

# Market Reaction to Corporate Disclosures of Hyped Emerging Technologies

By

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#### **Abstract**

The literature identifies that investor overreact to the corporate disclosure of Blockchain during the Blockchain mania. However, emerging technologies (hereafter ETs) are not always monolithic. Assuming that investors are all Fintech fans and ignoring the blossoming of other ETs fails to capture the true investor reaction to firms making disclosures related to ETs. Thus, this thesis examines investor reactions to corporate disclosure of a broad range of ETs using the Gartner Hype Cycle (hereafter GHC). Focusing on all US firms' initial 8-K filing each year from 2010 to 2019, this research uses textual analysis to find firms disclosing ETs.

First, I use an event study method to investigate the immediate and delayed reaction among investors to the disclosure of ETs. While the immediate reaction of investors is positive, this will be reversed shortly. Further, the GHC categorises ETs into five different phases according to the level of market hype, which provides the conditions for this research to compare the differences in market reactions to a firm's disclosure of ETs at different phases. The findings suggest that investors react differently to the disclosure of ETs during different hyped phases of the GHC.

Second, this research illustrates that the reason for the reversal of the delayed investor reaction to ETs disclosures is insider selling and further validate the robustness of the results when other events are excluded. The research also suggests that investors react negatively in the short-term to the intensity and frequency of ETs' disclosure. Regarding the different phases of market hype, investors' positive immediate reaction can only be observed for the disclosure of ETs at the 'innovation trigger' and the 'peak of inflated' phases while the disclosure ETs at the 'peak of inflated' phase receives opposite reactions.

Third, this research demonstrates that the disclosure of ETs increases stock price crash risk. Although according to signalling theory investors would see the disclosure as a possibility for the firm to actively participate in the technological wave for growth, the increased level of information asymmetry due to hidden potential risks and uncertainties leads to an increased risk of a share price crash. The relationship is made more pronounced by investors' short-term fervour for such disclosures and CEOs' overconfidence. However, this situation was reversed when the firm chose to disclose ETs at the phase of 'plateau of productivity'.

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#### **Abbreviations**

**2SLS** Two-stage-least-square

8-K 8K Form10-K 10K Form10-Q 10Q Form

AI Artificial Intelligence

**AR** Abnormal returns

BHARs Buy-and-Hold abnormal returns

**BoW** Bag-of-words

C4 Carhart four-factor model

**CARs** Cumulative abnormal returns

**CEO** Chief executive officer

CIK Central Index Key

**CRSP** The Center for Research in Security Prices

**CSR** Corporate social responsibility

**EDGAR** Electronic Data Gathering, Analysis and Retrieval

**ESG** Environmental, Social, and Governance

**ETs** Emerging Technologies

**FASB** Financial Accounting Standards Board

**FF3** Fama-French three-factor model

**FinTech** Financial Technologies

**GHC** Gartner Hype Cycle

**GHC-ET** Gartner Hype Cycle Emerging Technologies

GI General Inquirer

GIC Global Industry Classification

HTML Hyper Text Markup Language

**IBES** Institutional Brokers' Estimate System

**IBM** International Business Machines Corporation

**IDC** International Data Corporation

**IFRS** International Financial Reporting Standards

**IoT** Internet of Things

IVs Instrumental variablesIPO Initial Public OfferingKMO Kaiser-Meyer-Olkin

**LDA** Latent Dirichlet Allocation

LIWC Linguistic Inquiry and Word Count

**M&A** Merger and Acquisition

NASDAQ National Association of Securities Dealers Automated Quotations

**NLTK** Natural Language Toolkit

**NYSE** The New York Stock Exchange

**OSTP** Office of Science and Technology Policy

**OTC** Over-the-counter

**PCA** Principal Component Analysis

**PSM** Propensity Score Matching

**R&D** Research and Development

**Reg FD** Regulation FD disclosure

**SEC** The U.S. Securities and Exchange Commission

SIC Standard Industrial Classification codes

**SOEs** State-owned Enterprises

**SOX** Sarbanes-Oxley Act

URL Uniform Resource Locator

US United States

**WRDS** Wharton Research Data Services

### **Chapter 1. Introduction**

This thesis, at first, investigates the market's reaction to US firms' disclosures related to emerging technologies based on the Gartner Hype Cycle (hereafter referred to as GHC-ET). Based on the difference between short-term and delayed investors reactions, this research further examines the causes and mechanisms that lead to the reversal of investors reaction. In addition, to explore the firm's delayed impact on GHC-ET disclosure, the thesis also investigates its relationship with the risk of stock price crash.

This opening chapter begins by sketching the research's contextual landscape and clarifying the motivations propelling this study. Informed by a review of previous studies, I have formulated three research objectives which are achieved by three separate empirical chapters. To address these, this chapter comprehensively explains the main research methodologies employed. The subsequent section highlights the contributions of this research, as evidenced through market reactions and stock price crash risks due to GHC-ET disclosure. Finally, the chapter provides a coherent framework that delineates the structure of the following chapters of this thesis.

#### 1.1 Research background and motivations

In the current digital era, a ubiquitous presence of information is observed, rendering access to the right data crucial for investors when formulating informed investment decisions. According to the International Data Corporation (IDC) statistics, the volume of data generated globally has skyrocketed, reaching a staggering 2.5 quintillion bytes per day by 2022 (Rydning, 2022). This exponential growth provides investors with a plethora of potentially advantageous information, spanning from economic indices (closely related to the firm's operating environment) and corporate financial reports to market dynamics and beyond.

