3%	0.3%	3.2%	53.3%	3.6%	2.7%

4.2.3.6. *By replies topics – Uruguay*

In Uruguay (Figure 21), the most prominent Topic at the level of responses, which groups general words, has an emotional distribution similar to the average, mirroring the results in the UK. Topic 14, identified through topic modelling as tweets expressing anger towards crime, supports this observation, exhibiting a proportion well above the average in the emotions of anger and sadness, with more than half classified as "anger." Topic 1, associated with gun violence, has a higher proportion of "neutral" responses compared to other topics. This result does not imply that this type of violence does not evoke punitive attitudes or expressions of anger; instead, these attitudes are clustered in Topic 14, as explained in the UK case. Topics 6, 3, 8, and 12, associated with security policy, social violence, support for the government, and the Law of Urgent Consideration ("LUC"), respectively, display emotional responses close to the average. Topics 4 (Sexual Violence), 5 (Marset), 2 (Drug Trafficking), and 13 (Fraud) have a slightly higher proportion of neutral tweets while maintaining high levels of anger in all cases. Topic 15, primarily composed of sarcasm and laughter, has a higher proportion of tweets classified as "neutral." Topic 10, which groups a particular user's tweets and other included tweets, presents a higher proportion of anger. The remaining cases are traditional spam, where the "neutral" category carries more weight than previous topics.

Figure 21 Emotion distribution for the replies and quotes of crime-related news in the UK 2022 by topic



4.3. Expressions of political leaders on crime in social media

The study also analysed tweets from members of parliament, accounts of parties with parliamentary representation, and the president and vice president in the Uruguayan case. When analysing the communications made by politicians on Twitter, specific considerations should be taken into account. One crucial aspect is the number of retweets made by politicians. In the United Kingdom, 25,278 tweets were collected (before filtering), of which 13,985 were retweets. In Uruguay, 3,544 tweets were

collected, with 2,179 being retweets. These retweets are significant as they reflect communications to which the followers of these politicians are exposed. However, there are instances of extensive retweeting within the political system, which can artificially amplify the perceived importance of specific communication⁷.

This issue poses a particular problem for topic modelling, as it creates strong links between words due to the specific repetition of particular tweets. Therefore, the descriptive analysis will use the entire dataset. The topic modelling will use a single instance of each retweet. The analysis will retain the original tweet if the tweet originates from the political system. If the tweet comes from outside the political system and a politician retweeted it, the analysis will use the first retweet.

4.3.1. Descriptives

In the United Kingdom, 557 out of 660⁸ members of parliament and political parties are represented on Twitter, whereas 122 politicians out of 135⁹ have an online presence on Twitter in Uruguay. After filtering, the total number of tweets collected, including retweets, is 18,426 for the UK. While the daily output appears stable, there is a notable outlier on Holocaust Day, when much of the political system made commemorative posts on Twitter. In contrast, political communication on Twitter in Uruguay is significantly smaller. After filtering, 3,519 tweets were collected for Uruguay, including retweets. The distribution in Uruguay appears relatively homogeneous, with specific peaks during the interpellation of the Minister of the Interior and the discussion regarding the Urgent Consideration Law (LUC).

Figure 22 shows the top unigrams and bigrams for the tweets gathered from the UK. The British political system appears to have focused much of its discussion on Twitter on issues related to sexual, domestic, and gender-based violence. Predictably, terms associated with politics, such as "taxpayer money," also appear. Additionally, "Boris

⁷For example, Keir Starmer, MP for Holborn and St. Pancras and leader of the Labour Party, tweeted, in reference to Boris Johnson (Prime Minister for the Conservative party, when the tweet was created):

Honesty and decency matter.

After months of denials the Prime Minister is now under criminal investigations for breaking his own lockdown laws.

He needs to do the decent thing and resign.

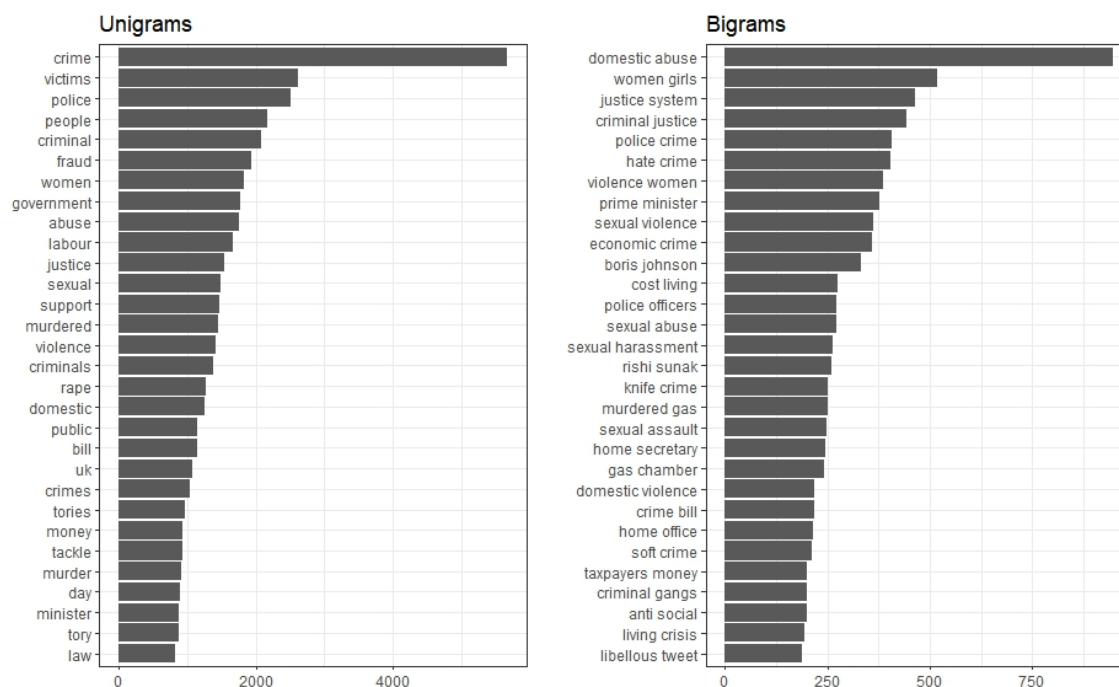
This tweet was retweeted 54 times by British politicians.

⁸ 650 members of the parliament plus 10 political parties accounts (Conservatives, Labour, SNP, Liberal Democrats, Sinn Féin, Democratic Unionist Party, Plaid Cymru, Social Democratic and Labour Party, Alliance Party of Northern Ireland", and Green Party)

⁹ 129 members of the parliament plus 6 political parties accounts (Partido Nacional, Partido Colorado, Cabilido Abierto, Partido Independiente, Frente Amplio, Partido Ecologista)

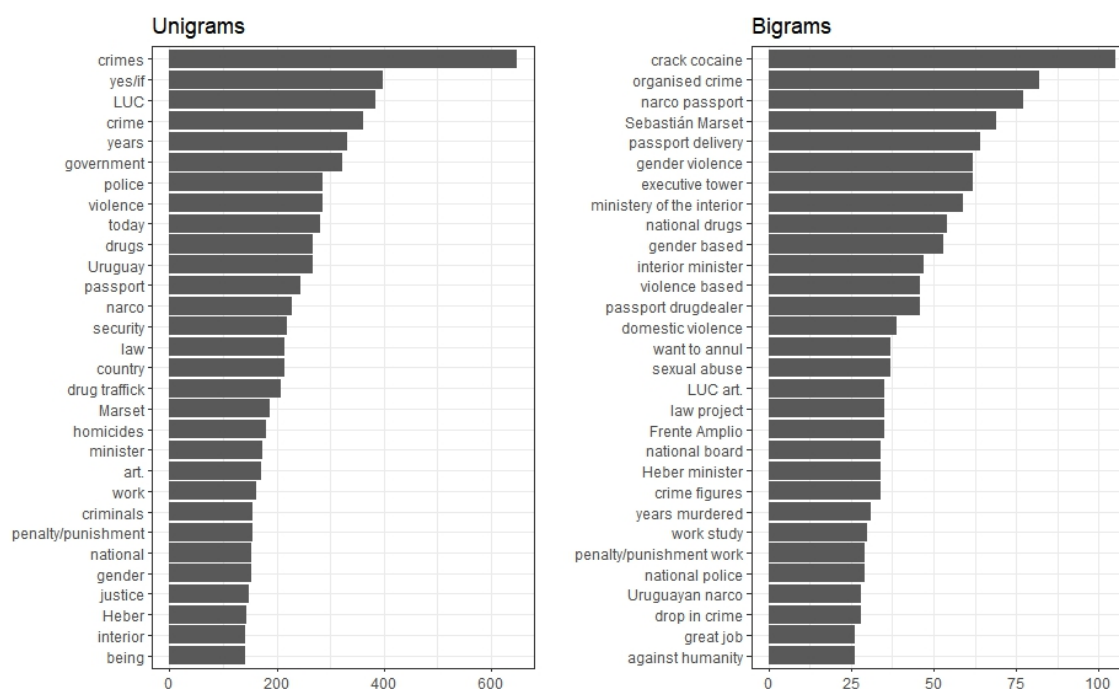
Johnson" and "Prime Minister" are among the top bigrams, reflecting discussions against a backdrop of allegations of corruption and crime during the COVID-19 quarantine, as seen when analysing a random sample of tweets containing those terms.

Figure 22 Top unigrams and bigrams for crime-related tweets from MPs and political parties in UK 2022



Meanwhile, in Uruguay (Figure 23), the political system and the press seem to walk hand in hand regarding the discussion around crime, as far as can be seen from the keywords and bigrams. Drug trafficking, drug gangs, and homicides seem to occupy the central place of discussion. The LUC and Marset, two central issues linked to the political system, are among the most mentioned.

Figure 23 Top unigrams and bigrams for crime-related tweets from MPs, president, vice-president, and political parties in Uruguay 2022

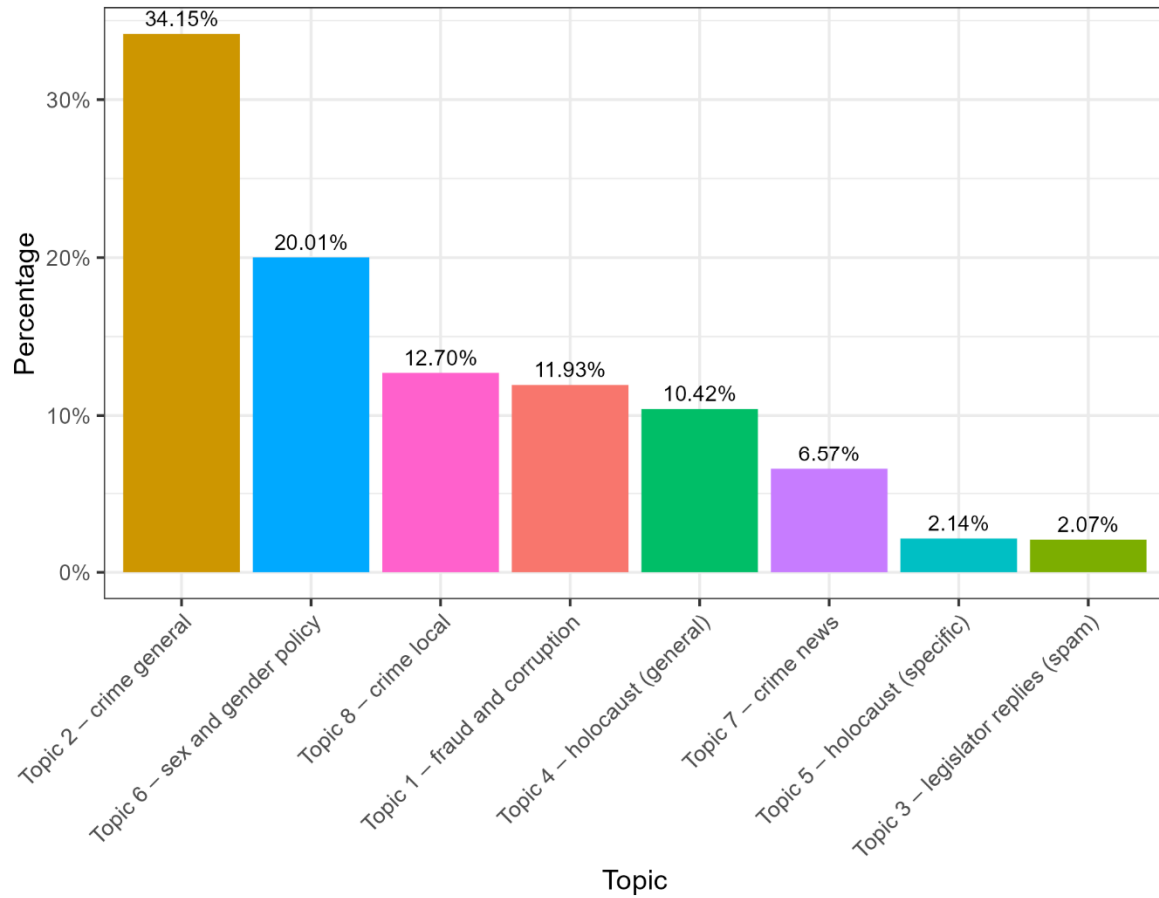


4.3.2. Topic Modelling

The analysis of tweets from the political system followed the same procedure used to analyse news. Figure 24 presents Topic Proportions, and Figure 25 presents Top Words by Topic.

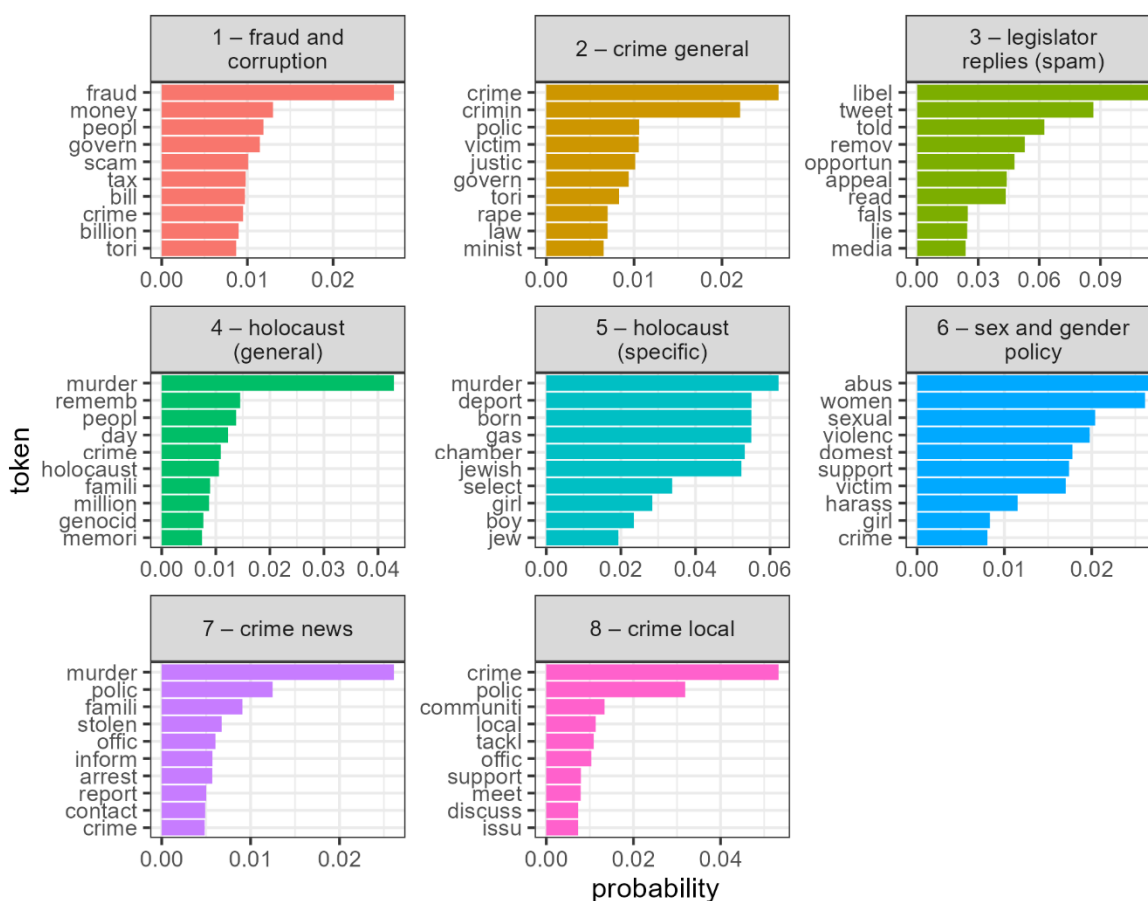
4.3.2.1. Topic Modelling – UK.

Figure 24 Topic proportion in crime-related tweets from MPs and political parties in UK 2022



N = 18,426

Figure 25 Top words by Topic based on phi values – UK.



Topic 2 holds the first place in the proportion of classified tweets with 34.15%. As with the responses to news, this topic clusters common words associated with the discussion of crime in general. It includes a significant amount of content defending and attacking various actions taken by the political system and specific politicians, especially in cases of accusations of misconduct or corruption. It also covers communication about security policies and the fight against crime. Topic 8, with 12.70%, also focuses on political communications regarding the fight against crime, but with a local level emphasis, including mentions of meetings with police officials or specific programs in various localities. Unlike Topic 2, Topic 8 does not address crime or corruption on a large scale but specific local initiatives.

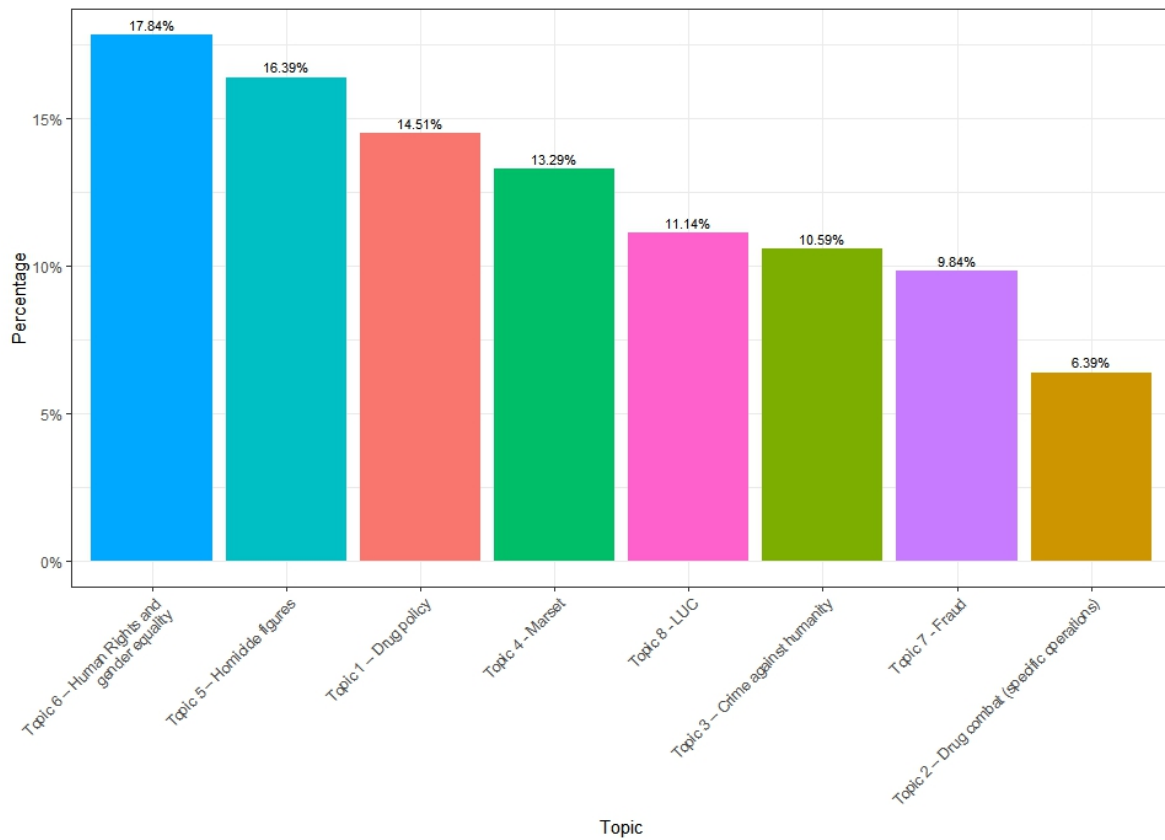
Topic 6, accounting for 20.01% of the tweets, reflects a specific concern of the political system that, based on previous analysis, is disconnected from the media's news agenda. This Topic focuses on communications and demands regarding gender policies, particularly against sexual and domestic violence, a concern that was especially relevant in the context of reduced mobility caused by the COVID-19

pandemic. Topic 1, with 11.93%, is also associated with issues partially emerging from the pandemic, including claims and allegations of fraud and corruption, mostly criticising the conservative government's spending. It covers many instances of police persecution during the COVID-19 lockdown of those who took advantage of the situation to commit various types of fraud (including cases of fraud coming from the political system).

Topics 4 (10.42%) and 5 (2.14%) pertain to commemorations of the Holocaust. Topic 4 refers to general acknowledgements, while Topic 5 is more narrative, highlighting specific examples of Nazi persecution. Topic 7, with 6.57%, clusters tweets that reproduce news, either as direct retweets or as information provided by politicians about various events, including crimes and the prosecution or capture of criminals. Finally, Topic 3, accounting for 2.07% of the tweets, refers to the responses of a particular legislator who was accused and sentenced for harassment. This legislator's account has been responsible for multiple replies to various accusations. Although many tweets from this account are repetitive, only those with exactly duplicated text were deleted. Because of the spam-like nature of these tweets, their volume and style make them a distinct topic.

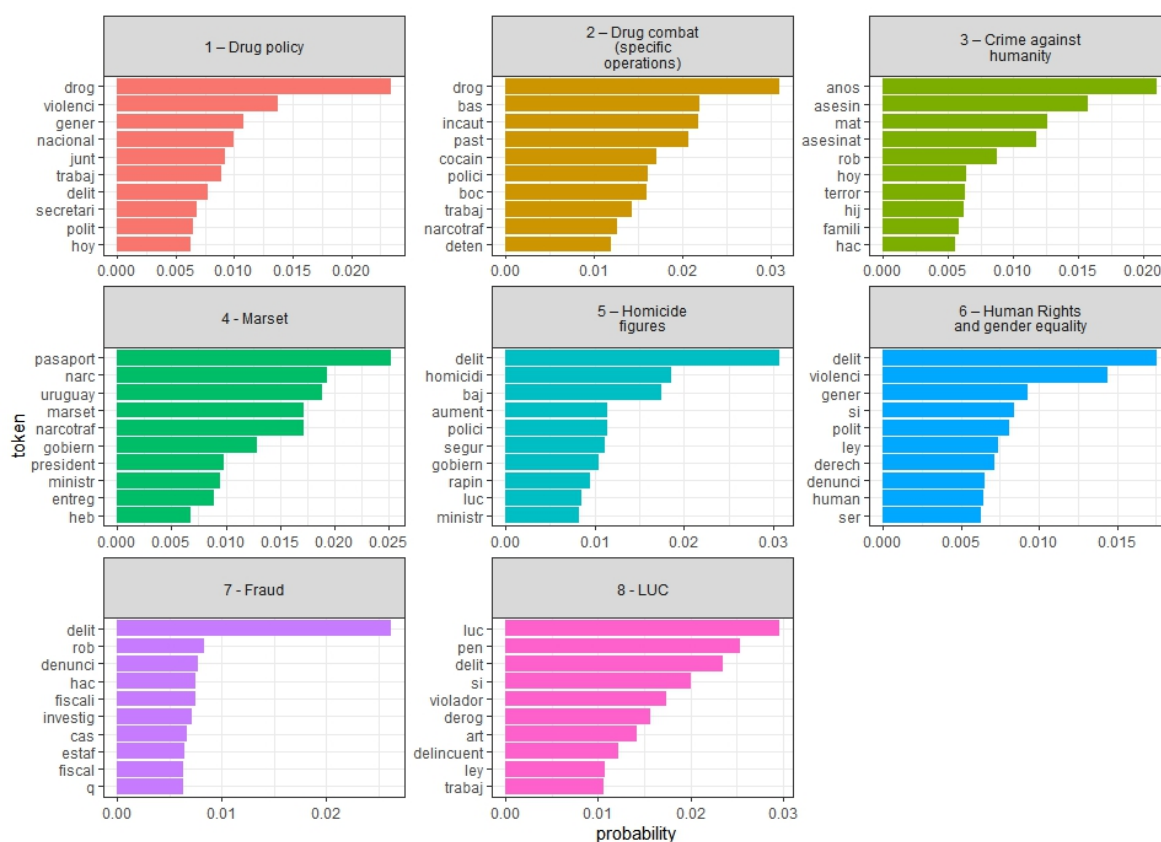
4.3.2.2. Topic Modelling – Uruguay

Figure 26 Topic proportion in crime-related tweets from MPs, president, vice-president, and political parties in Uruguay. 2022



N = 3,519

Figure 27 Top words by Topic based on phi values – Uruguay



Figures 26 and 27 present the results for Uruguay. Topic 6, in the first place, with 17.84%, brings together two types of communications from the Uruguayan political system that contain similar formats of expression: on the one hand, expressions regarding the importance of basic human rights, especially freedom of expression and the rejection of crimes against humanity. On the other hand, support for gender policies, particularly the defence of women's rights and equality before the law.

Topic 5, which follows closely behind with 16.39% of the distribution, primarily refers to homicide figures, a topic of discussion at the parliamentary level and in the press, given that they experienced a significant drop during the pandemic, which was partially maintained in 2022. Uruguay's homicide figures have been rising steadily over the years, particularly during the last few years of left-wing government (Rojido et al. 2023). The governing coalition considered this drop a sign of success, while the opposition strongly disputed it, arguing that it was a context-specific consequence.

Topics 1 (14.51%), 2 (6.39%), and 4 (13.29%) focus on problems related to drug trafficking. Topic 1 refers specifically to drug-related crime control policies, as well as drug policy in general, associated with the prevention of drug abuse, the relationship

between drug use and crime, and the rehabilitation of people with a substance use disorder, in particular those who are also in contact with the penal system. Topic 2 covers the communication of operations to combat drug trafficking, particularly the seizure of drugs and the closure of drug shops, which has been a major focus of the current government. Topic 4 refers specifically to the case of Sebastian Marset. While part of this discussion is related to the potential connections between large-scale drug trafficking and the political system, the discussion extends beyond this, examining the specifics of the case and various allegations of corruption in general. Meanwhile, Topic 7 (9.84%) refers to corruption and fraud within the government and at the national trade union centre level (PIT-CNT), besides the specificities of the Marset episode. Different accusations and defences appear concerning specific government and opposition cases that gathered public attention.

Topic 8 (11.14%) reflects some aspects observed in the news discussion, particularly the defence of the LUC for its implications in punishing sex offenders. Many politicians addressed this concern from the electorate and used it as a reason to oppose the referendum. In turn, several opposition politicians respond to these arguments, contributing to the discussion within this Topic. The proportion of this discussion at the political system level with respect to the Topic that emerges in the responses to the news is significantly higher.

Topic 3 (10.59%) pertains to historical facts related to crimes against humanity and terrorism. Unlike topic 6, these are not demonstrations in favour of human rights but rather expressions of repudiation of historical events considered criminal. While some refer to international events (such as acts of genocide), in the Uruguayan case, many seem to be associated with victims of state terrorism or guerrilla warfare during the last dictatorship period (1973 – 1985).

4.4. Reactions to the political communications about crime in Uruguay and the UK

The analysis of responses to political communications followed a different data filtering strategy. Keeping the retweets made by politicians incorporates communications originating outside the political system. For example, if a member of parliament retweets a message from the press, including this retweet would involve analysing all the responses to the news, even those independent of the politician's retweet. Therefore, only the responses to the original tweets or quotes from the politicians are considered when analysing citizen reactions to political communications.

4.4.1. Descriptives

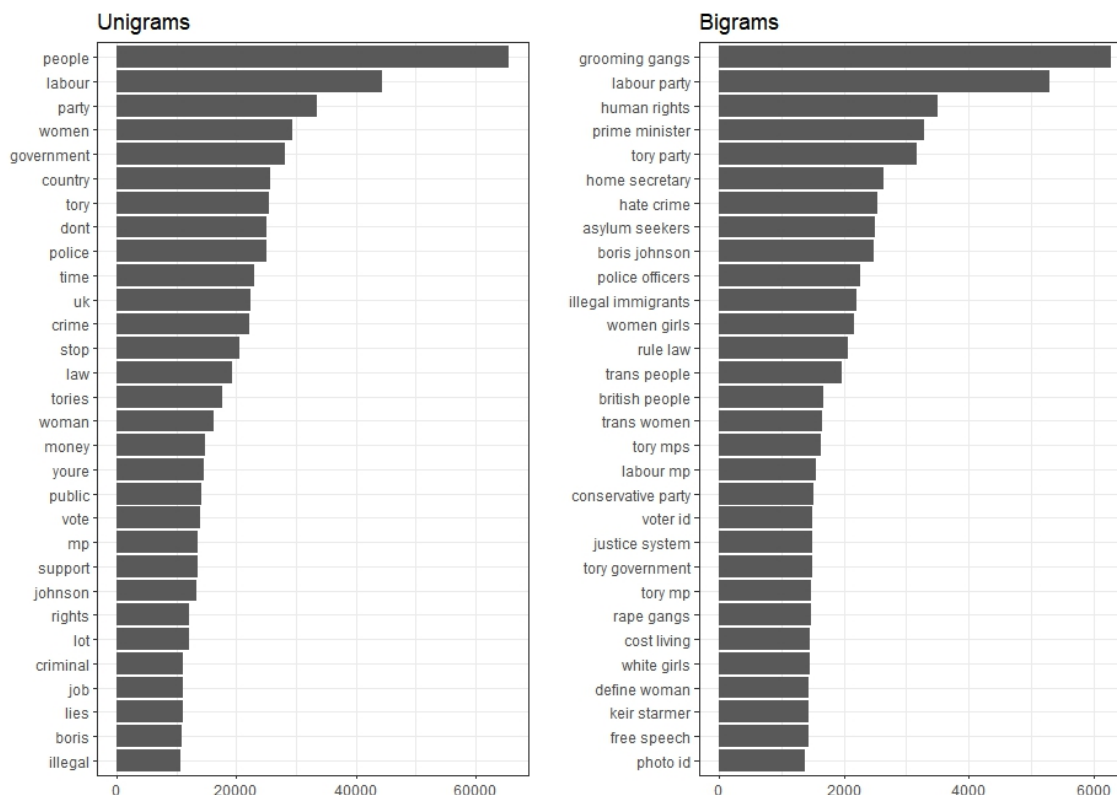
After filtering, 791,840 responses to crime-related tweets from UK politicians were obtained from 212,905 unique users. The top 5% most engaged users accounted for just over 38% of the responses, while the least engaged 75% contributed around 29%. While the average number of responses is 2,175 per day, several key peak dates were identified, with the maximum reaching nearly 30,000 responses. This peak occurred on February 7, 2022, primarily driven by responses to Boris Johnson's condemnation of the harassment of opposition leader Keir Starmer by an angry anti-vaccine mob. The second peak, on November 25, 2022, resulted from reactions to a set of tweets by Starmer proposing measures to address violence against women and girls. Interestingly, these proposals were fundamentally punitive, focusing on increasing the length of sentences. The third peak of interest occurred on July 21, triggered by former Finance Minister Kwasi Kwarteng's announcement of a new law allowing businesses to hire temporary workers to mitigate the adverse effects of strikes. Kwarteng noted that this practice was previously considered a crime, which is why it was captured by the search conducted in this project.

In the Uruguayan case, 52,822 tweets were collected from 13,727 users. The 5% most engaged users accounted for just over 34% of the responses, while the least participative 75% generated 34.49%. The ratio of responses per user is similar in Uruguay and the UK, at 3.85 and 3.72, respectively. The average number of responses per day is 191; however, as in the UK case, there are peaks, with three days exceeding 2,000 responses. The highest peak occurred on September 2, following the assassination attempt on Argentina's vice-president Cristina Kirchner. The second peak occurred on August 28, surrounding a tweet by the Mayor of Canelones, one of the most prominent figures in the opposition to the left-wing government, regarding the degradation of the country's image due to the events surrounding the Sebastian Marset case. The third spike was triggered by a government legislator's message, which, while discussing the fight against drug trafficking in the Latin American context, included a fake photo of the Colombian president next to the drug trafficker Pablo Escobar.

Figure 28 presents the 30 most frequently mentioned unigrams and bigrams in the UK responses. The bigrams, in particular, highlight some of the main concerns of UK citizens in 2022. "Grooming gangs" is the most prominent bigram, reflecting a major controversy in 2022 involving several cases of grooming gangs across various UK regions. In these cases, there was significant discussion about the perceived inaction, particularly by Labour Party representatives. Discussions about various minorities and

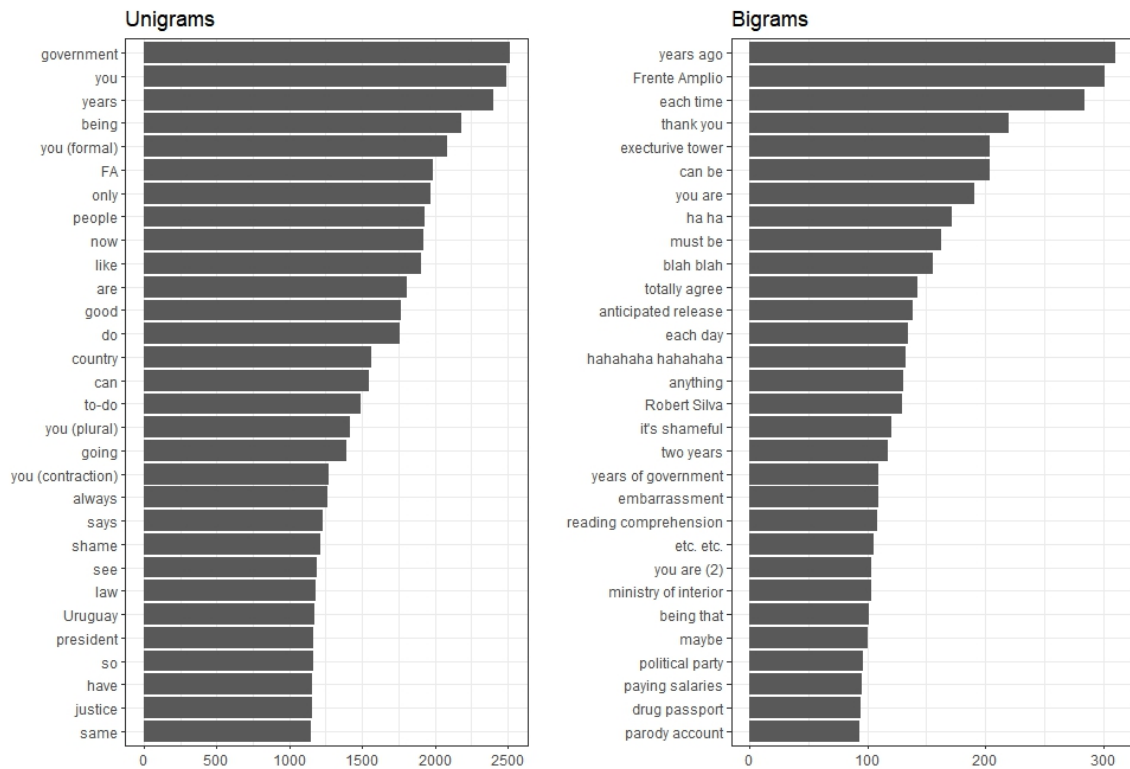
the respect for their rights are noticeable in bigrams such as "human rights," "hate crime," "asylum seekers," "illegal immigrants," "trans women," and "trans people".

Figure 28 Top unigrams and bigrams for the replies and quotes for crime-related tweets from MPs and political parties in UK 2022



The Uruguayan case, at first glance, appears somewhat less informative. Many of the words are inherent to the political discussion. Interestingly, compared to the British discourse, words associated with disbelief or lack of trust emerge to a greater extent. Terms such as different types of laugh, "blah blah," "shame," and "embarrassment" appear to be prevalent (Figure 29).

Figure 29 top 30 unigrams and bigrams for the replies and quotes for crime-related tweets from MPs, president, vice-president, and political parties in Uruguay 2022

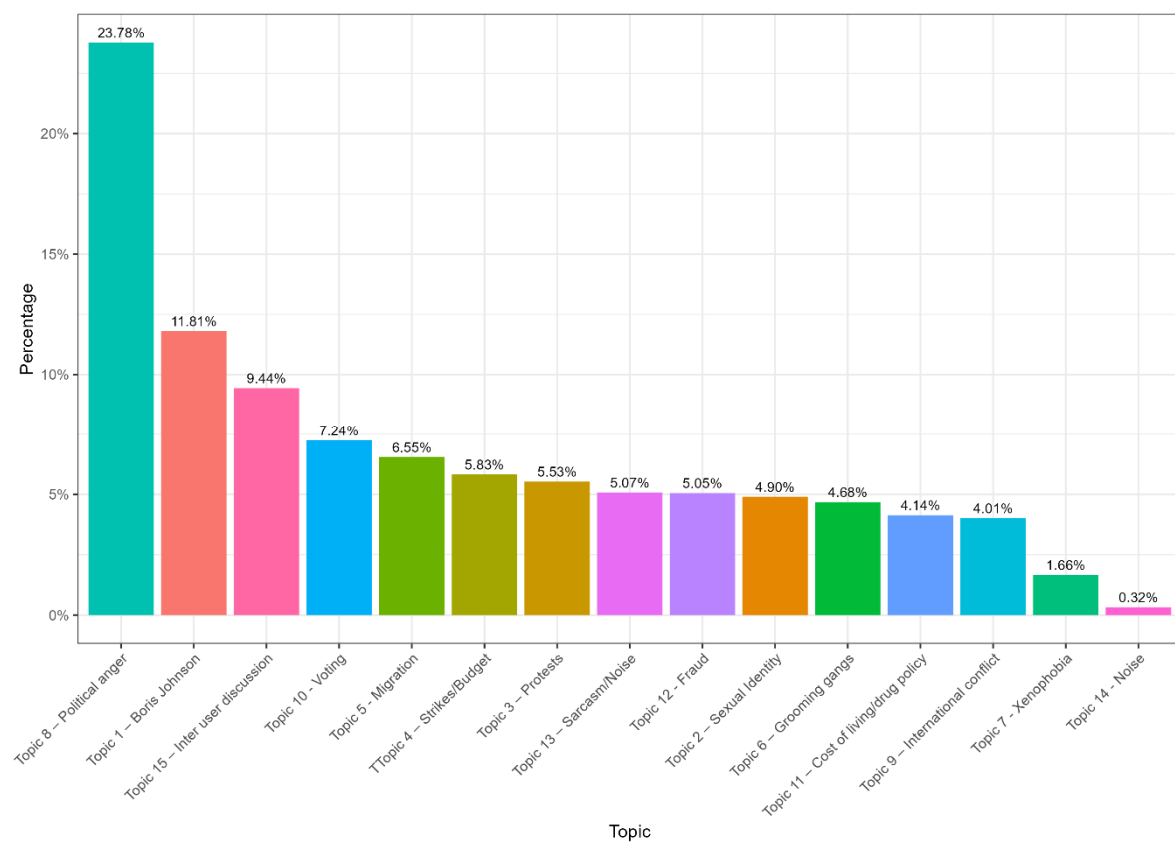


4.4.2. Topic Modelling

4.4.2.1. Topic Modelling – UK

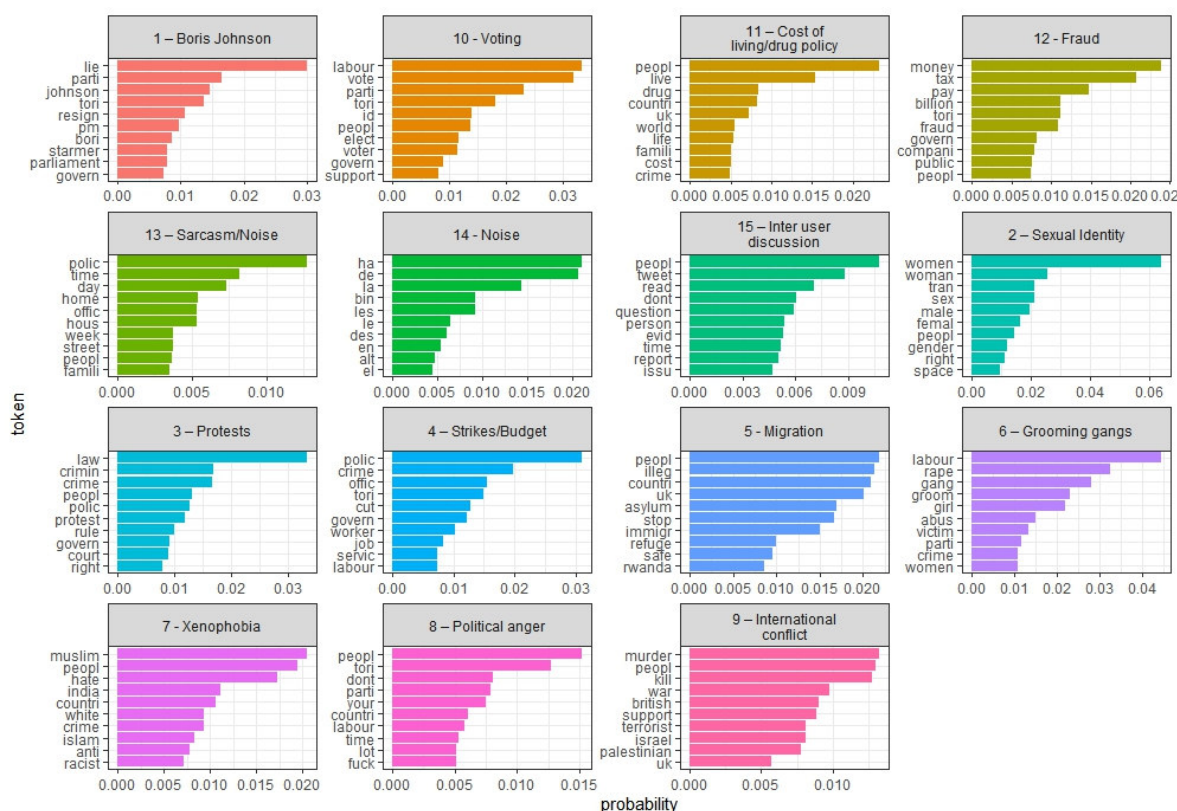
The topic modelling of responses to political communications followed the same pipeline as before. Figure 30 shows Topic proportions for the UK, and Figure 31 shows the most important words by Topic.

Figure 30 Topic proportion in the replies and quotes for crime-related tweets from MPs and political parties in UK 2022



N = 791,840

Figure 31 Top Words by phi value – UK.



Topic 8 has the highest number of cases (23.78%) and groups reactions of anger toward the politician in question, their party, or the political system in general. This Topic is closely related to Topic 1, which ranks second (11.81%) and refers explicitly to Boris Johnson and the pressure from users for his resignation. Topic 12, with a smaller proportion of tweets (5.05%), also relates to discontent with the political system, focusing mainly on allegations of fraud and embezzlement by the government and Topic 6 (4.68%) includes responses to Labour Party members, accusing them of neglect or complicity in the emergence of grooming gangs. Such accusations aim to delegitimise these politicians' communications regarding gender and policies for children and adolescents. This concern is also reflected in the significant bigrams from the overall response data.

Topic 15 (9.44%) mainly involves interactions between users in discussion scenarios. The first 200 tweets classified in this Topic reveal short messages containing questions, criticisms, or arguments between users, making it complex to interpret without context. Similarly, Topic 13 (5.07%) is complex to interpret using keywords alone. Analysing the first 200 tweets on this Topic reveals short, often sarcastic messages, resulting in considerable internal noise. Topic 14, with the smallest share

(0.32%), contains noise from tweets in languages other than English that are not correctly filtered.

Topic 10 (7.24%) revolves around various voting instances in the UK during 2022, including discussions on modifying voting procedures, such as the inclusion of IDVote or the application of stricter rules on postal voting. It also includes discussions and references to voting choices and "the voters" of different parties.

Topic 5 (6.55%) discusses border control policy, migration, and asylum seekers. While this topic gathers responses with specific language characteristics, it includes different perspectives, from those open to accepting immigrants and asylum seekers to those advocating punitive measures, such as deportation, for illegal entrants. The importance of this discussion was evident in the most frequently used words and bigrams. Topic 5 is closely related to Topic 7 (1.66%), which addresses discussions on xenophobia, particularly in relation to migration in the UK. In some cases, these discussions involve accusations, while in others, a defence of the xenophobic stance.

Topic 4 (5.83%) combines two partially related elements. First, it encompasses responses to Kwasi Kwarteng's message about allowing businesses to hire temporary workers during strikes, which elicited negative reactions. Additionally, it includes mentions of police budget cuts, which are discussed in a critical manner. This overlap occurs because specific keywords appear in both discussions ("cut," "worker," "job").

Topic 3 (5.53%) addresses two types of events that the political system reports. One involves responses to various protests, such as the case of young people accused and cleared of criminal damage for removing Edward Colston's statue in Bristol. These protests sparked calls for harsher punishments, while others defended the right to protest and the need to protect free expression. This discussion, which often involves monitoring specific cases, is linked to the monitoring of government corruption cases, especially those concerning Boris Johnson, albeit to a lesser extent.

Conversely, Topic 2 (4.90%) focuses mainly on discussions of sexual identity issues. In scenarios where politicians propose gender identity policies or refer to trans women as women, it provokes responses from users who oppose such perspectives, often using biological arguments. This type of communication usually generates counter-responses, depending on the tweet's content.

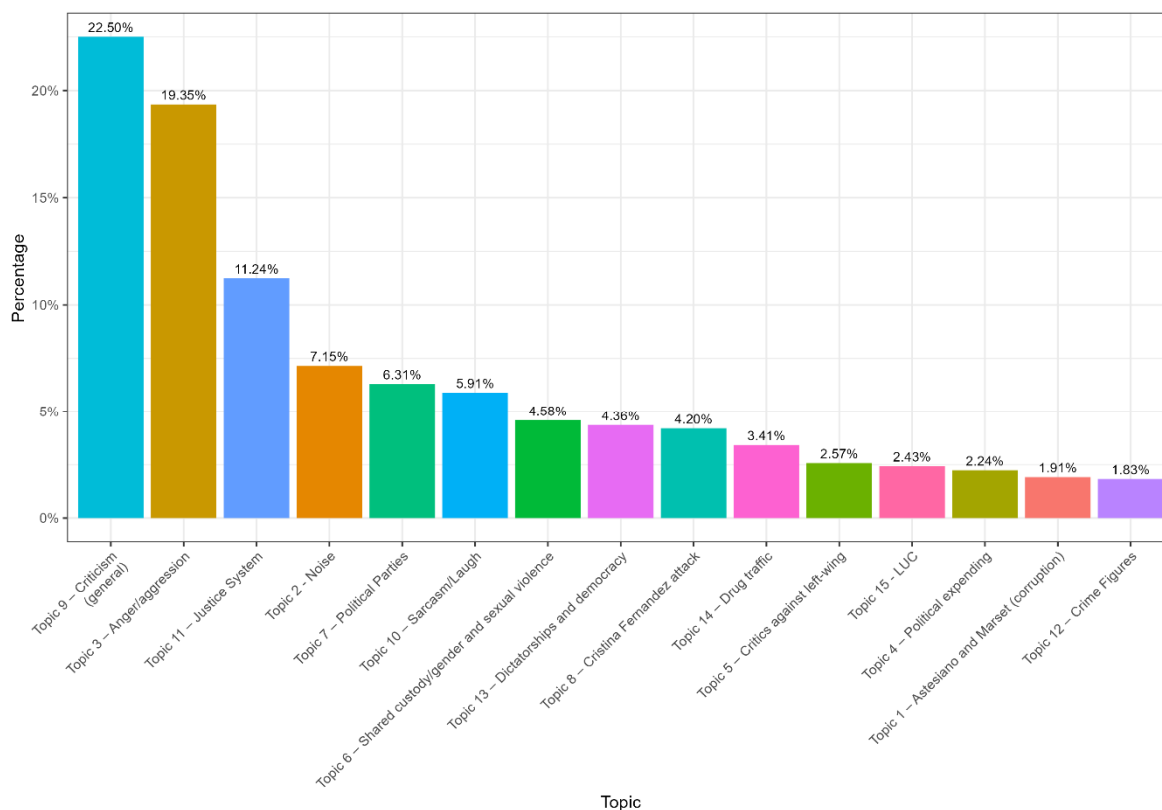
Topic 11 (4.14%) combines two distinct response types: mentions of the cost of living crisis, sometimes linked to crime complaints, and discussions supporting new and more flexible drug legalisation. These topics merge under the common theme of financial concerns (discussions around money appear in replies linked to drug

trafficking and the amount of money it mobilises, as well as around the problems of the rising cost of living). Finally, Topic 9 (4.01%) addresses responses to international conflicts, with particular emphasis on the Israeli-Palestinian conflict.

4.4.2.2. Topic Modelling – Uruguay

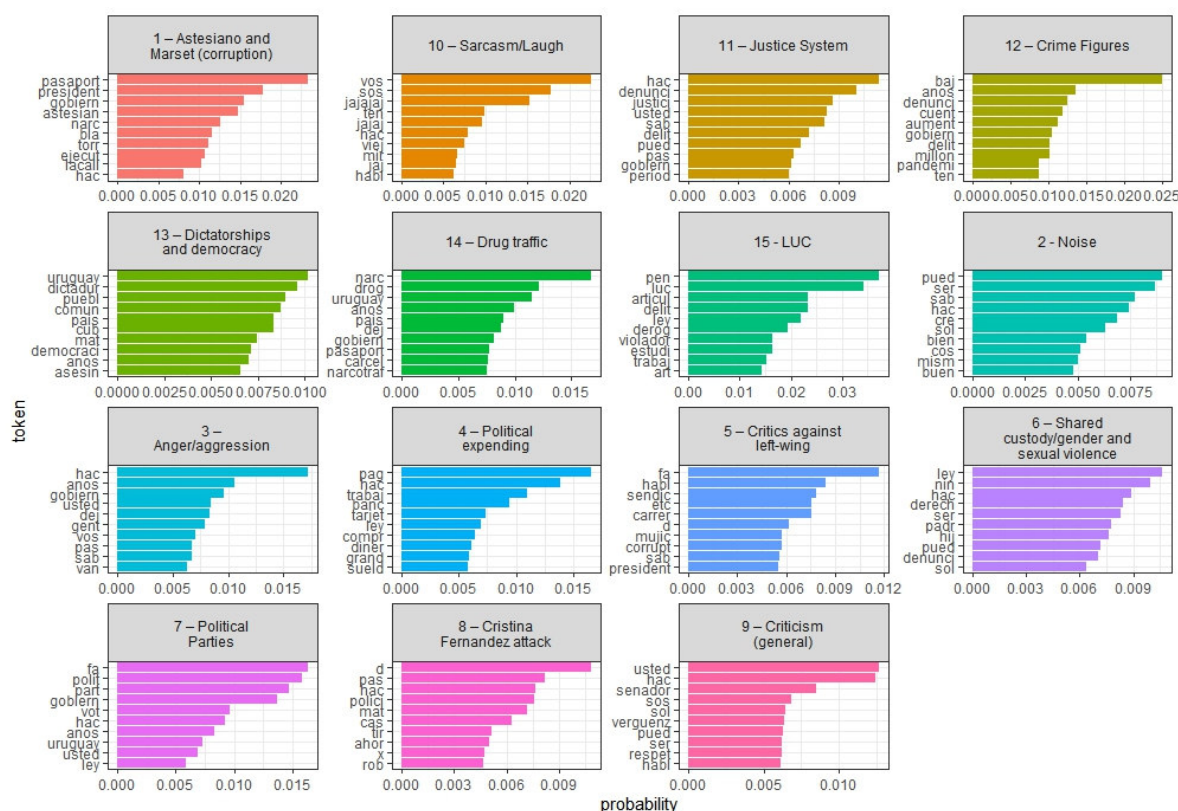
Figures 32 and 33 provide the results for Uruguay.

Figure 32 Topic proportion in the replies and quotes for crime-related tweets from MPs, president, vice-president, and political parties in Uruguay 2022



N = 52,822

Figure 33 Top words based in phi values - Uruguay



Topic 9 tops the list, accounting for 22.50% of the distribution. Although this Topic includes a certain amount of noise and words present across the corpus of tweets, it primarily refers to various responses signalling criticism and disqualification of the different political figures they are interacting with. Words such as "shame" or "respect" are among the Topic's keywords. Topic 3 (19.35%) is similar; however, disqualification involves aggression and insult in this case. This characteristic is evident from analysing the first 200 tweets classified in this Topic. Additionally, Topic 4 (2.24%) includes two criticisms associated with government resource management: direct criticism or accusations of corruption against politicians and criticism based on the justification of salaries, questioning whether politicians earn too much given their work and results. Similarly, but with specific characteristics that create a distinct cluster, Topic 5 (2.57%) groups criticisms mainly directed at the opposition (the left-wing coalition). Its counterpart is Topic 1 (1.91%), specifically referring to the Marset and some other newsworthy cases with strong criticism against the current government. Additionally, Topic 7 (6.31%) focuses on reactions related to political parties and the functioning of politics, rather than the personal characteristics of politicians, as in the previous topics. However, analysing the tweets in this cluster

reveals that, similarly to previous topics, a climate of illegitimacy and discontent prevails.

Topic 11 (11.24%) focuses on issues related to the justice system and is discussed in various ways. In some instances, the responses are to specific events that have resonated within the political system, where politicians have followed issues in court, and citizens have followed and commented on their opinions on Twitter. Alternatively, politicians have criticised the results of different judicial processes. Here, citizens also interact with these opinions, often criticising the executive branch's interference in the judiciary. Additionally, some responses address different security and crime control proposals by the political system, raising concerns about respect for the law and due process. Citizens appear to be worried about potential government overreach in this context.

Topic 2 (7.15%) contains a significant amount of noise, consisting of short tweets that are difficult to interpret without the context of the conversation. Similarly, Topic 10 (5.91%) groups laughter and sarcastic answers. Topic 8 (4.20%), while also noisy, appears to revolve around the controversy surrounding the assassination attempt on Argentina's Vice-President Cristina Fernández, particularly around a comment by Congressman Zubía, who questioned the authenticity of the attempt, insinuating it might have been staged to promote Fernández.

Topic 6 (4.58%) centres around gender issues, with much of the discussion focused on "shared custody" between parents – a topic discussed in the parliament at the time. It also includes discussions about violence and recognition of minorities, domestic violence, and sexual violence.

Topic 13 (4.36%) involves mentions and discussions about the dictatorship process in Uruguay. This Topic also emerged as significant in news coverage. At the political level, the issue remains relevant, as some Uruguayan politicians lived and participated in politics during that era. Within this Topic, users also discuss the state of democracies in other regional countries, often used as arguments against ideologically similar parties (e.g., Venezuela as an argument against the left coalition).

Topic 14 (3.41%) is clearly defined and straightforward in its content, focusing on discussions around drug trafficking in Uruguay and various instances of government involvement and corruption (both during current and previous governments).

Topic 15 (2.43%) centres around the aforementioned LUC, particularly defending increased penalties for rape and sexual crimes. Finally, Topic 12 (1.83%) involves

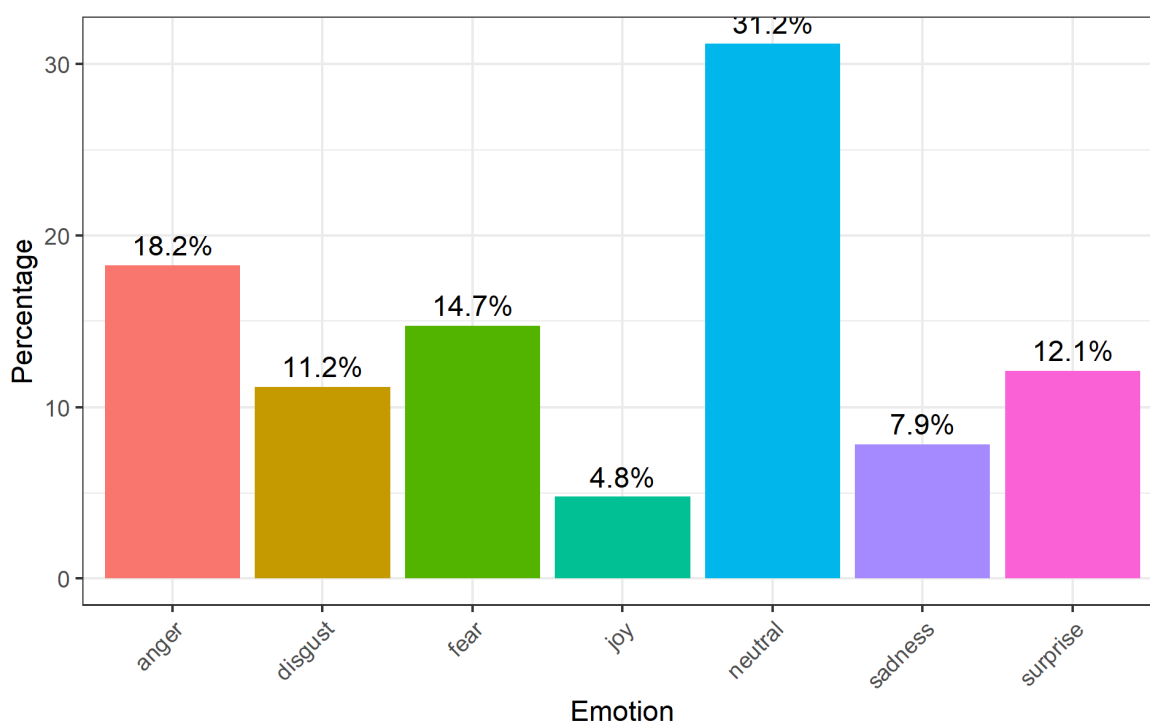
discussions about the legitimacy of crime figures released by the government, especially in the context of the pandemic.

4.4.3. Sentiment and emotion analysis

4.4.3.1. General – UK

Analysing the overall picture of users' emotional reactions to politicians' communications about crime in the UK reveals broad similarities with the emotions represented in the news. As shown in Figure 34, the most common emotion remains "neutral," with "anger" in second place. However, in reactions to politicians' communications, there is a noticeable increase in the "fear" category, which rises to 14.7% compared to 9.3% for news communications. "Disgust" also increases, while "surprise" and "sadness" decrease slightly.

Figure 34 Emotion distribution for the replies and quotes for crime-related tweets from MPs and political parties in UK 2022



N = 791,840

4.4.3.2. By Political Topics – UK.

The analysis conducted for the news was replicated by grouping responses according to the political topics they address to examine how emotions cluster around them. Unlike the news analysis, this scenario shows interesting differences between groups, as shown in Table 6. Responses to political commentary on crime do not necessarily

cluster around more negative communications within each Topic. In some cases, these responses cluster around issues that spark citizen discussion, without necessarily responding to negative events, such as the merits or drawbacks of changes to voting formalities aimed at preventing fraud (Topic 10). The topics that gather the most anger seem to be linked to crime in general—the most prevalent Topic—gender policy, sexual and domestic violence, and the reproduction or comments on crime news by politicians. These topics also tend to cluster around feelings of disgust.

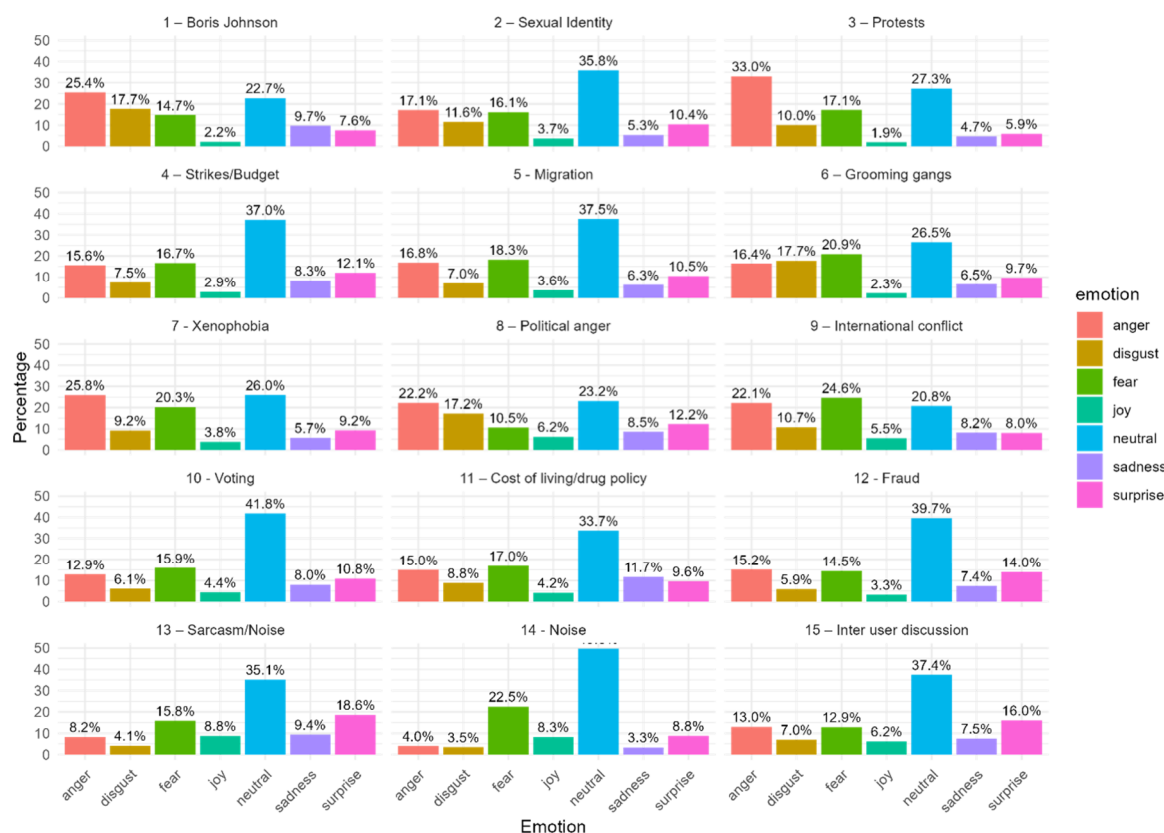
Table 6 Emotion distribution for the replies and quotes for crime-related tweets from MPs and political parties in UK 2022 by political communication topic

Political Topic	Anger	Disgust	Fear	Joy	Neutral	Sadness	Surprise
Topic 1 – fraud and corruption	13.3%	10.8%	13.0%	7.2%	26.3%	10.8%	18.6%
Topic 2 – crime general	21.8%	13.7%	14.3%	4.7%	26.5%	8.0%	11.0%
Topic 3 – legislator replies (spam)	16.8%	9.7%	15.4%	5.4%	30.8%	8.5%	13.4%
Topic 4 – Holocaust (general)	17.6%	11.2%	13.8%	4.7%	33.1%	7.2%	12.3%
Topic 5 – Holocaust (specific)	15.4%	9.8%	16.3%	6.6%	29.7%	8.5%	13.7%
Topic 6 – sex and gender policy	19.0%	10.4%	15.8%	6.5%	26.0%	9.9%	12.4%
Topic 7 – crime news	18.9%	11.7%	15.4%	3.6%	31.6%	7.6%	11.2%
Topic 8 – crime local	14.8%	8.0%	14.0%	4.4%	39.0%	7.4%	12.4%

4.4.3.3. *By Replies Topics – UK.*

Following the same logic as the one used for the responses to news, Figure 35 presents the emotions associated with each Topic in the responses to political communications.

Figure 35 Emotion distribution for the replies and quotes for crime-related tweets from MPs and political parties in UK 2022 by topic



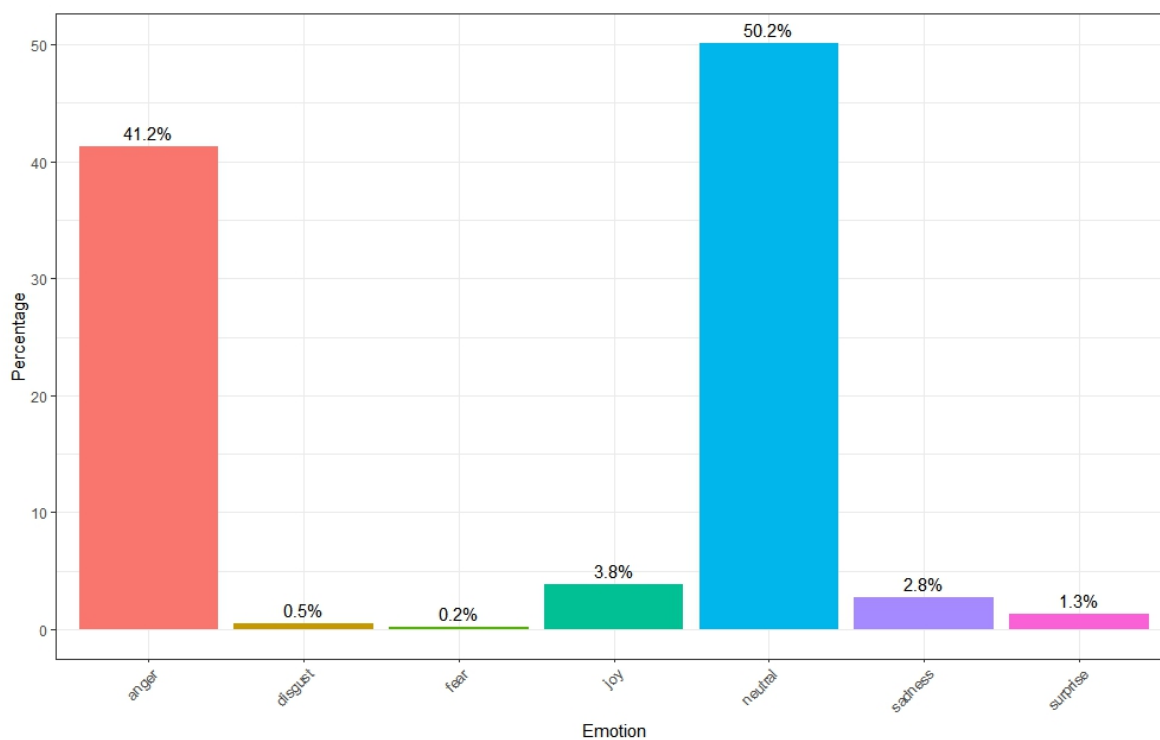
The analysis by Topic shows that Topic 8, related to angry reactions to the political system, concentrates, as expected, a large proportion of anger and disgust, with fewer cases classified as neutral. The same applies to Topic 1, which primarily refers to Boris Johnson. In contrast, Topics 15 and 10, which involve discussions between users and voting instances, respectively, have a very high proportion of neutral tweets. Topic 5, which encompasses discussions around border control, migration, and asylum seekers, has a higher proportion of fear than the other topics. Topic 4, associated with Kwasi Kwarteng's policy on temporary workers and budget cuts, has a proportion similar to the average (Figure 34). Similar cases in terms of emotion are Topic 2, associated with discussions about sexual identity and Topic 11, related to the cost of living and drug policy. Topic 3, in response mainly to protests, groups a significant proportion of angry reactions. Topic 13, with short and sarcastic responses, groups reactions of surprise, likely due to the use of sarcasm, which the algorithm interprets as such. Topic 12, associated with government fraud and embezzlement, has a high proportion of neutral responses, as with replies in related news cases. Topic 6, which refers to complaints about grooming gangs, exhibits significant negative emotions, such as anger, fear, and, above all, disgust. Topics

related to international conflicts (Topic 9) have high levels of anger and fear, similar to what occurs with Topic 7, which groups various forms of xenophobia. Finally, Topic 14, which mainly includes tweets in languages other than English, is classified as neutral, given that the model was trained on data in English.

4.4.3.4. General – Uruguay

Analysing users' emotional reactions to Uruguay (Figure 36), it is evident that the predominant emotion is anger, similar to the news replies scenario. The remaining categories, excluding "neutral," are marginal. A qualitative analysis of tweets classified according to their emotions suggests that this categorisation is reasonably accurate. In many cases, these expressions of anger could be categorised as "outrage," reflecting criticisms of the government or the opposition, their stances, policies, and perceived failures. When analysed by sentiment, there is also a large majority of negative reactions (66.3%), while only 7.1% express positive opinions (the remaining 26.6% are neutral).

Figure 36 Emotion distribution for the replies and quotes for crime-related tweets from MPs, president, vice-president, and political parties in Uruguay 2022



N = 52,822

4.4.3.5. By Political Topics – Uruguay

Table 7 presents the emotions expressed in the responses, grouped by the Topic of the original political communication. Some differences can be observed, although they

are not very pronounced. The topics of fraud and corruption, the controversy surrounding Marset, and the discussion around the LUC are where the most significant expressions of anger seem to be concentrated, although this emotion is prevalent across all topics. Expressions of joy appear to be more prominent in discussions about crimes against humanity. This result occurs mainly because these communications often celebrate democracy, which tends to garner greater support from users.

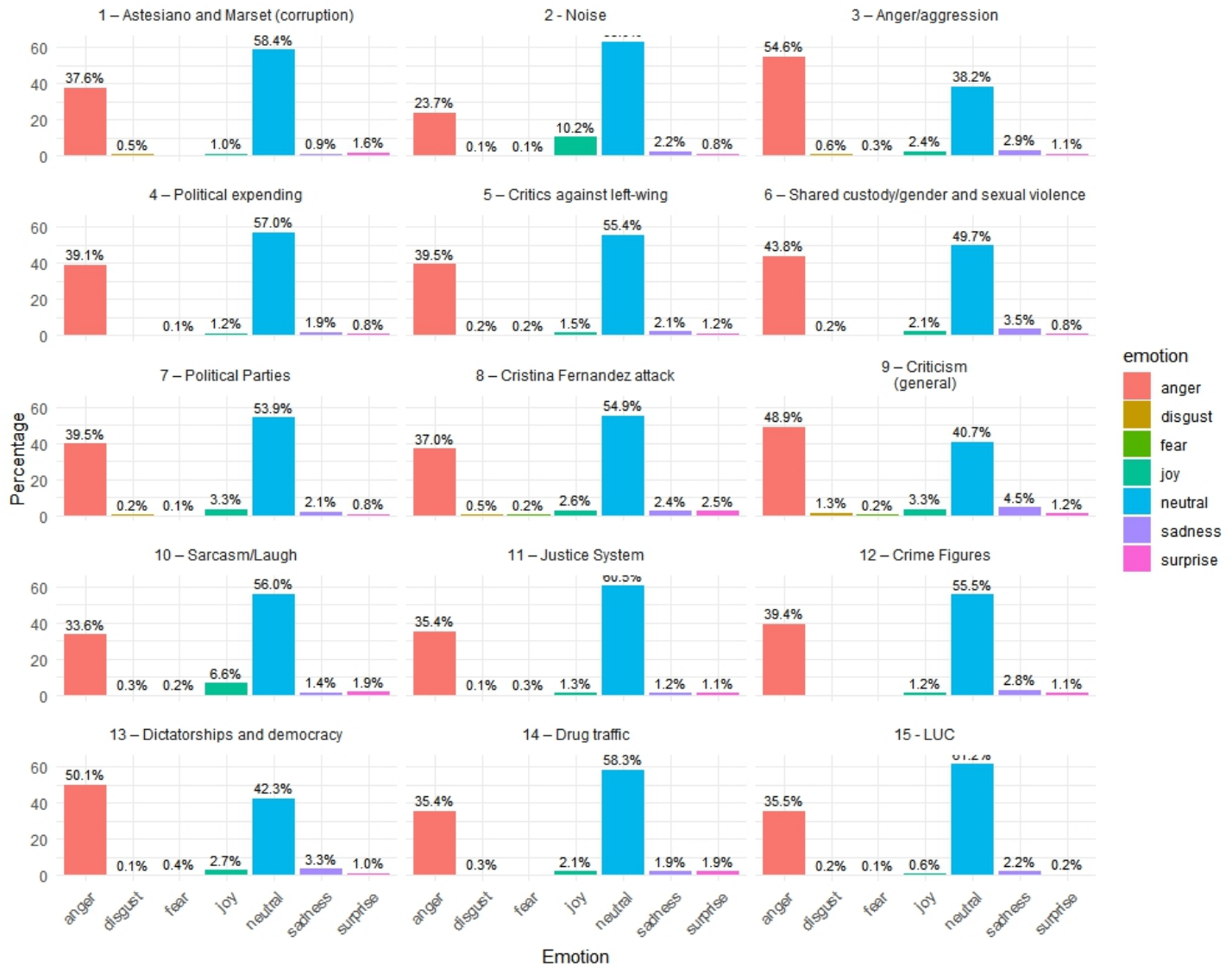
Table 7 Emotion distribution for the replies and quotes for crime-related tweets from MPs, president, vice-president, and political parties in Uruguay 2022 by political communication topic.

Political Topic	Anger	Disgust	Fear	Joy	Others	Sadness	Surprise
Topic 1 – Drug policy	38.4%	0.4%	0.1%	3.9%	53.7%	2.5%	1.1%
Topic 2 – Drug combat (specific operations)	38.3%	0.3%	0.1%	3.3%	53.8%	2.8%	1.3%
Topic 3 – Crime against humanity	41.3%	0.6%	0.1%	11.9%	41.4%	3.5%	1.2%
Topic 4 - Marset	44.8%	0.4%	0.2%	1.9%	48.7%	2.5%	1.4%
Topic 5 – Homicide figures	40.6%	0.4%	0.1%	2.6%	52.2%	2.8%	1.3%
Topic 6 – Human and gender rights	43.2%	0.7%	0.2%	2.6%	48.9%	3.1%	1.2%
Topic 7 - Fraud	44.3%	0.3%	0.2%	1.8%	50.0%	2.1%	1.2%
Topic 8 - LUC	44.7%	0.4%	0.2%	2.0%	49.7%	2.2%	0.7%

4.4.3.6. By replies Topics – Uruguay

When analysing emotions by the Topics estimated for the replies (Figure 37), it is possible to corroborate some elements from the initial analysis. Topic 9, which seems to group noise and critical reactions, has a high proportion of neutral cases compared to Topic 3, which is similar but more focused on insults and expressing anger. The remaining proportions are reasonably stable, except for a few specific cases. Topic 7, which refers to criticism of the parties—but not their members—has fewer components of anger and more neutrality. In contrast, Topic 14, which refers to the Marset case, contains the greatest amount of anger.

Figure 37 Emotion distribution for the replies and quotes for crime-related tweets from MPs, president, vice-president, and political parties in Uruguay 2022 by topic



4.4.4. Preliminary discussion and conclusions

The first chapter presents a descriptive analysis of crime-related discourse across different datasets from the United Kingdom and Uruguay, focusing on the portrayal of crime in news media and the political system, with the corresponding public reactions. Focusing on how the media portrays crime, the similarity between the two countries stands out. Despite structural differences in security and safety, violence, and criminality, Uruguay and the UK give similar attention to violent crimes. However, the press also highlights specific concerns. While the UK focuses on violent crime in general, with some emphasis on knife crime, Uruguay reports mostly homicides and gang violence. In addition to the emphasis on physical violence and homicide,

Uruguay shows concern about the fight against drug trafficking, driven by the increase in violence associated with it and the notoriety of the Marset affair. Meanwhile, the UK reports more extensively on the consequences of various crimes linked to COVID-19, the impact of which in Uruguay was arguably smaller.

However, the most significant results for this thesis emerge at the level of user responses. First and foremost, both countries show the emergence of a Topic that can be interpreted as punitive. In both cases, this Topic accounts for a significant proportion of the online discussion about crime. Nevertheless, the UK presents a more coherent punitive response, at least in semantic terms, which the modelling technique can capture. In contrast, Uruguay's response appears more diffuse, merging other types of communications that could be categorised as expressions of anger at crime. This finding effectively answers the first question of this chapter. The result validates the initial hypothesis – that social media serves as a space for communicating punitive attitudes - and the findings in later chapters, where the automated classifier is applied, further confirm it. The inductive emergence of this Topic suggests that the results obtained through supervised learning are not an artefact of the deductive nature of the strategy.

Turning to question two, which concerns the context in which punitive communications emerge, some differences in public concerns between the two countries emerge. In the UK, much of the attention focuses on sexual abuse offences and the relationship between race, ethnicity, and crime. In Uruguay, however, the public is more concerned with security policy, the government's role in combating crime, and, in particular, issues related to criminal gangs and drug trafficking. These contextual differences are clearer in public responses to crime-related news than in the news itself. The discussion chapter will further explore the possible meanings of these observations.

Focusing on political communications, the UK appears to have a more independent discussion from the press compared to Uruguay, where the issues discussed online by both actors seem more closely aligned. British politicians tend to discuss crime prevention and crime fighting at a general level, with a particular focus on sexual offences. In contrast, much of the discussion in Uruguay centres on the previously mentioned issues of homicide and the fight against criminal gangs.

At the level of user response, a common theme that emerges in both countries is a climate of distrust, lack of legitimacy, and weariness with the political system. The implications of this will be discussed later. Specifically regarding punitive attitudes, unlike in the press, a clear punitive theme does not seem to emerge. This result

suggests that punitive attitudes are more likely to be activated as a reaction to crime rather than translating into direct demands for a "tough-on-crime" approach from the political system—at least not in a manner that the technique used can capture.

These findings lay the groundwork for the subsequent chapters, where the implications of these observed patterns will be explored in greater depth, particularly concerning how and when punitive attitudes emerge and how the broader social and political context influences them.

5. The determinants of punitive attitudes

5.1. Introduction

Following the first descriptive chapter, which provides an overview of the communications on Twitter surrounding news and political messages about crime in Uruguay and the United Kingdom, this chapter employs the trained automatic classifier to detect punitive attitudes in user responses and analyse their determinants. The overarching objective is to identify the features of the news, users, and replies that correlate with online punitive attitudes.

This chapter does not expand on the punitive attitudes expressed around political communications for several reasons. First, the automatic classifier does not adequately distinguish between punitive attitudes directed at politicians and those targeting the judicial system at a general level, which is the primary focus of this thesis. The first type of expression often reflects frustration and contempt for the political system and its representatives, with demands to punish specific politicians for alleged wrongdoing or corruption, regardless of the accusations' veracity. The second type refers to what is more commonly recognised in the literature as punitive attitudes (see Chapter 1), where there is a request for the authorities to increase the cost of crime, either at a general level or for particular cases. Both attitudes could be considered punitive, but they appear to be triggered by different determinants, requiring a differentiation between them for analysis. This prevalence of frustration in communications with the political system aligns with the Topic Modelling conducted in Chapter 2. Additionally, punitive attitudes represent a much smaller percentage of political communications (0.94% in the UK and 0.91% in Uruguay) as classified by the trained transformer models. These factors pose difficulties for statistical analysis, as most estimates yield high standard errors and non-significant hypothesis testing results. For reasons of space and considering the limited insights gained from analysing punitive attitudes in political communications, the analysis will focus on responses to crime-related news. The data on political communications will be revisited in the next chapter during the time series analysis.

As this is the first study to use social media data for the estimation of punitive attitudes and their determinants, the choice of variables to include in the successive models is partially guided by the accumulated knowledge in the field but also by the exploratory analysis of some variables that have not been tested before, such as the characteristics of the online persona, their number of followers, their degree of participation in the platform, among others. This chapter unfolds as follows: it begins

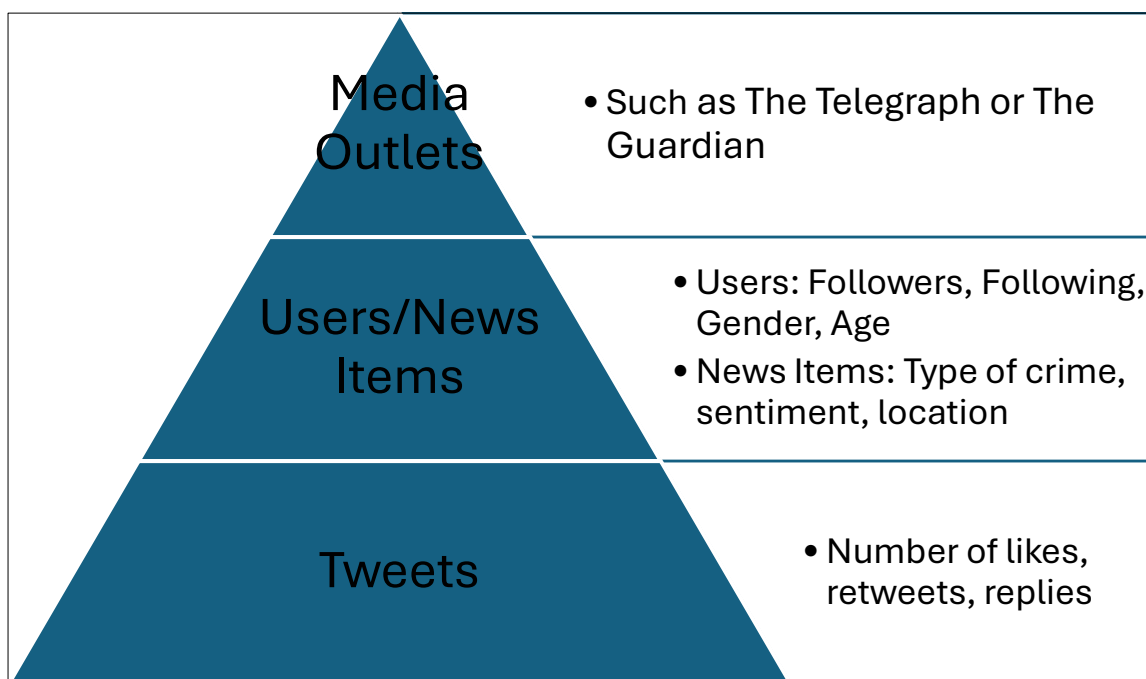
by describing the database used, detailing the variables and their distribution. Next, a series of multivariate analyses is conducted to explore the range of possibilities in the relationship between punitive attitudes and the dependent variables. Finally, the chapter presents a preliminary discussion of these results.

5.2. Descriptives

This thesis analyses punitive attitudes in user responses to both crime-related news from media outlets on Twitter and communications from political representatives regarding criminal topics on the platform. The analysis assumes the presence of four levels of determinants or independent variables, portrayed in Figure 38:

- 1) At the bottom are the characteristics of the tweet in response to the specific news item or political communication, such as the number of likes or retweets. These may benefit the task of predicting and estimating punitive attitudes, providing relevant information regarding the characteristics of punitive attitudes. However, they cannot be considered determinants strictly, as they occur after the punitive communication has happened.
- 2) These responses come from specific users who can participate more than once in the conversation, grouping more than one tweet from level one. User characteristics such as number of followers and follower numbers, as well as estimated gender and age, are incorporated as determinants.
- 3) Additionally, these responses are directed to particular news items. Each news item can accumulate more than one response. Characteristics of the news item are also incorporated into the analysis, such as the type of crime reported or the sentiment analysis of the news item.
- 4) All these news items come specifically from a sample of 20 press outlets for both Uruguay and the UK. However, given the low number of clusters and the relatively low ICC for both countries (.10), this level will not be incorporated as such but as an independent variable.

Figure 38 Data levels



The following section explains each variable used, detailing what it represents and how it was constructed. Tables 1 and 2 present the descriptive statistics for Uruguay and the United Kingdom. A brief commentary on the results of the descriptive analysis is also provided. Firstly, the dependent variable is presented. This binary variable has two possible states: whether or not a response expresses punitive attitudes. The inference of this quality utilises fine-tuned Transformer models trained on data that has been annotated by humans (see the methodological chapter for details).

The United Kingdom exhibits a higher proportion of punitive responses than Uruguay, with 4.7% and 3.9%, respectively. This difference of 0.8 percentage points in favour of the United Kingdom is statistically significant ($z = 10.818$, $p < .00001$). Shifting the focus from tweets to individuals, 8.44% of users in the UK posted at least one tweet classified as punitive, compared to 11.88% in Uruguay. This difference, in favour of Uruguay, is also statistically significant ($z = -16.691$, $p < .00001$).

In the UK, 86.7% of punitive users (those who expressed at least one punitive opinion) did so only once, 8.9% did so twice, and the remaining 4.5% did so three or more times, accounting for 16.3% of the punitive responses. In Uruguay, 74.9% of punitive users made a single punitive tweet, 14.4% made two punitive tweets, and 10.7% made three or more, accounting for 35.1% of the total punitive responses. These results indicate that the punitive response is more concentrated in Uruguay than in the UK. The UK has a lower proportion of punitive users but a higher proportion of

punitive tweets due to the greater number of single-instance users. The ratio is 2.22 tweets per user in the UK, compared to 4.81 in Uruguay. In Uruguay, the same punitive users are also making non-punitive tweets, which decreases the overall proportion, concentrates the production of punitive tweets, and increases the proportion of total punitive users.

In a similar analysis by news item, 10.0% of crime-related news in the UK receives at least one punitive response, compared to 7.0% in Uruguay. In the UK, news with a single punitive tweet accounts for 43.0% of these cases, those with 2 to 9 punitive replies make up 24.7%, and those with 10 or more account for the remaining 32.3%. A notable outlier in the UK accumulates 622 punitive replies, representing 4.6% of the total and 3.5 percentage points more than the next highest news item. This case specifically refers to a tweet from *The Independent*:

[siren emoji] *Breaking: Parkland school shooter Nikolas Cruz avoids death penalty and is sentenced to life* <https://t.co/ONS2qdWFZw>.

The analyses presented do not eliminate the outlier for several reasons. First, although the outlier accumulates a high number of punitive cases, it also gathers many non-punitive responses, with a punitiveness ratio that, while high, is not exceptional. Second, removing the outlier would result in losing relevant information, particularly in a scenario with few positive cases. Third, the analyses were replicated without the outlier, and no pronounced differences between the models were observed.

In Uruguay, news with a single punitive reply accounted for 43.8% of all punitive tweets. News items with 2 to 9 punitive replies account for 33.8%, and those with ten or more account for the remaining 22.7%.

The following section describes the dependent variables, organised by levels (tweets, users, news). The descriptive statistics are presented in Tables 8 (categorical variables) and 9 (numerical variables).

5.2.1. Tweet level

At the tweet level, characteristics of the temporal distribution of responses are shown, including descriptive statistics on the number of communications per day (Table 9). Additionally, the data includes information on the number of retweets, replies, and likes these communications received, as well as whether they are geo-located. This data comes directly from the Twitter API.

5.2.2. User level

Next, the information collected at the user level is presented. First, data on user-reported location is shown. Users may choose to display this information in their profile, and in both cases, the number of users who choose to submit this information is similar (roughly half of the users). However, in the Uruguayan case, the proportion of users reporting being in the country is much higher than in the British case, likely due to the international popularity of information sources. To identify those reporting to be in the country (Uruguay or the UK), this project used a zero-shot classification approach. This technique leverages pre-trained Large Language Models to perform text classification in an unsupervised manner (Pushp and Srivastava 2017). The AI determined whether the location was in the United Kingdom or Uruguay. An analysis of a sample of the results from each country yielded satisfactory outcomes. For users indicating a location in the United Kingdom or Uruguay, the analysis further identified their specific region. Although efforts to achieve greater disaggregation encountered limited success, the classification ultimately distinguished between users in Montevideo (the capital) and elsewhere in Uruguay and identified the country of location within the United Kingdom¹⁰.

Additionally, the Twitter API provides various data regarding the characteristics of the user or account from which tweets are collected. Based on the account creation date, the account's "age" can be estimated and is expressed in months in Table 9. The API

¹⁰ In both cases, the analysis utilised the public access model developed by Laurer et al. (2022). The model first classified cases corresponding to the countries of interest. Then, within those cases classified as being in either Uruguay or the UK, the model further classified the regions. The pipeline followed two tests to verify the accuracy of the strategy. First, the 250 locations with the highest number of cases were selected and manually verified for correct classification. Second, a random sample (excluding the first 250 locations) was selected, and the same corroboration process was applied. In the UK, the first 250 sites accumulated a total of 67.80% of the cases and 230 were correctly classified to be in the UK or somewhere else (implying a precision of .92). When these 250 locations are converted into number of cases, this level of accuracy equates to 98.73% of correctly classified units (over the 250 locations multiplied by the number of cases each one accumulates). Taking a randomised sample, the accuracy decreases, as a few more outlier cases confound the algorithm, yielding an accuracy of .75. Among those classified in the United Kingdom, the classifier correctly distinguishes 197 of the 250 localities with the most accumulated cases within the different countries in the UK or non-mention to any specific place (78.8% accuracy). This implies a total of 93.4% of correctly classified cases within a sample representing 67.9% of the total of cases within the UK. Doing the same analysis for Uruguay, of the 250 most self-reported locations, 206 were correctly identified inside or outside the country (82.4% accuracy). In terms of the number of cases represented, this implies a total of 97.9% of cases correctly classified within a sample representing 90.2% of the total number of cases). Taking a random sample of locations, 80.8% of the locations are correctly classified. Among those classified in Uruguay, the classifier correctly distinguishes 241 of the 250 localities with the most accumulated cases within Montevideo (96.4% accuracy). This implies a total of 99.4% of correctly classified cases within a sample representing 95.0% of the total cases within Uruguay.

also provides data on the user's type of account (verified¹¹ or not), number of followers, following, and overall activity (how many tweets the account has produced). Various of these account features were also used to estimate the age and gender of each user, employing the algorithm trained by Wang et al. (2019). This analysis holds significant potential for contrasting the results with previous studies on punitiveness.