While the abundance of information has provided investors with unprecedented decision-making convenience, this information explosion has also brought about information disruption, requiring investors to spend more time and effort identifying useful information. For example, according to IBM's report in 2020, 80% of worldwide data will be unstructured by 2025,

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implying that a vast majority of such information will be neither organised nor categorised, thereby offering limited assistance to investors in their decision-making process. In such a context, investors are required to have the ability to screen irrelevant or misleading information.

The emergence and development of ETs is one of the main engines of the information explosion (Ahmad et al., 2021; Nguyen et al., 2021). On the one hand, the development of the Internet has provided a means for the dissemination of corporate information, and the development of 5G has increased the speed of information dissemination. On the other hand, some ETs such as Blockchain, Artificial Intelligence (AI), Big data, and Cloud Calculation help investors to process a huge amount of information (Agrawal et al., 2018; Chen et al., 2012; Radziwill, 2018).

Technological innovations are the engine of growth for many developed economies. Of all technological innovations, financial innovations have unique attributes in that they are more intangible (dealing with money as an intangible construct) and engage people's emotions and desire for wealth. Whether the firm is keen to capture the application and development of ETs in the industry and thus play a catalytic role in the change and innovation of the existing business model is also a type of useful information that investors should pay attention to. Investors often want to understand a firm's technology strategy and R&D activities to assess its future growth potential and sustainability. If a firm can demonstrate that it is utilising or exploring ETs, this may increase investor confidence in the firm's future success (Hermalin and Weisbach, 2012). In addition, investments in ETs may be high risk, but they may also offer high returns. Disclosure of such information can attract investors who are willing to take higher risks in exchange for higher returns (Beyer et al., 2010; Healy and Palepu, 2001; Lev and Zarowin, 1999).

However, all technological innovations can run the risk of "temporarily exceeding our ability to use those technologies wisely" (Lo, 2008). Tuckett and Taffler (2008) point out that "whether it was South Sea or Internet stock, tulip bulbs, railways, joint-stock companies in the 1920s, or junk bonds in the 1980s, in each case there was patchy excitement about an innovation leading to growing excitement, leading to manic or euphoric excitement, then turning to panic and finally resulting in blame." Therefore, it is instructive to examine whether

firms disclose ET-related information and whether investor reactions to such information change.

#### 1.2 Research objectives

#### 1.2.1 Investors' attitudes towards a broad of emerging technologies

Prior studies have found that investors overreact to Blockchain-related disclosures (e.g., Akyildirim et al., 2021; Cahill et al., 2020; Cheng et al., 2019; Klöckner et al., 2022; Liu et al., 2022), especially in particular market environments such as Bitcoin mania. However, one fact that cannot be ignored is that not all investors are interested in Fintech. Capital market participants may also have backgrounds in other areas of specialisation, for example, physics, chemistry, and medicine. It is unclear whether investors are interested in the broader ET-related information disclosed by the firm.

An investor's attention to information can be affected by several factors, and not all information is met with sustained enthusiasm. For example, investors are usually more interested in information that directly affects their return on investment (Barber and Odean, 2008). Complex information about ETs may require specialist knowledge to understand, appealing only to investors who have in-depth knowledge of the field (Gennaioli et al., 2015). In Chapter 4, I explore whether investors' reactions to GHC-ET disclosures made by firms change, as evidenced by a reversal or even negativity in delayed responses.

Prospect theory proposed by Kahneman and Tversky (2013) identifies the psychological biases of investors in the face of gains and losses, which may affect their interpretation of and reaction to voluntary disclosures. The GHC, according to different market expectations, provides an opportunity to explore investor responses to different hyped phases of ETs. Thus, Chapter 4 also compares the differences of market reactions between various GHC phases for each group of ETs.

#### 1.2.2 Investor reaction change and the impact of disclosure characteristics

If investors can be attracted to a firm's GHC-ET disclosures in the short term, does their delayed reaction change? If it changes, what are the reasons? There are two possibilities that could cause a reversal in investor reaction to disclosures related to GHC-ET. The first is that investors themselves are no longer enthusiastic about ETs. The second is whether there are other events after a firm's first GHC-ET disclosure that cause investors to recognise speculative disclosure behaviour by the firm and thus change the positive feedback. Chapter 5 attempts to address these concerns.

Chapter 5 also focuses on differences in investors' reactions to disclosure intensity and frequency. In general, detailed, and transparent disclosure can help investors better understand a firm's operations, financial performance, and strategic plans (Bushee and Noe, 2000). This can reduce investors' information asymmetry and risk assessment difficulties and increase their trust and willingness to invest in the firm (Beyer et al., 2010; Lang and Lundholm, 1993). Second, frequent disclosure of information by a firm allows investors to obtain updated information about the firm, better track the latest developments of the firm (Beyer et al., 2010; Healy and Palepu, 2000). Thus, higher disclosure intensity and frequency may lead to more positive investor responses.

However, Bloomfield (2002) argues that while disclosure is beneficial to investors, excessive information may lead to information overload, making it difficult for investors to understand and process the information. Further, high intensity and frequency disclosure means high disclosure cost. Excessive disclosure costs may be detrimental to shareholders' interests and thus lead to negative reactions from investors (Leuz and Wysocki, 2016). Finally, the high intensity and frequency of disclosure for information related to ETs lacks surprise for investors. Therefore, I investigate the impact of firms in changing the intensity and frequency of disclosures related to ETs on investor overreaction in Chapter 5.

#### 1.2.3 The disclosure of emerging technologies and stock price crash risk

Comprehending the risk of a stock price crash is crucial for the protection of investor value (Habib et al., 2018). Prior studies have primarily approached the causes of stock price

crashes from two perspectives. The first perspective pertains to information asymmetry between corporate insiders and external stakeholders (e.g., An et al., 2015; Jin and Myers, 2006; Kim and Zhang, 2016a). The second perspective revolves around conflicts of interest between managers and shareholders, which is reflected in the withholding of bad news (e.g., Benmelech et al., 2010; Bleck and Liu, 2007; Callen and Fang, 2015).