Another element of interest is the presence of a profile picture, as it implies higher levels of "personalisation" and, to some extent, "exposure" of the user. To further refine this analysis, zero-shot image classification was used to identify cases where the photo depicts a person with only one person appearing in the image. Although some "false positives" occur (e.g., when the photo is not of the account owner), this generally identifies users who present their faces in the profile, indicating lower levels of anonymity on the platform.

Subsequently, the users' descriptions were analysed to gather more information about their characteristics. A challenge in this regard is extracting usable information from this data. Zero-shot classification strategies were applied to estimate two characteristics of interest based on a qualitative analysis of the descriptions: whether the user identifies as religious and whether they express a political identity (and on which side of the left-right political spectrum they align). The classification of religious descriptions was successful¹² for the UK but not for Uruguay. The classification of political identification was less accurate, often confusing contradictory messages based on keywords (for example, "anti-Tory" was mistakenly classified as sympathetic to the right).

Additionally, the analysis applied the same topic modelling technique used in Chapter 1 to the user descriptions as an alternative strategy to extract useful information from them. The selection process focused on topics with clear, direct interpretations relevant to the analysis. A primary finding in both countries shows that users most commonly mention the football or sports team they support in their descriptions. The analysis also differentiates users who identify themselves based on their professional background. In the United Kingdom, users who identify themselves based on their political affiliation can be distinguished, although the specific type of affiliation

¹¹ Being verified on Twitter (2022) indicated that the account was authentic and belonged to a notable individual, organization, or brand, marked by a blue checkmark to prevent impersonation

¹² Given the lower number of positive cases in descriptions classified as religious (see Table 1), the strategy for validating the technique differed slightly. A random selection of 125 positive and 125 negative cases was made. In the UK sample, 60.8% of the tweets classified as religious were manually confirmed as religious (True Positives). Of those classified as negative, 99.2% were True Negatives. On this balanced sample, the F-Score is .75.

cannot be inferred. This distinction does not emerge in Uruguay, but one topic revolves around descriptions focused on family roles (mother, father, grandparents, etc.). The analysis includes all these topics associated with the users.

5.2.3. News items level

Finally, information regarding the news was collected. First, there are the news portals that produce each of the news items mentioned at the beginning of this section. The analysis also includes information regarding likes, retweets, and responses received by the news items. Additionally, four extra variables were extracted from the gathered information. First, sentiment analysis (Elbagir and Yang 2019) was conducted to identify and categorise the news as positive, negative, or neutral and determine the polarity of each sentiment. This variable ranges from -1 to 1, with -1 indicating completely negative polarity, 0 indicating neutrality, and 1 indicating completely positive polarity. However, to facilitate the interpretation of the coefficients in the model estimation, this variable was transformed to vary between -10 and 10. Second, Named Entity Recognition (Li et al. 2020) identifies whether the tweets mention a specific place or person.

Finally, the analysis incorporates information regarding which keyword (see methodology) was identified during data collection. Some overlap occurs, as a tweet may contain words associated with more than one group. To distinguish between these categories, an approach was taken based on the seriousness of the crimes. The category labelled "murder and physical violence" is considered the most serious, although it does not include sexual offences without homicide or other types of physical harm, which could arguably be considered equally or more serious. If cases of sexual violence include any of the keywords in the "murder and physical violence query", they are included in that category. Cases of sexual assault that do not contain any of the keywords for murder and physical violence are categorised under the sex crime label. The process follows the same process for all other categories.

Table 8 Descriptives (categorical) - UK and Uruguay

Level	UK.			Uruguay		
	Variable	Category	Percentage	Variable	Category	Percentage
Tweet	Punitive	Yes	4.7%	Punitive	Yes	3.9%
		No	95.3%		No	96.1%
User	User Location	Other	24.6%	User Location	Other	11.9%
		United Kingdom	26.5%		Uruguay	41.2%
		No location	48.9%		No Location	46.9%
	User Location (disaggregated)	England	60.1%	User Location (disaggregated)	Montevideo	56.8%
		Northern Ireland	2.0%		Other	43.2%
		Scotland	7.9%		-	-
		UK non specified	25.2%		-	-
		Wales	4.8%		-	-
	Verified	Yes	0.9%	Verified	Yes	0.2%
		No	99.1%		No	99.8%
	Estimated Gender	Masculine	72.1%	Estimated Gender	Masculine	70.5%
		Femenine	27.9%		Femenine	29.5%
	Estimated Age	age_<=18	16.8%	Estimated Age	age_<=18	24.5%
		age_>=40	39.1%		age_>=40	36.2%
		age_19-29	21.5%		age_19-29	13.9%
		age_30-39	22.6%		age_30-39	25.4%
	Photo	No photo	29.8%	Photo	No photo	32.9%
		Photo (no person)	26.2%		Photo (no person)	24.0%
		Photo (person)	44.0%		Photo (person)	43.1%
	Football description	Yes	3.7%	Football description	Yes	3.6%
		No	69.1%		No	62.0%

News	Source	Non valid description	27.2%	Family description	Non valid description	34.4%
		Political description	Yes		Yes	5.2%
			No		No	60.4%
			Non valid description		Non valid description	34.4%
		Professional description	Yes		Yes	2.4%
			No		No	63.2%
			Non valid description		Non valid description	34.4%
		Religious description	Religious		-	-
			Other		-	-
			No Description		-	-
		SkyNews	23.8%		TelemundoUY	26.3%
		BBCNews	20.5%		portalmvd	18.9%
News	Source	thetimes	14.4%	Source	Subrayado	15.5%
		Independent	13.4%		elpaisuy	8.8%
		Telegraph	9.1%		MVDNoticias	6.9%
		guardian	5.7%		TelenocheUy	6.3%
		DailyMailUK	3.7%		ladiaria	6.2%
		MENnewsdesk	1.7%		ObservadorUY	4.6%
		LivEchonews	1.4%		LeoPedrouza	2.3%
		TheSun	1.1%		CronicasDelEste	2.3%
		standardnews	1.0%		BUSQUEDAonline	0.6%
		BBCNewsNI	0.9%		RadioSarandi690	0.4%
		DailyMirror	0.8%		5noticiasuy	0.3%
		WalesOnline	0.8%		vtvnoticiasuy	0.3%
		BBCScotlandNews	0.4%		diariolaruy	0.3%
		EveningStandard	0.4%		uypress	0.0%
		birmingham_live	0.4%		InformaCarve850	0.0%
		dailystar	0.4%		MaldoNoti	0.0%

		bbcsoutheast	0.2%		LaRed21	0.0%
		looknorthBBC	0.0%		ElEspectador810	0.0%
	Person mentioned	Yes	46.3%	Person mentioned	Yes	39.6%
		No	53.7%		No	60.4%
	Location mentioned	Yes	31.5%	Location mentioned	Yes	57.0%
		No	68.5%		No	43.0%
	Keyword	Fraud and theft	11.9%	Keyword	Fraud and theft	12.7%
		Crime (general)	15.7%		Crime (general)	22.0%
		Drugs and gangs	3.8%		Drugs and gangs	21.7%
		Sex - IPV - domestic (no murder)	24.1%		Sex - IPV - domestic (no murder)	11.1%
		Violent crime - murder	26.3%		Violent crime - murder	23.7%
		Others	18.3%		Others	8.9%

UK: Total N tweets = 334,827. Uruguay: Total N tweets = 107,828.

Table 9 Descriptives (numerical) - UK and Uruguay

UK.										
Level	Variable	Min	Max	Mean	SD.	Median	Quartile 1. 25%	Quartile 3. 75%	Skewness	Kurtosis
Tweet	Tweets by day	52	7700	787.67	733.41	584	372.75	968.75	4.17	28.52
	Retweets	0	17135	0.43	45.19	0	0	0	331.53	117751.50
	Replies	0	1442	0.43	3.92	0	0	1	222.76	71184.80
	Likes	0	79258	4.02	220.79	0	0	1	311.71	106909.40
User	Account Age	0	197	78.19	56.60	73	22	133	0.17	-1.48
	User Tweet Count	1	2758710	28233.50	63800.05	9236	2781	27119	9.75	233.18
	User Followers Count	0	8366251	1780.72	39295.86	204	46	783	164.09	32224.10
	User Following Count	0	561455	1161.45	3594.02	455	140	1216	47.22	4008.84
	Author production	1	9011	861.61	1772.48	120	18	795	3.28	11.51
News	News by day*	43	291	150.76	53.68	154	106.75	191.25	0.00	-0.77

	Retweets	0	5721	175.61	459.59	36	11	131	6.74	64.61
	Replies	0	10316	631.58	1367.06	137	36	507	3.71	15.30
	Likes	0	10316	15.51	101.42	3	1	9	46.92	3357.55
	Conversation Interaction	1	9011	861.61	1772.48	120	18	795	3.28	11.51
	Sentiment (-1 to 1)	-0.985	0.961	-0.54	0.38	-0.66	-0.832	-0.361	1.22	0.79
Uruguay										
Tweet	Tweets by day	19	1652	295.78	231.60	240	132.75	394.5	1.82	4.60
	Retweets	0	383	0.45	4.41	0	0	0	36.65	1999.32
	Replies	0	367	0.40	2.78	0	0	0	62.23	5808.38
	Likes	0	2332	3.21	23.49	0	0	2	42.66	2831.14
User	Account Age	0	189	70.53	50.70	61	22	116	0.32	-1.34
	User Tweet Count	1	803448	22832.15	39849.28	9077	2777.25	25404	4.49	31.11
	User Followers Count	0	3571117	1370.16	13291.89	338	80	1026	186.81	48504.63
	User Following Count	0	98171	1035.99	1607.71	510	171	1223	8.85	318.55
	Author production	1	710	40.96	81.08	14	4	42	4.92	31.73
News	News by day*	11	1578	295.68	270.55	205	109	378	1.74	3.24
	Retweets	0	808	54.96	105.90	13	3	53	3.60	15.69
	Replies	0	293	49.22	63.73	23	6	69	1.92	3.42
	Likes	0	2346	167.46	299.20	46	12	176	3.34	13.94
	Conversation Interaction	1	832	122.27	167.04	55	11	155	2.03	3.93
	Sentiment (-1 to 1)	-0.9913	0.9118	-0.42	0.45	-0.5678	-0.7964	0	0.79	-0.35

5.3. Multivariate analysis

This chapter examines the impact of these variables on users' punitive attitudes through a series of multivariate analyses, with punitive attitudes as the dependent variable, presented in various formats to yield diverse insights. The first step involved modelling user characteristics influencing the likelihood of expressing punitive attitudes. Users were categorised as punitive or non-punitive based on the expression of at least one punitive attitude, defined as having at least one tweet classified as punitive by the automatic classifier. Given the rarity of such attitudes and the tendency for most individuals to tweet infrequently, this strategy effectively retains a maximum number of positive cases. Additionally, considering an individual who expresses at least one punitive attitude as "punitive" seems theoretically appropriate. Logistic regression was applied to this format, offering a straightforward estimation method but omitting relevant information regarding the characteristics of the news.

A specific analysis of the news items was conducted to address this gap. The same strategy (considering at least one punitive response) is problematic for news items, given their greater variation in the number of responses and a generally higher mean. With fewer news items than unique users and a larger number of replies or quotes per news item, the punitive response count was modelled using a negative binomial model. Since news items have varying numbers of replies and quotes, the number of responses per news item was incorporated as an offset to account for exposure or differences in the units of observation. The offset term adjusts the model to account for these differences in exposure by effectively normalising the count data to reflect the rate of punitive responses per unit of exposure (e.g., per reply or quote) rather than the raw count. By including the offset, the model estimates the effect of predictors on the rate of events per unit of exposure, providing a more accurate interpretation of the data (Weisburd et al. 2022).

The logistic regression at the user level and the count model at the news level do not account for the influence of each level on the other. One way to address this is by running a regression on the entire dataset to estimate the likelihood that a tweet is punitive based on user and news characteristics. However, this violates regression assumptions because the observations are not independent. Two multi-level models partially addressed this issue: one using the individual as the second-level cluster and the other using the news-item ID. The dataset was filtered for these models to include only users or news items with at least 10 cases¹³. This filtering introduces bias into the

¹³ The debate over the required number of cases per cluster has generated differing viewpoints. Some researchers argue that cluster size is less important as long as there are enough clusters, with a

analysis to the extent that the characteristics of the most active users and the most responded-to news items differ from those of the entire sample. Therefore, the results should be interpreted cautiously and considered in conjunction with other findings. It is not feasible to incorporate a three-level model because the tweets are not necessarily nested within a hierarchical structure.

5.3.1. Punitive individuals

Table 10 presents the results by country, with the first variable of interest being users' geo-location. The underlying hypothesis suggests that users located within the country will exhibit more punitive attitudes as they are directly impacted by the news, which, although sometimes international in content, predominantly relates to local crimes. This hypothesis seems to be supported by the UK but not by Uruguay in terms of statistical significance. However, in both cases, the effects align with the expected direction. In Uruguay, Tukey's Honest Significant Difference test was used for pairwise comparisons, particularly to analyse the differences between the 'Other' category and both 'Interior' and 'Montevideo'. Nevertheless, these results are not statistically significant.

The number of verified users was not included in the Uruguayan case because of the small number of cases. In the British case, this variable follows the expected logic, reducing the chance that the user has made at least one punitive tweet by approximately 50%.

In both countries, older accounts (Q4) are less likely to express punitive attitudes compared to newer accounts (Q1), with the effect being stronger in Uruguay (OR=0.781) than in the UK (OR=0.899). Conversely, users with higher tweet counts show an increased likelihood of expressing punitive attitudes, particularly in Uruguay, where those in Q4 are 56.5% more likely compared to a 14.9% increase in the UK. Interestingly, a higher follower count tends to decrease the likelihood of expressing punitive attitudes, with Q4 users in the UK and Uruguay showing a reduction of 13.3% and 20.8%, respectively. Similarly, following more users is associated with a decreased likelihood of punitive attitudes, with a stronger effect observed in the UK (OR=0.783) than in Uruguay (OR=0.809). These results suggest that while tweet

minimum of one case (Bell et al. 2008), while others recommend a minimum of five (Clarke 2008) or ten (Hox et al. 2017). cases per cluster. In this analysis, convergence issues arose when no minimum number of cases was set, likely due to the dataset's size. However, given the time-intensive nature of this type of analysis—where models can take more than a day to run—detailed experiments to investigate this issue were not feasible. As a robustness check, a minimum of ten cases per cluster was used to mitigate convergence problems, though several rounds of correction were still necessary.

activity increases the propensity for punitive attitudes, larger social networks (in terms of followers and following) may have a decreasing effect, particularly in the UK.

Regarding the inferred sociodemographics, the analysis did not find significant differences between genders in Uruguay. However, in the UK, being male reduces the likelihood of a user expressing punitive attitudes by approximately 12%. Analysis of the estimated ages reveals a statistically significant difference between older and younger users in both Uruguay (≥ 40 , $OR=0.865$) and the United Kingdom (≥ 40 , $OR=0.910$). The exposure hypothesis, as measured by the use of profile pictures, seems to hold true for the UK. Users in the 'No Person' category show a reduction of around 30% in the likelihood of expressing punitive attitudes, while those in the 'Person' category show a reduction of just under 25%. Uruguay results are not statistically significant, with ORs close to 1.

Next, the effects of variables generated from the descriptions are analysed. An interesting finding is the positive, high, and significant effect of descriptions based on sports affiliations. This effect is similar in both countries. Of the remaining descriptions, the only one significant at 5% is the description as a professional, which reduces users' chances of expressing punitive attitudes by almost 40%.

Finally, the number of responses generated by the user is added as a control variable. This variable aims to avoid overestimating the other indicators by excluding the increase in the probability of generating a tweet classified as punitive solely due to participating to a greater extent in the discussion. This variable is significant with a marginal effect (the analysis will elaborate on this later by analysing the remaining models).

The model conducted for British users obtains a Nagelkerke's R^2 of .047, while the Uruguayan model obtains an R^2 of .129. It is worth noting that the UK dataset includes 129,136 unique users participating in the discussion, compared to only 22,392 unique users in Uruguay. The difference in R^2 values between the British and Uruguayan models could be attributed to the disparity in sample sizes. The larger British sample may capture more variability in the data, resulting in a lower R^2 , while the smaller Uruguayan sample might display a higher R^2 due to potential overfitting to the smaller dataset (Akossou and Palm 2013). None of the models show outliers (Cook's test, threshold = .7) or multicollinearity ($VIF > 10$). However, it is important to note that for Uruguay, only about 70% of the residuals are within the error bounds, indicating a potential issue with model fit. The accuracy (95% CI) for Uruguay is 71.61% [69.18%, 74.06%], measured using the Area under the Curve (AUC) method. Similarly, the UK

model indicates that only about 80% of the residuals fall within the error bounds, with an accuracy (95% CI) of 64.85% [64.21%, 65.42%].

Table 10 Logistic Model for Punitive Individuals - UK and Uruguay

Variable	UK				URUGUAY			
	Categoeries	Estimate	OR	Sig.		Estimate	OR	Sig.
Intercept	Intercept	-2.187	0.112	***	Intercept	-2.225	0.108	***
Location (ref. No location)	Other	-0.029	0.971		Other	-0.124	0.884	
	England	0.134	1.144	***	Interior	0.041	1.042	
	Northern Ireland	0.323	1.382	**	Montevideo	0.003	1.003	
	Scotland	0.084	1.087		-	-		
	UK non specified	0.139	1.149	**	-	-		
	Wales	0.308	1.361	***	-	-		
Verified (ref. No)	Yes	-0.707	0.493	***	-	-		
Account age in quartiles (ref. Q1)	Q2	-0.031	0.970		Q2	-0.091	0.913	
	Q3	0.033	1.034		Q3	-0.066	0.936	
	Q4	-0.106	0.899	**	Q4	-0.248	0.781	***
User tweet count in quartiles (ref. Q1)	Q2	0.033	1.033		Q2	0.167	1.182	*
	Q3	0.018	1.018		Q3	0.325	1.384	***
	Q4	0.139	1.149	**	Q4	0.448	1.565	***
User followers count in quartiles (ref. Q1)	Q2	-0.062	0.940	.	Q2	-0.010	0.990	
	Q3	-0.074	0.928	.	Q3	-0.151	0.860	
	Q4	-0.143	0.867	**	Q4	-0.234	0.792	.
User following count in quartiles (ref. Q1)	Q2	-0.006	0.994		Q2	-0.154	0.858	*
	Q3	-0.094	0.910	*	Q3	-0.151	0.860	.
	Q4	-0.245	0.783	***	Q4	-0.211	0.809	*
Estimated gender (ref. Female)	Male	-0.126	0.881	***	Male	0.015	1.015	
Estimated age (ref. <18)	>=40	-0.094	0.910	**	>=40	-0.145	0.865	*
	19-29	0.036	1.037		19-29	-0.070	0.932	
	30-39	-0.038	0.963		30-39	-0.102	0.903	.
Photo (ref. no photo)	No person	-0.317	0.729	***	No person	0.027	1.028	
	Person	-0.263	0.769	***	Person	-0.024	0.976	
Football description (ref. no)	Yes	0.527	1.693	***	Yes	0.391	1.479	***
Political description (ref. no)	Yes	0.003	1.003		Family description (ref. no)	0.033	1.035	
Professional description (ref. no)	Yes	-0.500	0.606	***	Yes	-0.003	0.997	
Religious description (ref. no)	Yes	-0.088	0.916	.	-	-		
Number of collected replies or quotes	N	0.078	1.081	***	N	0.066	1.069	***

5.3.2. Punitive counts in news items

This section presents the count models for the news and their punitive responses. The dependent variable is the ratio of punitive responses to total responses, with the total responses included as the offset in the model. The column labelled "Percent Rate Change" expresses the expected change in the ratio of punitive responses to total responses compared to the reference category.

First, Table 11 presents the sources of the news and their corresponding punitive responses. In the UK, smaller and more local media outlets generally receive a higher punitive response. For example, BBC Scotland News and Liverpool Echo News exhibit notable increases in punitive responses compared to the BBC News reference category. Conversely, larger national outlets, such as The Telegraph and The Times, show significant decreases in punitive responses, with rates 52.4% and 56.0% lower, respectively. It is important to note that extremely high percentage changes in some categories may be attributed to small counts within those groups. In Uruguay, the trend is the opposite. The most prominent media outlets, including Telemundo, Telenoche, Subrayado, Portal Montevideo, and El Observador, show positive rate changes or no statistically significant difference, indicating they receive the same or more punitive replies compared to the reference category, El País Uruguay, one of the most important media outlets in the country. For instance, Telenoche and Subrayado show increases of 37.4% and 28.4%, respectively. On the other hand, smaller outlets like Radio Sarandi 690 and VTV Noticias exhibit significant decreases in punitive responses, with rates 65.9% and 76.7% lower, respectively. These numbers suggest that larger media outlets in Uruguay attract more punitive responses, unlike the pattern observed in the UK.

The number of likes a news item receives does not significantly impact the likelihood of a punitive response, as evidenced by the non-significant results across all quartiles in both the UK and Uruguay. In contrast, as expected, the sentiment of the news item influences the ratio of punitive responses. A higher ratio of punitive responses is associated with more negative sentiment, even when controlling for other variables, including the type of crime. Specifically, in the UK, a one-unit increase in the positive polarity of news sentiment is associated with a 7.3% decrease in punitive responses, while in Uruguay, the exact change leads to an 8.9% decrease in punitive responses. This consistent relationship between negative sentiment and punitive reactions underscores the importance of news framing and its effect on public attitudes.

Regarding the specification of place or person in the news item, the results reveal contrasting effects between the UK and Uruguay. In the UK, mentioning a specific

individual in the news increases the likelihood of a punitive response by 16.3%, while mentioning a location decreases it by 15.6%. This aligns with the expectation that personalising a story through individuals garners more punitive reactions, whereas mentioning locations does not have the same effect. In Uruguay, the results show an opposite trend for the personalisation case. Mentioning a specific individual reduces the punitive response by 30.5%. The mention of a location follows a similar pattern to that of the UK, leading to a 10.6% reduction. These findings contradict the expected direction and suggest that the Uruguayan audience may react differently to personalised news content.

The keyword analysis complements these observations. In the UK, the expected pattern holds that more severe crimes like violent crime and murder lead to a significant increase in punitive responses (176.2%) against the less severe reference category (theft and fraud). In Uruguay, violent crime and murder also increase punitive responses by 25.6%, but interestingly, it is the "sex, IPV, and domestic violence" category the one that further increases punitive reactions (57.0%), indicating a different public perception of these issues. In the UK, the mention of "drugs and gangs" does not have significant differences from the reference category "theft and fraud", but the ratio follows the expected direction. However, in Uruguay, this category represents a significant reduction (-45.7%) in the punitive response.

Finally, the number of replies and quotes to the news item is included as a control variable. Although this variable is incorporated as an offset, its inclusion enables an assessment of whether the ratio of punitive responses varies across different levels of interaction with the news item. The effects, however, appear to be marginal, indicating that the interaction volume does not significantly alter the ratio of punitive responses.

The models do not suffer from problems of overdispersion, multicollinearity, or zero inflation (Gelman and Hill 2006; Lüdtke et al. 2021). The Nagelkerke's R^2 is 0.151 for the U.K. and 0.142 for Uruguay. However, the models do exhibit some issues with residuals: for Uruguay, approximately 86% of the residuals fall within the error bounds, and for the UK, approximately 91% of the residuals fall within the error bounds.

Table 11 Negative Binomial model for punitive replies counts - UK and Uruguay

	UK					URUGUAY				
Variable	Category	Estimate	Std. Error	% Rate Change	Sig	Category	Estimate	Std. Error	% Rate Change	Sig
Intercept	Intercept	-3.962	0.086	-98.1%	***	Intercept	-3.584	0.118	-97.2%	***
Source (ref. BBCNews/elpaisuy)	BBCNewsNI	-0.129	0.153	-12.1%		5noticiasuy	-0.623	0.472	-46.4%	
	BBCScotlandNews	0.553	0.162	73.8%	***	BUSQUEDAonline	-0.861	0.496	-57.7%	.
	bbcsoutheast	0.335	0.283	39.8%		CronicasDelEste	-0.491	0.276	-38.8%	.
	birmingham_live	0.374	0.148	45.3%	*	diariolaruy	-0.084	0.329	-8.1%	
	DailyMailUK	0.311	0.078	36.4%	***	ladiaria	-0.160	0.138	-14.8%	
	DailyMirror	0.181	0.112	19.9%		LeoPedrouza	0.278	0.162	32.0%	.
	dailystar	-0.515	0.234	-40.3%	*	MaldoNoti	1.572	0.674	381.8%	*
	EveningStandard	-0.038	0.181	-3.8%		MVDNoticias	-0.336	0.175	-28.5%	.
	guardian	-0.655	0.082	-48.0%	***	ObservadorUY	0.102	0.142	10.8%	
	Independent	-0.285	0.076	-24.8%	***	portalnvd	0.156	0.097	16.9%	
	LivEchonews	0.466	0.099	59.3%	***	RadioSarandi690	-1.077	0.540	-65.9%	*
	looknorthBBC	1.352	0.309	286.5%	***	Subrayado	0.250	0.107	28.4%	*
	MENnewsdesk	0.438	0.095	55.0%	***	TelemundoUY	0.147	0.096	15.9%	
	SkyNews	-0.071	0.061	-6.9%		TelenocheUy	0.318	0.113	37.4%	**
	standardnews	0.077	0.117	8.0%		uypress	-0.697	1.120	-50.2%	
	Telegraph	-0.743	0.099	-52.4%	***	vtvnnoticiasuy	-1.456	0.804	-76.7%	.
	TheSun	0.035	0.109	3.6%		-	-	-	-	
	thetimes	-0.820	0.112	-56.0%	***	-	-	-	-	
	WalesOnline	0.645	0.118	90.6%	***	-	-	-	-	
Likes received in quartiles (ref. Q1)	Q2	-0.045	0.050	-4.4%		Q2	0.004	0.063	0.4%	
	Q3	0.071	0.069	7.3%		Q3	-0.055	0.091	-5.4%	
	Q4	0.136	0.122	14.6%		Q4	0.061	0.138	6.3%	
Sentiment (-10 to 10)	sentiment	-0.076	0.006	-7.3%	***	sentiment	-0.094	0.008	-8.9%	***
Mentions an individual (ref. No)	YES	0.151	0.035	16.3%	***	YES	-0.363	0.060	-30.5%	***
Mentions a Location (ref. No)	YES	-0.170	0.038	-15.6%	***	YES	-0.112	0.055	-10.6%	*
Keyowrd (ref. theft and fraud)	Crime (general)	0.084	0.080	8.8%		Crime (general)	0.012	0.097	1.2%	
	Drugs and gangs	0.108	0.109	11.4%		Drugs and gangs	-0.611	0.110	-45.7%	***
	Sex - IPV - domestic (no murder)	0.597	0.067	81.6%	***	Sex - IPV - domestic (no murder)	0.451	0.110	57.0%	***
	Violent crime - murder	1.016	0.062	176.2%	***	Violent crime - murder	0.228	0.093	25.6%	*

	Others	0.696	0.069	100.5%	***	Others	0.309	0.115	36.2%	**
Conversation interaction	N	0.000	0.000	0.0%	.	N	-0.001	0.001	-0.1%	**

5.3.3. Punitive tweets

Finally, this section aggregates information by estimating the likelihood that a specific tweet is punitive at the tweet level. The strategy is as follows: Tables 12 and 13 present the logistic model applied to the entire dataset alongside the statistically significant coefficients from the multi-level models (authors and news items). Given the characteristics of the data and the number of cases, achieving proper convergence for the multi-level models required multiple iterations. The models with the full set of variables encountered convergence issues at both the optimiser level and the gradient-based convergence criterion. To address these issues, simplified models were estimated, retaining only the initially significant variables, and various optimisers were tested. Notably, the gradient-based criterion still failed at the UK news level after several attempts. Therefore, the results should be interpreted with caution.

The Intraclass Correlation Coefficient (ICC) of the empty multi-level models (only incorporating the random intercepts for each group) was estimated to account for the need to consider these levels. The ICC is important because it indicates the proportion of the total variance attributable to the grouping structure in the data, such as users or news items in this case. A higher ICC suggests that a significant portion of the variance is due to differences between these groups rather than within them. The ICC for the multi-level model per user in the UK is 0.442, while for Uruguay it is 0.332. For the multi-level models per news item, the ICCs are 0.465 and 0.449, respectively. In all cases, these values are well above the minimum rule of thumb of double-digit percentages (>.10) (Chen and Chen 2021).

The models also incorporated the month of each response as a control. In this sense, there seems to be no variation by month in the UK, but there are peaks and troughs by month in Uruguay. Incorporating this element is important to avoid omitted variable bias, specifically to control for the effect of unmeasured events that may be temporarily situated.

The number of replies and quotes a news item receives does not directly influence the likelihood of a tweet being punitive, as this factor comes into play after the tweet is created. However, it can still provide insight into the nature of the communication. In the UK, an increase in replies and quotes is associated with a slight decrease in the odds of a tweet being punitive, with a 7.3% reduction per unit increase in replies (OR = 0.927) in the collapsed model and similar effects observed in the multi-level news

model (OR = 0.949). In contrast, in Uruguay, the number of replies and quotes does not significantly affect punitive attitudes (OR = 0.993).

Regarding the account's location, the effects seem to align with what has been observed in previous models. Tweets generated by accounts claiming to be outside the country are less likely to be classified as punitive, while the reverse is true for those claiming to be in some UK countries and outside the capital in Uruguay.

The age of the account remains consistent across models for Uruguay. However, in the UK, some variation in the sign of the coefficient appears, although the estimates are relatively small. This variation may result from differences in tweet production across age groups and their respective proportions in terms of punitive responses. A similar pattern emerges concerning the tweet counts of the accounts. While accounts that have a higher likelihood of submitting at least one punitive communication tend to have higher tweet production (replies to more news items), the probability of an individual tweet being punitive is higher for accounts with lower overall output. This suggests that users who participate less in discussions and on Twitter in general tend to exhibit a higher proportion of punitive attitudes. In contrast, those who engage more in conversations and generate more tweets do not increase the number of punitive tweets in direct proportion to their activity; instead, the expression of punitive opinions slows down or stagnates as participation increases. Regarding followers and followings, the results are consistent with the logistic regression at the user level, showing that accounts with fewer followers and followings are more likely to produce punitive tweets.

The estimated gender results are consistent with the user-level model. In the UK, the fact that the tweet comes from an account classified as male reduces the chances of the tweet being punitive. This result holds throughout the multi-level models. In Uruguay, the effect is positive but not significant in the tweet-level logit model, was not included at the author level, and is positive and significant in the multi-level news logit model. Regarding the estimated age, the results for Uruguay at the tweet level are consistent with those of the individual logit model. However, in the UK, these results at the tweet level are neutralised and even inverted when the news level is incorporated, albeit with a small OR. In any case, beyond being significant, the effect is small and is probably explained by a slight over-representation of the top quartile in the production of tweets.

The presence of a profile picture and its disaggregation also align with the individual-level model. In Uruguay, no significant effects are observed regarding whether an account has a profile picture. However, in the UK, tweets from accounts without a

photo (the reference category) are more likely to be classified as punitive. This pattern suggests that anonymity or lower personal exposure levels might contribute to more punitive expressions. Similarly, the conclusions drawn from user descriptions, such as professional, political, and football-related identifiers, remain consistent across models, further reinforcing the observed trends in user behaviour.

The output per author, measured by the number of responses collected per author on crime-related news over the year, was categorised into quartiles due to its strong right-skewed distribution. The results for this variable are consistent across both the UK and Uruguay, although they are somewhat unexpected at first glance. Despite the higher output volume, authors in the top quartile do not necessarily produce more punitive tweets. The likelihood of a tweet being punitive tends to decrease as the author's overall output increases, suggesting that those more active in discussions may express punitive attitudes less frequently than they do in proportion to their overall participation.

Analysing news sources reveals no surprises for the UK. The portals associated with a higher punitive response rate are the same portals that increase the likelihood that the response to their news items will be classified as punitive. By incorporating the different levels and observing that these effects are maintained, it is clear that some portals have specific slopes, even beyond the characteristics of the particular news item, which could indicate a public segmentation. Considering the difference in random effects per news item and the characteristics analysed, it could be thought that this difference at the portal level is due to the characteristics of the audience that consumes each portal. However, there may be other characteristics of the news items associated with each portal that are not being captured. For the Uruguayan case, it is particularly relevant to note that the effects per source disappear when incorporating the news-item level. This disappearance suggests that the differences in punitive attitudes are more strongly associated with the specific news items than with the portals themselves. In other words, the content or context of the news items, regardless of the portal, plays a critical role in shaping punitive attitudes. The news portal's effect observed in the non-hierarchical model may have been confounded by the specific news items presented on those portals.

The number of responses collected per news item was also categorised into quartiles, and the results were similarly surprising. News items with the fewest replies were more likely to generate punitive responses. This finding contrasts with the initial expectation that popular news stories, particularly those involving exceptional or violent events, would attract more responses and a higher proportion of punitive replies. However, the models indicate—and an analysis of the dataset with the

predictions made by the classifier algorithm confirms—that the opposite is true. Many news items that receive only a handful of responses tend to have most of those responses classified as punitive. Interestingly, the reverse pattern is observed with likes, where more popular news items garner more likes but do not necessarily correlate with a higher proportion of punitive replies.

Sentiment scores remain stable across all models and consistently emerge as one of the strongest predictors of punitive responses. In both the UK and Uruguay, more negative sentiment is strongly associated with a higher likelihood of punitive replies, as shown in Tables 12 and 13. The impact of keywords is similarly robust, with terms related to more severe crimes significantly increasing the odds of a punitive response.

The mention of location or individuals also shows stability in the models for Uruguay. In the UK, however, the effect of location presents a more complex pattern. In the logistic model (Table 12), tweets responding to news items that mention a location are more likely to be punitive ($OR = 1.203$). However, when considering the rate of punitive replies across all responses to the same news item (Table 11, section 3.2), news stories mentioning a location have a lower rate of punitive replies. This reversal suggests that while individual tweets might be more punitive when a location is mentioned, the overall discussion around those news items tends to be less so. The multi-level models, which incorporate the news-item level, further complicate this relationship as the location effect again shifts, indicating a nuanced interaction between these variables. The coherence between the count and multi-level models suggests that the relationship between location mentions and punitive responses may be one of reducing the probability of a punitive response when considered in aggregate. This complexity underscores the benefits of employing count and multi-level models to fully capture the interactions between variables.

In the UK, without considering levels, the logistic model at the tweet level achieves a Nagelkerke's R^2 of 0.100. When clustered by the author, the multi-level model shows an unconditional R^2 of 0.168 and a conditional R^2 of 0.468. At the news level, these values are 0.123 and 0.451, respectively. Without considering levels, the logistic model yields a Nagelkerke's R^2 of 0.09 for Uruguay. The author-level model shows an unconditional R^2 of 0.143 and a conditional R^2 of 0.381, while the news-level model shows values of 0.150 and 0.448, respectively.

While none of the models exhibit multicollinearity or outlier issues, the residual distribution presents some challenges, particularly when considering the multi-level models. In the UK, the collapsed model has about 88% of the residuals within the error bound, but this percentage drops to 50% for the author-level model and 75% for

the news-level model. Similarly, in Uruguay, 89% of the residuals fall within the error bound for the collapsed model, but only 61% do so for the author-level model and 63% for the news-level model. These residual distribution issues suggest that the models perform adequately at the tweet level but face increasing challenges when additional levels are introduced.

Additionally, the difference between the unconditional and conditional R2 values on the multi-level models highlights the significant role of individual characteristics and specific news factors not accounted for by the variables used in the model.

Table 12 Determinants of punitive attitudes at the tweet level for the UK (collapsed and multi-level)

Variable	Categories	Collapsed			Author		News	
		Estimate	OR	Sig.	OR	Sig	OR	Sig
(Intercept)	(Intercept)	-3.498	0.030	***				
Month	Month 02	0.005	1.005					
	Month 03	-0.036	0.964					
	Month 04	-0.053	0.949					
	Month 05	-0.021	0.980					
	Month 06	-0.064	0.938					
	Month 07	-0.002	0.998					
	Month 08	-0.033	0.967					
	Month 09	0.023	1.023					
	Month 10	0.002	1.002					
	Month 11	-0.042	0.959					
	Month 12	0.004	1.004					
Number of replies received	N	-0.076	0.927	***			0.949	***
Location (ref. No location)	Other	-0.037	0.964		0.817	*	0.898	***
	England	0.049	1.050	.				
	Northern Ireland	0.257	1.293	*				
	Scotland	0.007	1.007					
	UK non specified	0.056	1.058					
	Wales	-0.009	0.991					
Verified (ref. No)	Yes	-0.531	0.588	***			0.643	**
Account age in quartiles (ref. Q1)	Q2	0.081	1.084	**				
	Q3	0.190	1.209	***			1.115	***
	Q4	0.056	1.057	.				
User tweet count in quartiles (ref. Q1)	Q2	-0.065	0.938	*			0.936	*
	Q3	-0.126	0.881	***			0.865	***
	Q4	-0.172	0.842	***	0.771	**	0.792	***
	Q2	-0.008	0.992					

User followers count in quartiles (ref. Q1)	Q3	0.018	1.018					
	Q4	0.057	1.059					
User following count in quartiles (ref. Q1)	Q2	-0.098	0.906	***	0.784	**	0.891	***
	Q3	-0.240	0.786	***	0.664	***	0.854	***
	Q4	-0.297	0.743	***	0.715	**	0.909	*
Estimated gender (ref. Female)	Male	-0.157	0.855	***	0.836	*	0.937	**
Estimated age (ref. <18)	>=40	0.016	1.016				1.085	***
	19-29	0.043	1.044					
	30-39	-0.008	0.992					
Photo (ref. no photo)	No person	-0.221	0.802	***			0.942	*
	Person	-0.200	0.818	***			0.916	***
Football description (ref. no)	Yes	0.365	1.441	***			1.323	***
Political description (ref. no)	Yes	-0.078	0.925					
Professional description (ref. no)	Yes	-0.340	0.712	***			0.747	**
Religious description (ref. no)	Yes	-0.025	0.975					
Author production (categorical) (ref. 1)	2-3 replies	-0.170	0.844	***			0.891	***
	4-11 replies	-0.265	0.767	***	0.786	*	0.776	***
	More than 11	-0.529	0.589	***	0.575	***	0.684	***
Source(ref. BBCNews/elpaisuy)	BBCNewsNI	-0.984	0.374	***			0.483	*
	BBCScotlandNews	0.193	1.213	.				
	bbcsoutheast	-0.087	0.916					
	birmingham_live	0.081	1.084					
	DailyMailUK	0.268	1.308	***	1.289	**	1.523	**
	DailyMirror	0.019	1.020					
	dailystar	-1.335	0.263	***	0.319	*	0.125	*
	EveningStandard	0.054	1.056					
	guardian	-0.971	0.379	***	0.335	***	0.421	***
	Independent	-0.147	0.863	***			0.685	**
	LivEchonews	0.349	1.418	***			2.616	***
	looknorthBBC	1.374	3.952	***				
	MENnewsdesk	0.132	1.142	*				
	SkyNews	-0.271	0.763	***	0.700	***		
	standardnews	-0.268	0.765	**	0.548	*		
	Telegraph	-1.440	0.237	***	0.231	***	0.441	***
	TheSun	-0.089	0.915					
	thetimes	-1.206	0.299	***	0.331	***	0.401	***
	WalesOnline	0.555	1.742	***	1.790	*	1.994	*

Conversation interaction in quartiles (ref. Q1)	Q2	-0.089	0.915	**	0.853	**	0.634	***
	Q3	-0.051	0.950		0.853	*	0.703	*
	Q4	-0.194	0.824	***	0.363	***	0.424	**
Likes received in quartiles (ref. Q1)	Q2	-0.016	0.985					
	Q3	0.157	1.169	***			1.384	***
	Q4	0.107	1.113	*	0.707	***	1.514	***
Sentiment (-10 to 10)	sentiment	-0.116	0.890	***	0.910	***	0.911	***
Mentions an individual (ref. No)	YES	0.221	1.248	***				
Mentions a Location (ref. No)	YES	0.185	1.203	***			0.749	***
Keyrowrd (ref. theft and fraud)	Crime (general)	-0.410	0.663	***				
	Drugs and gangs	0.011	1.011					
	Sex - IPV - domestic (no murder)	0.337	1.401	***	1.532	***	1.939	***
	Violent crime - murder	0.982	2.671	***	2.406	***	3.239	***
	Others	1.054	2.870	***	1.916	***	2.297	***

Table 13 Determinants of punitive attitudes at the tweet level for Uruguay (collapsed and multi-level)

Variable	Categories	Collapsed			Author		News	
		Estimate	OR	Sig	OR	Sig	OR	Sig
(Intercept)	(Intercept)	-2.659	0.070	***				
Month	Month 02	-0.445	0.641	***	0.708	***		
	Month 03	-0.372	0.689	***				
	Month 04	0.134	1.143	.	1.360	***		
	Month 05	-0.068	0.935					
	Month 06	-0.338	0.713	***	0.773	**		
	Month 07	-0.346	0.708	***				
	Month 08	-0.469	0.626	***	0.715	***	0.744	*
	Month 09	-0.498	0.608	***	0.723	***	0.533	***
	Month 10	-0.348	0.706	***	0.707	**		
	Month 11	-0.276	0.759	***				
	Month 12	0.016	1.016					
Number of replies received	N	-0.007	0.993					
Location (ref. No Location)	Interior	0.125	1.134	**				
	Montevideo	-0.007	0.993					
	Otro	-0.004	0.996					
Account age in quartiles (ref. Q1)	Q2	-0.159	0.853	***				
	Q3	-0.128	0.880	**				
	Q4	-0.126	0.882	*				
	Q2	-0.108	0.898	*				

User tweet count in quartiles (ref. Q1)	Q3	-0.122	0.885	.				
	Q4	-0.177	0.838	*				
User followers count in quartiles (ref. Q1)	Q2	-0.204	0.815	***	0.675	***	0.754	***
	Q3	-0.346	0.707	***	0.546	***	0.689	***
	Q4	-0.494	0.610	***	0.468	***	0.616	***
User following count in quartiles (ref. Q1)	Q2	0.000	1.000					
	Q3	-0.019	0.981					
	Q4	0.018	1.018					
Estimated gender (ref. Female)	Male	0.026	1.026				1.121	*
Estimated age (ref. <18)	>=40	-0.158	0.854	***			0.856	**
	19-29	-0.099	0.906	.				
	30-39	-0.108	0.898	*			0.863	**
Photo (ref. no photo)	No person	0.013	1.013					
	Person	-0.055	0.946					
Football description (ref. no)	Yes	0.466	1.593	***	1.978	***	1.522	***
Family description (ref. no)	Yes	0.061	1.063					
Professional description (ref. no)	Yes	-0.033	0.967					
Religious description (ref. no)	Yes	-	-	-	-	-	-	-
Author production in quartiles (ref. Q1)	Q2	0.009	1.009		0.822	*		
	Q3	-0.102	0.903	*				
	Q4	-0.161	0.851	**			0.765	***
Source(ref. BBCNews/elpaisuy)	5noticiasuy	-0.874	0.417	.				
	BUSQUEDAonline	-0.721	0.486					
	CronicasDelEste	-0.582	0.559	**				
	diariolaruy	-0.080	0.923					
	ElEspectador810	-9.325	0.000					
	InformaCarve850	-9.394	0.000					
	ladiaria	0.050	1.052		1.526	***		
	LaRed21	-10.040	0.000					
	LeoPedrouza	0.153	1.165					
	MaldoNoti	1.748	5.745	**				
	MVDNoticias	-0.172	0.842					
	ObservadorUY	0.158	1.171		1.384	*		
	portalmvd	0.389	1.476	***	1.675	***		

	RadioSarandi690	-1.012	0.364	*				
	Subrayado	0.156	1.169	*	1.341	**		
	TelemundoUY	0.357	1.429	***	1.489	***		
	TelenocheUy	0.400	1.491	***	1.615	***		
	uyypres	-0.472	0.624					
	vtvnoticiasuy	-1.505	0.222	*				
Conversation interaction in quartiles (ref. Q1)	Q2	-0.290	0.749	***	0.783	***	0.618	***
	Q3	-0.921	0.398	***	0.463	***	0.406	***
	Q4	-0.787	0.455	***	0.562	***		
Likes received in quartiles (ref. Q1)	Q2	0.042	1.043					
	Q3	0.165	1.179	**				
	Q4	0.621	1.860	***	1.418	***		
Sentiment (-10 to 10)	sentiment	-0.100	0.905	***	0.919	***	0.911	***
Mentions an individual (ref. No)	YES	-0.419	0.658	***	0.679	***	0.611	***
Mentions a Location (ref. No)	YES	-0.213	0.808	***	0.901	*		
Keyrowrd (ref. theft and fraud)	Crime (general)	-0.151	0.860	*				
	Drugs and gangs	-0.746	0.474	***	0.551	***	0.441	***
	Sex - IPV - domestic (no murder)	0.497	1.643	***	1.570	***	1.441	*
	Violent crime - murder	0.020	1.020		1.202	*		
	Others	0.244	1.276	**			1.549	*

5.4. Preliminary discussion and conclusions

This chapter explored the determinants of punitive attitudes on Twitter in response to crime-related news in Uruguay and the United Kingdom. The study utilised a trained automatic classifier to detect punitive attitudes and employed various statistical models to identify the factors associated with such attitudes. An important aspect to consider is that, beyond the initial evidence gathered during the training of the automatic classifier, the analysis of determinants serves as a form of predictive validity test. Particularly given that the dependent variable is strongly associated with factors known to correlate with punitive attitudes, such as the type of offence, this provides further evidence supporting the measure's validity. Consequently, the tools developed in this thesis not only enable real-time tracking of punitive attitudes on social media platforms like Twitter but also have the potential to be adapted for use across various media channels that rely on textual communication. This extension underscores the robustness and applicability of the methodology in understanding and predicting public responses to crime-related issues.

The analysis revealed some differences and similarities between the two countries. Regarding the distribution of the dependent variable, in the United Kingdom, a higher proportion of tweets were classified as punitive than in Uruguay. However, Uruguay had a higher proportion of users who posted at least one punitive tweet. This suggests that while fewer users in the UK express punitive attitudes, those who do tend to express them more frequently.

Meanwhile, focusing on the determinants, several user characteristics were found to influence the likelihood of expressing punitive attitudes. Users with older accounts, higher tweet counts, and larger social networks (in terms of followers and followings) were less likely to express punitive attitudes. Interestingly, users who identified themselves with sports affiliations were more likely to express punitive attitudes, while those with professional descriptions were less likely to do so. Additionally, the presence of a profile picture was associated with a lower likelihood of expressing punitive attitudes, but only in the UK.

At the news item level, the sentiment of the news and the specific keywords used in the query were strong predictors of punitive responses. Negative sentiment and news related to violent crimes or severe offences were associated with higher rates of punitive replies. The relationship between news sources and punitive attitudes differed between the two countries. In the UK, smaller and more local media outlets tended to receive higher punitive responses, while in Uruguay, larger and more prominent media outlets attracted more punitive responses.

Overall, this chapter highlighted the complexity of punitive attitudes on social media, demonstrating that both individual user characteristics and the nature of the news content significantly influence the expression of punitive attitudes. The results underscore the importance of considering both user demographics and media framing in understanding public attitudes towards crime and punishment.

6. Time series analysis: punitive attitudes, crime discussion, and political communications

6.1. Introduction

The previous empirical chapters conducted cross-sectional analyses that contributed to an understanding of the core themes in the discussion of crime, the relative importance of punitive attitudes, and the main characteristics of news and the users associated with the expression of these. However, they did not account for variations over time in punitive attitudes, their potential determinants, or their possible consequences.

Capturing temporal dynamics is a key advantage of New and Emerging Forms of Data (NEFDs), especially since gathering such data from traditional sources, such as surveys, can be costly and infrequent. This thesis has primarily focused on the impact of individual characteristics and the content of news or political communications, which aligns with *cultivation theory* (the idea that media shapes perceptions of reality) and *framing theory* (how the presentation of information affects interpretation). However, it has yet to examine how actual crime rates, as reflected in official statistics, might influence public attitudes—a perspective grounded in *real-world theory*, which posits that real-world conditions, like crime rates, directly shape perceptions (see Chapter 1). Time series analysis provides a means to examine these real-world influences over time. Additionally, while earlier analyses focused on describing the nature and determinants of social media communications, time series analysis provides a way to examine whether these communications have a broader influence on political behaviour. However, this analysis is currently limited to social media interactions.

The analysis employs a time series approach to account for variations in punitive attitudes over time, offering insights into how these attitudes shift gradually or react to specific events—subtleties that a static, cross-sectional analysis might miss. It investigates how variations in online punitive attitudes are influenced by changes in independent variables using Autoregressive Integrated Moving Average with Explanatory Variables (ARIMAX) models (see Chapter 2, Methodology). Additionally, it assesses how these variables impact the behaviour of Members of Parliament (MPs), particularly whether shifts in online punitive attitudes affect the volume of political communications about crime on social media.

The chapter proceeds as follows: the analysis is divided by country, beginning with the United Kingdom and followed by Uruguay. Each country's analysis follows a structured approach: first, a brief descriptive analysis of the time series and univariate modelling is presented. This univariate model serves as a baseline for comparison with more complex multivariate models that include exogenous variables. Second, the determinants of variations in punitive attitudes over time are examined, starting with bivariate relationships for each independent variable, guiding the inclusion of variables in the multivariate model. This is followed by a multivariate analysis, which assesses the effects of the variables of interest while controlling for third variables. Third, recognising that the number of responses per day is a key explanatory variable in both the UK and Uruguay (as expected), the analysis shifts to the determinants of replies and quotes to crime-related news. Finally, the chapter explores how punitive attitudes influence political communications while controlling for other variables. After completing the analysis for each country, a comparison of results is provided, followed by a brief discussion and conclusion.

6.2. United Kingdom

6.2.1. Descriptive analysis & univariate ARIMA

The graphical representation of all series used in the analysis for the United Kingdom is presented in Appendix 4. All series are standardised (z-score) to enhance readability and enable comparison. The primary dependent variable of the analysis—punitive attitudes expressed in responses to crime-related news stories—is highlighted in red. The first noticeable feature is the presence of a significant outlier in the dependent variable, explained by two key events. The primary source is a news item from *The Independent* regarding the Nikolas Cruz case involving a school shooting in Florida, which accumulated a large number of responses. Additionally, this peak is compounded by another story with a high level of punitive response: the *Sky News* report on a nurse who killed a five-year-old boy by injecting air into his veins. For both the bivariate and multivariate analyses, this outlier will be controlled by introducing a dummy variable corresponding to the specific day of the peak.

The test for stationarity, which indicates that a time series' statistical properties remain consistent over time, is presented below for each series used in the modelling (Table 14). Stationarity is a requirement for ARIMAX models (see Chapter 2, Methodology). The variables collected from Twitter data are all stationary. When analysing the graphs, a noticeable difference emerges between the series derived from Google Trends and YouGov data and the other series. *Google Trends* reflects the popularity of specific search terms over time in a given country based on search

frequency on Google. *YouGov*, a global public opinion and data company, conducts regular surveys on various topics, including public attitudes and social trends. Both series are presented weekly, contributing to the non-stationarity of these variables. To incorporate this data into the analysis, the other variables must be transformed into a weekly frequency for consistency.

Table 14 Variable list and stationarity test

Variable	ADF_p_value	Stationary
Punitive replies to news	0.01	Yes
Replies to crime-related News	0.01	Yes
Crime-related News	0.021901564	Yes
News Sentiment (mean)	0.01	Yes
Topic 1 News	0.01	Yes
Topic 2 News	0.01	Yes
Topic 3 News	0.01	Yes
Topic 4 News	0.01	Yes
Topic 5 News	0.038151054	Yes
Topic 6 News	0.01	Yes
Topic 7 News	0.01	Yes
Topic 8 News	0.01	Yes
Crime general query	0.01	Yes
Drug and gangs query	0.01	Yes
Fraud query	0.01	Yes
Murder and physical violence query	0.01	Yes
Sex Violence query	0.01	Yes
Theft query	0.01	Yes
No-word query	0.01	Yes
Political tweets about crime	0.01	Yes
Punitive political communications	0.01	Yes
Google Trends Violence	0.628205378	No
Google Trends Gun Violence	0.474803095	No
Google Trends Punishment	0.360008898	No
Google Trends Capital Punishment	0.204350901	No
Crime handle Well	0.628598394	No
Crime handle Badly	0.701682595	No
terrorism_handle_Well	0.590726584	No
terrorism_handle_Badly	0.337866285	No
MOI Immigration & Asylum	0.431505517	No
MOI Crime	0.543106955	No
MOI The economy	0.99	No
MOI Welfare Benefits	0.316404518	No

MOI Defense ans Security	0.190370374	No

The analysis of each dependent variable started with an ARIMA model. For all analyses, the selection of the model parameters (autoregression, differencing, and moving averages) was performed in an automated way using the `auto.arima()` function of the `forecast` package. (Hyndman and Athanasopoulos 2018). First, the analysis of punitive responses yielded an ARIMA (1, 0, 0) model with a non-zero mean. Punitive replies are moderately influenced by their previous values, indicating persistence in public punitive reactions over time (coef: 0.396, SE: 0.048). This persistence may stem from continued replies and quotes beyond the initial day of the crime-related news tweet. However, the automatic selection of model parameters retained only the first-order autoregressive parameter, suggesting that this persistence is short-term.

Table 15 presents the fit statistics for the univariate ARIMA model on punitive attitudes in responses to crime news. These indicators will serve as a basis for comparison with the multivariate models.

Table 15 Fit statistics ARIMA model for punitive replies

Log Likelihood	AIC	AICc	BIC
-2087.4	4180.8	4180.87	4192.49

Table 16 presents indicators of the model's predictive performance, evaluated using the data provided. The mean percentage error (MPE) of -118.1034 and the mean absolute percentage error (MAPE) of 139.8755 indicate significant relative errors, likely due to the variability and extreme values in the data.

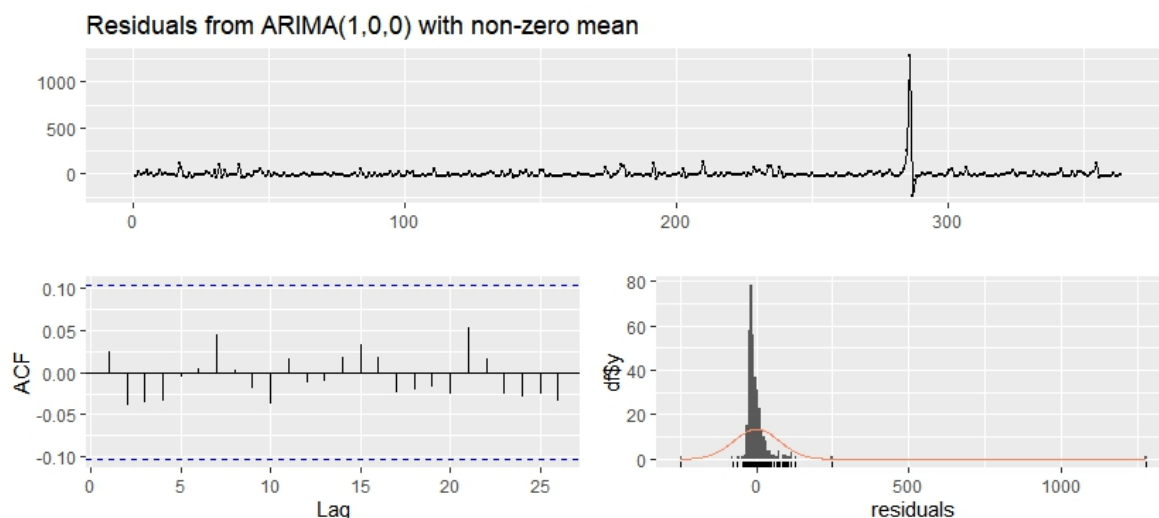
Table 16 ARIMA model for punitive replies performance

Mean Error (ME.)	RMSE	MAE	MPE	MAPE	MASE
0.028	74.847	25.001	-118.103	139.876	0.869

Finally, the residuals were analysed to assess how well the ARIMA model fits the data. The Ljung-Box test, which checks for any remaining patterns in the residuals, showed a high p-value ($p = .96$), suggesting that the residuals resemble white noise—meaning they lack systematic patterns or autocorrelation, which would indicate a good fit. The *ACF plot* (Autocorrelation Function plot) further supports this, showing no autocorrelation in the residuals, meaning there is no remaining relationship between data points over time. However, examining the residuals by day and their histogram

revealed an outlier, indicating that some unusual event or data point still deviates from the model's expected pattern.

Figure 39 Residuals for ARIMA model for punitive replies



Univariate analysis was also conducted for the two other series: general replies to news and political communications on crime. An ARIMA(0,0,2) model with a non-zero mean emerged as the best-fitting model for the time series of replies to crime-related news on Twitter. The mean response rate was 786.61 daily replies (SE: 54.96). The moving average coefficients were 0.5352 (SE: 0.052) and 0.101 (SE: 0.053), indicating that the weighted sum of past error terms influences the number of replies. Fit statistics are provided in Table 17, and predictive performance in Table 18.

Table 17 Fit statistics ARIMA model for replies to crime-related news UK.

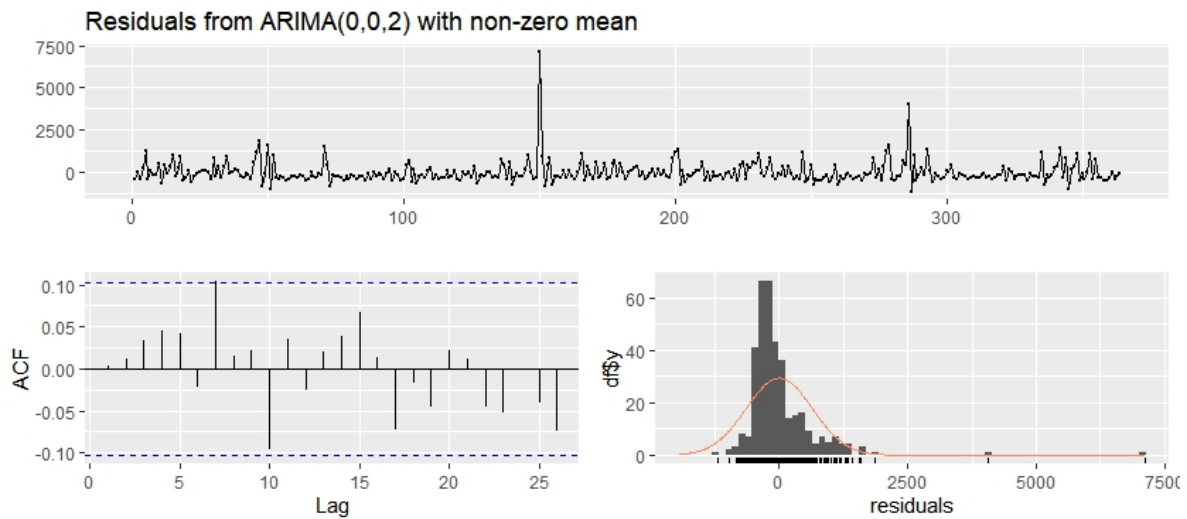
Log Likelihood	AIC	AICc	BIC
-2869.6	5747.21	5747.32	5762.8

The statistics in Table 18, in conjunction with the analysis of the residuals in Figure 40, show that while the residuals do not appear autocorrelated and resemble white noise (Ljung-Box $p = .27$), there are substantial errors around specific events, indicating the presence of potential outliers, as happened for the analysis of punitive replies.

Table 18 ARIMA model for replies to crime-related news performance

Mean Error (ME.)	RMSE	MAE	MPE	MAPE	MASE
0.671	641.745	392.770	-52.430	75.239	0.888

Figure 40 Residuals for ARIMA model for crime-related news replies



Finally, an ARIMA(2,1,2) model was employed to analyse the political communications about crime. The differentiated series has autoregressive components (coef. 0.974, s.e. 0.148 and -0.406, SE 0.076) and moving average components (1.443, s.e. 0.149, and 0.539, SE 0.138). These coefficients indicate that the weighted sum of past values and error terms influences the number of political communications—tables 19 and 20 present fit and performance, respectively. Pronounced errors around specific dates are also observed in this case (Figure 41). Additionally, in this case, the residuals do not pass the Ljung-Box test ($p = .030$).

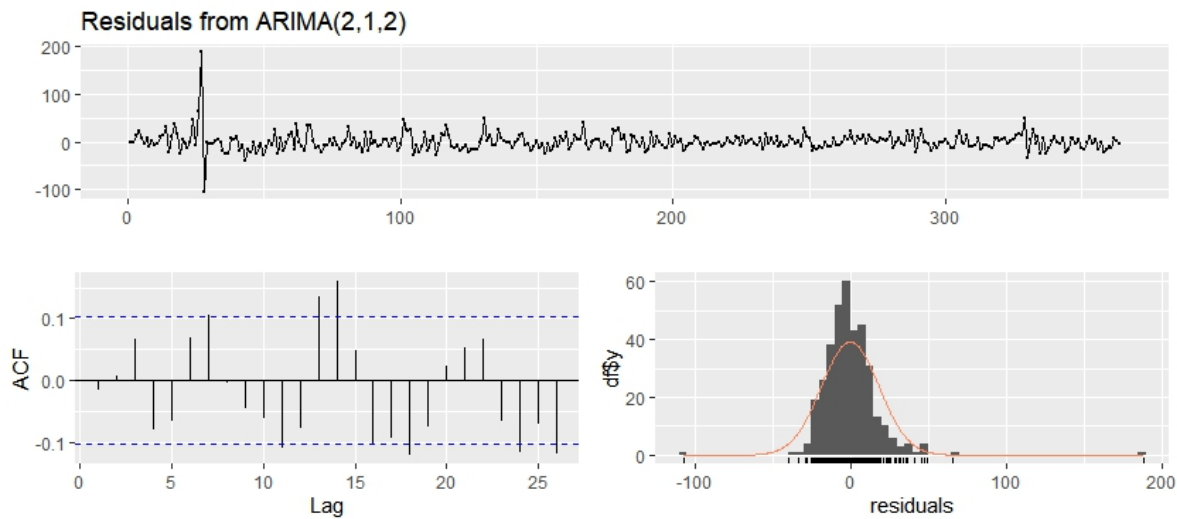
Table 19 Fit statistics ARIMA model for crime-related political communications

Log Likelihood	AIC	AICc	BIC
-1575.49	3160.98	3161.14	3180.45

Table 20 ARIMA model for crime-related political communications performance

Mean Error (ME.)	RMSE	MAE	MPE	MAPE	MASE
-0.0511	18.5113	12.017	-28.4682	51.444	0.8926

Figure 41 Residuals for ARIMA model for crime-related political communications



These models will serve as a basis for comparison with multivariate models in the following sections. The models for punitive responses and responses to news achieve an adequate fit using only the past values of the series. However, outliers can be observed in both cases due to trendy news items. Political communications present less pronounced outliers, but the univariate series exhibits fit problems, as observed in the residuals. The estimation of successive models will enable the study to determine whether the inclusion of independent variables resolves these problems.

6.2.2. Initial variable selection

Given the presence of outliers or extreme values, the analysis began by creating dummy variables to incorporate these values into the respective models. Subsequent analyses control for these variables and include each series individually, following the logic of bivariate analysis but without being strictly bivariate. This initial approach aids in selecting series for inclusion in the multivariate models. Additionally, given the series' complexity, this approach provides a more precise overview without issues of multicollinearity, although it lacks the control supplied by additional variables.

The selection of variables was guided by the availability of relevant secondary data and temporal data extractable from Twitter. From Twitter, variables such as news sentiment, topics, and keywords identified in the data download (see chapters 3 and 4) were included. Although Twitter data can be temporally disaggregated into smaller intervals due to the exact posting time in the metadata, a daily partition was maintained to ensure compatibility with most secondary data available on a daily basis (particularly for crime data in Uruguay). This approach ensures comparability

across countries. Later, weekly partition tests are conducted to incorporate variables from Google Trends and YouGov.

The visual analysis informs the selection of tested lags of the series and the Cross Correlation Function (CCF). The CCF measures the correlation between two time series at different time lags, aiding in the identification of lagged relationships between variables. The bivariate analysis results are presented in Appendix 5, displaying only the coefficient of the variable of interest, its standard error, and the corresponding p-value. The other model parameters (autoregression, moving average, and mean) are omitted at this stage. Notably, while the bivariate analyses for the series of punitive news responses and general responses did not require differentiation, the automatic model selection did require differentiation for the analysis of political communications (except for Topic 7). These results will not be elaborated on at this stage but will be revisited in the multivariate analysis of the series.

6.2.3. Multivariate analysis – punitive replies to crime-related news

The primary objective of this analysis is to examine the multivariate correlation of punitive attitudes with a set of dependent variables derived from Twitter at the daily level. Broadly, it is anticipated that findings from the cross-sectional analysis will be replicated, with increases in negatively framed news about violent crime correlating with heightened punitive attitudes. Additionally, a correlation is expected between citizens' expressions of punitivism in response to news and political system communications, both in general crime-related content and strictly punitive communications.

Based on the results of the bivariate models, variables were selected for inclusion in the multivariate model. From this, a simplified model was estimated, as multiple variables introduced multicollinearity issues and reduced degrees of freedom. Iteratively, other variables close to significance in the initial multivariate model were tested to ensure no relevant variables were omitted. The results of this process are presented in Table 21.

Table 21 Multivariate ARIMAX models for punitive replies for crime-related news

Variable	xreg	se	p	sig.	xreg	se	p	sig.
AR 1	0.517	0.051	0.000	***	0.508	0.052	0.000	***
outlier_2022_10_13	1127.971	30.185	0.000	***	1135.341	30.493	0.000	***
Replies to crime-related News	0.013	0.003	0.000	***	0.012	0.003	0.000	***
Lag 1	0.005	0.003	0.053		0.005	0.002	0.057	*

News Sentiment (mean)	27.400	12.619	0.030	**	27.185	11.772	0.021	**
Sex Violence query	0.076	0.276	0.783		-	-	-	
Lag 1	-0.026	0.264	0.922		-	-	-	
Murder and physical violence query	0.186	0.162	0.249		-	-	-	
Crime general query	-0.265	0.263	0.313		-	-	-	
Theft query	0.081	0.304	0.790		-	-	-	
Topic 5 News	0.303	0.163	0.062		0.385	0.128	0.003	***
Topic 7 News	0.153	0.161	0.342		-	-	-	
Topic 8 News	0.086	0.192	0.654		-	-	-	
Lag 1	-0.025	0.166	0.882		-	-	-	
Topic 2 News	-0.030	0.274	0.914		-	-	-	
Topic 6 News	-0.217	0.234	0.354		-	-	-	
Lag 1	0.214	0.232	0.357		-	-	-	
Topic 1 News	0.404	0.223	0.070		0.357	0.238	0.134	
Lag 1	0.514	0.211	0.015	**	0.514	0.205	0.012	**
Political tweets about crime	0.052	0.092	0.573		-	-	-	
Lag 1	0.002	0.093	0.985		-	-	-	
Punitive political communications	1.488	1.107	0.179		1.321	1.093	0.227	
Crime-related News	-	-	-		0.085	0.046	0.064	*

*** p < .01 ** p < .05 * p < .1

In the final model, only a few significant variables are retained. The initial multivariate model excluded the variable for crime-related news per day due to multicollinearity issues. In the subsequent simplified model, this variable was reintroduced without multicollinearity problems, achieving significance at the 10% level ($p = .064$) but not at the 5% level. The positive value of the first-order autoregressive parameter indicates moderate persistence in the series. Additionally, an increase in the number of responses (excluding punitive responses) has a positive and significant effect on punitive responses, suggesting that as general crime discussion increases, so does the number of punitive reactions. This correlation also holds with the number of responses from the previous day, though the coefficient and significance are weaker.

An unexpected finding is the positive correlation between punitive responses and the average daily news sentiment, with sentiment values ranging from -1 (completely negative) to 1 (completely positive). The coefficient indicates the change associated with a one-unit shift in sentiment. Additionally, two variables remain significant based on the Topic Modelling classification in Chapter 1: Topic 5, related to violent, anonymous crimes, and Topic 1, concerning international news (particularly from the USA) with a one-day lag, which may capture the delayed impact of the Nikolas Cruz case. Punitive political communications were retained in the model to rigorously test

the correlation between punitive citizen attitudes and punitive political attitudes. Although the relationship is positive, it does not reach statistical significance. In terms of fit and predictive power, this model outperforms the univariate model across all indicators (Tables 22 and 23).

Table 22 Fit statistics ARIMAX model for punitive replies

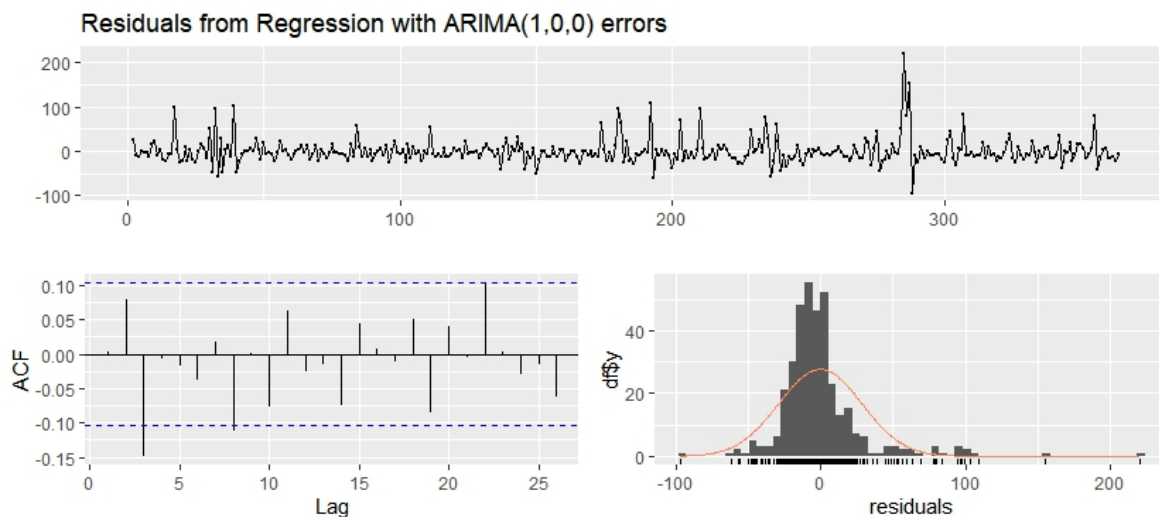
Log Likelihood	AIC	AICc	BIC
-1733.28	3488.56	3489.31	3531.4

Table 23 ARIMA model for punitive replies performance

Mean Error (ME.)	RMSE	MAE	MPE	MAPE	MASE
-0.429	28.661	17.575	-43.464	77.617	0.611

However, the analysis of the residuals reveals significant variations that the model does not capture, and the Ljung-Box test indicates autocorrelation in the residuals ($p = .034$). The presence of autocorrelation in the residuals, as shown by the Ljung-Box test, suggests that the model has not fully captured the temporal dependencies within the data, violating a fundamental assumption of ARIMA models and necessarily tempering the results.

Figure 42 Residual check for simplified ARIMAX model for punitive replies



It is logically expected that as the overall volume of replies to crime-related news increases, the number of punitive responses will also rise, provided the proportion of punitive replies remains relatively constant. Consequently, examining the factors influencing responses to crime news, in general, is of analytical interest, as it may

uncover potential indirect effects of variables that do not appear significant within the model specifically targeting punitive replies. Such an exploration could offer insights into the underlying drivers of engagement with crime news, which may indirectly contribute to the volume of punitive responses. This analysis is made in the next section.

6.2.4. Multivariate analysis – replies to crime-related news

The same procedure was followed to analyse responses to crime-related news. Three of the variables of interest (discounting autoregression, intercept, and outlier) are relevant in explaining the variation in the number of responses: news related to sexual and domestic violence (captured by the sex-violence query), news about fraud (topic 8) in lag 1, and international news (topic 1). Given the analysis of the determinants of punitive attitudes carried out in the previous chapter, the increase in news about crime and sexual violence may have an indirect influence on punitive attitudes, considering their significance in the bivariate analysis.

Table 24 Multivariate ARIMAX models for replies to crime-related news

Variable	Coef.	SE.	p	sig.	xreg	se	p	sig.
AR 1	0.390	0.051	0.000	***	0.393	0.051	0.000	***
Intercept	-	-	-		218.167	95.754	0.023	**
outlier_2022_05_30	5535.208	518.897	0.000	***	5435.606	513.641	0.000	***
Crime-related News Lag 1	-0.467	1.269	0.713		-	-	-	
Sex Violence query	9.793	5.019	0.051		13.510	2.991	0.000	***
Murder and physical violence query	1.451	1.955	0.458		-	-	-	
Crime general query	3.402	5.167	0.510		-	-	-	
Lag 1	0.690	5.262	0.896		-	-	-	
Theft query	1.789	5.868	0.760		-	-	-	
Topic 5 News (Lag 1)	2.245	2.515	0.372		-	-	-	
Topic 7 News	-0.594	2.797	0.832		-	-	-	
Topic 8 News	-0.766	3.736	0.837		-	-	-	
Lag 1	7.037	4.163	0.091		5.372	2.635	0.041	**
Topic 2 News	4.225	5.248	0.421		-	-	-	
Topic 6 News	5.422	4.337	0.211		-	-	-	
Topic 1 News	12.631	4.015	0.002	***	14.194	3.786	0.000	***
Lag 1	7.401	4.383	0.091		5.955	3.779	0.115	
Punitive political communications	-1.630	1.747	0.351		-	-	-	
Lag 1	-0.658	1.782	0.712		-	-	-	

*** p < .01 ** p < .05 * p < .1

The fit and predictive performance indicators show a marginal improvement over the base model (Tables 13 and 14). The residuals are not auto-correlated (Ljung-Box p =

.281) and seem close to normally distributed, with a slight right skew. Additionally, some shocks or unexplained variations can be observed (Figure 5).

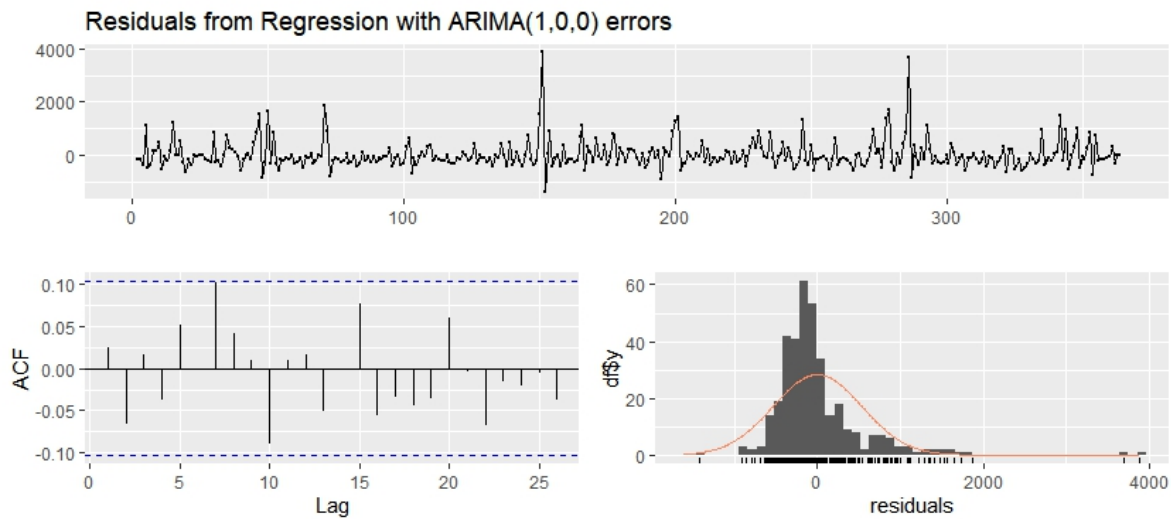
Table 25 Fit statistics ARIMAX model for crime-related news replies

Log Likelihood	AIC	AICc	BIC
-1733.28	5605.42	5605.83	5636.57

Table 26 ARIMA model for crime-related news replies performance

Mean Error (ME.)	RMSE	MAE	MPE	MAPE	MASE
0.183	533.656	344.316	55.693	0.778	0.611

Figure 43 Residual check for simplified ARIMAX model for replies to crime-related news



6.2.5. Multivariate analysis – political communications Twitter

Finally, the same procedure was followed for political communications. This analysis aims to investigate whether individuals' punitive responses to the news have an independent effect on the amount of crime-related communication by politicians. Potentially, this analysis could be done on politicians' punitive communications. However, there are a few positive (punitive) cases with a significant zero inflation, so this analysis is omitted.

The central hypothesis of this analysis, regarding the effect of punitive responses at the news level on political communications, does not appear to be supported. However, it is noteworthy that political communications do correlate with specific

news trends, particularly with news related to theft, murder, and physical violence (Topic 7), fraud (Topic 8), sexual violence (Topic 6), and international news (Topic 1).

Table 27 Multivariate ARIMAX models political communications

Variable	xreg	se	p	sig.	xreg	se	p	sig.
AR 1	0.449	0.056	0.000	***	0.728	0.074	0.000	***
AR 2	0.132	0.056	0.018	**	-	-	-	
MA 1	-	-	-		-0.307	0.107	0.004	***
Intercept	6.891	3.411	0.043	**	5.560	2.303	0.016	**
outlier_2022_01_27	205.945	10.840	0.000	***	202.631	10.662	0.000	***
Crime-related News	-	-	-		0.042	0.035	0.224	
Lag 2	-0.006	0.013	0.632		-	-	-	
Sex Violence query	0.036	0.109	0.741		-	-	-	
Murder and physical violence query	-0.055	0.066	0.408		-	-	-	
Crime general query	-0.021	0.110	0.847		-	-	-	
Fraud query	0.184	0.134	0.170		-	-	-	
Theft query	0.507	0.127	0.000	***	0.496	0.090	0.000	***
Topic 5 News	0.062	0.067	0.355		-	-	-	
Topic 7 News	0.215	0.065	0.001	***	0.181	0.045	0.000	***
Topic 8 News	0.246	0.089	0.006	**	0.320	0.065	0.000	***
Topic 2 News	-0.023	0.114	0.839		-	-	-	
Topic 6 News	0.219	0.093	0.018	**	0.251	0.063	0.000	***
Topic 1 News	0.257	0.092	0.005	**	0.297	0.084	0.000	***
Topic 4 News	0.050	0.109	0.644		-	-	-	
Punitive replies (news)	0.004	0.008	0.654		-	-	-	

*** p < .01 ** p < .05 * p < .1

As with the previous models, this model exhibits improved performance compared to the base model (refer to Tables 16 and 17). The residual analysis approximates white noise (Ljung-Box p = .510), indicating no significant autocorrelation or discernible outliers (see Figure 6).

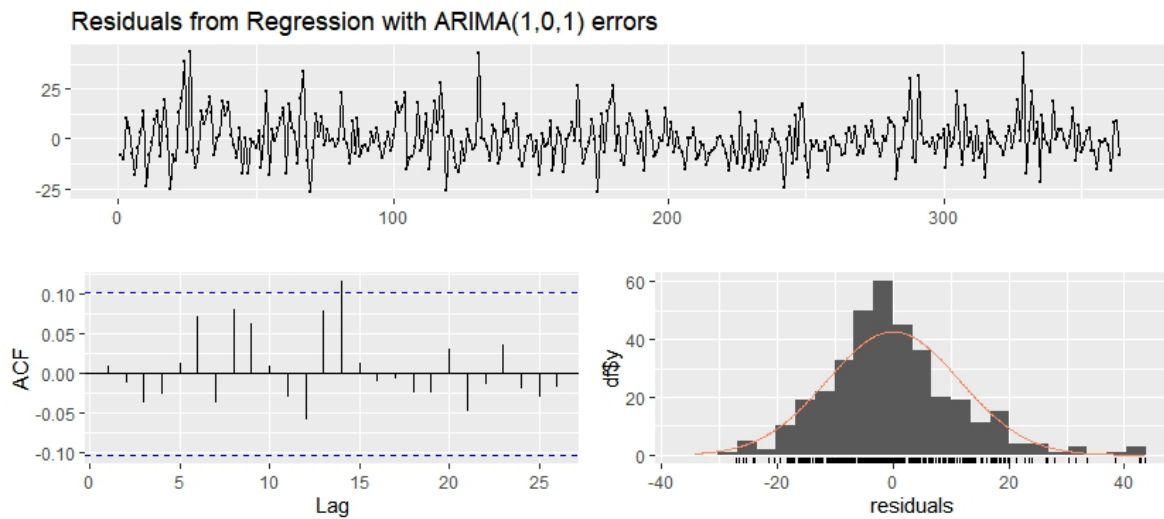
Table 28 Fit statistics ARIMAX model for political communications

Log Likelihood	AIC	AICc	BIC
-1403	2828.01	2828.76	2870.88

Table 29 ARIMA model for political communications performance

Mean Error (ME.)	RMSE	MAE	MPE	MAPE	MASE
0.033	11.416	8.522	-14.382	33.005	0.633

Figure 44 Residual check for simplified ARIMAX model for political communications



6.3. Uruguay

6.3.1. Descriptive analysis & univariate ARIMA

As explained above, the variables available for both cases are different. Uruguay has available data about the number of daily crimes, disaggregated by type of crime. As a counterpart, there are no time series of public opinion surveys with sufficient granularity to incorporate them into the analysis as those used for the United Kingdom. From Google Trends, given the traffic volume, only two series of interest could be extracted: "punishment" and "violence". The graphical representation of these variables is presented in Appendix 6. Similar to what has been observed in the UK, there are significant peaks in the reporting of punitive attitudes around specific news items. The same three variables will be used as dependent variables in the successive models, utilising the remaining variables as independent variables. As with the UK case, the analysis will begin with the univariate series using the ARIMA model.

The analysis of the punitive replies to news began with an ARIMA (0, 0, 1) model with a non-zero mean. This model indicates that the punitive replies are primarily influenced by a positive moving average coefficient (0.347), suggesting a moderate impact of the previous day's error. A non-zero mean indicates an average level of punitive replies around 11.67.

Tables 30 and 31 present the fit and performance statistics. The residual analysis does not show auto-correlation (Ljung-Box $p = .765$); however, similar to the UK, case-

specific shocks are observed (figure 45). The values of MPE and MAPE are infinite due to the presence of 0s in the series, a result of lower traffic compared to the UK.

Table 30 Fit statistics ARIMA model for punitive replies

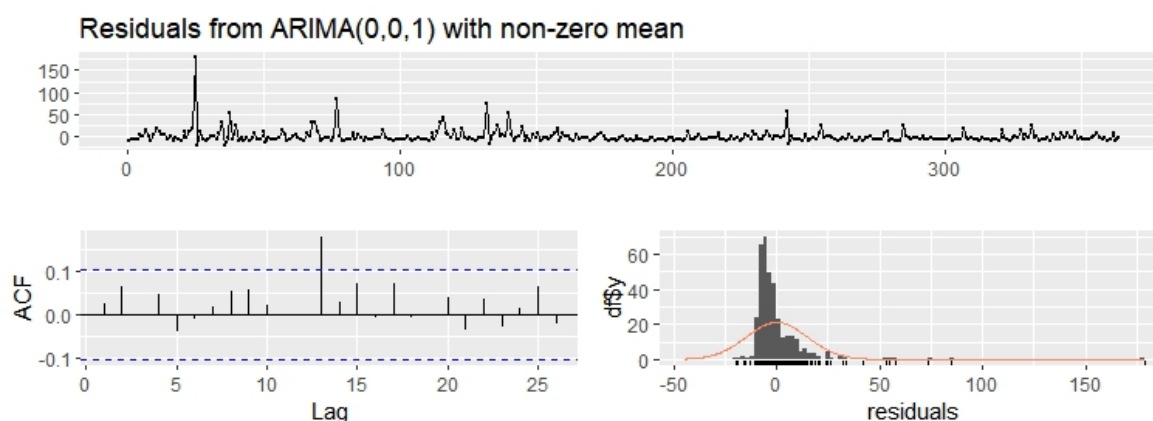
Log Likelihood	AIC	AICc	BIC
-1497.73	3001.46	3001.52	3013.15

Table 31 ARIMA model for punitive replies performance

Mean Error (ME.)	RMSE	MAE	MPE	MAPE	MASE
0.004113607	14.81327	7.740933	-Inf	Inf	0.8438314

a

Figure 45 Residual check for ARIMA model for punitive replies



An ARIMA (1, 0, 2) model with a non-zero mean was estimated to analyse replies to crime-related news. This model suggests that responses to crime-related news are influenced by both autoregressive and moving average components. The high positive AR1 coefficient (0.8918) suggests a strong influence of the previous day's replies on the current day's replies, indicating a significant persistence in public engagement. The negative MA1 and MA2 coefficients (-0.435 and -0.275, respectively) indicate that past errors also influence the replies. The mean news replies by day is 291.823.

Table 32 Fit statistics ARIMA model for replies to crime-related news

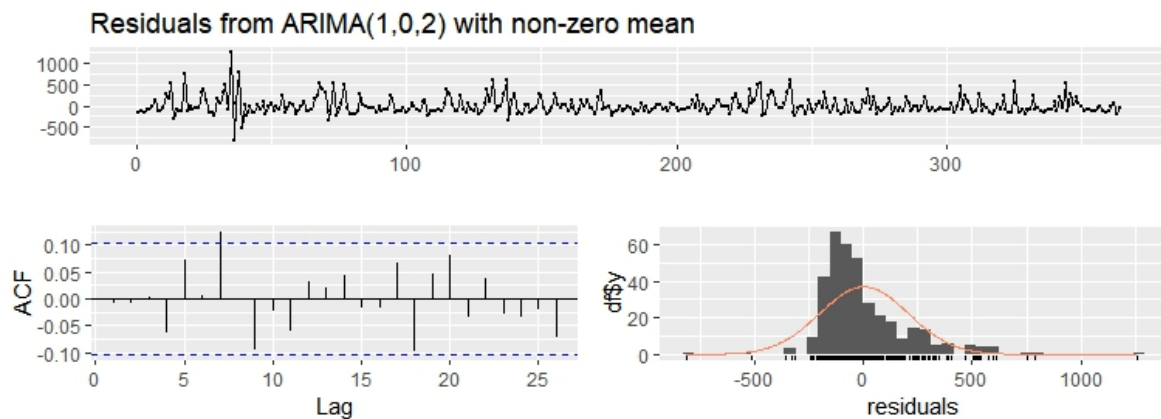
Log Likelihood	AIC	AICc	BIC
-2451.73	4913.47	4913.63	4932.95

Table 33 ARIMA model for replies to crime-related news performance

Mean Error (ME.)	RMSE	MAE	MPE	MAPE	MASE
1.034	203.560	145.485	- 54.366	78.790	0.896

The Ljung-Box test for residuals has a p-value close to the 0.05 threshold (0.079), suggesting slight autocorrelation. The ACF plot shows a few spikes outside the confidence interval, indicating residual dependencies. The histogram reveals a rightward skew. Finally, the time series plot of residuals shows significant fluctuations, hinting that certain variations are not fully captured by the model (Figure 46).

Figure 46 Residual check for ARIMA model for replies to crime-related news



Finally, the search for a univariate model for political communications about crime yielded an ARIMA (1,0,0) model ($AR1 = .442$) with a non-zero mean (6.99). Tables 34 and 35 present the fit and performance indices. The residual analysis reveals outliers, and the Ljung-Box test indicates the presence of autocorrelation ($p = 0.002$).