Whilst the disclosure of information concerning ETs may mitigate information asymmetry, the inherent high uncertainty associated with these technologies is often easily downplayed or concealed. Should an ET fail to find its market application, there is a considerable risk that firms engaged in this technology will experience a stock price crash. Therefore, it is important to consider these factors when evaluating a firm's exposure to the risks associated with ETs. Chapter 6 of this thesis aims to investigate the relationship between GHC-ET disclosures and the stock price crash risk.

#### 1.3 Research methodology

GHC-ET disclosures by listed firms in the US market, arguably the global leader in ETs development. For example, the US is a global leader in AI research and development. Many startups and large tech firms, such as Google, Apple and Facebook, are investing in R&D of AI and machine learning (ML) technologies for self-driving cars, personalised recommendation systems, smart home devices, healthcare and more (Zhang et al., 2021). Cloud computing and big data have become major drivers in the US market, with Amazon, Microsoft, and Google being the global market leaders in cloud services. Big data analytics are also widely used in finance, healthcare, and marketing to provide better services and decision support.

This research examines the market reactions to GHC-ET disclosures across all US firms. The definition of ETs is derived from the GHC, an annually updated database that tracks the evolution of ETs. It is important to note that shifts in the market environment can influence investors' attention to information. For instance, during a recession, investors may be more attuned to a firm's financial stability, whereas in a boom, they might be more interested in the firm's growth potential (Baker and Wurgler, 2007). To minimise the effects of the market environment, such as those caused by the financial crisis or events like the COVID-19 pandemic, the sample period has been limited to the years 2010 through 2019. To achieve the

research objectives, this thesis employs an event study method to measure investors' reactions to disclosures related to ETs. Additionally, the Ordinary Least Squares (OLS) model is utilised to confirm the causal relationship between GHC-ET disclosures and market reactions (or stock price crash risk) after controlling firm-level characteristics, with a particular focus on the causes of delayed reversals in market reactions. To mitigate potential endogeneity issues, methodologies such as Propensity Score Matching (PSM) and Two-Stage Least-Squares Regression (2SLS) are employed.

#### 1.4 Contributions

#### 1.4.1 To the voluntary disclosure and market reaction literature

This thesis contributes significantly to the literature on voluntary disclosure and market reactions. Firstly, in alignment with prior studies, the empirical results of this research corroborate the documented positive market reaction to the disclosure of FinTech-type ETs such as Blockchain (e.g., Cahill et al., 2020; Cheng et al., 2019; Klöckner et al., 2022; Liu et al., 2022). However, unlike these studies that focus solely on a specific ET, this thesis utilises the GHC to broaden the scope of ETs. This approach encompasses a wide range of technologies, some of which, even outside the finance sector, command considerable attention from investors with diverse backgrounds and interests. Furthermore, in the short term, investors may find it challenging to distinguish between speculative disclosures and genuine investment opportunities, especially in a frenzied market. Therefore, the immediate overreaction among investors could be temporary. This thesis presents evidence of a reversal in investor reaction in response to the true intentions of a firm disclosing GHC-ET, thus substantiating this claim.

Secondly, this research validates the variation in investor reactions because of differing market hype expectations associated with ETs. In other words, while ETs represent novel concepts to investors, they are more likely to be attracted to those ETs that are the subjects of market hype as opposed to those in their infancy. The research findings suggest that investors are not uniformly enthusiastic about all ETs; their reactions differ depending on the intensity of ET's market hype. This research does not follow Lin et al.'s (2018) approach of exploring whether managers make selective disclosures based on the proportion of institutional investors.

Instead, it examines whether institutional investors exhibit interest in GHC-ET disclosures. Moreover, rather than validating Kim's (2019) view that analysts reduce information asymmetry, the thesis finds that the presence of analysts leads managers to exercise caution in disclosing ETs.

Thirdly, this thesis explores the debate over whether investors are more likely to believe a voluntary disclosure that is reiterated multiple times, or if they are more surprised upon encountering such information for the first time. Numerous studies have focused on the content of voluntary disclosure, for instance, tone (e.g., Allee and DeAngelis, 2015; Rogers et al., 2011) and readability (e.g., Asay et al., 2017; Dyer et al., 2016; Guay et al., 2016). Nevertheless, the intensity and frequency of voluntary disclosure also warrant investigation. Investors might be susceptible to the illusory truth effect, tending to trust voluntary disclosures that are repeated multiple times and offer rich detail (Hasher et al., 1977). Following this logic, the intensity and frequency of GHC-ET disclosures should correlate positively with investor responses. However, this thesis finds that investors' immediate reaction is negative to managers' excessive promotion of ET-related information.

#### 1.4.2 To the voluntary disclosure and stock price crash risk literature

For measuring the long-term impact of 'technology hype' on a firm, this research provides evidence about GHC-ET disclosures and stock price crash risk by adding to the literature by presenting a novel direction for investors to evaluate voluntary disclosures. While the existing literature on voluntary disclosure has explored the impact of social responsibility information (Kim et al., 2014) and environment-related information (Zaman et al., 2021) on stock price crash risk. Past studies have come to inconsistent conclusions about voluntary disclosure and the risk of stock price crashes. Voluntary disclosure, on the one hand, gives investors more information about the firm to make decisions and reduces the level of information asymmetry between managers and investors. However, voluntary disclosure may serve as a means for managers to hide bad news or to satisfy their self-interests, thus increasing the likelihood of a stock price crash.