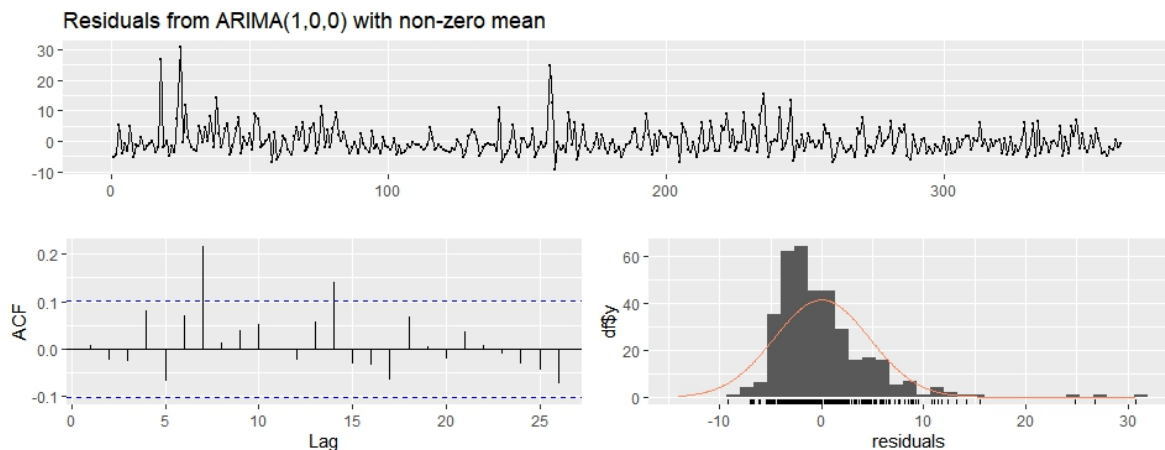
Table 34 Fit statistics ARIMA model for crime-related political communications

Log Likelihood	AIC	AICc	BIC
- 1076.92	2159.85	2159.91	2171.54

Table 35 ARIMA model for crime-related political communications performance

Mean Error (ME.)	RMSE	MAE	MPE	MAPE	MASE
0.009	4.662	3.284	- Inf	Inf	0.853

Figure 47 Residual check for ARIMA model for political crime-related communications



6.3.2. Initial variable selection

As with the UK, this section presents the data used for the initial variable selection. The chosen lags are based on an analysis of the CCFs and subsequent tests. For punitive replies, all tests account for an outlier associated with the heightened punitive response generated by a report of sexual abuse of a minor by three men. This step guides the selection of variables for incorporation into the multivariate models. These results, which will be revisited during the multivariate analysis, are provided in Appendix 7.

6.3.3. Multivariate analysis – punitive replies to crime-related news

Based on the results of the bivariate models, two multivariate models were estimated: the first included all significant variables, while the second retained only those variables that remained significant in the initial multivariate analysis. Notably, all variables associated with crime statistics lose significance when controlled for the other variables. However, news related to violent crime (Topic 2) and organised crime and gangs (where the Marset case plays a significant role - Topic 5) remain significant. Additionally, news captured by the query associated with theft also remains significant. These results suggest that the effects of actual crime rate variations may be mediated by crime-related news coverage—a hypothesis partially evaluated in the general replies model presented in the next section. As expected, the general volume of responses remains significant. Topic 7, which addresses crimes against humanity, particularly those linked to cases from the Uruguayan dictatorship (1973–1985), also remains significant. The most notable finding in this analysis is the significant correlation between punitive political communications and daily punitive responses, even after controlling for the remaining variables. However, it is worth noting that the

dataset for punitive political communications comprises a limited number of cases, so these results should be interpreted with caution.

Table 36 Multivariate ARIMAX models for punitive replies for crime-related news

Variable	Coef.	SE.	p	sig.	Coef.	SE.	p	sig.
AR 1	0.282	0.054	0.000	***	0.305	0.051	0.000	***
intercept	-14.439	7.342	0.049	**	-2.455	1.299	0.059	
outlier_2022_01_25	148.403	10.780	0.000	***	150.077	10.099	0.000	***
Replies to crime-related News	0.029	0.003	0.000	***	0.031	0.003	0.000	***
Lag 1	0.001	0.003	0.716		-	-	-	
Crime-related News (Diff)	-0.050	0.036	0.157		-	-	-	
Lag 1	-0.017	0.020	0.373		-	-	-	
Sex Violence query	0.115	0.148	0.436		-	-	-	
Murder and physical violence query	-0.036	0.093	0.696		-	-	-	
Lag 1	-0.033	0.085	0.699		-	-	-	
Crime general query	0.061	0.093	0.509		-	-	-	
Lag 1	-0.054	0.080	0.501		-	-	-	
Theft query	0.296	0.132	0.025	**	0.248	0.095	0.009	**
Topic 2 News	0.216	0.105	0.040	**	0.160	0.045	0.000	***
Lag 1	0.037	0.092	0.685		-	-	-	
Topic 5 News	-0.172	0.079	0.029	**	-0.189	0.058	0.001	***
Topic 6 News	0.036	0.108	0.741		-	-	-	
Topic 4 News	0.046	0.121	0.701		-	-	-	
Lag 1	0.077	0.099	0.435		-	-	-	
Topic 7 News	0.317	0.127	0.012	**	0.327	0.093	0.000	***
All Crimes	0.038	0.029	0.196		-	-	-	
Robbery (lag 1)	0.028	0.048	0.556		-	-	-	
Theft (statistics)	-0.035	0.039	0.362		-	-	-	
Lag 7	-0.002	0.018	0.911		-	-	-	
Assault	-0.044	0.081	0.584		-	-	-	
Political tweets about crime	0.026	0.129	0.843		-	-	-	
Lag 1	0.134	0.114	0.243		-	-	-	
Punitive political communications	2.586	1.225	0.035	**	2.858	1.181	0.016	**

*** p < .01 ** p < .05 * p < .1

The model outperforms the baseline model presented initially (Tables 37 and 38). The analysis of the residuals yields a normal distribution with no evidence of autocorrelation (Ljung-Box test p = .279). The residuals indicate unexplained shocks or outliers, which likely correspond to specific cases.

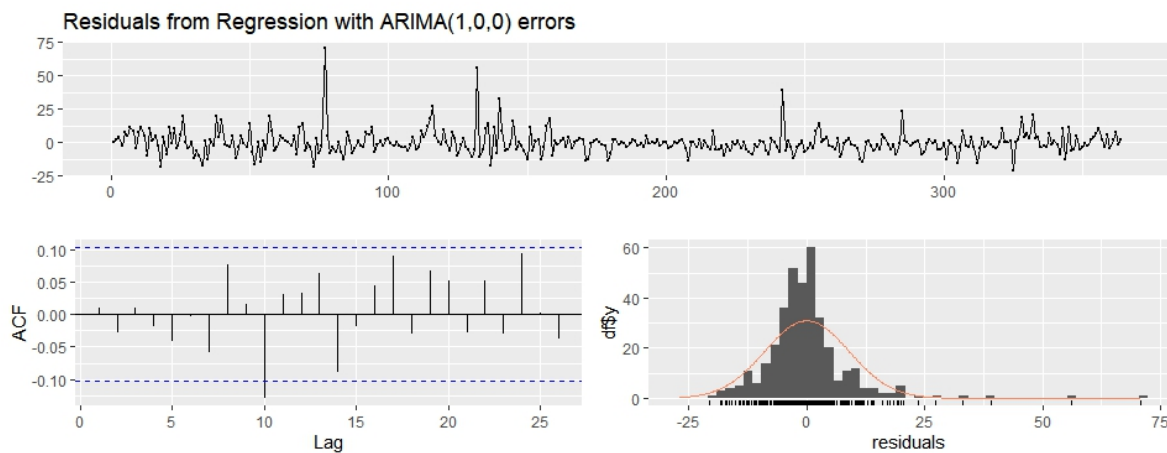
Table 37 Fit statistics ARIMAX model for punitive replies

Log Likelihood	AIC	AICc	BIC
- 1313.25	2646.49	2647.12	2685.47

Table 38 ARIMA model for punitive replies performance

Mean Error (ME.)	RMSE	MAE	MPE	MAPE	MASE
0.000	8.924	5.695647	- Inf	Inf	0.621

Figure 48 Residual check for simplified ARIMAX model for punitive replies



Additionally, tests were carried out using the two variables extracted from Google Trends, with the data transformed by week, but no statistically significant results were found.

6.3.4. Multivariate analysis – replies to crime-related news

An analysis of replies to crime-related news reveals that some variables, which were not significant in the multivariate model on punitive responses, show a significant correlation in this model. Specifically, news about sex crimes (captured through keywords), homicides on the previous day, and robberies on the same day display significant associations. Additionally, news captured with keywords related to "theft" and associated with Topic 5 affects the overall volume of responses, while also maintaining a direct impact on punitive online attitudes.

Table 39 Multivariate ARIMAX models for replies to crime-related news

Variable	Coef.	SE.	p	Sig.	Coef.	SE.	p	Sig.
AR 1	0.367	0.052	0.000	***	0.382	0.049	0.000	***
Intercept	-	-	-		-160.462	100.558	0.111	

Crime-related News (Diff)	0.409	0.530	0.440		-	-	-	
Lag 1	0.326	0.382	0.393		-	-	-	
Sex Violence query	6.851	2.820	0.015	**	10.348	2.225	0.000	***
Murder and physical violence query	0.006	1.749	0.997		-	-	-	
Crime general query	2.292	1.940	0.237		-	-	-	
Drug and gangs query	0.881	1.984	0.657		-	-	-	
Lag 1	1.253	1.164	0.282		-	-	-	
Theft query	5.777	2.507	0.021	**	8.205	1.810	0.000	***
Topic 2 News	0.754	2.009	0.708		-	-	-	
Topic 5 News	5.021	2.069	0.015	**	7.431	1.116	0.000	***
Lag 1	1.001	1.401	0.475		-	-	-	
Topic 6 News	0.715	2.220	0.748		-	-	-	
Topic 1 News	0.616	2.644	0.816		-	-	-	
Topic 4 News	1.660	2.432	0.495		-	-	-	
Topic 7 News	-1.420	2.468	0.565		-	-	-	
Robbery (statistics) (Lag 7)	1.322	0.954	0.166		-	-	-	
Homicide (statistics) (Lag 1)	23.712	8.398	0.005	**	26.382	7.936	0.001	***
Theft (statistics)	0.603	0.296	0.041	**	0.771	0.312	0.013	**
Lag 7	-0.615	0.318	0.053		-	-	-	
Assault (statistics)	-1.358	1.048	0.195		-	-	-	
Political tweets about crime (Lag 1)	0.116	2.282	0.959		-	-	-	

*** p < .01 ** p < .05 * p < .1

As for the other models, incorporating exogenous variables significantly improves the index fit and predictive performance (Tables 40 and 41). The analysis of the residuals shows no autocorrelation (Ljung-Box test $p = .340$), and the residuals appear to be approximately normally distributed (Fig. 49).

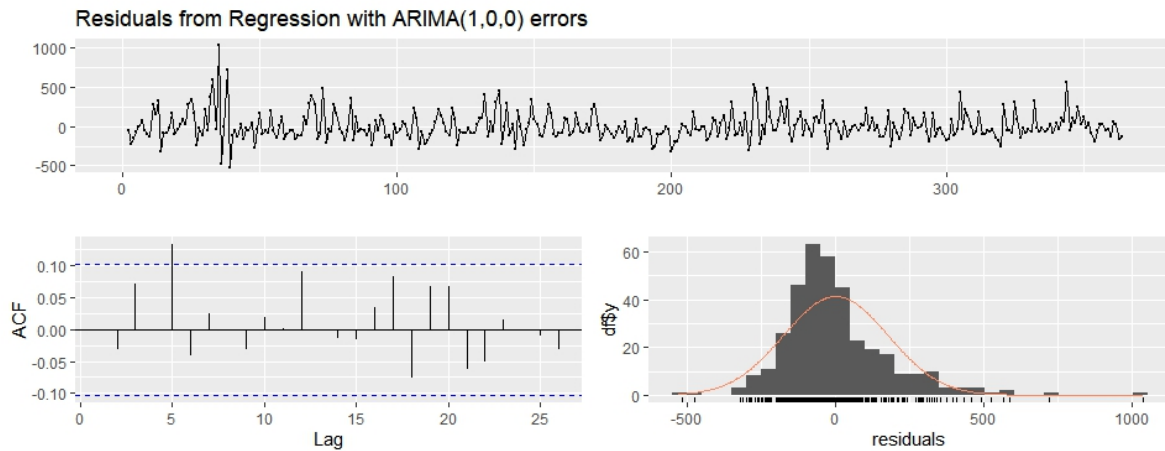
Table 40 Fit statistics ARIMAX model for replies to crime-related news

Log Likelihood	AIC	AICc	BIC
- 2392.23	4800.46	4800.87	4831.61

Table 41 ARIMA model for replies to crime-related news performance

Mean Error (ME.)	RMSE	MAE	MPE	MAPE	MASE
0.039	176.092	127.600	-38.872	63.567	0.786

Figure 49 Residual check for simplified ARIMAX model for replies to crime-related news



6.3.5. Multivariate analysis – political communications

The analysis concludes with the estimation of ARIMAX models for political communications about crime on Twitter in Uruguay. A notable finding is the positive and significant, albeit small (0.068), effect of users' punitive responses to crime-related news on political communications related to crime, even when controlling for other variables. This result suggests that for approximately every 15 punitive communications, a one-unit increase in political communications can be anticipated. Although the quantitative effect is marginal, this finding provides preliminary evidence supporting the plausibility of a direct influence of citizen attitudes expressed on social media on political behaviour.

Beyond the specific effect observed in punitive user responses to the news, there does not appear to be a significant impact of the measured elements of press activity, except for the fluctuations in Topic 5 related to drug trafficking and the case of Sebastian Marset, which is closely associated with the government (see Chapter 1). Additionally, statistics for robbery (lag 1), homicides (lag 10), and assault appear to be associated with political communications. In the case of assaults, the effect is opposite to the one expected. Finally, responses to political communications are incorporated, although this may be linked as a consequence rather than a cause (although both hypotheses are possible).

Table 42 Multivariate ARIMAX models for crime-related political communications

Variable	Coef.	SE.	p	Sig.	Coef.	SE.	p	Sig.
ar1	0.295	0.055	0.000	***	0.303	0.054	0.000	***
ar2	0.135	0.055	0.015	**	0.105	0.054	0.051	
Replies to political communications	0.006	0.001	0.000	***	0.006	0.001	0.000	***
Crime-related News (Diff)	0.011	0.009	0.257		-	-	-	

Lag 1	0.009	0.007	0.219		-	-	-	
Replies to crime-related News	-0.001	0.001	0.599		-	-	-	
Punitive replies to news	0.064	0.015	0.000	***	0.068	0.013	0.000	***
Sex Violence query	-0.029	0.054	0.586		-	-	-	
Murder and physical violence query	-0.032	0.018	0.079		-	-	-	
Crime general query	0.045	0.035	0.206		-	-	-	
Drug and gangs query	-0.011	0.024	0.655		-	-	-	
Fraud query	0.072	0.061	0.235		-	-	-	
Theft query	-0.026	0.041	0.527		-	-	-	
Topic 2 News (lag 7)	0.010	0.018	0.599		-	-	-	
Topic 5 News	0.173	0.030	0.000	***	0.195	0.021	0.000	***
Lag 7	-0.012	0.024	0.602		-	-	-	
Topic 4 News	0.040	0.045	0.375		-	-	-	
Lag 1	0.021	0.035	0.555		-	-	-	
Topic 7 News	-0.017	0.045	0.709		-	-	-	
Robbery (statistics) (lag 1)	0.048	0.018	0.009	**	0.055	0.017	0.002	***
Homicide (statistics) (lag 10)	0.379	0.162	0.019	**	0.427	0.162	0.008	**
Theft (statistics)	0.008	0.006	0.167		-	-	-	
Lag 7	-0.002	0.007	0.748		-	-	-	
Assault (statistics)	-0.055	0.022	0.011	**	-0.063	0.021	0.003	***

*** p < .01 ** p < .05 * p < .1

While the model performs better than the base model (tables 43 and 44) and the analysis of the residuals (Figure 50) suggests a normal-like distribution, there is some evidence of autocorrelation of the residuals (Ljung-Box test p = .062), which may indicate a sub-optimal fit (the results should be analysed with caution).

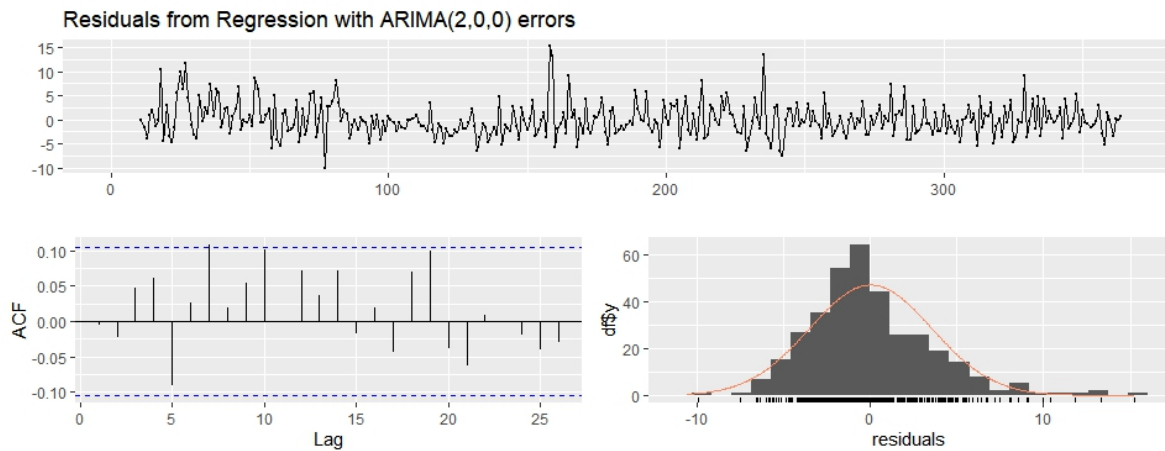
Table 43 Fit statistics ARIMAX model for replies to crime-related political communications

Log Likelihood	AIC	AICc	BIC
- 948.21	1916.43	1917.07	1955.12

Table 44 ARIMA model for replies to crime-related political communications performance

Mean Error (ME.)	RMSE	MAE	MPE	MAPE	MASE
0.010	3.523	2.650	-Inf	Inf	0.690

Figure 50 Residual check for simplified ARIMAX model for replies to crime-related political communications



6.4. Preliminary discussion and conclusions

This section concludes with a comprehensive analysis of results across the different stages, comparing findings for both countries. First, it is noteworthy that all models incorporating exogenous variables outperform the baseline models significantly. The fluctuation in punitive attitudes on Twitter displays several peaks that seem to correspond to specific cases without consistent behavioural patterns. Consequently, it is expected that the time series alone lacks substantial predictive power, and that incorporating exogenous variables—specifically, controlling for outliers—significantly improves the model fit.

Secondly, in both cases, the number of variables that remain significant in the multivariate analysis is considerably lower than those that are significant in the bivariate analysis. Complex correlations may exist between all variables included in the model. Multicollinearity analyses indicate no significant issues; when such issues did arise, the corresponding variables were excluded from the analysis. However, other types of analyses, such as Vector Autoregressive Models (VAR) (Vliegthart 2014), could be employed to test for these correlations. Diversifying the analytical approach in future research could enhance the robustness of the results if they prove consistent across methods, representing an opportunity for future exploration. Additionally, the complexity observed in this time series data suggests a need for caution in drawing conclusions, particularly when making causal inferences or hypotheses, due to the potential presence of numerous omitted relevant variables.

Turning attention to the variables included in the successive models, one somewhat expected finding is that the number of punitive responses directly correlates with the

overall number of responses in both countries. This observation warrants both clarification and comment. First, it is important to note that although increases in the total number of communications correlate with increases in punitive comments, the proportion is not constant, as observed in the series. Certain events trigger an increase in punitive responses independently of general increases in replies, and vice versa. This justifies the inclusion of additional variables and the specific analysis of punitive attitudes beyond a general analysis of public attention and discussion on crime. Second, while this relationship might seem expected, it was not necessarily guaranteed. Punitive discussions could, theoretically, be independent of broader crime discussions, even though this appears unlikely at first glance. The analysis, however, confirms a positive relationship between these two variables.

Apart from the general replies, the determinants differ in the two countries. However, two commonalities can be identified: in both countries, in addition to the exogenous variables, only a first-order autoregressive component is incorporated without differentiation or moving average components. The presence of a first-order autoregressive (AR(1)) component in the model indicates that today's level of punitive communications is partly dependent on yesterday's level, suggesting a certain degree of persistence or momentum in punitive communications, where the response or engagement does not reset each day entirely but instead builds upon the recent past. However, the fact that no higher-order autoregressive, moving average, or differencing terms were necessary implies that this persistence is relatively short-term and does not involve complex patterns over multiple days.

Furthermore, the only variables consistently explaining variations in punitiveness in both cases are those linked to changes in press characteristics. Tests in the UK, incorporating weekly data from other sources, generally found no evidence of correlation—except in the case of searches for "gun violence" and crime tracking as the MOI (Appendix 8). In Uruguay, however, punitive political communications also demonstrate an immediate effect, a pattern not observed in the UK.

Analysing the fluctuations in responses to overall crime-related news in both countries reveals that news about sexual offences increases response volumes. News concerning fraud and corruption impacts the UK, while in Uruguay, topics related to drug trafficking and the Sebastián Marset case drive responses. A substantial portion of this discussion centres on political corruption in both contexts.

Finally, when comparing the results of political communications in both countries, the most striking element is the positive effect of punitive communications on the news replies for Uruguay compared to the UK case. Additionally, in the UK, fluctuations in

political communications seem to be associated to a greater extent with the effects of press discussion than in the Uruguayan case. Notably, variables associated with crime statistics are significant in the Uruguayan case.

In conclusion, the comparative analysis of punitive communications and political responses in Uruguay and the UK highlights some commonalities and differences. The study underscores the importance of incorporating exogenous variables to enhance predictive power, acknowledges the complexity and randomness inherent in punitive communications, and emphasises the critical role of press characteristics in shaping these dynamics. Future research should aim to diversify analytical approaches and extend time series data to build a more robust understanding of these phenomena.

7. Discussion, limitations, and conclusion

This section presents the empirical findings of the research, situating them within existing theoretical knowledge on punitive attitudes and, where relevant, other online attitudes and behaviours. The chapter starts with a general recapitulation of the thesis, synthesising the research process and outlining its theoretical and empirical contributions. The discussion is structured into three parts. The first part examines the key findings related to the measurement and prevalence of punitive attitudes, focusing on research questions 1 and 2, which explore the potential use of NEFDs in measuring punitive attitudes and the broader online context in which such attitudes emerge. The second part investigates the determinants of punitive attitudes, engaging with prior literature on traditional studies of punitive attitudes and incorporating insights from online behaviour studies, particularly hate studies. This section revisits research question 3, considering both cross-sectional (as analysed in Chapter 3) and longitudinal (as analysed in Chapter 4) perspectives. The third and final part briefly discusses the analysis of political communications, underscoring the effects of punitive attitudes. This discussion pertains to Research Question 4, which investigates the potential of online measurements of punitive attitudes to explain other social phenomena. The chapter then outlines the study's limitations and proposes directions for future research. It ends up with the main conclusions.

7.1. Summary

Before addressing the quantification of online punitive attitudes, this thesis considers a primarily methodological question: the feasibility of using New and Emerging Forms of Data (NEFDs) to infer individual punitiveness from user communications. This methodological interest is tied to broader discussions regarding the conceptualisation of punitive attitudes. A key challenge identified in the literature was the lack of a clear and consistent definition of punitive attitudes—a recurring issue noted, particularly in studies attempting to synthesise information on the topic (Matthews 2005; Adriaenssen and Aertsen 2015; Aguilar-Jurado 2018). To address this gap, it is necessary to clarify the various components of the concept, specifically what is meant by 'punishment' and what is meant by 'attitudes'. The thesis begins by defining punishment as the deliberate infliction of suffering or loss on an individual for transgressing a norm carried out voluntarily by another individual or group (Duff 2001; Miethe and Lu 2005). This definition accounts for the necessary components of the concept. However, it is broad for empirical research, potentially including very different phenomena, such as the punishment of parents to children in the family context, of employers to employees in work contexts, as well as what is of interest in

this thesis, which is the punishment of those who break the law in the penal and judicial system context. This thesis adheres to this restriction, as does Garland (1990) in his study of punishment in modern society, and is explicitly limited to citizen attitudes towards the punishment of criminal law offenders, those who are defined as criminals by the justice systems of the states in question.

The type of mental state to which punitive attitudes refer has been widely debated in the literature (Trajtenberg et al. 2024). This thesis adopts the concept of attitude as an individual's evaluation of a psychological object—here, criminal punishment—along a continuum from negative to positive (Bohner and Dickel 2011; Albarracin and Shavitt 2018), where higher levels of punitive attitudes correspond to greater approval of punishment severity, expressed as pain or suffering infliction. However, existing research reveals persistent disagreement regarding the core components of punitive attitudes. This thesis argues that punishment severity is the central component of punitive attitudes (see Chapter 1), building on Adriaenssen and Aertsen's (2015) conceptualisation and refining it through Goertz's (2006) framework of necessary and sufficient conditions in social science concept formation. Punitive attitudes are defined as those that endorse increasing the cost of crime for offenders by intensifying their suffering (or potentially opposing reductions in the same cost). This definition encompasses support for or rejection of various forms of punishment—such as the death penalty, imprisonment, or alternative measures—as well as preferences regarding their specific characteristics, including prison conditions, the nature of executions, or rehabilitative efforts aimed at reintegration. The arguments supporting this conceptualisation, developed in Chapter 1, are specific to this thesis. A review of the literature highlights a significant gap in conceptual discussions on the mental state underlying punitive attitudes, with most studies focusing instead on their determinants. Nevertheless, a recurring theme is that punitive attitudes necessarily imply advocating harsher penalties. Other dimensions identified by Adriaenssen and Aertsen—such as sentencing policies or forms of punishment—are primarily relevant due to their implications for suffering, which is conceptually equivalent to severity. Additionally, the goals of punishment, often included in definitions of punitive attitudes, exhibit an ambiguous relationship with severity. This presents two possibilities: either punishment goals could be considered a necessary condition—thus defining punitive attitudes as those that involve both increased severity and, for instance, a retributive orientation—or, as adopted in this thesis and supported by previous studies (Oswald et al. 2002; Payne et al. 2004; Gerber and Jackson 2013; Pickett and Baker 2014; Maguire and Johnson 2015; Armbrorst 2017), punishment goals can be treated as a separate construct, functioning as a potential covariate or

determinant of punitive attitudes. This conceptual foundation informs the operationalisation of punitive attitudes in this thesis, which are inferred from expressions of punitive communications on social media.

7.2. Discussion

7.2.1. measurement and prevalence

7.2.1.1. *Measurement strategy*

Following the conceptualisation of the scientific object of interest, the next step addresses the first research question of this thesis: whether social media data—specifically from Twitter—can be used to capture users' punitive attitudes. Using a supervised learning approach, this study successfully trained an algorithm to automatically classify punitive posts based on the previously established conceptual framework. The claim of success is supported by the algorithm's classification performance, which surpassed the reliability thresholds required for the valid use of this measure (Ozalp et al. 2020; Williams et al. 2020), obtaining an f-score of .772 for the United Kingdom and .851 for Uruguay.

Achieving this outcome required a foundational step: a group of annotators manually classified a sample of tweets. Through multiple iterations of training and refinement, they achieved sufficient levels of agreement, with an average kappa score of .74, ensuring the reliability of the manual classifications. This iterative process was particularly significant in assessing both the communicative capacity and validity of the concept of punitive attitudes developed in this thesis. The ability to achieve intersubjective agreement—defined as the consistent understanding and application of the concept across individuals—is a key aspect of concept validity, as emphasised by Babbie (2020). These results underscore that the specifications and restrictions applied to the concept of punitive attitudes in this thesis facilitated intersubjective agreement among independent annotators in determining what constitutes punitive online communication. Crucially, this agreement met the standards for training a reliable automated classification algorithm.

7.2.1.2. *Punitive attitudes prevalence*

The development of algorithms for the automated detection of punitive attitudes allowed the estimation of their prevalence and temporal variation, the identification of punitive users, and the quantification of cumulative punitiveness associated with individual news items. It is important to note that while the analysis captured a sufficient percentage of punitive communications around crime-related news to allow for robust examination (approximately 5% both in Uruguay and the UK), this was not

the case for crime-related political communications. Two primary reasons explain this limitation. First, the proportion of tweets classified as punitive in response to political content was approximately 1%, a figure too small for reliable model estimation despite the large dataset generated by the collection strategy. Second, the algorithm captured two distinct types of attitudes: (a) punitive attitudes, as defined in this thesis as support for harsher measures against criminals, and (b) expressions of disapproval towards the political system, which often included demands for penalties for politicians. While both types of attitudes could be considered punitive in a broader sense, they likely reflect different motivations and serve distinct communicative purposes. For these reasons, the analysis of the prevalence and determinants of punitive attitudes in response to political communications was excluded. This exclusion, however, is itself a significant finding. It suggests that punitive attitudes predominantly emerge as reactions to the stimulus generated by exposure to crime rather than as communications or demands directed at the political system, at least in this specific setting.

It is also important to acknowledge the multiple filters that shape data collection, which in turn affect the inferences drawn, whether when generalising results to the broader population, social media users, or even Twitter users specifically. To be included in this study, a user had to meet several specific conditions. First, the individual needed to hold a Twitter account. Second, they had to follow, or be exposed to, at least one of the selected news outlets (to be included in the analysis of determinants). Third, they had to respond to at least one news item. Consequently, the observed universe in this thesis refers specifically to Twitter users who follow news portals and actively engage in the discussions generated around them through replies or reposts. At this early stage, it isn't easy to know how this affects the results obtained, both in terms of prevalence and determinants. Alternative data collection strategies may yield different results, as is the case, for example, in the study conducted by Ravid and Dror (2023).

In terms of prevalence, future studies could generate external data through representative longitudinal samples, enabling an assessment of whether variations in punitive attitudes observed online mirror shifts in punitive attitudes within the general offline population. Moreover, the use of alternative data collection strategies, such as analyses based on specific cases or targeted keywords, could help to determine the extent to which communications from users engaging with crime-related news reflect, or potentially distort, the broader representation of punitive attitudes in other forms of online discourse. When analysing the determinants, it is essential to take these filters into account. The evidence gathered on the characteristics of punitive users is

specific to this subset of users, even though several of the observed patterns are consistent with findings in the broader literature for the general population. These filters were particularly relevant, for example, when hypothesising about gender differences in punitive attitudes. The finding that accounts inferred to belong to women were more likely to post at least one punitive tweet does not imply that women are generally more punitive than men. Rather, it suggests that among those users who choose to participate in such conversations, women appear to contribute proportionally more punitive content than men, controlling for other variables (but women participate overall less in the conversation).

Beyond these limitations, the study of punitive attitudes within this specific population remains highly relevant. First, it lays the groundwork for future research of the kind outlined above, thereby advancing the field. Second, it offers a proof of concept: demonstrating that this type of communication can be classified and analysed effectively using these data and tools. Finally, this form of communication is itself a component of social reality whose development and effects remain poorly understood and in this thesis are being systematically described for the first time.

Based on topic modelling, the prevalence analysis highlights a distinct and significant discussion about punishment, particularly in the United Kingdom, where keywords and classifications are more explicitly punitive than in Uruguay. In both countries, topic modelling identified a prominent discourse on punishment, ranking as the second most important topic, following an uninformative first topic that captures commonalities across various tweets. In the UK, this topic accounted for 12.72% of responses, while it represented 14.35% in Uruguay. However, in Uruguay, discussions on punishment are more intertwined with emotional reactions, particularly anger toward crime. This distinction is relevant, as it suggests different communicative styles between the two countries, potentially reflecting underlying cultural differences in attitudes toward crime and punishment. In this sense, several studies have explored the specificity of the Anglo-Saxon model in both the United States and the United Kingdom, potentially explaining the difference between the countries. The Anglo-Saxon model has been associated with a culture of retributive punishment (Monterosso 2009), a tendency toward individualism (Kornhauser 2015), and a discourse of punishment linked to the expression of moral order (Brown 2009). Additionally, the UK abolished the death penalty much more recently than Uruguay. Meanwhile, Aller's (2010) analysis of the evolution of Uruguayan penal law suggests that the country's penal system is more eclectic, historically progressive, and primarily influenced by European legal traditions, particularly Spanish and Italian.

These findings align partially with Ravid and Dror (2023), who used topic modelling to examine the prevalence of discussions on crime and punishment in social media. Their analysis of US cases revealed similar proportions in terms of punitive communications, though the exact prevalence varied depending on the specific case. It is relevant to note this concordance, even in a context where the data collection strategy differed significantly, as Ravid and Dror used keywords related to the cases of interest, whereas this thesis utilised responses to the news. While this type of research is highly emergent and at an early stage, it may point to certain regularities in terms of punitive opinions, even in very different contexts.

7.2.1.3. Contextual discussion

Beyond punitive discussions, topic modelling highlights cross-national differences in broader crime-related discourse, addressing the second research question of this thesis concerning public discussions of crime on social media. In the UK, the top-ranked topics include sexual crime, the lack of legitimacy of government and police, and the Heard v. Depp media case. In Uruguay, discussions focus on political polarisation, debating whether the government or opposition has better-managed security, the presence of weapons and insecurity, and widespread levels of violence. These differences in social media discourse reflect the distinct crime contexts in each country—Uruguay experiences significantly higher levels of violence than the UK (Rojido et al. 2023; Ministerio del Interior 2024; ONS 2024), and public concern about crime is notably higher (Latinobarómetro 2023; YouGov 2023b). Interestingly, however, these stark contrasts in crime rates and online discourse do not appear to significantly affect the prevalence of punitive attitudes when comparing the two countries.

These figures were refined using the transformer models designed to classify punitive tweets. The UK exhibits a higher proportion of punitive responses among tweets (4.7% compared to 3.9% in Uruguay). In contrast, Uruguay has a larger share of users expressing at least one punitive opinion (11.88% compared to 8.44% in the UK). Engagement patterns also differ significantly: in the UK, most punitive users (86.7%) expressed their opinion only once, while in Uruguay, a larger proportion of users (25.1%) contributed two or more punitive tweets. This higher frequency of engagement in Uruguay is reflected in its bigger ratio of punitive tweets per user (4.81 compared to 2.22 in the UK). Additionally, many Uruguayan users who posted punitive tweets also shared non-punitive content, creating a dynamic where punitive responses are more concentrated but also more intertwined with other types of communication. These findings indicate a divergence in the nature of punitive expression between the two countries. In the UK, punitive attitudes appear to be more

dispersed, with a higher prevalence of single-instance expressions. In contrast, in Uruguay, they are more concentrated among a smaller, yet more vocal, group of users.

7.2.1.4. *News Media*

Examining the context in which these discussions emerge, the topic modelling of crime-related news provides compelling comparative insights. The way the press reports crime has long been a subject of interest in criminological and communication studies (Smith 1984; Chermak 1994; McGregor 2017). The literature broadly agrees on several cross-cultural and enduring characteristics of crime reporting (Jewkes 2015). Marsh (1991) summarises these features in four key points: the over-representation of violent crime, the lack of correlation between this over-representation and actual crime figures, the overestimation of the effectiveness of the justice system and police, and the failure to adequately address the likelihood of victimisation, effective crime prevention strategies, or the underlying causes of crime. Some of these trends are evident in the social media analysis done in this thesis. Both keyword and bigram analyses for the UK and Uruguay, as well as the topic modelling, indicate a clear over-representation of violent crime in online media reports. Interestingly, the overall proportion of crime news devoted to violent crime is similar, despite the significant differences in crime and security contexts between the two countries. Regarding the efficacy of the police and justice system, terms such as "prison," "incarcerated," "arrested," and similar words appear prominently in news portal tweets, suggesting a significant focus on and potential over-representation of police effectiveness. These terms are also central to the most prominent topics identified in the analysis. The longitudinal data analysis conducted in this thesis shows that peaks in crime-related news reporting do not align with actual crime or violent crime statistics. Instead, they tend to coincide with cases deemed particularly "newsworthy"—those possessing high value as consumable news items. Examples include the highly publicised case of Olivia Pratt-Korbel's death in the UK and the public release of details surrounding the Sebastián Marset case in Uruguay. However, while the Twitter news analysis offers valuable insights into the prevalence and framing of crime-related topics, it does not provide sufficient detail to evaluate the nuances of how crimes are interpreted or explained. That kind of exploration would require delving into the news and conducting a more detailed analysis than the headline and scant information provided in the tweets.

This feature of news reporting, focusing on violent crimes such as homicides or sexual crimes, may explain the relatively high prevalence of punitive reactions in comparison with other topics in the topic modelling. Stalans (2013) suggests that surveys on punitiveness often "inflate" punitive attitudes because respondents tend to associate

crime with the most violent offences. Exposure to crime-related news media can serve as a micro-trigger for punitive attitudes by portraying scenarios that align with these mental images. If the punitive response originates from exceptionally violent crimes or the image of rational and predatory offenders, the prominence of news stories portraying these types of crimes or offenders could generate an exacerbated punitive response. This pattern of heightened punitive responses to particularly violent crimes is consistent with findings from several cross-cultural vignette studies (Payne et al. 2004; Sööt 2013; Tajalli et al. 2013; Aizpurúa and Fernández 2016; Vigna et al. 2019). This result is also observed in the analysis of the determinants of punitive attitudes, comparing different types of news and sentiment polarity associated with the news—an aspect explored in greater depth later in this chapter.

7.2.1.5. Political communications

The same analysis conducted for crime-related news was also applied to crime-related political communications. While political communications represent a smaller content volume than press communications, they generate a significantly larger public response. Regarding the nature of political communication, the observed data align with trends documented in the literature (Jungherr 2016; McGregor 2017). In both countries, politicians primarily use social media to broadcast information or share opinions about current events. Members of governing parties, in particular, often use these platforms to provide real-time updates on policy measures, a trend that emerged as a distinct topic in both the UK and Uruguay.

A particularly noteworthy finding is the strong correlation between discussions on crime-related news and political discourse. An analysis of keywords and bigrams reveals similar patterns in both the UK and Uruguay. Violent crime features prominently in these discussions, though with country-specific nuances: in the UK, terms related to sexual crimes are more frequent, while in Uruguay, drug trafficking is a dominant theme. Additionally, in both countries, terms explicitly associated with the political domain—such as party, government, and legislation—appear frequently, aligning with expectations. Topic modelling further supports these observations, indicating that violent crime is the most widely discussed topic in crime-related political discourse. The time series analysis complements this finding, showing that this type of news generates the strongest response from users in terms of general engagement and punitive reactions. These results align with previous research, such as Barberá et al. (2019), which examined the interplay between the public, the political system, and the media in the United States. Their findings suggest a likely causal link between public discussions and political and media narratives, and vice versa. These results challenge the traditional "top-down" model of political

communication, which assumes that politicians set the agenda and the public follows. Instead, the findings suggest a bidirectional relationship between political communication and public discourse. Additionally, they highlight the critical role of mainstream media in filtering and amplifying issues, shaping both political and public attention. The findings also raise important policy concerns. If politicians primarily react to public discussions on crime, crime policy may be shaped more by media-fuelled perceptions than by actual crime trends. This raises concerns about whether political decisions on crime, such as harsher sentencing or police funding, are driven by evidence-based policymaking or reactive responses to public sentiment.

Turning to the public responses to political communications, the analysis observes notable differences between the two countries. In the UK, keywords suggest a somewhat neutral tone, replicating the political discourse that focuses on resource management, discussions of rights (particularly gender and minority rights), and sexual crimes. In contrast, Uruguay presents a more confrontational tone, with responses referring to politicians as "you people" (in contrast to citizens) and frequently employing negative terms or mockery, such as "shame," "blah blah," and "hahaha." However, combining topic modelling with sentiment and emotion analysis reveals commonalities across both countries: anger and indignation dominate the responses, reflecting widespread disenchantment and a perceived lack of legitimacy within the political system. These findings align with survey data on institutional trust in both countries, providing potential context for the observed sentiments. In the UK, according to the ONS (2023b), trust in government stands at 35%, with 49% expressing distrust and the remainder remaining neutral. Trust in parliament—where the political communications analysed in this thesis originate—stands at 34%, with 46% expressing distrust. In Uruguay, data from the LAPOP (2023) survey provides a comparable picture, albeit measured on a Likert scale from 1 to 7. Transforming these values, low trust in government (levels 1–3) accounts for 44.7%, while high trust (levels 5–7) accounts for 42.5%. For political parties, 49.3% of respondents reported low trust, compared to 29.6% with high trust. Although LAPOP does not offer specific data on trust in parliament, the figures for political parties provide a helpful proxy. This widespread lack of trust in government and institutions is concerning, particularly in the context of crime control. Low legitimacy has been linked to increased support for vigilante justice (Nivette 2016) and tough-on-crime policies (Zimring and Johnson 2006; Lappi-Seppälä 2011).

7.2.2. Determinants

Building on this contextualisation, primarily drawn from the first empirical chapter of this thesis, the discussion now shifts to analysing the determinants of punitive

attitudes, addressing research question three, which examines the characteristics of tweets, users, and news items that influence the likelihood of expressing punitive attitudes. This analysis is conducted at two levels: cross-sectionally, by assessing all responses to news aggregated throughout 2022, and longitudinally, through a time series analysis of daily punitive responses.

7.2.2.1. Cross-sectional analysis

The cross-sectional analysis was conducted at three levels: news, users, and individual tweets. At the user level, one of the key findings is that users who participate more frequently, have newer accounts, and maintain smaller networks (in terms of followers and followings) are more likely to post at least one punitive tweet. This pattern aligns with observations from studies on hate speech in social media (Ribeiro et al. 2018; Siegel 2020; Geissler et al. 2024). Although punitive attitudes differ from hate speech, they share elements of aggression and antagonism, advocating for the suffering of others. Many of the punitive tweets analysed reflect extreme viewpoints, calling for punishments deemed inhumane. In this sense, Brown (2018) addresses the problem of hate speech, underscoring the role of online anonymity and the instantaneous nature of social media interactions as critical drivers of spontaneous and often unfiltered responses. These features, combined with the reduced visibility and accountability available on social media platforms, can lower self-censorship, making newer or less socially embedded users particularly prone to engaging in punitive discourse, suggesting a possible causal mechanism associated with the observed effects of user networks on punitive attitudes. Additionally, the unique affordances of social media—such as rapid content dissemination, ease of access, and the absence of physical interaction—facilitate immediate emotional expressions since the content that arouses these emotions and the possibility to respond are immediately available (Coffey and Woolworth 2004; Brown 2018). Brown (2018) further highlights the role of online communities in fostering such behaviour, noting that individuals who engage in hate speech online may not necessarily express these views in offline settings. Users can selectively shape their online environments, reducing the perceived social costs of expressing punitive views by controlling their audience (Uyheng and Carley 2021; Schmitz et al. 2022). By associating in small networks of like-minded individuals, the potential social costs of disapproval that can occur when expressing extreme attitudes are reduced, as potentially antagonistic users are not confronted with these comments. However, this control is only partial—especially when responding to widely visible crime-related news. This fact occurs to the extent that the communications analysed in this thesis respond to public communications from either political accounts or

news portals. In this sense, the communications will necessarily be visible to the general public, who will choose to review the responses. However, the exposure of other users to these communications in the timeline will depend on the networks that these users establish. Furthermore, curating these networks can contribute to the formation of "echo chambers" and "filter bubbles," where users are primarily exposed to like-minded individuals and ideas. The emergence of these networks can amplify and reinforce their views on various issues, including crime and punishment (Luzsa and Mayr 2021; Wolfowicz et al. 2023).

Regarding inferred sociodemographics, the analysis found no significant gender differences in Uruguay. However, in the UK, being male was associated with a 12% lower likelihood of expressing punitive attitudes. Prior research on the relationship between gender and punitive attitudes has yielded mixed results. Some studies have found no statistically significant correlation (King and Maruna 2009; Unnever et al. 2010; Unnever and Cullen 2010; Armbrorst 2017; Intravia 2019), while others have identified a positive effect of being male on punitive attitudes (Van Damme and Pauwels 2012; Tam et al. 2013; Stewart et al. 2018). To a lesser extent, some studies have suggested that women can be more punitive (Payne et al. 2004; Otamendi 2015), particularly in scenarios where women are victims or in crimes that predominantly affect women (Palasinski and Shortland 2016; Palasinski and Shortland 2017). It is important to note, however, the non-random nature of the sample in this study. Twitter users are not representative of the general population, and the analysis focuses on those who actively engage in public discussions around crime-related news, introducing a dual filter and potential bias. The descriptive analysis reveals that men dominate the crime debate on social media news. This result aligns with prior studies suggesting that women engage less frequently in open discussions on social media, are more concerned with privacy (Kim et al. 2021a), and are less confrontational on controversial topics (Bode 2017). However, the findings of this thesis suggest that when women do participate, they are proportionally more punitive than men, even when controlling for other variables. A possible explanation for this unexpected result is the concentration of punitive responses around a specific case in the UK dataset—a nurse convicted of murdering several babies by injecting them with air. Due to its emotional and subjective proximity, this case may have elicited stronger punitive reactions from women, particularly mothers. Future studies could further explore this by comparing responses to different types of cases. Such a specific case type may explain why this effect has been observed in the UK and not in Uruguay. Additionally, women in the UK engaged more actively in discussions about sexual offences, accounting for 20% of replies compared to 15% for men. This result aligns with

previous literature showing that women tend to be more punitive than men when it comes to sexual offences, where they are often the victims (Pickett et al. 2013; Palasinski and Shortland 2016; King 2019). Analysing some of the patterns observed for the UK, the gendered response to sexual offences was less pronounced, with women accounting for 11.4% of responses and men for 8%. Moreover, sexual offences appeared to generate less public attention in Uruguay, potentially contributing to the observed discrepancy. Future research could further investigate these dynamics by filtering data to focus exclusively on sexual offences and analysing gendered responses in greater detail. Another possible factor is the performance of the gender inference algorithm, which relies heavily on English-language data (Wang et al. 2019). This fact may have resulted in greater accuracy for the UK dataset, potentially influencing the observed differences.

The analysis of estimated ages reveals a statistically significant difference between older and younger users in both Uruguay and the United Kingdom, with older users expressing less punitive attitudes. While the literature offers mixed findings regarding the relationship between age and punitive attitudes (Adriaenssen and Aertsen 2015), this result contrasts with some studies suggesting a positive correlation between age and punitiveness (Chiricos et al. 2004; Payne et al. 2004; Hanslmaier and Baier 2015; Silver and Silver 2017). Schwartz et al. (1993) propose that this relationship may follow a U-shaped curve, potentially accounting for the observed results, particularly given that the algorithm used in this study categorises all individuals over 40 as a single group. Several alternative explanations warrant consideration. The differences may reflect age-based self-selection biases in social media engagement, generational effects either within society at large or specific to Twitter users, or the possibility that the relationship between age and punitiveness is mediated by other age-related factors, such as impulsivity, which could influence the likelihood of expressing punitive attitudes.

The exposure hypothesis, which mirrors findings from studies on hate speech, suggests that anonymous users are more likely to produce hateful content due to reduced risk of unintended consequences (Brown 2018). This hypothesis, operationalised through the presence or absence of profile pictures, holds for the UK. Users in the "No Person" category exhibit a roughly 30% lower likelihood of expressing punitive attitudes, while those in the "Person" category show a just under 25% reduction. In contrast, results from Uruguay are not statistically significant. The absence of this effect in Uruguay raises questions. Notably, the proportions of users across profile categories are similar in both countries, complicating straightforward interpretation. One possibility is that the social cost of punitive expression in Uruguay

is lower than in the UK, making anonymity a less relevant factor. Alternatively, the difference may reflect a greater digital divide in Uruguay, particularly between adults and younger users. In this scenario, the lack of profile pictures could stem not from a desire for anonymity but from limited digital literacy, resulting in a higher proportion of "anonymous" users by default. However, these interpretations remain speculative. A more thorough analysis would require a qualitative review of user accounts to explore potential explanations for the observed discrepancies inductively.

The analysis next considered the effects of user profile descriptions. A surprising finding is the strong, positive, and significant effect of descriptions referencing sports affiliations, with similar results observed in both the UK and Uruguay. Among the remaining categories, the only description significant at the 5% level was "professional," which reduced the likelihood of expressing punitive attitudes by nearly 40%. The primary hypothesis regarding the influence of sports affiliations is that such descriptions typically signal accounts belonging to "ordinary" users—citizens who can be representative of the general population. This category likely excludes professional, organisational, or artistic accounts. By contrast, professional accounts may be less likely to engage in punitive discourse, as their owners potentially face greater reputational risks when expressing violent or extreme views online (Brown 2018). Moreover, the association between professional descriptions and lower levels of punitive expression may reflect broader trends in the literature, which link higher education levels to reduced punitiveness (Roberts and Indermaur 2007; Maruna and King 2009; Unnever et al. 2010; Spiranovic et al. 2012; Singer et al. 2020).

Regarding user location, the initial assumption was that accounts based in the respective countries would be more likely to produce punitive tweets. This correlation stems from the proximity to the events being portrayed. Although international crimes receive coverage, most news outlets in each country prioritise local incidents. Crimes occurring within one's own country can represent a symbolic affront to the broader society, provoking anger and indignation that manifest as punitive attitudes. In this context, individuals may experience the offence collectively, responding as members of the affected society (Garland 1990; Garland 2001). Additionally, prior research suggests that empathy and perceived closeness to victims can elicit similar reactions, as individuals may feel personally threatened or vicariously targeted by crime (Hammer et al. 2009; Hanslmaier and Baier 2015; Rozmann and Walsh 2018). This thesis offers partial evidence in support of this hypothesis. In the UK, proximity appears to influence punitive expression for specific regions, while in others, the effect is less pronounced when compared to the reference category of 'no location.'

Although the odds ratios (ORs) align with expectations in Uruguay, the results do not reach statistical significance in the individual-level model. However, in the multilevel model, a significant effect is observed for users outside the capital, Montevideo, suggesting that individuals from the interior regions are more likely to express punitive attitudes.

The output volume per author results were consistent across both the UK and Uruguay, though somewhat unexpected. The likelihood of a tweet being punitive decreased as the author's overall participation increased. This result suggests that more active users in crime-related discussions express punitive attitudes at a lower rate than less active users. Additionally, in the UK, 86.7% of punitive users (those who expressed at least one punitive opinion) did so only once, 8.9% did so twice, and the remaining 4.5% did so three or more times, accounting for 16.3% of the punitive responses. In Uruguay, 74.9% of punitive users made a single punitive tweet, 14.4% made two punitive tweets, and 10.7% made three or more, accounting for 35.1% of the total punitive responses. Taken together, these results suggest that most punitive tweets are produced by users who, over the course of the year, will express this type of attitude only a few times - usually only once - and who generally post very little, at least around criminal news. While expressing punitive opinions is not a crime, it reflects an attitude that could be interpreted as symbolic violence—a desire to inflict harm or suffering on others. Consequently, it was anticipated that the distribution of punitive tweets would mirror the power-law patterns observed in criminology, where a small number of individuals account for the majority of criminal activity, resulting in a "heavy-tailed" distribution (Cook et al. 2004; Falk et al. 2014). This observation typically means that a few prolific offenders or "hot spots" drive the bulk of offences. However, the findings here point to the opposite trend—punitive replies and quotes are more likely to originate from users with lower overall engagement in crime-related discussions who only tweet a few times. This observation does not necessarily rule out the presence of a power-law distribution in online punitive behaviour. Those who produce just a few punitive tweets in response to news media articles may contribute disproportionately to such discourse across multiple platforms or outside the context of direct responses to online news. A potential explanation can be found based on what is known about Twitter users' behaviour. Most Twitter users are passive consumers, rarely posting original content (Wojcik and Hughes 2019). They typically scroll through feeds, engaging with likes or retweets, but generating minimal new material. The factors that can motivate users to create content are varied. Many studies have specifically explored the factors that lead users to comment on news stories. Weber (2014) notes that the proximity of events (the psychological closeness

of the event to the reader) and the impact of the event (the ability to affect the lives of those involved) are key elements in motivating the user. Ziegel et al (2018), on the other hand, find that news stories with high controversy and negativity factors increase readers' willingness to post emotionally reactive comments (quick and emotionally charged comments) and to assume (or otherwise disregard) the costs associated with posting. The hypothesis here is that the confluence of these factors in a post with sufficient intensity for the user to bear the costs of posting is rather rare and relatively random. This occurs to the extent that a news item with these characteristics, the user who potentially finds these values in the news item, and the lack of disincentives to tweet must converge in the same virtual space. In this sense, a low probability of convergence would result in a rather uniform distribution.

This thesis also examined the characteristics of crime-related news that elicit punitive responses from users. In the UK, smaller and more local media outlets tend to generate a higher proportion of punitive reactions. This finding is consistent across both the count model and the multilevel model. The persistence of these effects, even after accounting for different levels of analysis, suggests that certain outlets elicit distinct patterns of response that extend beyond the specifics of individual news items. This result may indicate a form of audience segmentation (Fletcher and Nielsen 2017), reflecting differences in the characteristics of readers who consume content from each media outlet. However, other unmeasured factors—such as variations in reporting style beyond keyword use or sentiment—may also contribute to these patterns (Flaounas et al. 2013). In Uruguay, the trend diverges. Here, the effect of individual media outlets diminishes when the analysis incorporates the news-item level. This result suggests that differences in punitive responses are driven more by the content and context of specific news items than by the outlets that publish them. In other words, while the outlet may initially appear to influence punitive attitudes, this effect is likely confounded by the nature of the stories those outlets choose to cover. The reasons for this divergence between the two countries remain difficult to pinpoint with the available data. One plausible explanation relates to the differing sizes of the media landscapes in the UK and Uruguay, as well as the scale of Twitter engagement in each country. In the UK, the larger population and more fragmented media environment enable the discussion of localised events within regional outlets that still achieve significant reach and public impact. Conversely, in Uruguay, public discourse tends to be concentrated around a few dominant national media outlets, partly due to the country's smaller population, with half of it residing in the capital, Montevideo. Notably, three sources had to be excluded from the analysis because they generated very few responses despite ranking among Uruguay's 20 most

influential outlets. As a result, while UK users can engage in discussions about local issues through smaller regional newspapers, Uruguay users rely more on mainstream national media for public discourse. This structural difference may explain why media outlet effects are more pronounced in the UK and why, in Uruguay, the specific content of the news plays a more decisive role in shaping punitive responses.

The sentiment of the news item influences the ratio of punitive responses. A higher ratio of punitive reactions is associated with more negative sentiment, even when controlling for other variables, including the type of crime. Specifically, in the UK, a one-unit increase in the positive polarity of news sentiment is associated with a 7.3% decrease in punitive responses, while in Uruguay, the exact change leads to an 8.9% decrease in punitive responses. Sentiment scores remain stable across all models and consistently emerge as one of the strongest predictors of punitive responses. This consistent relationship between negative sentiment and punitive reactions underscores the importance of news framing and its effect on public attitudes. (Balzarotti and Ciceri 2014). Specifically, Kühne & Schemer (2015) demonstrate that anger-framed news increases accessibility to information related to punishment and preferences for retributive measures. In the future, it could be explored how similar news stories with different sentiments elicit - or do not elicit - different levels of punitive responses.

Regarding the specification of place or person in the news item, the results reveal contrasting effects between the UK and Uruguay. The intuition behind the processing and inclusion of these variables is that this type of detail may promote the expression of punitive attitudes through the identification with the victim or 'feeling of closeness' with the event that may arise in the reader - some evidence in this regard can be found in Hammer (2009), Hanslmaier and Baier (2015), and Rozmann & Walsh (2018). Specific characteristics of the perpetrator may also influence punitive responses, particularly in light of biases observed in the literature. Research indicates that media portrayals often emphasise racial and ethnic minorities or depict perpetrators as predators, reinforcing punitive attitudes (Dixon and Linz 2000; Baranauskas 2020; Moreno-Medina 2021). These characteristics have been shown to shape public perceptions and increase punitiveness (Chiricos et al. 2004; Brookman and Wiener 2017; Stewart et al. 2018; Lehmann et al. 2022). In the UK, news stories that mention a specific individual increase the likelihood of a punitive response by 16.3%, whereas references to a location decrease this likelihood by 15.6%. This aligns with the expectation that personalising a story by highlighting an individual evokes stronger punitive reactions, while mentioning locations does not elicit the same engagement. In contrast, the results from Uruguay reveal an inverse pattern in the case of

personalisation. Mentioning a specific individual reduces the likelihood of a punitive response by 30.5%, diverging from expectations. However, similar to the UK, references to locations in Uruguay lead to a 10.6% reduction in punitive responses. These findings challenge the initial hypothesis and suggest that the Uruguayan audience may respond differently to personalised news content. Further investigation is warranted to understand the underlying mechanisms driving these divergent reactions.

The keyword analysis complements these findings. In the UK, the results align with expectations: there are no significant differences in punitive responses across less serious crime categories, such as theft, fraud, general crime, and drug offences/gang activity. However, punitive responses increase significantly for cases involving domestic or sexual violence, violent crime, and homicide. In Uruguay, the highest rates of punitive responses are associated with sexual and domestic violence cases. Conversely, news about drug trafficking and gang-related offences elicits lower punitive reactions compared to the reference category. Two key factors may account for the divergence between Uruguay and the UK—one structural and the other related to media reporting styles. Structurally, Uruguay's homicide rate is significantly higher than that of the UK. Additionally, a large portion of homicide-related news in Uruguay appears to involve conflicts between criminal gangs. This combination may contribute to a form of "desensitisation" among news consumers (Krahé et al. 2011; Mrug et al. 2015). If emotions such as anger and indignation drive punitive attitudes, the death of someone portrayed as a gang member may not provoke this kind of reaction. In such cases, there may be an implicit perception that the individual "got what they deserved," reducing the impulse for punitive reactions. Since punitive responses are irrelevant after the death of the criminal (which in some way implies a kind of capital punishment), expressions of satisfaction or approval may occasionally surface, as detected by the algorithm, but these cases were found to be rare during the annotation stage. By contrast, news about sexual offences often features clearly defined victims and perpetrators, evoking stronger emotional responses. This effect aligns with findings from vignette studies, which show that portraying offenders as "predators" amplifies punitive attitudes (Horstman et al. 2021; Kruis et al. 2023). Similar effects are observed when offenders are perceived as responsible for their actions, increasing the likelihood of punitive responses (Cullen et al. 1985; Grasmick and McGill 1994; Unnever et al. 2010). This logic may also account for the negative effect observed in Uruguay regarding the mention of specific locations. As discussed in Chapter 1, Uruguayan media frequently emphasise successful police operations in gang-affiliated areas, often highlighting the individuals and places involved. In

contrast, UK reporting tends to focus more on the crime itself rather than subsequent police actions. This focus, coupled with lower levels of gang conflict and clearer distinctions between victims and perpetrators, may explain why personalising news stories increases punitive responses in the UK.

Additionally, a common theme across the empirical chapters is the prominence of Violence Against Women and Girls (VAWG). In Chapter 4, topic modelling of crime news and citizen reactions showed that gendered violence consistently emerged as one of the most salient categories in both Uruguay and the UK. This was not only reflected in media framing but also in the volume and tone of replies. In Chapter 5, the determinants analysis reinforced this finding: VAWG-related news items significantly increased the likelihood of punitive replies, even after controlling for user and news-level characteristics. Finally, the time-series analyses in Chapter 6 revealed that peaks in punitive attitudes often coincided with high-profile cases of gendered violence, and with increments in the amount of VAWG news.

This convergence through methods demonstrates that the discussion of VAWG on social media has a specific structure, with distinct characteristics, and a direct impact on punitive attitudes and the broader discussion of punishment. This result is somewhat expected, insofar as one of the main hypotheses of this thesis, based on the literature, is that more violent crimes generate greater punitiveness (Durham III 1988; Aizpurúa and Fernández 2016; Kirk 2022a; Fenimore and Jones 2024).

However, this finding also reflects the importance that this type of crime has recently gained in public opinion and debate, and the predominant role that social media has played in its discussion, activism, and even in generating manifestations of vigilantism, especially in contexts where justice institutions have low legitimacy (Mendes et al. 2018; Rodriguez et al. 2020; Castillo Ara 2025). This thesis acknowledges that punitive attitudes expressed online are deeply rooted in lived social harms that disproportionately affect women and girls, and that these harms travel across contexts, shaping discourse in both the Global North and South.

The results of this thesis, along with findings from other studies examining punitive attitudes towards more severe offences (Vigna et al. 2019; Kirk 2022a), challenge a widely held assertion in the literature on citizen punitiveness—namely, that punitive attitudes are overestimated. This assertion is rooted in the idea that when individuals are asked about punishment for criminals in general, without context, they often envision a 'super-predator,' a mental image that deviates significantly from the realities of crime (Stalans 2013). Research suggests that when citizens are presented with more typical, lower-level crime scenarios, their punitive attitudes diminish

considerably compared to when they respond to abstract or decontextualised questions about crime and punishment (Maruna and King 2009; Otamendi 2015). However, the rationale behind privileging average crime scenarios over more extreme cases to measure punitive attitudes is unclear, raising important questions about measurement and conceptualisation. For instance, should an individual who advocates for rehabilitative approaches for non-violent offenders but supports the death penalty for murderers be classified as punitive or non-punitive? In this thesis, such an individual would be categorised as punitive, as their stance reflects a desire to increase the cost of crime in specific contexts (sufficient condition). The methodological approach adopted here aligns with this perspective, considering any individual who expresses at least one punitive opinion detected by the created Machine Learning algorithm to be punitive. This approach acknowledges that punitive attitudes are often context-dependent and may surface selectively in response to more severe offences.

Before reflecting on the time series analysis, it is important to highlight that the multilevel analysis—conducted at both the news and user levels—produced high intraclass correlation (ICC) and conditional R^2 values. This outcome suggests two key insights. First, the characteristics of users and news items play a critical role in explaining punitive responses. Second, the high ICC and R^2 values indicate that, beyond the variables captured in this thesis, additional underlying factors at both levels significantly influence punitive attitudes but remain unaccounted for by the current analytical framework. These unobserved characteristics warrant further exploration in future research to provide a more comprehensive understanding of the drivers behind punitive expressions.

7.2.2.2. Time series analysis

The analysis of punitive attitudes through time series complements the previous findings, particularly by incorporating third-party variables from secondary data, still focusing on research question number three. This addition enables the thesis to examine how external factors beyond the Twitter environment impact punitive expressions on the platform. In Uruguay, the availability of public data on daily crime rates provides a unique opportunity to assess how 'real' crime—despite the inherent challenges in crime quantification, especially through police records (Buil-Gil et al. 2021)—affects the expression of punitive attitudes on social media. Therefore, official figures on crimes per day were incorporated into the analysis. A key debate in the literature concerns whether crime itself or external factors, such as political

discourse and media reports, drive punitiveness (Enns 2016; Kort-Butler and Habecker 2018; see also Chapter 1). In the UK, given the volume of internet traffic and the availability of secondary data sources, it was possible to incorporate information from Google Trends and representative public opinion surveys. Interestingly, the multivariate analysis reveals that all variables associated with external events—that means outside of the data collected from Twitter—are statistically insignificant. The fact that Uruguay's crime figures did not support the control of the other variables does not mean that they are inconsequential. The analysis by Enns (2016) supports this notion, noting that crime figures can influence press reporting, thereby generating a spillover effect. In this thesis, it is observed that in Uruguay, there is a correlation between theft and homicide figures, as reflected in the number of responses to press reports, which may partially account for this indirect effect. However, a thorough analysis of crime-related news should be carried out to assess that hypothesis. Additionally, in terms of punitive responses, this result accounts for the mediated effect of these crimes, as they increase the number of global responses, which is associated with an increase in specifically punitive responses. This fact is also true for other crime news in both countries, in particular, news items related to sexual offences. Meanwhile, the results in the UK should be considered with caution, given that they involved transforming daily information into weekly information, which reduced the N considerably.

In both the UK and Uruguay, fluctuations in punitive responses are primarily predicted by crime-related news (particularly the volume of news about violent crimes) and the number of responses such news generates each day. To fully understand these results, two important points must be emphasised. First, as observed in studies on hate speech, the time series data reveal distinct peaks driven by specific events that provoke public reaction (Ozalp et al. 2020; Williams et al. 2020). This phenomenon appears to reflect the nature of social media and news consumption (Lupu et al. 2023). Exceptional events, especially those perceived as abhorrent, capture public attention and evoke strong emotional responses, which can potentially lead to hate speech and punitive expressions. Second, while an increase in overall responses correlates with more punitive tweets, this rise is not proportional. As highlighted in the discussion about the determinants of online punitive attitudes, news items that generate fewer responses tend to elicit a higher proportion of punitive reactions. In other words, although greater public engagement results in more punitive content, punitive attitudes are most concentrated within lower-profile discussions.

A notable difference between the two countries is the correlation observed in Uruguay—but not in the UK—between punitive tweets from political accounts and

punitive reactions to crime-related news. However, the number of political communications is relatively small, so caution is warranted when interpreting these results. Moreover, the observed correlation is simultaneous, making it difficult to determine the direction of causality or whether a third variable influences both trends. While subdividing the analysis into shorter time intervals could provide further insight, such an approach falls beyond the scope of this thesis.

7.2.3. Effects

Finally, the analysis focused on observing the determinants of crime-related political communications on Twitter, addressing research question four about the potential effects of the variation on punitive attitudes in other types of related phenomena. The hypothesis to be tested was whether fluctuations in users' punitive responses are related to fluctuations in crime-related political communications of any kind. This hypothesis holds for Uruguay but not for the UK case. Again, this correlation occurs on the same day (no lag), so it is impossible to determine the direction of the correlation. These results give rise to three potential explanations, each corresponding to distinct causal hypotheses. First, heightened punitive demands following certain events may pressure the political system, prompting political actors to respond. This hypothesis suggests that user-driven punitive reactions trigger political communications, which finds partial support in the literature, particularly regarding the influence of public punitive attitudes on policymaking and political discourse (Enns 2014; Enns 2016; Jennings et al. 2017). A second, albeit less likely, hypothesis posits the reverse relationship—that statements from political actors incite increased public expressions of punitiveness, effectively encouraging users to adopt more punitive attitudes. This explanation appears less plausible due to the lack of substantial evidence and the observation that punitive responses on social media often show little direct correlation with the content of political communications. The third and perhaps most plausible hypothesis is that a common external factor drives both phenomena. In this scenario, crime-related news—particularly reports of violent incidents—could simultaneously provoke public outrage and elicit responses from the political system (Enns 2016). Additionally, it should be noted that these hypotheses are not necessarily mutually exclusive. For example, news media reports may generate responses from political accounts that also feel under public pressure. Moreover, political communications may generate a form of public validation for conveying these attitudes. While each hypothesis warrants further investigation, the available data suggests a complex interplay between public sentiment, media reporting, and political discourse, reinforcing the need for a more nuanced

understanding of the relationship between crime, punitive attitudes, and political engagement.

7.3. Limitations

As one of the first explorations into the expression of punitive attitudes online, this study inevitably carries several limitations. These shortcomings highlight areas for caution when interpreting the results and suggest promising future research directions. While some of these constraints have been noted throughout this chapter, this section provides a more in-depth discussion of their implications and potential pathways for further investigation.

A primary set of limitations arises from the data used in this study. First, the analysis is conducted exclusively on a single platform. The existing literature suggests that platform effects are not neutral, as each platform offers distinct functionalities and user experiences (Alhabash and Ma 2017). For example, platforms such as Instagram and TikTok are predominantly audio-visual, whereas Twitter (X) and Reddit are mostly text-oriented. Furthermore, each platform employs unique algorithms that mediate communication and shape user engagement differently (Whittaker et al. 2021). The demographic profiles, attitudes, and behaviours of users also vary across platforms, potentially influencing the types of content shared and the nature of public discourse (Gambo and Özad 2020). While the alignment of some findings with previous research suggests broader applicability, the extent to which the conclusions of this thesis hold across other platforms requires empirical validation. Additionally, Twitter's data extraction process introduces its own specific biases. While methodologically justified (see methods chapter), selecting responses to crime-related news and political communications represents just one of many possible approaches. Future research could explore whether similar results emerge from alternative strategies, such as focusing on high-profile cases, analysing informal news sources, or capturing all crime-related communications using broad keyword searches—an approach adopted by Kostakos (2018) in his analysis of organised crime. Moreover, the selected accounts from which tweets and replies were extracted may also introduce bias. For instance, local news outlets have been linked to higher levels of punitiveness (Simmons 2017), and this thesis provides supporting evidence for the UK context. A similar dynamic may arise if political account selection were expanded to include local government representatives, potentially amplifying certain patterns. Likewise, the keywords chosen to filter data could inadvertently exclude relevant content related to offender punishment, as this thesis focused exclusively on crime-related keywords. Future research may consider incorporating terms related to sentencing

and judicial outcomes to broaden the scope. Temporal factors may also contribute to bias. Although the selected time frame aimed to reflect a "return to normal" following the COVID-19 pandemic, the potential influence of this period remains. However, earlier data collected during the preparatory stages of this thesis could offer an opportunity for longitudinal analysis in future studies, particularly for time series investigations. Limitations also stem from the variables extracted for analysis. Despite drawing extensively from the literature and attempting to capture a wide array of relevant content, the multilevel analysis revealed significant unexplained variance at both the user and news item levels. The feasibility of extracting additional information remains uncertain without further research. Expanding this analysis could involve integrating network-level data, such as specific followers and followings, or analysing other tweets unrelated to crime to gain deeper insights into user characteristics. This idea will be further developed for future research later in this chapter. For instance, Hu and Kearney (2021) demonstrated the value of examining broader communication patterns to uncover additional predictive variables like social status or thinking styles.

Despite efforts to strengthen the validity of results through diverse analytical strategies, this thesis is subject to several methodological limitations. Although the topic modelling techniques employed are optimised for short text, they do not account for relevant covariates, such as temporality. Alternative approaches, such as Structural Topic Modelling (Roberts et al. 2019), can incorporate temporal dynamics and other contextual factors, potentially yielding additional insights, for example, related to temporal dynamics. Moreover, advancements in the field during the development of this thesis—particularly the rise of text-embedding methods for topic modelling (Esposito et al. 2016)—offer new opportunities for comparison and refinement. Future research could benefit from integrating these more recent techniques to assess their impact on the findings. Word embeddings are better at capturing the subtleties of language, so it is possible that this type of vector representation of text may reveal insights that the techniques used in this thesis did not. Similarly, modelling strategies could be expanded to address potential violations of assumptions identified during analysis. For example, the application of fixed effects models could help isolate user- or news-specific effects, thereby controlling for cumulative influences at these levels (Hanck et al. 2024). This issue was partially addressed using multilevel models; however, diversification of testing can lead to higher levels of validity. Testing the robustness of results through such methods remains an avenue for future publications. Regarding time series analysis, while ARIMAX models offer significant advantages for hypothesis testing, alternative approaches, such as Vector Autoregressive (VAR) models, could provide deeper

insights into the directionality of observed correlations. This extension, although beyond the scope of the current thesis, represents a promising direction for subsequent research.

In addition to the limitations related to data and methods, this thesis highlights several potential avenues for expanding research on online punitive attitudes, thereby contributing to a broader research agenda in this emerging field. One promising direction is the application of network analysis, a widely used approach in social media studies (Tremayne 2014; Milani et al. 2020; Haunschild et al. 2021). Network analysis provides valuable insights into the dynamics of punitive discourse, enabling researchers to investigate whether users expressing punitive attitudes operate within echo chambers or engage with diverse communities. This method can also identify users' similarities, assess the influence of key actors in disseminating punitive messages, and track the flow and amplification of such content. Himelboim et al. (2016), for example, analyse how contact with users with similar communication styles in the context of the US presidential election can promote the posting of positive or critical tweets about the candidates on various issues. Although this thesis does not incorporate network analysis, it represents a logical next step for advancing the field. Another potential expansion involves integrating additional data sources—such as surveys of social media users—to validate the measurements derived from social media platforms and enrich the range of explanatory variables. Future studies can better assess how these expressions reflect underlying differences in attitudes by measuring punitive attitudes through traditional survey methods and comparing punitive and non-punitive users online. This methodological triangulation approach (Bekhet and Zauszniewski 2012) would enhance the robustness of findings and provide a more comprehensive understanding of punitive sentiment in digital spaces.

Conceptually, one avenue worth further exploration, and repeatedly highlighted throughout this thesis, is the relationship between punitive attitudes and vigilantism. A central concern in the literature on punitive attitudes is their possible effect on the support for vigilante justice and, moreover, on behaviours consistent with such attitudes (Van Damme and Pauwels 2012; Nivette 2016). While this thesis identifies some emerging evidence of such expressions online (for example, Chapter 4 notes references to vigilante justice in Uruguay), the automatic classifier used here may capture such content only when it simultaneously implies an increase in punishment. However, it does not explicitly distinguish expressions of support for vigilante justice. Nor did this theme emerge inductively through topic modelling. A more detailed investigation, perhaps using a classifier tailored to detect vigilante discourse or through alternative data collection strategies, could offer valuable insights into how

this socially relevant phenomenon, particularly salient in the Global South (Nivette 2016; Rossi et al. 2017), appears in online conversations.

7.4. Policy implications

The findings of this thesis hold significant academic implications and pave the way for future research. However, they also possess social relevance for policymakers and stakeholders. First and foremost, social media serves as a vital forum for discussing the appropriate punishment for criminals, particularly facilitating the expression and debate of punitive attitudes. The examples discussed in the introduction, such as the cases of Lucas Zanolli in Uruguay and Alesha MacPhail, demonstrate how online networks can influence real-world events, such as the rise of citizen reactions to crime in the form of marches and protests, or exert pressure on key actors within the criminal justice system through directed online messages.

Monitoring online punitive attitudes equips politicians and decision-makers with the foresight needed to address these phenomena effectively. This can lead to informed decision-making tailored to specific contexts, enhanced communication with the press and public, protection for vulnerable individuals online, and educating the general populace about the mechanisms of the criminal justice system. Furthermore, this thesis illustrates a correlation between users' punitive attitudes and political communication on social networks. Such analysis can help politicians mitigate the impact of sudden spikes in punitive attitudes online, while providing external actors with the ability to counterbalance potentially populist measures.

The literature underscores that fluctuations in public opinion regarding punishment can significantly influence criminal policy (Enns 2014; Enns 2016; Jennings et al. 2017), often resulting in economically burdensome strategies that fail to reduce crime, rehabilitate offenders, and may inflict severe human rights violations (Cullen et al. 2011; Liu et al. 2018; Loeffler and Nagin 2022). Both the political sphere and civil society have a vested interest in informing citizens and promoting more effective crime control strategies. By analysing online determinants, stakeholders can disseminate tailored information aimed at those most likely to exhibit extremely punitive attitudes, thereby attempting to weaken – at least – echo chambers and filter bubbles. Additionally, enhancing this thesis with network analysis can identify key agents involved in the spread of these communications and quantify the influence of connections with other punitive individuals on personal attitudes.

Lastly, expanding this thesis to incorporate data from diverse sources (as other online and offline data) could offer a more cost-effective and granular measure of online punitive attitudes compared to surveys, ultimately reducing the costs associated with

tracking public opinion and facilitating options for the political system and society as a whole to react and debate.

7.5. Conclusions

The first and most fundamental question guiding this thesis concerns the manifestation and prevalence of the phenomenon under investigation—the expression of punitive attitudes on social media. Do social media users leverage these platforms to express punitive attitudes? This thesis provides a clear and affirmative answer to this question. However, this finding must be appropriately contextualised. Analysis of responses to crime-related news reveals that approximately 5% of replies reflect punitive attitudes. This number translates to between 12% and 14% of users who engage with such news, expressing at least one punitive opinion. Notably, this pattern is observed similarly in both Uruguay and the UK. By contrast, punitive attitudes are significantly less prevalent in responses to political accounts addressing crime, where the incidence drops to around 1%. This answer aligns with another key research question, which is more methodological in nature: Can computational social science tools effectively detect punitive attitudes online? The application of transformer models in both countries yielded F-scores exceeding the .70 benchmark, confirming the viability of this approach. As natural language processing (NLP) techniques continue to evolve and as multimodal strategies are increasingly integrated, these detection capabilities are anticipated to improve further in future research.

Additionally, this thesis asks about the context in which punitive communications emerge in response to media and political representatives. This objective involved analysing communications from both sources and their general responses. This thesis corroborates several findings from previous studies regarding media reporting of crime. First, violent crime is consistently overrepresented in news coverage. Interestingly, this pattern is observed to a similar extent in both Uruguay and the UK, despite significant differences in the actual incidence of violent crime between the two countries. Second, as highlighted in the literature, crime reporting does not correlate directly with actual crime rates. While reporting levels remain relatively stable over time, this thesis finds that user responses to crime-related news reflect actual fluctuations in crime, suggesting that public engagement may align more closely with actual crime patterns than media coverage itself. Third, there is evidence of an overrepresentation of police effectiveness in media narratives in both countries. This result reinforces prior research indicating that news outlets frequently emphasise

successful law enforcement actions, potentially shaping public perceptions of crime and justice.

Concerning political communications on crime, the findings align with existing literature, which highlights that such communications primarily broadcast information about policymakers' efforts in crime control. User responses to these communications indicate that punitive attitudes remain a minority. However, a notable secondary finding—though peripheral to the core focus of this thesis—is the significant prevalence of antagonistic or distrustful responses directed at the political system. While not directly related to punitive attitudes, this phenomenon holds criminological relevance. Research suggests that distrust in political institutions can influence punitive attitudes and contribute to related phenomena, such as support for vigilante justice.

Following the classification of punitive communications, this thesis examines the determinants of punitive attitudes at both the user and news item levels. The analysis reveals notable commonalities and differences between the United Kingdom and Uruguay. At the user level, factors such as account age, tweet volume, and network size (followers and following) significantly influence the likelihood of expressing punitive attitudes. In both countries, users with older accounts and larger followings are less likely to engage in punitive communications. Conversely, higher tweet activity is correlated with an increased likelihood of punitive expression. Profile characteristics also play a role. Users with profile pictures—particularly those featuring personal images—exhibit lower levels of punitive communication, suggesting a link between anonymity and punitiveness. Additionally, users who describe themselves with professional affiliations demonstrate a reduced likelihood of punitive expression. In contrast, affiliations with sports teams are associated with higher levels of punitive communication in both countries. A key divergence emerges in the role of gender: in the UK, male users are less likely to express punitive attitudes, whereas in Uruguay, gender differences are not statistically significant. At the news level, the characteristics and framing of crime-related content shape the prevalence of punitive responses. News with negative sentiment consistently correlates with heightened punitive reactions, underscoring the influence of emotional framing on public attitudes. Violent crime and murder generate the highest levels of punitive engagement, while theft and fraud elicit comparatively lower responses. Country-specific differences are also observed in media dynamics. In the UK, smaller or regional media outlets attract more punitive engagement than larger national outlets. Conversely, in Uruguay, prominent national media sources elicit higher levels of punitive responses, reflecting the central role of major news channels in shaping

public discourse. The inclusion of specific individuals or locations in crime reports produces varying effects across contexts, suggesting that the personalisation or localisation of crime stories can amplify or attenuate punitive reactions. This multi-layered analysis highlights the critical role that both user characteristics and media framing play in shaping online punitive attitudes, offering a comprehensive perspective on the factors driving public expressions of punitiveness.

The time series analysis offers valuable insights into the temporal dynamics of punitive communications on social media, shedding light on the evolving nature of public responses to crime-related content. By employing ARIMAX models, this analysis demonstrates how fluctuations in online punitive attitudes are correlated with variations in crime news coverage, public engagement, and political discourse. The findings reveal that while certain trends in punitive attitudes persist over time, specific events and outliers exert considerable influence, driving sharp spikes in punitive responses—patterns that static models fail to capture. Public reactions to crime news in both the United Kingdom and Uruguay closely mirror media narratives. Peaks in punitiveness frequently coincide with sensationalised news stories or highly publicised crimes, underscoring the pivotal role of media in shaping public perceptions. However, notable differences emerge in the persistence of punitive attitudes between the two countries. The UK exhibits greater temporal stability, with punitive responses maintaining a more consistent pattern, whereas Uruguay displays sharper, event-driven fluctuations. A critical takeaway from the analysis is the reciprocal relationship between public expressions of punitiveness and political engagement. In Uruguay, public attitudes are correlated with the frequency of political communications related to crime. Despite including official crime statistics in the models, no consistent or significant correlation is found between real-world crime rates and fluctuations in online punitive responses. These findings reinforce the notion that public perceptions of crime—and the punitive attitudes they foster—are more influenced by media representation and political discourse than by objective crime data. This result underscores the intricate interplay between social media dynamics, public sentiment, and the broader socio-political context.

Despite its limitations, this thesis marks a significant step toward renewing the study of punitive attitudes by integrating the online dimension and leveraging tools from computational social sciences. As one of the first exploratory studies in this area, it demonstrates that social media platforms are important arenas for discussions about punishment. The findings suggest that valuable insights can be gained by examining this emerging facet of social life, where public sentiment and discourse increasingly manifest through digital communications.

Appendix

1. Annotator guidelines

English

This project objective is to capture punitive attitudes on social media. We are training an automated classifier for this purpose. As a preliminary step to training this classifier, it is necessary to feed it with examples manually annotated by humans. That's where you come in!

We understand punitive attitudes as the support for measures that increase the cost of crime. In terms of social media communications - you will be working with Twitter data - this implies the expression of support for harsher measures for the treatment of criminals. This includes support for the death penalty, support for longer or life sentences, reduction of rehabilitation policies, criticism of improvements in prison living conditions, among others.

Some examples of punitive attitudes - taken from the database of the project we are working on:

“They need to bring back d*ath by firing squad”

“Unconditional bail????????? Why are yall letting him roam free wtf” – complex one

“Lowlife waste of oxygen, throw away the key”

“@user let those damned devils rot in jail. And may the little Angel rest in peace”

“@user @user Keep him in a small, dark, lice-ridden cell”

Some tweets can be difficult to classify. Some rules can help the classification process:

Tweets should be able to be classified as punitive or non-punitive without any information other than the tweet itself. In some cases, there may be tweets that are punitive given the context, but without knowing the context of the conversation, it is impossible to know for sure. These tweets should be classified as NON-punitive. An example:

“@user Failure of law at it's absolute worst. Despicable.”

Punitive tweets are not the majority of the base. So don't worry if you are slow to find punitive tweets or if you think the distribution of punitive and non-punitive is not even - it shouldn't be.

Read the entire tweet carefully. In many cases it may happen that the tweet contains more than one message, and only part of it expresses punitive attitudes. These tweets should be classified as punitive. An example:

“@user We must remember his name...Peter. Peter would be 15 years old today. The post-mortem revealed he had swallowed a tooth after being punched. Other injuries included a broken back, broken ribs, mutilated fingertips, and missing fingernails. **She should never be let out of prison.**”

Take your time. It is best to do it in short intervals.

The information in many cases is harsh. We are talking about reactions to crime. If at any time you feel it may be too much, please do not hesitate to ask us how we can make it easier for you.

Spanish

Sobre el Proyecto

El objetivo general de este proyecto es el análisis comparativo de las actitudes punitivas en redes sociales (Twitter – X) entre Uruguay y Reino Unido. En esta etapa, estamos entrenando una herramienta de Inteligencia Artificial que permitirá la detección automática de este tipo de comunicaciones, sin la necesidad de la revisión humana tweet a tweet. Como paso previo para el entrenamiento del clasificador, es necesario “alimentar” al algoritmo con algunos ejemplos anotados manualmente por humanos. Aquí es donde te necesito!

Entendemos por actitudes punitivas el apoyo a medidas que incrementan el costo del delito. En términos de comunicaciones en redes sociales, esto implica la expresión de apoyo a medidas más severas para el tratamiento de los criminales. Esto incluye el apoyo a la pena de muerte, el apoyo a penas más largas o de por vida, la reducción de políticas de rehabilitación, el apoyo a condiciones de reclusión degradantes, el escrache o circulación de la identidad de los ofensores, el pedido de “mano dura”, entre otros. Las posibilidades son casi infinitas, por lo que es necesaria cierta creatividad y pensamiento crítico a la hora de determinar si se trata de una “actitud punitiva” o no.

Algunos ejemplos

Estos son algunos ejemplos - tomados de la base de datos con la que estamos trabajando:

- “@user Colón tiene varios lugares donde amontonaron pichaje de lo peor. Hay que arar y prender fuego para matar los yuyos de raíz”
- “@user Lo peor para este roedor!! Pobre chico, q cabeza tan retorcida, es su hijo 😞”
- “@user @user Los violadores no tendrían que salir nunca más !!!”
- “@user @user Pasamos de tirar piedras desde arriba del puente a tirar troncos ???? 😬 Mano dura o lamentablemente tendremos que armarnos.”
- “@user Salvando las distancias, las condenas de robo (que si no me equivoco) son de 45 días a 4 meses, cosa ridícula. Así que no me extraña que un par de años pensando en el rincón por este crimen, sea el único castigo. Porque de rehabilitar en cárcel ni ahí y menos en un psiquiátrico.”
- “@user Se la llevo fácil el hijo de puta. Los vecinos tendrían que haberlos atado a un camión a estas basuras y arrastrarlos por la calle.”
- “@user @user Es de lo ÚNICO que hablamos. Al que delinque PRESO. Si se puede empezar a rehabilitar gente mejor. Este gobierno no va a solucionar en 2 lo que se incrementó en 15. Simple. Si votaste sí, mejor no hables por un tiempo. Defendés delincuentes. Yo no.”
- “@user Me encanta que ahora hay delincuentes abatidos.. si roban los persiguen.. Se acuerdan que hasta hace 2 años nunca atrapaban a los chorros? Los titulares eran otros. Que bien hizo el cambio!”

Guía

Algunos tweets pueden ser difíciles de clasificar. Algunas reglas pueden ayudar en el proceso:

- Los tweets deberían poder clasificarse como punitivos o no-punitivos sin más información que el tweet en sí mismo. En algunos casos, pueden existir tweets que – conociendo el contexto de la discusión – podrían ser considerados punitivos, pero que, sin dicho contexto, es imposible estar seguro. Estos tweets deberían clasificarse como NO-PUNITIVOS. Por ejemplo:
 - “@user Fracasó la ley. Terrible.”
- Los tweets punitivos no son la mayoría de la base. De hecho se trata de una cifra bastante pequeña. Por tanto, no desesperes si ves que demoras en encontrar tweets punitivos o te das cuenta que la distribución no es pareja. No debería serlo.
- Leé el tweet entero y con cuidado. En algunos casos el tweet contiene más de un mensaje y sólo una parte expresa actitudes punitivas. Estos tweets deben ser clasificados como punitivos. Por ejemplo:
 - “@user Cada vez se leen cosas peores , pobrecita esa niña lo q habrá pasado 😬😬 y la madre ? Si estaba amenazada me van a decir , pero ante una muerte de un hijito puede encubrir a un asesino? Pienso q a

ella tmb le corresponde una larga pena ...y quien sabe sino siguió con el monstruo.”

- Tomate tu tiempo, es buena idea trabajar en intervalos cortos y no sobrecargarte.
- No te olvides de revisar los hashtags (#), a veces estos contienen comentarios punitivos (#penademuerte).

Cosas que no son actitudes punitivas

Las actitudes punitivas tienen que tener un componente explícito de castigo al delito. Si esto no está presente, no debería ser considerado punitivo.

Tweets que insultan al criminal pero no piden un castigo específico no son considerados punitivos. Algunos ejemplos (**No-Punitivo**):

- “@user Así se le hace a estos HP k quieren todo fácil y no quieren trabajar 🍌🍌 cucu”
- “@user Rata inmunda.”
- “@user COLIBRÍES ZURDOS ????”

Las críticas al sistema de justicia tampoco son necesariamente punitivas, a menos que explícitamente pidan más castigo o trato más severo de alguna forma. Algunos ejemplos (**No-Punitivos**).