Secondly, this research diverges from studies focusing on corporate innovation and stock price crash risk, such as Jia (2018). Jia finds that firms engaged in exploratory activities are more susceptible to stock price crashes due to a high failure rate and are less likely to disclose ad hoc negative news about their innovation projects. This research did not verify whether firms invested in or applied the GHC-ET mentioned in their disclosures; instead, I focused on the act of disclosure itself. In other words, this research traces the source of high-tech innovations and tries to explain what would happen to stock prices if firms only presented ET-related information to investors to indicate the direction of potential investments or innovations. To the best of my knowledge, the impact of voluntary disclosure of ET-related information on stock price crash risk has not been previously investigated.

Thirdly, this study measures the impact of 'technology hype' with a high degree of specificity and resolution. There is a difference in investor attitudes towards disclosure of ETs at different phases of 'technology hype'. Specifically, when ETs are in their infancy, the risk of potential information hiding is elevated. Conversely, when the ET is in a highly productive stage, disclosing information about the ET provides additional information to investors, thereby reducing information asymmetry. Moreover, this research finds no increased risk of a stock price crash if the firm alludes to potential risks following the disclosure of information related to ETs.

#### 1.5 Thesis structure

This thesis is composed of seven chapters. The second chapter offers theoretical guidance for investigating corporate disclosures related to ETs. It is crucial to note that the nature of the disclosures studied in this thesis is voluntary. Agency theory, proprietary cost theory, and upper echelons theory are used to support the managerial incentives for GHC-ET disclosures. Another set of theories, stakeholder theory, legitimacy theory, and signalling theory, corroborate the information requirements. Finally, two groups of behavioural finance theories are discussed to explain the GHC-ET disclosures of firms and investors overreaction to such information.

Chapter 3 presents the institutional background, textual analysis, and sample processing. The main objective of this chapter is to introduce the guidance provided by the Securities and

Exchange Commission (hereafter SEC) and the high-frequency disclosure format 8-K filing, which is the focus of this thesis. It then details the use of the GHC, from its various components to its five different phases. Additionally, starting from the history and development of textual analysis, this chapter elaborately describes the process and steps of textual analysis conducted in this thesis, particularly the cleaning of text data and the construction of the dictionary. The process of sample clarification is also delineated.

The subsequent three chapters contain empirical analyses. Chapter 4 employs an event study approach to observe immediate and delayed investors' reaction arising from disclosures of the GHC-ET. Chapter 5 further validates the causal relationship between GHC-ET disclosures and market reactions as well as exploring the factors causing shifts in investors' attitudes towards ETs-related information. Chapter 6 assesses whether GHC-ET disclosures lead to an increased risk of a firm's stock price crash, particularly in terms of the concealment of risk and uncertainty information.

Chapter 7 summarises the research findings for GHC-ET disclosures and its effects on market reactions. Some potential implications for managers and investors are also elaborated while the limitations of this thesis are recognised and discussed. Finally, this chapter provides further research recommendations

## Chapter 2. The Nature and Theories of Corporate Disclosure

#### 2.1 Introduction

Corporate disclosure serves as a vital medium of communication between management and stakeholders, bridging the gap between the two parties. It plays a critical role, particularly for the efficient functioning of capital markets (Healy and Palepu, 2001). Through diverse forms and frequencies of reporting, adhering to various frameworks and requirements, stakeholders can access the information they need to make informed decisions. For instance, regulated financial reports, including financial statements, notes to the statements, and management analysis and discussions, are amongst the most significant types of reports that firms are obligated to disclose. Besides financial reports, some countries mandate listed firms to disclose ESG (Environmental, Social, and Governance) information. Additionally, many firms voluntarily engage in disclosures, including conference calls, press releases, and corporate social responsibility reports.

This chapter begins with an overview of the nature of corporate disclosure, summarising various types of disclosures. Furthermore, this chapter aims to provide theoretical underpinnings for corporate disclosure. Firstly, from the perspective of information providers, several theories explain why firms make disclosures, considering motives such as agency theory, political cost theory, and upper echelons theory. Secondly, this chapter addresses the significance of corporate disclosure from the perspective of the information receivers, including theories such as stakeholder theory, legitimacy theory, and signalling theory. Finally, two groups of behavioural finance theories are discussed to explain the GHC-ET disclosures of firms and investors overreaction to such information.

#### 2.2 The nature of corporate disclosure

A precise understanding of the nature of corporate disclosures is crucial for the successful execution of this thesis. According to Healy and Palepu (2001), the primary

motivation for a firm to disclose information is "to communicate firm performance and governance to outside investors". Hence, the broad definition of corporate disclosure encompasses any information communicated from individuals inside a firm to those outside it.

While there are various classification criteria for corporate disclosures, they can broadly be categorised into two types from the perspective of disclosure motivation. First is mandatory disclosure, where firms are obligated by legislation or regulations to disclose information to investors and other stakeholders. Common mandatory corporate disclosures include annual reports featuring financial statements, notes to the statements, and management analysis and discussion. Secondly, there are voluntary disclosures, where firms elect to disclose information to outsiders without regulatory requirements, such as performance reports on social responsibility or governance. The disclosure of information related to ETs is not mandated by the SEC, categorising such disclosures as voluntary. From the perspective of content, corporate disclosures can be classified as financial and non-financial. Financial-related disclosures primarily focus on quantitative information, such as tables and numbers, while non-financialrelated disclosures are more concerned with qualitative information conveyed through pictures and descriptions. The information related to ETs in 8-K filings can be reflected in both quantitative and qualitative forms. For instance, the slides presented during investor open days may contain ETs-related information portrayed through numerous investment figures and forward-looking descriptions.

#### 2.3 Theoretical framework for corporate disclosure research

Theories, according to Watts and Zimmerman (1986), serve as an explanation for a variety of phenomena, linking observation and comprehension to theoretical and empirical research issues (Venable, 2006). Even when there is a direct connection between an abstract concept and the topic at hand, it can still be challenging to evaluate the validity of various hypotheses. Many established theories in accounting and finance can elucidate managers' decisions and the market's reactions. A literature review conducted from theoretical perspectives is a sound approach. It is important to note that no single theory can fully explain the intricate phenomenon of corporate disclosure (Zamil et al., 2021). In other words, corporate

disclosure is explained by a compendium of theories that spans multiple dimensions. To examine the motivations or incentives behind firms' disclosures related to GHC-ET, as well as market reactions, this section constructs a theoretical framework from two dimensions: 1) traditional finance theories, and 2) behavioural finance theories. The traditional theory will be developed in two dimensions: the information provider and the information receiver. Behavioural finance theories include two groups, one is "regret theory and herding behaviour", and the other is "overconfidence and optimism bias". The structure of this section is illustrated in Figure 2.1

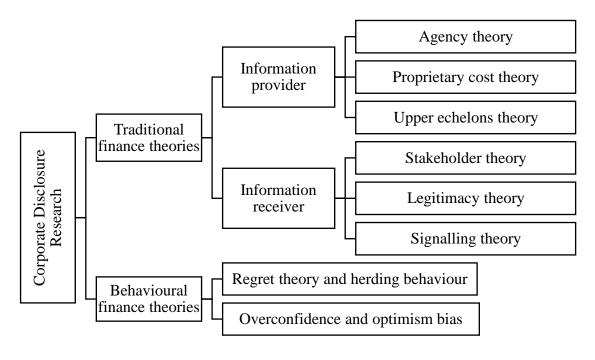


Figure 2.1 Key Theories Related to Corporate Disclosure Research

Note: This figure presents theories related to corporate disclosure research in terms of traditional and behavioural perspectives.

#### 2.3.1 Traditional finance theories

#### 2.3.1.1 Information provider

Motivation underpins the behaviour of firms. Exploring the reasons for corporate disclosures at their source helps to decipher the implications of such disclosures. As direct participants in the firm's activities and the decision-makers regarding the extent and nature of disclosures, managers' motivations for corporate disclosure warrant examination. This perspective forms an essential part of the discussion.

#### 2.3.1.1.1 Agency theory

In 1970s, information economics introduced agency theory into accounting studies, and it has since become one of the most influential theoretical frameworks in management and organisational research (Subramaniam, 2018). According to Jensen and Meckling (1976), a relationship between a principal and an agent is a contractual one that not only constrains the agent's decisions but also grants them substantial managerial powers. O'Donnell and Sanders (2003) define agency theory as "an economic theory that views the firm as a set of contracts among self-interested individuals" (p. 101).

To maintain alignment of interests, it is crucial for the principals to be able to monitor the agent's actions. This supervisory role arises from two foundational assumptions of agency theory: both parties seek to maximise their own benefits, and divergent interests could lead to conflict (Jensen and Meckling, 1976). The evolution of agency theory can be seen as comprising two components: positivism and the principal-agent relationship (Harris and Raviv, 1978). Positivists identify the conflict between the principal and the agent based on the premises, leading them to propose that corporate governance procedures could help alleviate this conflict. From the perspective of the principal-agent relationship, efforts are made to craft an idealised contractual relationship that minimises potential disputes.

Agency theory provides explanations for corporate disclosure from two distinct perspectives: the reduction of agency costs and the minimisation of information asymmetry.

First, according to Hill and Jones (1992), conflicts of interest, or agency problems, between managers and stakeholders often lead to unnecessary losses, termed as stakeholder-agent costs. Non-financial disclosures by a firm decrease the cost to stakeholders of acquiring information about the firm's commitment to satisfying a broad array of stakeholders (Gao et al, 2012). Lower costs of accessing information led to greater transparency in managerial decisions, as the actions of managers become more visible to their stakeholders, which can in turn incentivise managers to align their interests with those of the stakeholders.

Second, information asymmetry has emerged as one of the key concerns among stakeholders, especially investors (Lu and Chueh, 2015). Access to adequate information is vital for stakeholders to achieve symmetry, necessitating that both providers and users have access to the information they need. However, a perfectly symmetrical financial market with evenly distributed information is an idealised concept. The agency costs are, in part, a result of information asymmetry. In other words, reducing the information asymmetry between insiders and external users can help mitigate the agency costs.

#### 2.3.1.1.2 Proprietary cost theory

The cost of disclosing proprietary information is defined as the potential expenses or negative impacts experienced by a firm because of sharing its confidential and proprietary data or trade secrets with external parties (Dye 1985). Proprietary costs play a significant role in decisions pertaining to voluntary disclosure (Meek et al., 1995). As Verrecchia (1983) suggests, "disclosure related cost should not only include the cost of preparing and disseminating information for traders' inspection, but also the cost associated with disclosing information which may be proprietary in nature". These proprietary costs can be categorised into two dimensions.

Firstly, internal costs arise during the process of preparing and releasing information to the market. Secondly, external costs are those incurred when competitors capitalise on the disclosed information from the firm. Dye (1985) posits that proprietary cost is independent and constant, which helps elucidate the manager's nondisclosure behaviour. Prior to making

disclosures, particularly voluntary ones, managers meticulously balance the advantages and drawbacks of conveying information to stakeholders. If managers perceive that the disclosure of certain information could potentially harm their firm, they might choose not to voluntarily disclose some information (Healy and Palepu, 2001).