- “@user La justicia no tiene la mas mínima verguenza.”
- “@user Ya debe de estar libre... 😂”
- “@user @user La policia no sirve para nada”

2. Search Keywords

English

Group	Queries
assault_query	"assault, "assaults", "assaulter", "assaulters", "assaulted", "assaulting", "assailant", "assailants"
crime_query	"crime, "crimes", "criminal", "criminals"
drug_query	"criminal gang", "criminal gangs", "drug gang", "drug gangs", "gangster", "organised crime", "illegal drug", "illegal drugs", "drug dealer", "drug dealers", "drug dealing", "drug smuggler", "drug smugglers", "drug smuggling", "drug trafficking", "drug trafficker", "drug traffickers", "drug cartel", "drug cartels", "drug peddler", "drug peddlers", "drug peddling", "cocaine", "mdma", "ecstasy", "ketamine", "heroin", "fentanyl", "meth"
fraud_query	"fraud", "frauds", "frauding", "frauded", "fraudster", "fraudsters", "scam", "scammer", "scams", "scammers", "scammed", "scamming"
murder_query	"murder", "murders", "murderer", "murderers", "murdered", "murdering", "murderess", "murderesses", "homicide", "homicides", "stab", "stabs", "stabbed", "stabbing", "knife crime", "knife-crime", "knife attack", "mugger", "muggers", "mugging", "mugged"
sex_query	"sex offender", "sex offenders", "rape", "raper", "raped", "raping", "rapers", "sex assault", "sexual assault", "sexual predator", "sex predator", "sexual predators", "sex predators", "sex abuse", "sexual abuse", "sex abuser", "sexual abuser", "sex abusers", "sexual abusers", "sexually abused", "sexually abusing", "harassment", "harasser", "harassers", "harassing", "harassed", "domestic violence", "femicide", "feminicide", "domestic abuse", "domestic abuser", "gender violence", "domestic violence", "sexual violence", "sex violence", "sexual victim", "sexual victimisation", "sexual victims", "intimate partner violence"
thief_query	"thief", "thieves", "thieved", "thieving", "theft", "thefts", "burglar", "burglary", "burglars", "burglaries", "robbers", "robbed", "robbing", "robber", "steal", "steals", "stolen", "stealing", "stealer", "stealers", "shoplifting", "shoplifter", "shoplifters", "shoplift", "shoplifted", "pickpocket", "pickpocketing", "pickpockets", "pickpocketed", "pickpocket"

Spanish

Group	Queries
assault_query	"asalto", "asaltos", "asaltante", "asaltantes", "asalta", "asaltan", "asaltaron"
crime_query	"crimen", "crímenes", "criminal", "criminales", "delito", "delitos", "delincuente", "delincuentes", "delictivo", "delictivos"
drug_query	"droga", "drogas", "narco", "narcos", "narcotráfico", "narcotraficante", "narcotraficantes", "narcomenudeo", "cocaína", "pasta base", "éxtasis", "MDMA", "ketamina", "metanfetamina", "metanfetaminas", "heroína", "fentanilo"
fraud_query	"fraude", "fraudes", "estafa", "estafas", "estafó", "estafaron", "estafar", "estafador", "estafadores", "estafado", "estafados"
murder_query	"asesinato", "asesinatos", "asesino", "asesinos", "asesina", "asesinas", "asesinan", "asesinaron", "asesinado", "homicidio", "homicidios", "homicida", "homicidas", "matar", "mataron", "matan", "mató", "rapiña", "rapiñas", "rapiñero", "rapiñeros", "rapiñera", "rapiñeros", "mano armada"
sex_query	"agresor sexual", "agresores sexuales", "agresión sexual", "agrede sexualmente", "agreden sexualmente", "agredieron sexualmente", "agredió sexualmente", "violador", "violadores", "viola", "violan", "violaron", "abusador sexual", "abusadores sexuales", "abuso sexual", "abusa sexualmente", "abusan sexualmente", "abusaron sexualmente", "acoso sexual", "acosador sexual", "acosadores sexuales", "acosa sexualmente", "acosan sexualmente", "acosaron sexualmente", "acoso sexualmente", "femicidio", "feminicidio", "violencia sexual", "violencia doméstica", "violencia de género", "violencia de pareja", "víctima sexual", "victimización sexual", "víctimas sexuales", "abuso doméstico"
thief_query	"ladrón", "ladrona", "ladrones", "ladronas", "robo", "robos", "roba", "roban", "robar", "robaron", "hurto", "hurtos", "hurta", "hurtan", "hurtaron"

3. Politicians list

United Kingdom

Name	Screen name	Party	Constituency	Followers
Zarah Sultana	@zarahsultana	Labour	Coventry South	292655
Yvonne Fovargue	@Y_FovargueMP	Labour	Makerfield	14292
Yvette Cooper	@YvetteCooperMP	Labour	Normanton, Pontefract and Castleford	395057
Yasmin Qureshi	@YasminQureshiMP	Labour	Bolton South East	25619
William Wragg	@William_Wragg	Conservative	Hazel Grove	21112
William Cash	@BillCashMP	Conservative	Stone	20651
Will Quince	@willquince	Conservative	Colchester	22613
Wes Streeting	@wesstreeting	Labour	Ilford North	161092
Wera Hobhouse	@Wera_Hobhouse	Liberal Democrat	Bath	24496
Wendy Morton	@morton_wendy	Conservative	Aldridge-Brownhills	20182
Wendy Chamberlain	@wendychambLD	Liberal Democrat	North East Fife	8070
Wayne David	@WayneDavid_MP	Labour	Caerphilly	15510
Virendra Sharma	@VirendraSharma	Labour	Ealing, Southall	20468
Victoria Prentis	@VictoriaPrentis	Conservative	Banbury	14886
Vicky Foxcroft	@vickyfoxcroft	Labour	Lewisham, Deptford	23208
Vicky Ford	@vickyford	Conservative	Chelmsford	46298
Valerie Vaz	@Valerie_VazMP	Labour	Walsall South	8585
Tulip Siddiq	@TulipSiddiq	Labour	Hampstead and Kilburn	198512
Tracy Brabin	@TracyBrabin	Labour	Batley and Spen	68174
Tracey Crouch	@tracey_crouch	Conservative	Chatham and Aylesford	41766
Tony Lloyd	@tony4rochdale	Labour	Rochdale	9583
Tonia Antoniazzi	@ToniaAntoniazzi	Labour	Gower	18449
Tommy Sheppard	@TommySheppard	Scottish National Party	Edinburgh East	41062
Tom Tugendhat	@TomTugendhat	Conservative	Tonbridge and Malling	139982
Tom Randall	@Tom_Randall	Conservative	Gedling	5301
Tom Pursglove	@VotePursglove	Conservative	Corby	15872
Tom Hunt	@tomhunt1988	Conservative	Ipswich	14529
Toby Perkins	@tobyperkinsmp	Labour	Chesterfield	30574
Tobias Ellwood	@Tobias_Ellwood	Conservative	Bournemouth East	92473
Tim Loughton	@timloughton	Conservative	East Worthing and Shoreham	22508
Tim Farron	@timfarron	Liberal Democrat	Westmorland and Lonsdale	290216
Theresa May	@theresa_may	Conservative	Maidenhead	1018764
Theo Clarke	@theodoraclarke	Conservative	Stafford	9451
Thangam Debbonaire	@ThangamMP	Labour	Bristol West	36789
Tanmanjit Singh Dhesi	@TanDhesi	Labour	Slough	98969
Taiwo Owatemi	@TaiwoOwatemi	Labour	Coventry North West	21433
Tahir Ali	@TahirAliMP	Labour	Birmingham, Hall Green	3851

Suzanne Webb	@Q66Suzi	Conservative	Stourbridge	5707
Suella Fernandes	@SuellaBraverman	Conservative	Fareham	65322
Stuart Paul Anderson	@Stuart4WolvesSW	Conservative	Wolverhampton South West	8513
Stuart C. McDonald	@Stuart_McDonald	Scottish National Party	Cumbernauld, Kilsyth and Kirkintilloch East	13851
Stuart Andrew	@StuartAndrew	Conservative	Pudsey	20882
Stewart Malcolm McDonald	@StewartMcDonald	Scottish National Party	Glasgow South	38919
Stewart Hosie	@StewartHosieSNP	Scottish National Party	Dundee East	28676
Steven Bonnar	@StevenBonnarSNP	Scottish National Party	Coatbridge, Chryston and Bellshill	4184
Steven Baker	@SteveBakerHW	Conservative	Wycombe	158426
Steve Reed	@SteveReedMP	Labour	Croydon North	38672
Steve McCabe	@steve_mccabe	Labour	Birmingham, Selly Oak	19365
Steve Double	@stevedouble	Conservative	St Austell and Newquay	15177
Steve Brine	@BrineMP	Conservative	Winchester	12511
Stephen Timms	@stephenctimms	Labour	East Ham	19618
Stephen Morgan	@StephenMorganMP	Labour	Portsmouth South	17287
Stephen Metcalfe	@Metcalfe_SBET	Conservative	South Basildon and East Thurrock	8544
Stephen McPartland	@SMcPartland	Conservative	Stevenage	16915
Stephen Kinnock	@SKinnock	Labour	Aberavon	37388
Stephen Hammond	@S_Hammond	Conservative	Wimbledon	20523
Stephen Flynn	@StephenFlynnSNP	Scottish National Party	Aberdeen South	10994
Stephen Farry	@StephenFarryMP	Alliance Party of Northern Ireland	North Down	18410
Stephen Doughty	@SDoughtyMP	Labour	Cardiff South and Penarth	36844
Stephen Crabb	@SCrabbPembs	Conservative	Preseli Pembrokeshire	22732
Stephen Barclay	@SteveBarclay	Conservative	North East Cambridgeshire	44504
Stephanie Peacock	@Steph_Peacock	Labour	Barnsley East	11977
Stella Creasy	@stellacreasy	Labour	Walthamstow	160695
Siobhan Baillie	@Siobhan_Baillie	Conservative	Stroud	13654
Siobhain McDonagh	@Siobhain_Mc	Labour	Mitcham and Morden	27498
Simon Lightwood	@simonlightwood	Labour	Wakefield	13220
Simon Jupp	@simonjamesjupp	Conservative	East Devon	8646
Simon Hoare	@Simon4NDorset	Conservative	North Dorset	23509
Simon Hart	@Simonhartmp	Conservative	Carmarthen West and South Pembrokeshire	11987
Simon Fell	@simonfell	Conservative	Barrow and Furness	5287
Simon Clarke	@SimonClarkeMP	Conservative	Middlesbrough South and East Cleveland	24882
Simon Baynes	@baynes_simon	Conservative	Clwyd South	5345
Sheryll Murray	@sheryllmurray	Conservative	South East Cornwall	19236
Shaun Bailey	@Shaun4WBW	Conservative	West Bromwich West	5097
Sharon Hodgson	@SharonHodgsonMP	Labour	Washington and Sunderland West	34957
Shailesh Vara	@ShaileshVara	Conservative	North West Cambridgeshire	6806

Shabana Mahmood	@ShabanaMahmood	Labour	Birmingham, Ladywood	26196
Selaine Saxby	@SelaineSaxby	Conservative	North Devon	5532
Seema Malhotra	@SeemaMalhotra1	Labour	Feltham and Heston	26156
Scott Mann	@scottmann4NC	Conservative	North Cornwall	9754
Scott Lloyd Benton	@ScottBentonMP	Conservative	Blackpool South	8943
Sarah Owen	@SarahOwen_	Labour	Luton North	23444
Sarah Olney	@sarahjolney1	Liberal Democrat	Richmond Park	18424
Sarah Jones	@LabourSJ	Labour	Croydon Central	24087
Sarah Green	@SarahGreenLD	Liberal Democrat	Chesham and Amersham	11255
Sarah Dines	@Dines4Dales	Conservative	Derbyshire Dales	2818
Sarah Champion	@SarahChampionMP	Labour	Rotherham	50964
Sara Britcliffe	@SarBritcliffeMP	Conservative	Hyndburn	7714
Saqib Bhatti	@bhatti_saqib	Conservative	Meriden	8642
Sammy Wilson	@eastantrimmp	Democratic Unionist Party	East Antrim	23914
Sam Tarry	@SamTarry	Labour	Ilford South	37973
Sally-Ann Hart	@SallyAnn1066	Conservative	Hastings and Rye	5572
Sajid Javid	@sajidjavid	Conservative	Bromsgrove	298823
Ruth Jones	@RuthNewportWest	Labour	Newport West	7870
Ruth Edwards	@RuthEdwardsMP	Conservative	Rushcliffe	4431
Ruth Cadbury	@RuthCadbury	Labour	Brentford and Isleworth	23893
Rushanara Ali	@rushanaraali	Labour	Bethnal Green and Bow	48177
Royston Smith	@Royston_Smith	Conservative	Southampton, Itchen	8542
Rosie Duffield	@RosieDuffield1	Labour	Canterbury	50707
Rosie Cooper	@rosie4westlancs	Labour	West Lancashire	15079
Ronnie Cowan	@ronniecowan	Scottish National Party	Inverclyde	13647
Roger Gale	@SirRogerGale	Conservative	North Thanet	13581
Robin Walker	@WalkerWorcester	Conservative	Worcester	16783
Robin John Millar	@RobinMillarMP	Conservative	Aberconwy	4135
Robert Syms	@RobertSyms	Conservative	Poole	13869
Robert Neill	@neill_bob	Conservative	Bromley and Chislehurst	19411
Robert Largan	@robertlargan	Conservative	High Peak	7564
Robert Jenrick	@RobertJenrick	Conservative	Newark	55635
Robert Halfon	@halfon4harlowMP	Conservative	Harlow	37965
Robert Courts	@robertcourts	Conservative	Witney	10868
Robert Buckland	@RobertBuckland	Conservative	South Swindon	31582
Robbie Moore	@_RobbieMoore	Conservative	Keighley	6934
Rob Butler	@AylesburyTories	Conservative	Aylesbury	1053
Rishi Sunak	@RishiSunak	Conservative	Richmond (Yorks)	629169
Richard Holden	@RicHolden	Conservative	North West Durham	11140
Richard Graham	@RichardGrahamUK	Conservative	Gloucester	13698

Richard Gordon Thomson	@RThomsonMP	Scottish National Party	Gordon	3796
Richard Foord	@RichardFoordLD	Liberal Democrat	Tiverton and Honiton	9725
Richard Burgon	@RichardBurgon	Labour	Leeds East	185980
Richard Bacon	@richardbaconmp	Conservative	South Norfolk	1922
Rehman Chishti	@Rehman_Chishti	Conservative	Gillingham and Rainham	22019
Rebecca Pow	@pow_rebecca	Conservative	Taunton Deane	15518
Rebecca Long-Bailey	@RLong_Bailey	Labour	Salford and Eccles	197803
Rebecca Harris	@RebeccaHarrisMP	Conservative	Castle Point	7747
Ranil Jayawardena	@TeamRanil	Conservative	North East Hampshire	2246
Rachel Reeves	@RachelReevesMP	Labour	Leeds West	145609
Rachel Maclean	@redditchrachel	Conservative	Redditch	13490
Rachel Hopkins	@rach_hopkins	Labour	Luton South	9680
Rachael Maskell	@RachaelMaskell	Labour	York Central	36467
Priti Patel	@pritipatel	Conservative	Witham	426509
Preet Gill	@PreetKGillMP	Labour	Birmingham, Edgbaston	43093
Philip Dunne	@Dunne4Ludlow	Conservative	Ludlow	13139
Philip Davies	@PhilipDaviesUK	Conservative	Shipley	21844
Peter Kyle	@peterkyle	Labour	Hove	53675
Peter Grant	@PeterGrantMP	Scottish National Party	Glenrothes	16837
Peter Gibson	@Gibbo4Darlo	Conservative	Darlington	4633
Peter Dowd	@Peter_Dowd	Labour	Bootle	18706
Peter Bottomley	@PBottomleyMP	Conservative	Worthing West	6039
Peter Bone	@PeterBoneUK	Conservative	Wellingborough	47415
Peter Aldous	@peter_aldous	Conservative	Waveney	14798
Pete Wishart	@PeteWishart	Scottish National Party	Perth and North Perthshire	58338
Penny Mordaunt	@PennyMordaunt	Conservative	Portsmouth North	159023
Pauline Latham	@Pauline_Latham	Conservative	Mid Derbyshire	22153
Paula Barker	@PaulaBarkerMP	Labour	Liverpool, Wavertree	17590
Paul Scully	@scullyp	Conservative	Sutton and Cheam	17631
Paul Maynard	@PaulMaynardUK	Conservative	Blackpool North and Cleveleys	19601
Paul Maskey	@PaulMaskeyMP	Sinn Féin	Belfast West	20496
Paul Howell	@PaulHowellMP	Conservative	Sedgefield	4165
Paul Holmes	@pauljholmes	Conservative	Eastleigh	8270
Paul Girvan	@PaulGirvanMP	Democratic Unionist Party	South Antrim	6526
Paul Bristow	@paulbristow79	Conservative	Peterborough	11244
Paul Blomfield	@PaulBlomfieldMP	Labour	Sheffield Central	22652
Patrick Grady	@GradySNP	Scottish National Party	Glasgow North	16985
Patricia Gibson	@PGibsonSNP	Scottish National Party	North Ayrshire and Arran	13489
Pat McFadden	@patmcfaddenmp	Labour	Wolverhampton South East	28717
Owen Thompson	@OwenThompson	Scottish National Party	Midlothian	8506

Árthlaith Begley	@OrfhlaithBegley	Sinn Féin	West Tyrone	8916
Olivia Frances Blake	@_OliviaBlake	Labour	Sheffield, Hallam	18355
Oliver Heald QC	@OliverHealdUK	Conservative	North East Hertfordshire	12293
Oliver Dowden	@OliverDowden	Conservative	Hertsmere	44973
Nusrat Ghani	@Nus_Ghani	Conservative	Wealden	29998
Nigel Mills	@nigelmills	Conservative	Amber Valley	6869
Nigel Huddleston	@HuddlestonNigel	Conservative	Mid Worcestershire	19757
Nigel Evans	@nigelmp	Conservative	Ribble Valley	13740
Nigel Adams	@nadams	Conservative	Selby and Ainsty	14958
Nicola Faye Richards	@Nicola4WBE	Conservative	West Bromwich East	10173
Nickie Aiken	@twocitiesnickie	Conservative	Cities of London and Westminster	5268
Nick Thomas-Symonds	@NickTorfaen	Labour	Torfaen	34871
Nick Smith	@BlaenauGwentMP	Labour	Blaenau Gwent	11085
Nick Gibb	@NickGibbUK	Conservative	Bognor Regis and Littlehampton	18622
Nicholas Fletcher	@NickFletcherMP	Conservative	Don Valley	5405
Nia Griffith	@NiaGriffithMP	Labour	Llanelli	19042
Neil O'Brien	@NeilDotObrien	Conservative	Harborough	34542
Neil Hudson	@DrNeilHudson	Conservative	Penrith and The Border	4831
Neil Coyle	@coyleneil	Labour	Bermondsey and Old Southwark	28897
Neale Hanvey	@JNHanvey	Scottish National Party	Kirkcaldy and Cowdenbeath	9610
Naz Shah	@NazShahBfd	Labour	Bradford West	61077
Nav Mishra	@NavPMishra	Labour	Stockport	13365
Natalie Elphicke	@NatalieElphicke	Conservative	Dover	7890
Nadine Dorries	@NadineDorries	Conservative	Mid Bedfordshire	161332
Nadia Whittome	@NadiaWhittomeMP	Labour	Nottingham East	107759
Nadhim Zahawi	@nadhimzahawi	Conservative	Stratford-on-Avon	102530
Munira Wilson	@munirawilson	Liberal Democrat	Twickenham	17793
Mohammad Yasin	@YasinForBedford	Labour	Bedford	3446
Mims Davies	@mimsdaves	Conservative	Mid Sussex	17980
Mike Wood	@mikejwood	Conservative	Dudley South	8169
Mike Kane	@MikeKaneMP	Labour	Wythenshawe and Sale East	12505
Mike Amesbury	@MikeAmesburyMP	Labour	Weaver Vale	12443
Mickey Brady	@MickeyBradySF	Sinn Féin	Newry and Armagh	5444
Mick Whitley	@MickWhitleyMP	Labour	Birkenhead	13838
Michelle Gildernew	@gildernewm	Sinn Féin	Fermanagh and South Tyrone	21249
Michelle Donelan	@michelledonelan	Conservative	Chippenham	28080
Michael Tomlinson	@Michael4MDNP	Conservative	Mid Dorset and North Poole	11380
Michael Gove	@michaelgove	Conservative	Surrey Heath	247832
Michael Fabricant	@Mike_Fabricant	Conservative	Lichfield	59471
Michael Ellis	@Michael_Ellis1	Conservative	Northampton North	15756
Mhairi Black	@MhairiBlack	Scottish National Party	Paisley and Renfrewshire South	231266

Mel Stride	@MeUStride	Conservative	Central Devon	7021
Meg Hillier	@Meg_HillierMP	Labour	Hackney South and Shoreditch	21262
Matthew Pennycook	@mtpennycook	Labour	Greenwich and Woolwich	24668
Matthew Offord	@Offord4Hendon	Conservative	Hendon	10905
Matthew Hancock	@MattHancock	Conservative	West Suffolk	422168
Matt Western	@MattWestern_	Labour	Warwick and Leamington	13381
Matt Warman	@mattwarman	Conservative	Boston and Skegness	20207
Matt Vickers	@Matt_VickersMP	Conservative	Stockton South	7538
Matt Rodda	@MattRodda	Labour	Reading East	7648
Mary Robinson	@MaryRobinson01	Conservative	Cheadle	11192
Mary Glendon	@GlendonMary	Labour	North Tyneside	1467
Mary Foy	@marykfoy	Labour	City of Durham	17476
Martyn Day	@MartynDaySNP	Scottish National Party	Linlithgow and East Falkirk	11492
Martin Vickers	@MartinVickers	Conservative	Cleethorpes	12993
Martin Docherty-Hughes	@MartinJDocherty	Scottish National Party	West Dunbartonshire	14327
Marsha de Cordova	@MarshadeCordova	Labour	Battersea	41777
Mark Tami	@MarkTamiMP	Labour	Alyn and Deeside	10317
Mark Spencer	@Mark_Spencer	Conservative	Sherwood	22483
Mark Pritchard	@MPritchardUK	Conservative	The Wrekin	12502
Mark Pawsey	@MarkPawsey	Conservative	Rugby	8612
Mark Jenkinson	@markjenkinsonmp	Conservative	Workington	12232
Mark Hendrick	@MpHendrick	Labour	Preston	6040
Mark Harper	@Mark_J_Harper	Conservative	Forest of Dean	48424
Mark Garnier	@Mark4WyreForest	Conservative	Wyre Forest	16838
Mark Eastwood	@mark4dewsbury	Conservative	Dewsbury	5650
Marion Fellows	@marionfellows	Scottish National Party	Motherwell and Wishaw	12756
Marie Rimmer	@MarieRimmer	Labour	St Helens South and Whiston	13985
Maria Miller	@MariaMillerUK	Conservative	Basingstoke	21686
Maria Eagle	@meaglemp	Labour	Garston and Halewood	48384
Maria Caulfield	@mariacaulfield	Conservative	Lewes	24306
Margaret Hodge	@margarethodge	Labour	Barking	55766
Margaret Greenwood	@MGreenwoodWW	Labour	Wirral West	22586
Margaret Ferrier	@MargaretFerrier	Independent	Rutherglen and Hamilton West	15934
Marcus Jones	@Marcus4Nuneaton	Conservative	Nuneaton	11108
Marcus Fysh	@MarcusFysh	Conservative	Yeovil	25777
Marco Longhi	@marcolonghi4dn	Conservative	Dudley North	5450
Maggie Throup	@maggie_erewash	Conservative	Erewash	4133
Lyn Brown	@lynbrownmp	Labour	West Ham	14811
Luke Pollard	@LukePollard	Labour	Plymouth, Sutton and Devonport	44444
Luke Hall	@LukeHall	Conservative	Thornbury and Yate	5777
Luke Evans	@drlukeevans	Conservative	Bosworth	10701

Lucy Powell	@LucyMPowell	Labour	Manchester Central	65207
Lucy Frazer	@lucyfrazermp	Conservative	South East Cambridgeshire	10598
Lucy Allan	@lucyallan	Conservative	Telford	32957
Louise Haigh	@LouHaigh	Labour	Sheffield, Heeley	58679
Louie French	@louie_french	Conservative	Old Bexley and Sidcup	5348
Lloyd Russell-Moyle	@lloyd_rm	Labour	Brighton, Kemptown	32947
Liz Twist	@LizTwistMP	Labour	Blaydon	4901
Liz Saville Roberts	@LSRPlaid	Plaid Cymru	Dwyfor Meirionnydd	22041
Liz Kendall	@leicesterliz	Labour	Leicester West	96212
Lisa Nandy	@lisanandy	Labour	Wigan	278072
Lisa Cameron	@DrLisaCameronMP	Scottish National Party	East Kilbride, Strathaven and Lesmahagow	14684
Lindsay Hoyle	@LindsayHoyle_MP	Speaker	Chorley	41798
Lilian Greenwood	@LilianGreenwood	Labour	Nottingham South	30648
Liam Byrne	@liambyrnemp	Labour	Birmingham, Hodge Hill	38608
Lia Nici	@lia_nici	Conservative	Great Grimsby	4897
Leo Docherty	@LeoDochertyUK	Conservative	Aldershot	9448
Lee Benjamin Rowley	@Lee4NED	Conservative	North East Derbyshire	11145
Layla Moran	@LaylaMoran	Liberal Democrat	Oxford West and Abingdon	80296
Laurence Robertson	@lrobertsonTewks	Conservative	Tewkesbury	5282
Laura Farris	@Laura__Farris	Conservative	Newbury	8307
Kwasi Kwarteng	@KwasiKwarteng	Conservative	Spelthorne	49762
Kit Malthouse	@kitmalthouse	Conservative	North West Hampshire	22996
Kirsty Blackman	@KirstySNP	Scottish National Party	Aberdeen North	27439
Kirsten Oswald	@kirstenoswald	Scottish National Party	East Renfrewshire	16819
Kim Johnson	@KimJohnsonMP	Labour	Liverpool, Riverside	18723
Kieran John Mullan	@KieranMullanUK	Conservative	Crewe and Nantwich	5231
Khalid Mahmood	@khalid4PB	Labour	Birmingham, Perry Barr	7450
Kevin Hollinrake	@kevinhollinrake	Conservative	Thirsk and Malton	13086
Kevin Foster	@kevin_j_foster	Conservative	Torbay	9265
Kevin Brennan	@KevinBrennanMP	Labour	Cardiff West	26828
Kevan Jones	@KevanJonesMP	Labour	North Durham	23721
Kerry McCarthy	@KerryMP	Labour	Bristol East	33077
Kenny MacAskill	@KennyMacAskill	Scottish National Party	East Lothian	20018
Kemi Badenoch	@KemiBadenoch	Conservative	Saffron Walden	126063
Kelly Tolhurst	@KellyTolhurst	Conservative	Rochester and Strood	16246
Keir Starmer	@Keir_Starmer	Labour	Holborn and St Pancras	1289638
Katherine Fletcher	@K_Fletcher_MP	Conservative	South Ribble	5476
Kate Osborne	@KateOsborneMP	Labour	Jarrow	21014
Kate Osamor	@KateOsamor	Labour	Edmonton	36726
Kate Hollern	@Kate_HollernMP	Labour	Blackburn	10463
Kate Green	@KateGreenSU	Labour	Stretford and Urmston	50927

Karl Turner	@KarlTurnerMP	Labour	Kingston upon Hull East	45722
Karl McCartney	@karlmccartney	Conservative	Lincoln	11763
Karin Smyth	@karinsmyth	Labour	Bristol South	15143
Karen Buck	@KarenPBuckMP	Labour	Westminster North	19022
Justin Tomlinson	@JustinTomlinson	Conservative	North Swindon	21885
Justin Madders	@justinmadders	Labour	Ellesmere Port and Neston	31254
Julie Marson	@JulieMarsonMP	Conservative	Hertford and Stortford	5328
Julie Elliott	@JulieElliottMP	Labour	Sunderland Central	22523
Julian Sturdy	@JulianSturdy	Conservative	York Outer	3525
Julian Smith	@JulianSmithUK	Conservative	Skipton and Ripon	38324
Julian Knight	@julianknight15	Conservative	Solihull	14060
Julia Lopez	@JuliaLopezMP	Conservative	Hornchurch and Upminster	8867
Judith Cummins	@JudithCummins	Labour	Bradford South	15636
Joy Morrissey	@joymorrissey	Conservative	Beaconsfield	19323
Jonathan Reynolds	@jreynoldsMP	Labour	Stalybridge and Hyde	54819
Jonathan Lord	@JonathanLord	Conservative	Woking	3451
Jonathan Djanogly	@JDjanogly	Conservative	Huntingdon	19906
Jonathan Ashworth	@JonAshworth	Labour	Leicester South	118129
Jon Trickett	@jon_trickett	Labour	Hemsworth	96344
Jon Cruddas	@JonCruddas_1	Labour	Dagenham and Rainham	22096
Johnny Mercer	@JohnnyMercerUK	Conservative	Plymouth, Moor View	125189
Johnny McNally	@JohnMcNallySNP	Scottish National Party	Falkirk	9612
John Whittingdale	@JWhittingdale	Conservative	Maldon	9188
John Stevenson	@John4Carlisle	Conservative	Carlisle	14803
John Spellar	@spellar	Labour	Warley	12130
John Redwood	@johnredwood	Conservative	Wokingham	154705
John Penrose	@JohnPenroseNews	Conservative	Weston-super-Mare	38332
John Nicolson	@MrJohnNicolson	Scottish National Party	Ochil and South Perthshire	48901
John McDonnell	@johnmcdonnellMP	Labour	Hayes and Harlington	319860
John Lamont	@John2Win	Conservative	Berwickshire, Roxburgh and Selkirk	12700
John Howell	@JHowellUK	Conservative	Henley	8905
John Healey	@JohnHealey_MP	Labour	Wentworth and Dearne	33331
John Glen	@JohnGlenUK	Conservative	Salisbury	25632
John Finucane	@johnfinucane	Sinn Féin	Belfast North	38429
John Cryer	@JohnCryerMP	Labour	Leyton and Wanstead	7055
Joanna Cherry QC	@joannaccherry	Scottish National Party	Edinburgh South West	122574
Jo Stevens	@JoStevensLabour	Labour	Cardiff Central	34956
Jo Gideon	@jogideon	Conservative	Stoke-on-Trent Central	6008
Jo Churchill	@Jochurchill_MP	Conservative	Bury St Edmunds	14843
Jim Shannon	@JimShannonMP	Democratic Unionist Party	Strangford	4499
Jim McMahon	@JimfromOldham	Labour	Oldham West and Royton	29418

Jessica Morden	@jessicamordenmp	Labour	Newport East	15562
Jesse Norman	@Jesse_Norman	Conservative	Hereford and South Herefordshire	30530
Jess Phillips	@jessphillips	Labour	Birmingham, Yardley	574553
Jerome Mayhew	@JeromeMayhew	Conservative	Broadland	3653
Jeremy Hunt	@Jeremy_Hunt	Conservative	South West Surrey	233188
Jeremy Corbyn	@jeremycorbyn	Independent	Islington North	2495685
Jeffrey M. Donaldson	@J_Donaldson_MP	Democratic Unionist Party	Lagan Valley	31287
Jeff Smith	@JeffSmithetc	Labour	Manchester, Withington	11769
Jason McCartney	@JasonMcCartney	Conservative	Colne Valley	18289
Janet Daby	@JanetDaby	Labour	Lewisham East	12817
Jane Stevenson	@Jane_Stevenson_	Conservative	Wolverhampton North East	6292
Jane Hunt	@JaneMHunt	Conservative	Loughborough	4019
Jamie Stone	@Jamie4North	Liberal Democrat	Caithness, Sutherland and Easter Ross	14485
Jamie Hamilton Wallis	@JamieWallisMP	Conservative	Bridgend	8053
James Wild	@jamesowild	Conservative	North West Norfolk	3375
James Sunderland	@JamesSunderl	Conservative	Bracknell	4683
James Murray	@jamesmurray_ldn	Labour	Ealing North	9628
James Morris	@JamesMorris	Conservative	Halesowen and Rowley Regis	10609
James Heappey	@JSheappey	Conservative	Wells	21936
James Gray	@JGray	Conservative	North Wiltshire	19348
James Duddridge	@JamesDuddridge	Conservative	Rochford and Southend East	32507
James Davies	@JamesDavies	Conservative	Vale of Clwyd	6511
James Daly	@JamesDalyMP	Conservative	Bury North	6377
James Cleverly	@JamesCleverly	Conservative	Braintree	136567
James Cartlidge	@jcartlidgemp	Conservative	South Suffolk	11244
Jake Berry	@JakeBerry	Conservative	Rossendale and Darwen	21905
Jacob Young	@JacobYoungMP	Conservative	Redcar	12840
Jacob Rees-Mogg	@Jacob_Rees_Mogg	Conservative	North East Somerset	476300
Jackie Doyle-Price	@JackieDP	Conservative	Thurrock	14474
Jack Lopresti	@JackLopresti	Conservative	Filton and Bradley Stoke	10078
Jack Dromey	@JackDromeyMP	Labour	Birmingham, Erdington	24808
Imran Hussain	@Imran_HussainMP	Labour	Bradford East	22822
Ian Murray	@IanMurrayMP	Labour	Edinburgh South	34500
Ian Mearns	@IanMearnsMP	Labour	Gateshead	28655
Ian Lavery	@IanLaveryMP	Labour	Wansbeck	96175
Ian Byrne	@IanByrneMP	Labour	Liverpool, West Derby	43059
Ian Blackford	@ianblackford_MP	Scottish National Party	Ross, Skye and Lochaber	180639
Iain Stewart	@iainastewart	Conservative	Milton Keynes South	19993
Iain Duncan Smith	@MPlainDS	Conservative	Chingford and Woodford Green	63870
Hywel Williams	@HywelPlaidCymru	Plaid Cymru	Arfon	10656
Huw Merriman	@HuwMerriman	Conservative	Bexhill and Battle	21441

Holly Lynch	@HollyLynch5	Labour	Halifax	30816
Hilary Benn	@hilarybennmp	Labour	Leeds Central	172034
Henry Smith	@HenrySmithUK	Conservative	Crawley	17905
Helen Whately	@Helen_Whately	Conservative	Faversham and Mid Kent	25276
Helen Morgan	@HelenMorganMP	Liberal Democrat	North Shropshire	14991
Helen Hayes	@helenhayes_	Labour	Dulwich and West Norwood	27084
Helen Grant	@HelenGrantMP	Conservative	Maidstone and The Weald	23078
Heather Wheeler	@HeatherWheeler	Conservative	South Derbyshire	21530
Harriett Baldwin	@hbaldwin	Conservative	West Worcestershire	28844
Harriet Harman QC	@HarrietHarman	Labour	Camberwell and Peckham	191114
Hannah Bardell	@HannahB4LiviMP	Scottish National Party	Livingston	26345
Guy Opperman	@GuyOpperman	Conservative	Hexham	24536
Greg Smith	@gregsmith_uk	Conservative	Buckingham	8882
Greg Knight	@GregKnight	Conservative	East Yorkshire	12145
Greg Hands	@GregHands	Conservative	Chelsea and Fulham	47916
Greg Clark	@GregClarkMP	Conservative	Tunbridge Wells	33739
Grant Shapps	@grantshapps	Conservative	Welwyn Hatfield	175508
Grahame Morris	@grahamemorris	Labour	Easington	33225
Graham Stuart	@grahamstuart	Conservative	Beverley and Holderness	19908
Graham Brady	@SirGrahamBrady	Conservative	Altrincham and Sale West	24390
Gillian Keegan	@GillianKeegan	Conservative	Chichester	16765
Gill Furniss	@GillFurnissMP	Labour	Sheffield, Brightside and Hillsborough	7715
Giles Watling	@GilesWatling	Conservative	Clacton	4880
Gerald Jones	@GeraldJonesLAB	Labour	Merthyr Tydfil and Rhymney	8140
Geraint Davies	@GeraintDaviesMP	Labour	Swansea West	17328
George Freeman	@GeorgeFreemanMP	Conservative	Mid Norfolk	32817
Geoffrey Cox QC	@Geoffrey_Cox	Conservative	Torridge and West Devon	40358
Gavin Williamson	@GavinWilliamson	Conservative	South Staffordshire	104742
Gavin Robinson	@GRobinsonDUP	Democratic Unionist Party	Belfast East	15151
Gavin Newlands	@GavNewlandsSNP	Scottish National Party	Paisley and Renfrewshire North	14805
Gary Streeter	@garystreeterSWD	Conservative	South West Devon	5833
Gary Sambrook	@GarySambrook89	Conservative	Birmingham, Northfield	6140
Gareth Thomas	@GarethThomasMP	Labour	Harrow West	18201
Gareth Davies	@GarethDavies_MP	Conservative	Grantham and Stamford	7388
Gareth Bacon	@GarethBaconMP	Conservative	Orpington	6816
Gagan Mohindra	@gaganmohindra	Conservative	South West Hertfordshire	5293
Francie Molloy	@FrancieMolloy	Sinn Féin	Mid Ulster	13008
Florence Eshalomi	@FloEshalomi	Labour	Vauxhall	31437
Fleur Anderson	@PutneyFleur	Labour	Putney	17405
Fiona Bruce	@UK_FoRBEvny	Conservative	Congleton	3346
Feryal Clark	@FeryalClark	Labour	Enfield North	12813

Felicity Buchan	@FelicityBuchan	Conservative	Kensington	7728
Fay Alicia Jones	@JonesyFay	Conservative	Brecon and Radnorshire	7256
Fabian Hamilton	@FabianLeedsNE	Labour	Leeds North East	7399
Esther McVey	@EstherMcVey1	Conservative	Tatton	76991
Emma Lewell-Buck	@EmmaLewellBuck	Labour	South Shields	28018
Emma Hardy	@EmmaHardyMP	Labour	Kingston upon Hull West and Hessle	30352
Emily Thornberry	@EmilyThornberry	Labour	Islington South and Finsbury	261574
Elliot Colburn	@ElliotColburn	Conservative	Carshalton and Wallington	8960
Ellie Reeves	@elliereeves	Labour	Lewisham West and Penge	26154
Elizabeth Truss	@trussliz	Conservative	South West Norfolk	611303
Eleanor Laing	@eleanor4epping	Conservative	Epping Forest	14371
Edward Timpson	@edwardtimpson	Conservative	Eddisbury	7105
Edward Miliband	@Ed_Miliband	Labour	Doncaster North	788166
Edward Leigh	@EdwardLeighMP	Conservative	Gainsborough	16194
Edward Davey	@EdwardJDavey	Liberal Democrat	Kingston and Surbiton	91459
Eddie Hughes	@EddieHughes4WN	Conservative	Walsall North	13393
Duncan Charles Baker	@duncancbaker	Conservative	North Norfolk	5010
Drew Hendry	@drewhendrySNP	Scottish National Party	Inverness, Nairn, Badenoch and Strathspey	16392
Dr Theresa Coffey	@theresecoffey	Conservative	Suffolk Coastal	38010
Dr Rupa Huq	@RupaHuq	Labour	Ealing Central and Acton	50099
Dr Rosena Allin-Khan	@DrRosena	Labour	Tooting	209161
Dr Philippa Whitford	@Dr_PhilippaW	Scottish National Party	Central Ayrshire	40233
Dr Liam Fox	@LiamFox	Conservative	North Somerset	106054
Dr Caroline Johnson	@drcarolinej	Conservative	Sleaford and North Hykeham	7499
Dr Andrew Murrison	@AWMurrison	Conservative	South West Wiltshire	17249
Dr Alan Whitehead	@alanwhiteheadmp	Labour	Southampton, Test	8746
Douglas Ross	@Douglas4Moray	Conservative	Moray	41312
Douglas Chapman	@DougChapmanSNP	Scottish National Party	Dunfermline and West Fife	15723
Dominic Raab	@DominicRaab	Conservative	Esher and Walton	351109
Diane Abbott	@HackneyAbbott	Labour	Hackney North and Stoke Newington	404696
Diana Johnson	@DianaJohnsonMP	Labour	Kingston upon Hull North	30538
Desmond Swayne	@DesmondSwayne	Conservative	New Forest West	65675
Derek Twigg	@DerekTwiggMP	Labour	Halton	7065
Derek Thomas	@DerekThomasUK	Conservative	St Ives	6666
Deidre Brock	@DeidreBrock	Scottish National Party	Edinburgh North and Leith	17387
Dehenna Davison	@DehennaDavison	Conservative	Bishop Auckland	56589
Debbie Abrahams	@Debbie_abrahams	Labour	Oldham East and Saddleworth	54300
Dean Russell	@dean4watford	Conservative	Watford	5307
Dawn Butler	@DawnButlerBrent	Labour	Brent Central	245820
David Warburton	@DJWarburton	Conservative	Somerton and Frome	16792
David T. C. Davies	@DavidTCDavies	Conservative	Monmouth	16277

David Simmonds	@DSimmonds_RNP	Conservative	Ruislip, Northwood and Pinner	4487
David Rutley	@DavidRutley	Conservative	Macclesfield	14699
David Mundell	@DavidMundellDCT	Conservative	Dumfriesshire, Clydesdale & Tweeddale	17241
David Morris	@davidmorrisml	Conservative	Morecambe and Lunesdale	15395
David Linden	@DavidLinden	Scottish National Party	Glasgow East	13255
David Lammy	@DavidLammy	Labour	Tottenham	789168
David Jones	@DavidJonesMP	Conservative	Clwyd West	17682
David Johnston	@david4wantage	Conservative	Wantage	3304
David Evennett	@DavidEvennettMP	Conservative	Bexleyheath and Crayford	14879
David Duguid	@david_duguid	Conservative	Banff and Buchan	6681
David Davis	@DavidDavisMP	Conservative	Haltemprice and Howden	190519
Dave Doogan	@DaveDooganSNP	Scottish National Party	Angus	4759
Darren Jones	@darrenpjones	Labour	Bristol North West	35993
Darren George Henry	@DarrenG_Henry	Conservative	Broxtowe	10855
Danny Kruger	@danny__kruger	Conservative	Devizes	12697
Daniel Zeichner	@DanielZeichner	Labour	Cambridge	21747
Daniel Kawczynski	@DKShrewsbury	Conservative	Shrewsbury and Atcham	25596
Dan Jarvis	@DanJarvisMP	Labour	Barnsley Central	75075
Dan Carden	@DanCardenMP	Labour	Liverpool, Walton	53847
Damian Hinds	@DamianHinds	Conservative	East Hampshire	33943
Damian Green	@DamianGreen	Conservative	Ashford	22263
Damian Collins	@DamianCollins	Conservative	Folkestone and Hythe	30616
Daisy Cooper	@libdemdaisy	Liberal Democrat	St Albans	28456
Crispin Blunt	@CrispinBlunt	Conservative	Reigate	12519
Craig Williams	@craig4monty	Conservative	Montgomeryshire	5830
Craig Whittaker	@CWhittaker_MP	Conservative	Calder Valley	9962
Craig Tracey	@craig4nwards	Conservative	North Warwickshire	10500
Craig Mackinlay	@cmackinlay	Conservative	South Thanet	13833
Conor McGinn	@ConorMcGinn	Labour	St Helens North	18646
Conor Burns	@ConorBurnsUK	Conservative	Bournemouth West	27132
Colum Eastwood	@columeastwood	Social Democratic and Labour Party	Foyle	49754
Clive Lewis	@labourlewis	Labour	Norwich South	120497
Clive Efford	@CliveEfford	Labour	Eltham	15643
Claudia Webbe	@ClaudiaWebbe	Independent	Leicester East	77712
Claire Hanna	@ClaireHanna	Social Democratic and Labour Party	Belfast South	43369
Claire Coutinho	@ClaireCoutinho	Conservative	East Surrey	9998
Christopher Pincher	@ChrisPincher	Conservative	Tamworth	21715
Christopher Hazzard	@ChrisHazzardSF	Sinn Féin	South Down	25727
Christine Jardine	@cajardineMP	Liberal Democrat	Edinburgh West	15168
Christina Rees	@Rees4Neath	Labour	Neath	12510

Christian Wakeford	@Christian4BuryS	Labour	Bury South	14722
Christian Matheson	@ChrisM4Chester	Labour	City of Chester	16429
Chris Stephens	@ChrisStephens	Scottish National Party	Glasgow South West	17841
Chris Skidmore	@CSkidmoreUK	Conservative	Kingswood	26798
Chris Philp	@CPhilpOfficial	Conservative	Croydon South	16390
Chris Loder	@chrisloder	Conservative	West Dorset	7476
Chris Law	@ChrisLawSNP	Scottish National Party	Dundee West	20043
Chris Heaton-Harris	@chhcalling	Conservative	Daventry	28714
Chris Green	@CGreenUK	Conservative	Bolton West	15295
Chris Evans	@Chris_EvansMP	Labour	Islwyn	7571
Chris Elmore	@CPJElmore	Labour	Ogmore	14819
Chris Clarkson	@ChrisClarksonMP	Conservative	Heywood and Middleton	7087
Chris Bryant	@RhonddaBryant	Labour	Rhondda	229560
Chloe Smith	@NorwichChloe	Conservative	Norwich North	22413
Chi Onwurah	@ChiOnwurah	Labour	Newcastle upon Tyne Central	46670
Cherilyn Mackrory	@thisischerilyn	Conservative	Truro and Falmouth	4532
Charlotte Nichols	@charlotte2153	Labour	Warrington North	24229
Charles Walker	@CharlesWalkerMP	Conservative	Broxbourne	28899
Catherine West	@CatherineWest1	Labour	Hornsey and Wood Green	33531
Catherine McKinnell	@CatMcKinnell	Labour	Newcastle upon Tyne North	28831
Cat Smith	@CatSmithMP	Labour	Lancaster and Fleetwood	43353
Carolyn Harris	@carolynharris24	Labour	Swansea East	32791
Caroline Nokes	@carolinenokes	Conservative	Romsey and Southampton North	28234
Caroline Lucas	@CarolineLucas	Green Party	Brighton, Pavilion	590307
Caroline Dinenage	@cj_dinenage	Conservative	Gosport	23028
Caroline Ansell	@Caroline_Ansell	Conservative	Eastbourne	6507
Carol Monaghan	@CMonaghanSNP	Scottish National Party	Glasgow North West	21113
Carla Lockhart	@carlalockhart	Democratic Unionist Party	Upper Bann	13099
Bridget Phillipson	@bphillipsonMP	Labour	Houghton and Sunderland South	55175
Brendan O'Hara	@BrendanOHaraMP	Scottish National Party	Argyll and Bute	15306
Brendan Clarke-Smith	@Bren4Bassetlaw	Conservative	Bassetlaw	9079
Brandon Lewis	@BrandonLewis	Conservative	Great Yarmouth	65651
Boris Johnson	@BorisJohnson	Conservative	Uxbridge and South Ruislip	4668035
Bob Seely	@IoWBobSeely	Conservative	Isle of Wight	15671
Bob Blackman	@BobBlackman	Conservative	Harrow East	33114
Bim Afolami	@BimAfolami	Conservative	Hitchin and Harpenden	17093
Bill Esterson	@Bill_Esterson	Labour	Sefton Central	40727
Beth Winter	@BethWinterMP	Labour	Cynon Valley	12972
Bernard Jenkin	@bernardjenkin	Conservative	Harwich and North Essex	38758
Ben Wallace	@BWallaceMP	Conservative	Wyre and Preston North	73859
Ben Spencer	@DrBenSpencer	Conservative	Runnymede and Weybridge	7825