According to Verrecchia (1983), when proprietary costs exist and a firm opts not to disclose certain information, stakeholders cannot ascertain the nature of this undisclosed information, whether it represents 'bad news', or 'good news' that is just not good enough. Conversely, in the absence of proprietary costs, firms are incentivised to voluntarily disclose information to the market with the aim of reducing information asymmetries. Furthermore, Verrecchia (1983) observes that the higher the proprietary cost of disclosure, the less negative the investor reaction to the withholding of information. This in turn leads to a lower likelihood of voluntary disclosure by firms. Therefore, corporate disclosures, particularly voluntary ones, occur only when firms anticipate some form of benefit from the disclosure. For instance, both Botosan (1997) and Hail (2002) find that voluntary disclosure can decrease the cost of equity capital. Lastly, Dontoh (1989) argues that managers are motivated to disclose both positive and negative news to the market. Positive news targets investors, while negative news targets competitors. Overall, from a managerial incentive perspective, a manager's decision to disclose is driven by a situation where the benefits of disclosure considerably outweigh the proprietary costs.

#### 2.3.1.1.3 Upper echelons theory

Agency theory assumes that management decisions are rational (Lieberson and O'Connor, 1972), but discretionary, personal traits or irrational behaviour cannot be explained by traditional theory (Stumpf and Dunbar, 1991). The upper echelons theory (also known as the top management team theory) focuses on the top management team of the firm such as the chairman and CEO who are the competitive advantage for firms and determinants of its financial and non-financial performance. According to Hambrick and Mason (1984, pp.193), 'organisational outcomes-strategic choices and performance levels-are partially predicted by managerial background characteristics'. In other words, senior executives influence company

activities through their own highly individualised, inter-executive perspectives on experience, values, and personalities. The upper echelons theory is a theory that cannot be ignored when explaining the voluntary disclosure behaviour of firms (e.g., GHC-ET disclosures) from the perspective of managers' personal characteristics. This is because the managers determine the content and form of disclosure as an important part of corporate decision making.

The upper echelons theory focuses on the idea that the characteristics of top management significantly influence a firm's strategic choices (Hambrick and Mason, 1984). While this paper is not on what high-level traits would determine a firm to make GHC-ET disclosures, it is still important to understand the determinants behind the disclosure. The incentives of such disclosure can be explained by the upper echelons theory. For example, Hambrick and Mason (1984) find that firms with younger executives are more likely to pursue risky strategies because the age of the executive reflects risk-taking and physical and mental stamina.

#### 2.3.1.2 Information receiver

From the perspective of information needs, stakeholder theory, legitimacy theory, and signalling theory offer valuable insights into the motivations for GHC-ET disclosures. For example, stakeholder theory acknowledges the diverse information requirements of stakeholders, advocating that firms meet these needs through disclosure. Legitimacy theory pertains to how firms promote disclosures that align with societal norms and expectations. Signalling theory, on the other hand, delves into how firms strategically communicate information to reduce information asymmetries and shape stakeholder perceptions.

#### 2.3.2.2.1 Stakeholder theory

In accordance with neoclassical economics, the primary goal of a corporation is to maximise shareholder value. However, as the interests of various stakeholders come into play, managers may need to consider a broader spectrum of interests. Stakeholders, as defined by

Freeman (1984), refer to individuals and organisations that are impacted by the corporation's activities. This can include direct stakeholders such as shareholders and creditors, as well as indirect stakeholders like employees, customers, suppliers, government bodies, and the community at large.

Stakeholder theory extends the interest boundary beyond traditional paradigms, thus accounting for the diverse interests of internal and external stakeholders. It has grown to be one of the key theoretical foundations for explaining corporate disclosure practices (Chen and Roberts, 2010; Smith et al., 2005). As such, stakeholder theory can serve as a management tool to address and incorporate the needs, perspectives, and interests of a wide range of stakeholders (Fontaine et al., 2006). As agents for stakeholders, corporate managers have a responsibility to ensure their interests are safeguarded, as this enables the long-term sustainability of the organisation. Moreover, Freeman (2004) introduces a fresh premise to shareholder theory, suggesting that management should broaden their scope of consideration to include stakeholders. Barako and Brown (2008) distinguish two branches of this theory: managerial and ethical. Their research findings indicate that both branches can foster a mutually beneficial relationship between managers and stakeholders, thereby minimising potential conflicts.

According to stakeholder theory, corporations bear the responsibility of considering the needs and interests of various stakeholders when making decisions and taking actions. This theory offers a robust theoretical underpinning for corporations to engage in voluntary disclosures related to GHC-ET. Stakeholders, with their diverse expectations and priorities (Fontaine et al., 2006), may exhibit differing interests in such information. For instance, shareholders might be primarily concerned with the financial implications and potential risks associated with the adoption of new technologies. On the other hand, customers might express more concern over the potential benefits, as well as risks to their data security or privacy that such technologies could pose. Furthermore, the incentive for GHC-ET disclosures comes from the need for transparent and effective communication with stakeholders who have the right to be informed about the potential impacts and any associated risks of ETs. Such disclosure allows them to make informed decisions and provides an opportunity for them to contribute their input and feedback, thereby fostering an environment of transparency and trust.

# 2.3.2.2.2 Legitimacy theory

Legitimacy theory provides a potent explanation for the disclosure of non-financial information, distinguishing it from other theories. This theory contends that legitimacy is a social construct, defined by norms, values, and beliefs that determine the acceptable actions for an entity (Perrow, 1970). By focusing on corporate activities, legitimacy theory clarifies the pursuit of legitimate operations, particularly regarding societal and environmental contexts.

The foundation of legitimacy theory rests on the concepts of the political economy, with Gray et al. (1995) proposing that firms often achieve expected returns and positive market performance through adherence to the principle of legitimacy theory. Furthermore, the quest for legitimacy can exert pressure on corporations to submit to social oversight. This is to ensure that their operations align with societal norms and expectations, reinforcing the necessity for disclosure of pertinent information, including details related to ETs especially at a time of rapid technological development.

Legitimacy theory proposes that the disclosure of information pertaining to ETs can be perceived as a form of societal contract, designed to meet societal expectations. Various stakeholders, in their collective goal of ensuring the continued and legally compliant operation of firms, view legitimacy theory as an effective means towards this end (Hooghiemstra, 2000). For instance, during the Bitcoin mania, stakeholders, particularly shareholders, expect to see increased focus and investment in Blockchain by firms they are interested in. However, for such technological incorporation to be accepted and legitimised, it is incumbent upon firms to navigate and adhere to societal expectations.

In summation, legitimacy theory offers a robust framework for understanding GHC-ET disclosures. It highlights the influence of societal norms, values, and beliefs in defining what constitutes legitimate corporate actions. Moreover, it underscores the importance of aligning with societal expectations and operating within legal parameters. The theory further acknowledges the impact of the political economy, the necessity for social scrutiny, and the shaping effect of cultural aspects on corporate practices and their pursuit of legitimacy.

# 2.3.2.2.3 Signalling theory

Signalling theory stems from the study of market interactions in the context of information asymmetry between buyers and sellers. Job seekers communicate their quality through their education to reduce information asymmetry, thereby affecting the ability of potential employers to select (Spence, 1973). With the extension of signalling theory by Nöldeke and Samuelson (1997), it can also be applied to the study of corporate disclosure. In detail, signalling theory deals with the problem of information asymmetry between insiders and stakeholders (Spence, 2002). In situations marked by information disparity, the party with superior information can strategically signal its capabilities or intentions to secure a competitive advantage. Often, this party with an information advantage is the firm's management.

Within this context, corporate disclosures about ETs present a strategic opportunity for firms. Such disclosures allow them to signal their expertise, knowledge, and commitment towards these technologies, thereby mitigating the information asymmetry and shaping stakeholders' perceptions and actions. These signals can demonstrate a firm's preparedness to harness new technologies, its capacity for innovation, and its strategic alignment with technological advancements. Consequently, these signals can influence stakeholder behaviour, bolstering their trust and confidence in the firm.

Firms can leverage GHC-ET disclosures to underscore their commitment to innovation and technological progression. These disclosures can act as potent signals, serving to bridge the information gap between firms actively applying these technologies and their stakeholders. This can notably enhance stakeholder perceptions of a firm's capabilities, competitive standing, and prospects. Secondly, disclosures pertaining to ETs can also function as signals to investors and capital markets. By sharing information about the technology, its potential market impact, and the firm's commercialisation strategy, firms can attract investors keen on technological advancements and growth opportunities. Such disclosed information can provide insights into a firm's long-term prospects, innovation capabilities, and its potential to generate future returns. Moreover, the information about ETs can also signal a firm's willingness to engage in collaborative initiatives and partnership opportunities. In essence, strategic disclosure in the

context of ETs can serve as a powerful signalling tool, aiding firms in managing stakeholder perceptions and expectations.

## 2.3.2 Behavioural finance theories

"Investors can be swayed in their investment decisions by feelings of which they are consciously aware, and specially by those unconscious needs, drives and fears not directly accessible to conscious thought." Eshraghi and Taffler, 2014

While traditional financial theory usually assumes that market participants are perfectly rational, behavioural finance argues that decisions from managers and investors are often influenced by irrational factors (Hirshleifer, 2015). For example, when an investor misses out on a firm that explodes in popularity due to ET, the investor may follow the herd mentality and buy the stock that everyone is chasing to avoid regretting other bad investment decisions, leading to the "herd effect" in the stock market. On the other hand, managers may disclose ETS-related information because of overconfidence or be reluctant to disclose potentially negative information (i.e., high uncertainty and failure possibility of ETs) because of risk aversion. Thus, this section reviews behavioural theories from two perspectives, one is the regret theory and herding behaviour, and the other is overconfidence and optimism bias.

# 2.3.2.1 Regret theory and herding behaviour

Zeelenberg (1999, p. 93) defines regret as 'the negative, cognitively based emotion that we experience when realizing or imagining that our present situation would have been better had we acted differently'. Regret theory suggests that when making a decision, an investor considers not only the outcome of the decision, but also the regret that may result if another option is chosen.

When firms voluntarily disclose information about ETs, this information often contains a high degree of uncertainty and potentially high returns. In this case, investors may be influenced by the psychology of regret avoidance when making investment decisions. In other

words, according to the regret theory, investors may make decisions with excessive consideration of the possible regrets that may arise if they miss this investment opportunity. To avoid possible future regrets, investors may be eager to invest in firms that disclose information about ETs without adequate analysis and evaluation. In conjunction with the decision heuristic proposed by Fenn and Raskino (2008), when a firm makes the GHC-ET disclosure, investors may be reminded of previous successful examples of firms that have applied ETs, such as listed firms that changed their names during the dot-com wave or those that applied blockchain during the Bitcoin mania.

Whether aware of it or not, the impact of the group view is enough to sway any sceptical investor. On the one hand, investors may be less likely to react emotionally when they consider that many investors have also suffered losses on the same investment. On the other hand, in investment decisions, investors tend to follow group behaviour to avoid making regrettable decisions. Investors follow the herd mentality, and when firms that disclose ETs are constantly being speculated in the market, the "herd effect" in the stock market is created.