Ben Lake	@BenMLake	Plaid Cymru	Ceredigion	8779
Ben Everitt	@Ben_Everitt	Conservative	Milton Keynes North	9200
Ben Bradshaw	@BenPBradshaw	Labour	Exeter	79582
Ben Bradley	@BBradley_Mans	Conservative	Mansfield	34249
Bell Ribeiro-Addy	@BellRibeiroAddy	Labour	Streatham	64686
Barry Sheerman	@BarrySheerman	Labour	Huddersfield	24176
Barry Gardiner	@BarryGardiner	Labour	Brent North	98587
Barbara Keeley	@KeeleyMP	Labour	Worsley and Eccles South	27535
Bambos Charalambous	@Bambos_MP	Labour	Enfield, Southgate	12083
Apsana Begum	@ApsanaBegumMP	Labour	Poplar and Limehouse	41246
Anum Qaisar	@AnumSNP	Scottish National Party	Airdrie and Shotts	21327
Antony Higginbotham	@antony_hig	Conservative	Burnley	4524
Anthony Mangnall	@AnthonyMangnal1	Conservative	Totnes	9947
Anthony Browne	@ab4scams	Conservative	South Cambridgeshire	6128
Anneliese Dodds	@AnnelieseDodds	Labour	Oxford East	79253
Anne-Marie Trevelyan	@annietrev	Conservative	Berwick-upon-Tweed	34429
Anne McLaughlin	@AnneMcLaughlin	Scottish National Party	Glasgow North East	14251
Anne Marie Morris	@AnneMarieMorris	Conservative	Newton Abbot	22306
Anna McMorris	@AnnaMcMorris	Labour	Cardiff North	18862
Anna Firth	@Anna_Firth	Conservative	Southend West	11880
Angus MacNeil	@AngusMacNeilSNP	Scottish National Party	Na h-Eileanan an Iar	45451
Angela Richardson	@AJRichardsonMP	Conservative	Guildford	14968
Angela Rayner	@AngelaRayner	Labour	Ashton-under-Lyne	563598
Angela Eagle	@angelaeeagle	Labour	Wallasey	82647
Angela Crawley	@AngelaCrawley30	Scottish National Party	Lanark and Hamilton East	14048
Andy Slaughter	@hammersmithandy	Labour	Hammersmith	26152
Andy McDonald	@AndyMcDonaldMP	Labour	Middlesbrough	52187
Andy Carter	@MrAndy_Carter	Conservative	Warrington South	6415
Andrew Stephenson	@Andrew4Pendle	Conservative	Pendle	27299
Andrew Selous	@AndrewSelous	Conservative	South West Bedfordshire	22392
Andrew Rosindell	@AndrewRosindell	Conservative	Romford	23229
Andrew Lewer	@ALewerMBE	Conservative	Northampton South	5251
Andrew Jones	@AJonesMP	Conservative	Harrogate and Knaresborough	16097
Andrew Gwynne	@GwynneMP	Labour	Denton and Reddish	53115
Andrew Griffith	@griffitha	Conservative	Arundel and South Downs	6910
Andrew Bridgen	@ABridgen	Conservative	North West Leicestershire	44125
Andrew Bowie	@AndrewBowie_MP	Conservative	West Aberdeenshire and Kincardine	23403
Andrea Leadsom	@andrealeadsom	Conservative	South Northamptonshire	127905
Andrea Jenkyns	@andreajenkyns	Conservative	Morley and Outwood	67709
Amy Callaghan	@AmyCallaghanSNP	Scottish National Party	East Dunbartonshire	16074
Amanda Solloway	@ASollowayUK	Conservative	Derby North	6420

Amanda Milling	@amandamilling	Conservative	Cannock Chase	27263
Alyn Smith	@AlynSmith	Scottish National Party	Stirling	46747
Alun Cairns	@AlunCairns	Conservative	Vale of Glamorgan	14359
Alok Sharma	@AlokSharma_RDG	Conservative	Reading West	76012
Allan Dorans	@allandoransMP	Scottish National Party	Ayr, Carrick and Cumnock	943
Alistair Carmichael	@amcarmichaelMP	Liberal Democrat	Orkney and Shetland	24943
Alison Thewliss	@alisonthewliss	Scottish National Party	Glasgow Central	31626
Alison McGovern	@Alison_McGovern	Labour	Wirral South	57005
Alicia Kearns	@aliciakearns	Conservative	Rutland and Melton	19753
Alexander Stafford	@Alex_Stafford	Conservative	Rother Valley	7639
Alex Sobel	@alexsobel	Labour	Leeds North West	26193
Alex Norris	@AlexNorrisNN	Labour	Nottingham North	8689
Alex Davies-Jones	@AlexDaviesJones	Labour	Pontypridd	10396
Alex Cunningham	@ACunninghamMP	Labour	Stockton North	23927
Alex Chalk	@AlexChalkChelt	Conservative	Cheltenham	15338
Alex Burghart	@alexburghart	Conservative	Brentwood and Ongar	6987
Alec Shelbrooke	@AlecShelbrooke	Conservative	Elmet and Rothwell	16809
Alberto Costa	@AlbertoCostaMP	Conservative	South Leicestershire	11271
Alan Mak	@AlanMakMP	Conservative	Havant	10975
Alan Campbell	@alancampbellmp	Labour	Tynemouth	7633
Alan Brown	@AlanBrownSNP	Scottish National Party	Kilmarnock and Loudoun	13005
Afzal Khan	@Afzal4Gorton	Labour	Manchester, Gorton	36036
Adam Afriyie	@AdamAfriyie	Conservative	Windsor	17915
Abena Oppong-Asare	@abenaopp	Labour	Erith and Thamesmead	19239
Aaron Bell	@AaronBell4NUL	Conservative	Newcastle-under-Lyme	7258

Uruguay

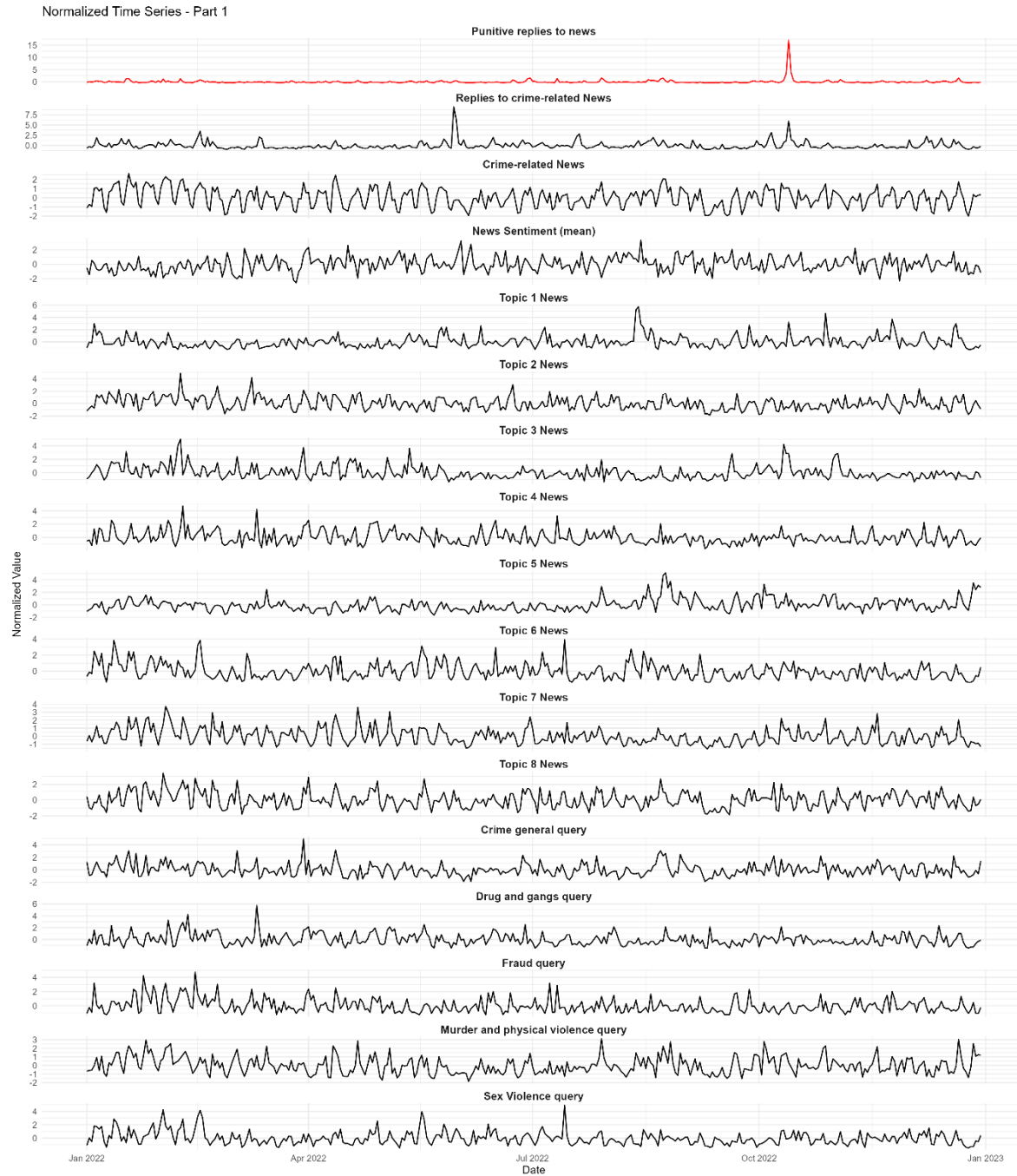
Nombre	Usuario	Partido	Rol
Luis Lacalle Pou	LuisLacallePou	Partido Nacional	Presidente
Beatriz Argimon	beatrizargimon	Partido Nacional	vicepresidente
Partido Nacional	PNACIONAL	Partido Nacional	Cuenta oficial Partido
Partido Colorado	PartidoColorado	Partido Colorado	Cuenta oficial Partido
Frente Amplio	Frente_Amplio	Frente Amplio	Cuenta oficial Partido
Partido Independiente	pindependiente	Partido Independiente	Cuenta oficial Partido
Partido Ecologista	pEcologistaUy	Partido Ecologista	Cuenta oficial Partido
Partido de la Gente	lagenteuy	Partido de la Gente	Cuenta oficial Partido
Cabildo Abierto	Cabildo_UY	Cabildo Abierto	Cuenta oficial Partido
Alejandro Sanchez	pachasanchez	Frente Amplio	Senador
Lucía Topolansky	TopolanskyLucia	Frente Amplio	Senador
Sebastián Sabini	tatisabini	Frente Amplio	Senador
Daniel Caggiani	DCaggiani	Frente Amplio	Senador
Sandra Lazo	sandralazo2	Frente Amplio	Senador
Charles Carrera	ChCarreraLeal	Frente Amplio	Senador
Mario Bergara	Mario_Bergara	Frente Amplio	Senador
Liliam Kechichian	likechichian	Frente Amplio	Senador
Enrique Rubio	EnriqueRubio_FA	Frente Amplio	Senador
Oscar Andrade	Oandradelallana	Frente Amplio	Senador
Carolina Cosse	CosseCarolina	Frente Amplio	Senador
Silvia Nane	SilviaNaneFA	Frente Amplio	Senador
Daniel Olesker	DanielOlesker	Frente Amplio	Senador
Jose Nunes	Josenunes1960	Frente Amplio	Senador
Jose Carlos Mahia	JoseCarlosMahia	Frente Amplio	Senador
Carmen Asiain	casaiain1	Partido Nacional	Senador
Alvaro Delgado	AlvaroDelgadoUy	Partido Nacional	Senador
Amin Niffouri	ANiffouri	Partido Nacional	Senador
Graciela Bianchi	gbianchi404	Partido Nacional	Senador
Luis Alberto Heber	Luisaheber	Partido Nacional	Senador
Gustavo Penadés	GustavoPenades	Partido Nacional	Senador
Sergio Botana	sergiobotana	Partido Nacional	Senador
Gloria Rodríguez	gloriasaravista	Partido Nacional	Senador
Javier García	JavierGarcia_Uy	Partido Nacional	Senador
Sebastian Da Silva	camboue	Partido Nacional	Senador
Carlos Camy	cdcamy	Partido Nacional	Senador
Jorge Gandini	jorgegandini	Partido Nacional	Senador
Juan Sartori	JuanSartoriUY	Partido Nacional	Senador
Carmen Sanguinetti	Carmensangui	Partido Colorado	Senador

Adrián Pena	adrianbatllista	Partido Colorado	Senador
Pablo Lanz	lanzadib	Partido Colorado	Senador
Julio María Sanguinetti	JMaSanguinetti	Partido Colorado	Senador
Tabaré Viera	Tabareviera	Partido Colorado	Senador
Germán Coutinho	germancoutinho	Partido Colorado	Senador
Guido Manini Rios	GuidoManiniRios	Cabildo Abierto	Senador
Guillermo Domenech	DomenechMG	Cabildo Abierto	Senador
Irene Moreira	IreneMoreiraUy	Cabildo Abierto	Senador
Raul Lozano	raul_lozanob	Cabildo Abierto	Senador
Martín Lema	MartinLemaUy	Partido Nacional	Diputado
Gerardo Amarilla	GerardoAmarilla	Partido Nacional	Diputado
Virginia Fros	VirginiaFrosAlv	Partido Nacional	Diputado
Sebastian Andujar	Sebandujar	Partido Nacional	Diputado
Rubén Bacigalupe	Bacigalupe50	Partido Nacional	Diputado
Guillermo Besozzi	besozzi_guille	Partido Nacional	Diputado
María Fajardo	DiputadaFajardo	Partido Nacional	Diputado
Rodrigo Blas	rodrigoblas_	Partido Nacional	Diputado
Armando Castaingdebat	ACastaingdebat	Partido Nacional	Diputado
Laura Burgoa	Laura_Burgoa_	Partido Nacional	Diputado
Mario Colman	mariocolman	Partido Nacional	Diputado
Alvaro Dastugue	AlvaroDastugue	Partido Nacional	Diputado
Alfredo de Mattos	alfredodeMattos	Partido Nacional	Diputado
Valentina Dos Santos	vds2525	Partido Nacional	Diputado
Diego Echeverría	echeverriadiego	Partido Nacional	Diputado
Carlos Enciso	PajaroEnciso	Partido Nacional	Diputado
Alexandra Inzaurrealde	AlexandraInza	Partido Nacional	Diputado
Gabriel Gianoli	GabrielGianoli	Partido Nacional	Diputado
Rodrigo Goni	DipRodrigoGoni	Partido Nacional	Diputado
Benjamín Irazabal	laloirazabal	Partido Nacional	Diputado
Omar Lafluf	tufilafluf	Partido Nacional	Diputado
Eduardo Lorenzo	dip_lorenzo	Partido Nacional	Diputado
Fernanda Araujo	faraujo404	Partido Nacional	Diputado
Christian Morel	cmorel93	Partido Nacional	Diputado
Carmen Tort	CarmenTort3000	Partido Nacional	Diputado
Gonzalo Mujica	GonzaloMujica17	Partido Nacional	Diputado
Alfonso Lereté	liclerete	Partido Nacional	Diputado
Juan José Olaizola	juanjoalaizola	Partido Nacional	Diputado
Pedro Jisdonián	pjisdonian	Partido Nacional	Diputado
Nicolás Olivera	OliveraPdu	Partido Nacional	Diputado
Nancy Nuñez	NancyNuezSoler4	Partido Nacional	Diputado
Gustavo Penades	GustavoPenades	Partido Nacional	Diputado

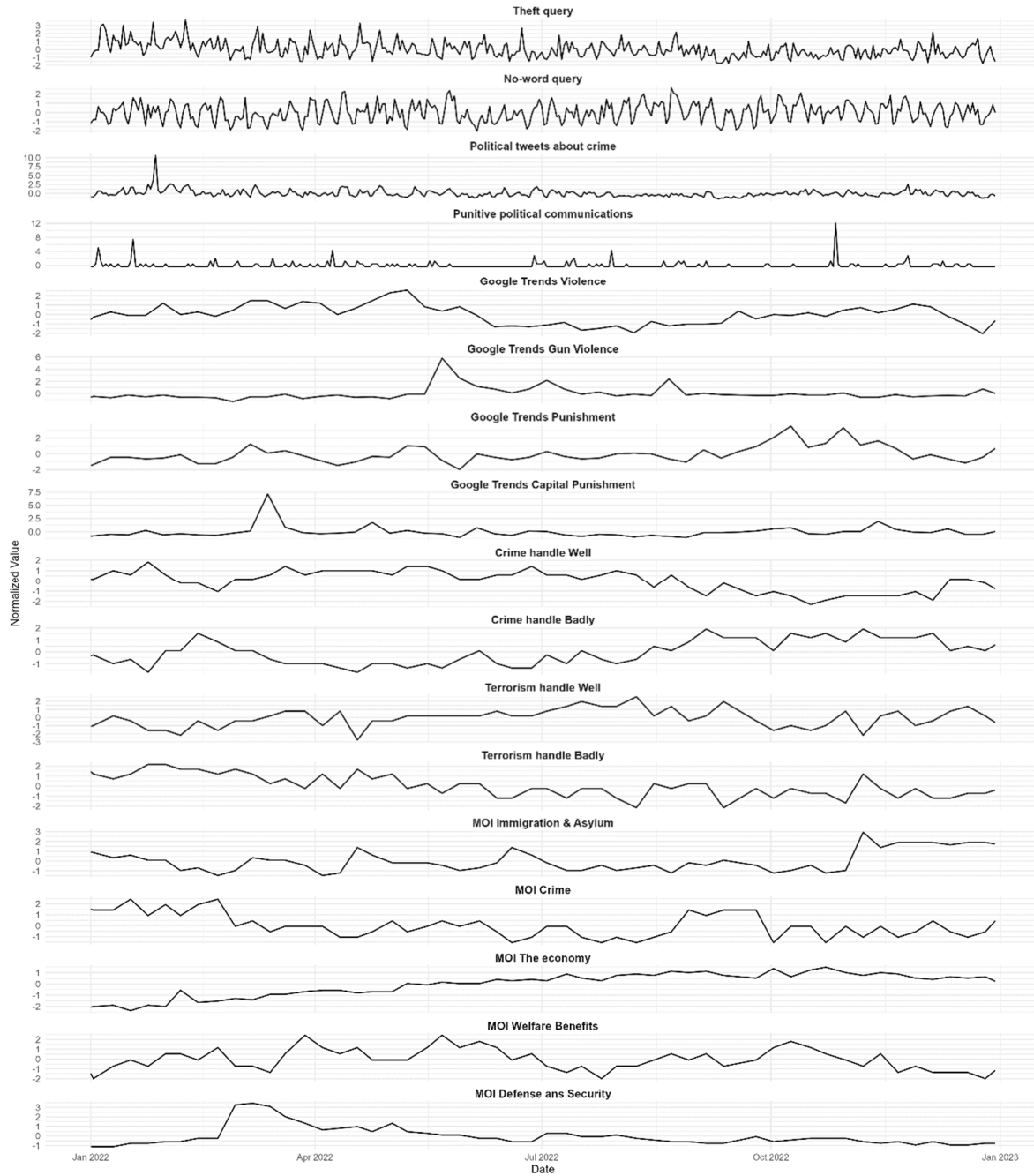
Andrés Abt	Andresabt	Partido Nacional	Diputado
Daniel Martínez Escames	D_Martinez71	Partido Nacional	Diputado
Javier Radiccioni	JRadiccioni	Partido Nacional	Diputado
Dardo Sánchez Cal	dardointendente	Partido Nacional	Diputado
Alejo Umpierrez	alejoumpierrez	Partido Nacional	Diputado
Milton Corbo	corbo_milton	Partido Nacional	Diputado
Pablo Viana	pabloviana_ok	Partido Nacional	Diputado
Alvaro Viviano	tatoviviano	Partido Nacional	Diputado
Ivan Posada	IvanPosada33	Partido Independiente	Diputado
Cesar Vega	CesarVega_Perí	Partido Ecologista	Diputado
Ope Pasquet	opepasquet	Partido Colorado	Diputado
Jorge Alvear	jalveargonzalez	Partido Colorado	Diputado
Germán Cardoso	CardosoGerman	Partido Colorado	Diputado
Eduardo Elinger	elingereduardo	Partido Colorado	Diputado
Walter Cervini	Wcervini	Partido Colorado	Diputado
Martín Melazzi	martinmelazzi	Partido Colorado	Diputado
Marne Osorio	MarneOsorioLima	Partido Colorado	Diputado
Nibia Reisch	NibiaReisch	Partido Colorado	Diputado
Conrado Rodríguez	Dip_ConradoRod	Partido Colorado	Diputado
María Eugenia Roselló	marurosello	Partido Colorado	Diputado
Felipe Schipani	FelipeSchipani	Partido Colorado	Diputado
Gustavo Zubía	GustavoZubia	Partido Colorado	Diputado
Ubaldo Aíta	AitaUbaldo	Frente Amplio	Diputado
Eduardo Antonini	antonini_edu	Frente Amplio	Diputado
Gabriela Barreiro	GabyBarreiro_uy	Frente Amplio	Diputado
Cecilia Bottino	ceciliabottino	Frente Amplio	Diputado
Diego Reyes	reyesmarroig	Frente Amplio	Diputado
Cecilia Cairo	CeciliaCairo1	Frente Amplio	Diputado
Felipe Carballo	fcarballo711	Frente Amplio	Diputado
Gonzalo Civila	gonzacivila	Frente Amplio	Diputado
Bettiana Díaz	bettianadiazrey	Frente Amplio	Diputado
Lucía Etcheverry	LuciaEtchever11	Frente Amplio	Diputado
Lilián Galán	liliangalan1	Frente Amplio	Diputado
Daniel Gerhard	DanielGerhard5	Frente Amplio	Diputado
Claudia Hugo	claudia_hugo	Frente Amplio	Diputado
Pedro Irigoin	IrigoinPedro	Frente Amplio	Diputado
Óscar Amigo	OscarAlFrente	Frente Amplio	Diputado
Nelson Larzábal	NLarzabal1	Frente Amplio	Diputado
Álvaro Lima	SaltoAlvaroLima	Frente Amplio	Diputado
Nicolás Lorenzo	NicolasLorenzoM	Frente Amplio	Diputado
Cristina Lustemberg	LustembergC	Frente Amplio	Diputado

Luis Enrique Gallo	GalloCantera	Frente Amplio	Diputado
Enzo Malán	EnzoMalanCastro	Frente Amplio	Diputado
Verónica Mato	Veronica_Mato	Frente Amplio	Diputado
Nicolás Mesa	nicomesawaller	Frente Amplio	Diputado
Sergio Mier	DiputadoMier	Frente Amplio	Diputado
Orquídea Minetti	OrquideaMinetti	Frente Amplio	Diputado
Gerardo Núñez	gera_nunez1001	Frente Amplio	Diputado
Ana Olivera	AnaO1001	Frente Amplio	Diputado
Gabriel Otero	GabrielOteroA	Frente Amplio	Diputado
Susana Pereyra	SPereyra609	Frente Amplio	Diputado
Federico Ruiz	FedericoRuizBri	Frente Amplio	Diputado
Agustín Mazzini	AgustinMazzini	Frente Amplio	Diputado
Sebastián Valdomir	SValdomir609	Frente Amplio	Diputado
Martín Tierno	martintf1	Frente Amplio	Diputado
Gabriel Tinaglini	GTinaglini	Frente Amplio	Diputado
Mariano Tucci	MarianoTucci46	Frente Amplio	Diputado
Javier Umpiérrez	jumperrez609	Frente Amplio	Diputado
Carlos Varela Nestier	varela2121	Frente Amplio	Diputado
Nicolás Viera	nicovieradiaz	Frente Amplio	Diputado
Rodrigo Albernaz	RodrigoAlberna3	Cabildo Abierto	Diputado
Sebastián Cal	SebastianCal1	Cabildo Abierto	Diputado
Nazmi Camargo	CamargoNazmi	Cabildo Abierto	Diputado
Elsa Capillera	ECapillera	Cabildo Abierto	Diputado
Solís Echeverría	SolisEcheverria	Cabildo Abierto	Diputado
Eduardo Lust	LustEduardo	Cabildo Abierto	Diputado
Silvana Pérez Bonavita	perezbonavita	Cabildo Abierto	Diputado
Álvaro Perrone	APerrone510	Cabildo Abierto	Diputado
Carlos Testa	CarlosTestaCA	Cabildo Abierto	Diputado

4. Normalised time series United Kingdom:



Normalized Time Series - Part 2



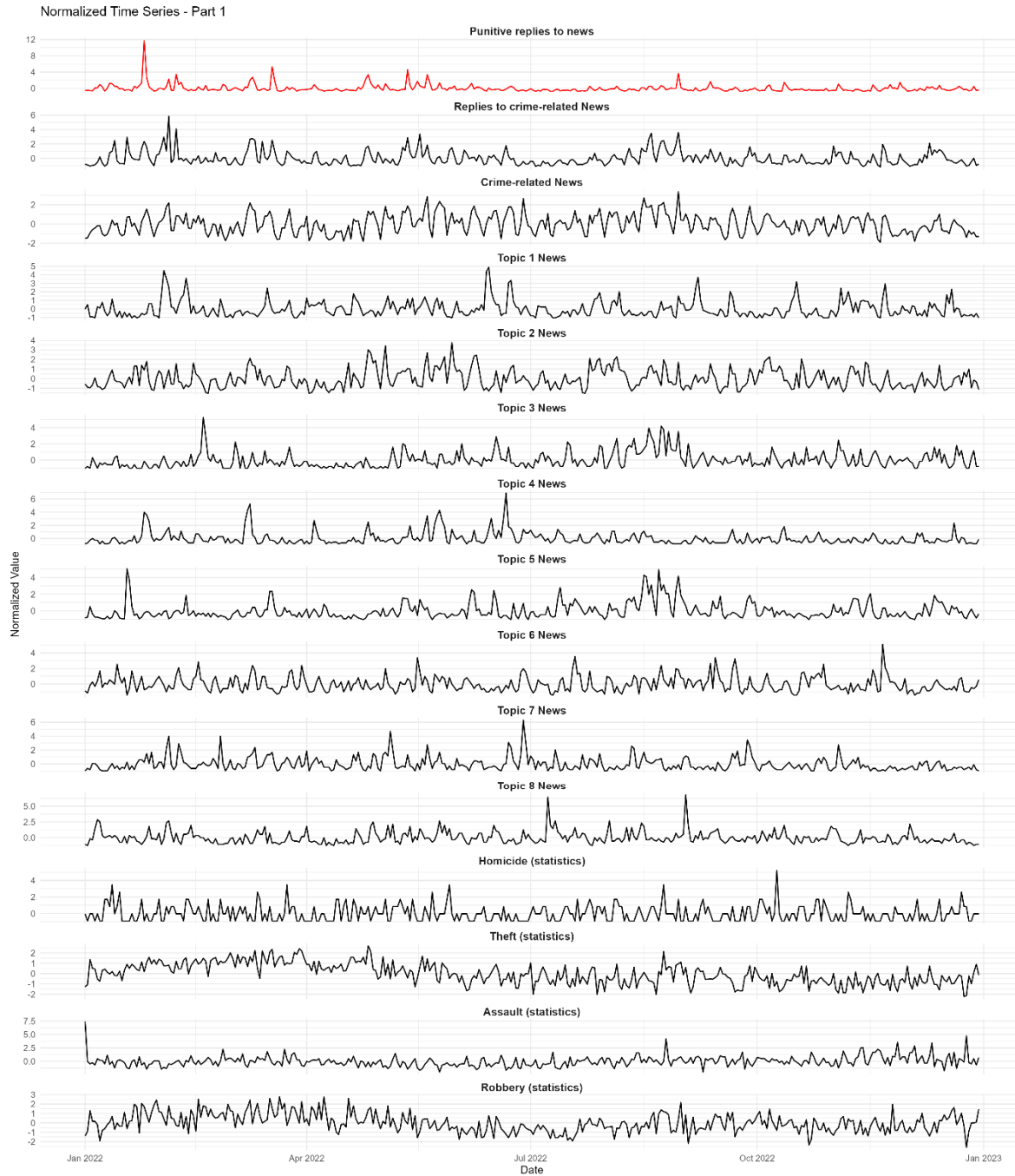
5. Bivariate Time Series United Kingdom

Variable	Punitive replies news			News Replies			Political communications		
	Coef.	SE.	p	coef.	SE.	p	Coef.	SE.	p
outlier_2022_10_13	1131.896	33.510	0.000	-	-	-	-	-	-
outlier_2022_05_30	-	-	-	5101.534	487.779	0.000	-	-	-
outlier_2022_01_27	-	-	-	-	-	-	190.765	12.735	0.000
Replies to crime-related News	0.017	0.003	0.000	-	-	-	0.001	0.001	0.211
Lag 1	0.008	0.003	0.008	-	-	-	-0.001	0.001	0.488
Crime-related News	0.229	0.017	0.000	3.200	0.607	0.000	0.185	0.013	0.000
Lag 1	0.101	0.037	0.007	1.821	0.632	0.004	0.017	0.018	0.345
Lag 2	0.012	0.037	0.748	-	-	-	-0.069	0.015	0.000
News Sentiment (mean)	-66.245	6.180	0.000	329.393	575.064	0.567	5.956	13.309	0.655
Lag 1	6.283	32.860	0.848	287.115	589.729	0.626	-7.977	13.074	0.542
Sex Violence query	0.617	0.178	0.001	16.502	3.035	0.000	0.582	0.080	0.000
Lag 1	0.459	0.177	0.009	3.840	3.305	0.245	0.028	0.080	0.731
Murder and physical violence query	0.517	0.075	0.000	4.269	1.401	0.002	0.195	0.037	0.000
Lag 1	0.114	0.083	0.169	2.158	1.425	0.130	0.053	0.035	0.135
Crime general query	0.494	0.231	0.033	8.736	4.170	0.036	0.458	0.101	0.000
Lag 1	0.369	0.240	0.124	8.903	4.199	0.034	0.158	0.102	0.120
Drug and gangs query	0.337	0.325	0.300	6.947	5.827	0.233	0.174	0.148	0.238
Fraud query	0.312	0.275	0.256	2.826	4.890	0.563	0.526	0.127	0.000
Lag 1	-	-	-	-	-	-	-0.063	0.120	0.602
Theft query	0.737	0.216	0.001	9.340	3.831	0.015	0.866	0.094	0.000
Lag 1	0.213	0.230	0.353	5.009	4.011	0.212	-0.095	0.102	0.352
Topic 5 News	0.643	0.102	0.000	2.957	1.876	0.115	0.208	0.049	0.000
Lag 1	0.010	0.114	0.933	4.370	1.908	0.022	0.066	0.049	0.181
Topic 7 News	0.562	0.107	0.000	6.236	1.942	0.001	0.434	0.049	0.000
Lag 1	0.181	0.114	0.112	2.827	1.981	0.154	0.014	0.051	0.788
Topic 8 News	0.462	0.151	0.002	6.682	2.771	0.016	0.642	0.068	0.000
Lag 1	0.385	0.156	0.013	8.002	2.732	0.003	0.031	0.071	0.663
Topic 2 News	0.703	0.184	0.000	10.430	3.355	0.002	0.668	0.089	0.000
Lag 1	-0.152	0.193	0.430	1.764	3.441	0.608	-0.055	0.085	0.516
Topic 6 News	0.402	0.169	0.017	14.619	2.767	0.000	0.375	0.079	0.000
Lag 1	0.490	0.165	0.003	3.182	3.068	0.300	0.003	0.073	0.966
Topic 1 News	0.838	0.218	0.000	16.045	3.960	0.000	0.530	0.091	0.000
Lag 1	0.691	0.228	0.002	8.767	4.046	0.030	0.059	0.094	0.528
Topic 4 News	0.377	0.270	0.163	5.711	4.860	0.240	0.340	0.122	0.005
Lag 1	-	-	-	-	-	-	-0.079	0.117	0.500
Political tweets about crime	0.308	0.087	0.000	3.203	1.587	0.044	-	-	-
Lag 1	0.195	0.091	0.033	3.083	1.586	0.052	-	-	-

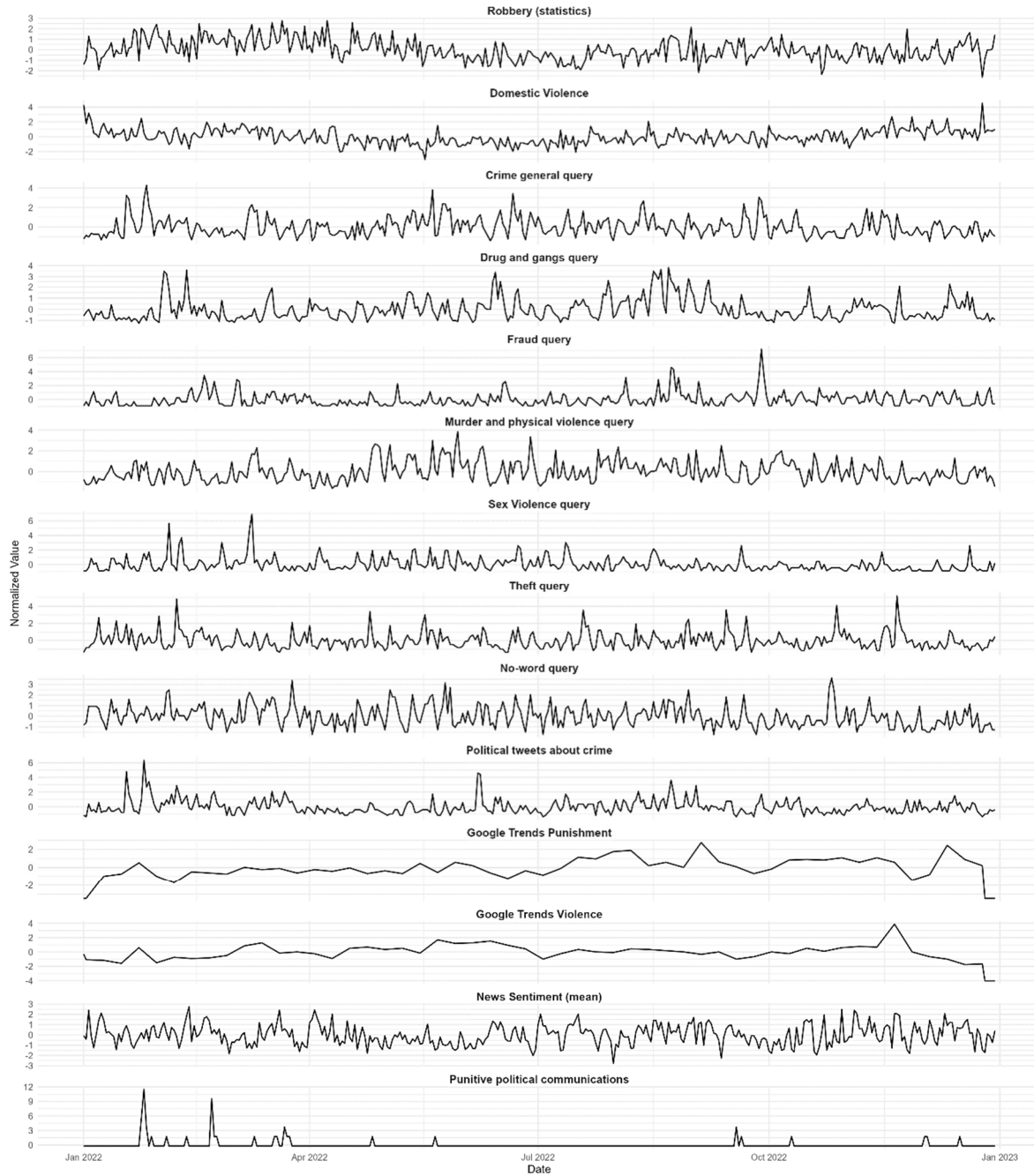
Punitive political communications	2.591	1.152	0.024	12.833	21.073	0.543	-	-	-
Lag 1	0.376	1.204	0.755	9.717	21.707	0.654	-	-	-
Punitive replies (News)	-	-	-	-	-	-	0.018	0.009	0.045
Lag 1	-	-	-	-0.415	0.478	0.386	0.001	0.010	0.875



6. Normalised time series Uruguay



Normalized Time Series - Part 2



7. Bivariate Time Series Uruguay

	Punitive replies			Replies			Political		
Variable	Coef.	SE.	p	Coef.	SE.	p	Coef.	SE.	p
outlier_2022_01_25	163.098	10.932	0.000	-	-	-	-	-	-
Replies to crime-related News	0.033	0.002	0.000	-	-	-	0.007	0.001	0.000
Lag 1	0.009	0.004	0.020	-	-	-	0.002	0.001	0.091
Crime-related News (Diff)	0.072	0.019	0.000	1.750	0.323	0.000	0.027	0.008	0.000
Lag 1	0.060	0.020	0.003	1.291	0.338	0.000	0.025	0.008	0.001
News Sentiment (mean)	-8.834	7.029	0.209	89.012	124.142	0.473	3.598	2.844	0.206
Sex Violence query	0.716	0.141	0.000	14.105	2.431	0.000	0.134	0.058	0.021
Lag 1	0.244	0.150	0.103	-0.443	2.635	0.866	-	-	-
Murder and physical violence query	0.256	0.046	0.000	4.321	0.842	0.000	0.048	0.020	0.014
Lag 1	0.103	0.050	0.038	1.265	0.881	0.151	-	-	-
Crime general query	0.409	0.062	0.000	8.717	1.067	0.000	0.192	0.024	0.000
Lag 1	0.146	0.067	0.028	1.601	1.201	0.182	0.031	0.027	0.252
Drug and gangs query	0.042	0.060	0.482	5.198	1.097	0.000	0.080	0.025	0.001
Lag 1	-	-	-	2.909	1.139	0.011	0.033	0.025	0.200
Fraud query	0.320	0.197	0.103	6.509	3.511	0.064	0.172	0.080	0.031
Theft query	0.571	0.113	0.000	10.589	1.969	0.000	0.101	0.046	0.028
Lag 1	0.223	0.118	0.058	2.030	2.067	0.326	-	-	-
Topic 2 News	0.343	0.053	0.000	5.144	0.975	0.000	0.044	0.023	0.054
Lag 1	0.128	0.058	0.027	1.147	1.033	0.267	-	-	-
Lag 7	-	-	-	-	-	-	0.048	0.023	0.041
Topic 5 News	0.152	0.068	0.025	9.017	1.163	0.000	0.233	0.025	0.000
Lag 1	-	-	-	-	-	-	0.043	0.030	0.161
Lag 7	0.115	0.072	0.113	3.313	1.318	0.012	0.123	0.028	0.000
Topic 6 News	0.421	0.091	0.000	7.628	1.589	0.000	0.027	0.037	0.473
Lag 1	0.141	0.094	0.132	1.896	1.657	0.253	-	-	-
Topic 1 News	0.101	0.091	0.265	4.062	1.606	0.011	-0.001	0.037	0.989
Topic 4 News	0.458	0.096	0.000	8.469	1.711	0.000	0.141	0.040	0.000
Lag 1	0.348	0.098	0.000	3.352	1.796	0.062	0.082	0.040	0.040
Topic 7 News	0.558	0.114	0.000	5.743	2.063	0.005	0.102	0.047	0.030
All crimes (statistics)	0.021	0.002	0.000	0.149	0.183	0.414	0.006	0.004	0.122
Violent crimes (statistics)	-0.017	0.018	0.361	-0.424	0.309	0.170	-0.006	0.007	0.395
Robbery (statistics)	0.067	0.056	0.234	0.436	1.021	0.670	0.031	0.023	0.170
Lag 1	0.171	0.013	0.000	0.686	1.020	0.501	0.046	0.023	0.044
Lag 7	-	-	-	2.205	1.023	0.031	-	-	-
Domestic violence (diff)	-0.016	0.029	0.568	-0.720	0.483	0.136	-0.004	0.016	0.786
Lag 2	0.069	0.028	0.015	-	-	-	0.004	0.011	0.706
Homicide (statistics)	0.296	0.527	0.574	-7.710	9.012	0.392	-0.336	0.205	0.101

Lag 1	-	-	-	20.943	9.000	0.020	-	-	-
Lag 10	-	-	-	-	-	-	0.627	0.207	0.002
Lag 11	-	-	-	19.704	9.357	0.035	-	-	-
Lag 13	0.627	0.542	0.247	-	-	-	-	-	-
Theft (statistics)	0.036	0.003	0.000	0.932	0.081	0.000	0.022	0.001	0.000
Lag 7	0.036	0.003	0.000	0.935	0.060	0.000	0.022	0.001	0.000
Assault (statistics)	-0.139	0.066	0.035	-3.671	1.180	0.002	-0.090	0.026	0.001
Political tweets about crime	0.496	0.134	0.000	13.935	2.235	0.000	-	-	-
Lag 1	1.068	0.156	0.000	4.781	2.437	0.050	-	-	-
Punitive political communications	4.306	1.431	0.003	37.007	22.442	0.099	-	-	-
Lag 1	2.179	1.307	0.095	20.431	22.988	0.374	-	-	-
Punitive replies (news)	-	-	-	0.777	0.786	0.323	0.106	0.016	0.000
Lag 1	-	-	-	-	-	-	0.006	0.018	0.748



8. Weekly time series analysis United Kingdom

Finally, the daily data was transformed into weekly data to test the influence of Google Trends and offline public opinion polls. Since this dramatically reduces the number of observations, only bivariate relationships were tested, controlling for the effect of the week that includes the observed outlier. In all cases, the independent variables were differentiated. The lag 1 represents a one-week lag.

Only two variables resulted in significant results: searches for the topic gun violence in Google Trends and crime as the country's Most Important Problem in lag 1. Interestingly, the one percentage point increase in crime as the most important problem over the previous week, in lag 1, implies a decrease in punitive responses. It is very important to take these results cautiously, given that there are only a few observations (51 weeks), so the chance of false negatives or spurious relationships is considerable.

Weekly bivariate ARIMAX model for punitive replies

Variable	Coef.	SE.	p
Crime handled well	8.514	10.416	0.414
Lag 1	-7.440	10.559	0.481
Crime handled badly	3.125	9.005	0.729
Lag 1	-0.756	8.911	0.932
Terrorism handled well	1.122	8.899	0.900
Lag 1	-6.346	9.077	0.484
Terrorism handled badly	9.126	8.662	0.292
Lag 1	8.072	8.771	0.357
Violence (topic - Google Trends)	-0.419	2.063	0.839
Lag 1	-1.382	2.113	0.513
Gun Violence (topic - Google Trends)	2.306	0.869	0.008
Lag 1	0.124	0.937	0.894
Punishment (topic - Google Trends)	-0.939	1.665	0.573
Lag 1	-0.057	1.676	0.973
Capital Punishment (Topic - Google Trends)	-0.581	1.039	0.576
Lag 1	0.295	1.057	0.780
MOI - Immigration	-5.870	5.135	0.253
Lag 1	-3.252	5.285	0.538
MOI - Crime	4.436	9.053	0.624
Lag 1	-21.767	9.638	0.024
MOI - Economy	-2.064	5.142	0.688
Lag 1	7.113	5.115	0.164
MOI - Defense and security	-2.921	4.912	0.552

Lag 1	-2.826	5.003	0.572

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