# 2.3.2.2 Overconfidence and optimism bias

Overconfidence and optimism bias are two widely studied concepts in psychology and behavioural finance that have important implications for firms' voluntary disclosure behaviour as well as investor responses. In other words, overconfidence and optimism bias may affect not only managers' voluntary disclosure decisions and the content of disclosures but also investors' attitude towards corporate disclosures.

In details, overconfidence refers to an individual's over-assessment of the correctness of the judgement. Among corporate management, this may manifest itself in overly optimistic expectations about the firm's future performance (Hribar and Yang, 2016). Whether the firm needs and can benefit from ETs requires rational judgement on the part of the manager. Managerial overconfidence may lead to blindly investing in high uncertainty ETs and disclosing this news to investors. On the other hand, overconfident managers may be influenced by peer pressure. The disclosure of information about ETs by a peer firm is likely to cause a

copycat effect, even if the firm will not be involved in the development of or investment in such ETs (Grennan, 2019). This speculative disclosure is clearly a positive signal from the manager to investors, which can cause the market to overreact. Similarly, managers affected by an optimism bias may overemphasise the positive news and potential of the firm without fully disclosing or even hiding possible risks and difficulties.

Investor reaction to a firm's GHC-ET disclosures can also be affected by their overconfidence and optimism bias. Overconfident investors are willing to take more risks to survive in a competitive market (Hirshleifer and Luo, 2001). Thus, investors may react favourably to optimistic forecasts or good news given by overconfident mangers, pushing up the stock price. However, if subsequent results fail to meet expectations, investor confidence may be undermined, leading to a fall in the stock price.

## 2.3 Conclusion

This chapter delves into the nature of corporate disclosure and summarised the various types of disclosure. It initially explores managerial perspectives, shedding light on the motivations behind firms' disclosure practices through agency theory, proprietary cost theory, and upper echelons theory. Subsequently, the chapter investigates the importance of corporate disclosure from the viewpoint of information demand, incorporating theories such as stakeholder theory, legitimacy theory, and signalling theory. Finally, some behavioural finance theories are discussed to explain managers' disclosure decisions related to GHC-ET and investors' overreactions.

# Chapter 3. Institutional Background, Textual Analysis, and Sample Processing

## 3.1 Introduction

This chapter commences by delineating the institutional background to which my thesis refers. The primary reflection of the regulatory framework concerning corporate disclosure is manifested in the regulation of US firms by the SEC. Furthermore, my thesis concentrates on a special class of high frequency disclosure, known as 8-K filings, which will be expounded upon in Section 3.2 of this chapter. In addition, the distinctive characteristics of disclosure, whether mandatory or voluntary, lead to varying market reactions. My thesis pivots on the study of voluntary corporate disclosure, hence, only 8-K filings corresponding to Item 7.01 are chosen for analysis. Subsequent to this, the chapter also clarifies the dictionary employed for textual analysis, specifically, how each technology is classified as emerging in its respective year (Section 3.3). Section 3.4 illustrates the process of textual analysis, such as the download and cleaning of each 8-K filing of US firms. Finally, Section 3.5 presents the final sample after performing the exclusion criteria, accompanied by a description of the data sources.

# 3.2 Corporate filings

# 3.2.1 SEC Guidance and 8-K filing

The SEC is an independent regulatory agency charged with the governance of financial markets. Its primary mission is to safeguard investors and ensure the fairness and orderly functioning of the securities market (SEC, 2020). To this end, the SEC mandates full public disclosure through various types of reports, all of which can be accessed and downloaded from the Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system on their website. Among these, the 8-K filing stands as a formal corporate report. This is supplementary to the annual reports (Form 10-K) and quarterly reports (Form 10-Q), all of which are required for public firms. Given its increased frequency, the 8-K filing serves as a 'current report', providing stakeholders with prompt updates on certain significant corporate events.

Following the enactment of the Sarbanes-Oxley Act (SOX), it became a requirement for firms to promptly disclose any material changes to the public (Coates IV, 2007). This legislation has had two major impacts on Form 8-K filings: 1) it has led to an increase in the number of items that need to be reported, and 2) it has necessitated a faster disclosure timeframe. The new regulations have expanded the list of required disclosure items from the original 12 to 31, which are divided into nine sections. These items can be classified as either mandatory or voluntary, depending on the specific regulatory requirements. The "Final Rule: Additional Form 8-K Disclosure Requirements and Acceleration of Filing Date" (SEC, 2004) introduces eight new mandatory items. These include two items in Section one (Registrant's Business and Operations), four items in Section two (Financial Information), one item in Section three (Securities and Trading Markets), and one item in Section four (Matters Related to Accountants and Financial Statements). In addition to these new requirements, the rule also transfers two specific items from Forms 10-K and 10-Q to the 8-K filings. These items are 'Unregistered Sales of Equity Securities' and 'Material Modification to Rights of Security Holders'. This shift further emphasises the heightened importance of timely and comprehensive disclosure in the current regulatory environment.

Carter and Soo (1999) and Lerman and Livnat (2010) have documented that 8-K filings comprise diverse disclosures in the form of both mandatory and voluntary reporting. On the one hand, firms are obligated to disclose any events occurring within the firm or those involving the firm. As a general rule, the SEC stipulates that firms must file 8-K reports containing mandatory items within four business days of the triggering event. However, certain exceptions apply. For example, Item 5.02, which concerns the announcement of a new officer, can be delayed until the next public announcement (i.e., a press release). Conversely, Item 4.02 (Non-Reliance on Previously Issued Financial Statements or a Related Audit Report or Completed Interim Review) must be filed within two business days.

Three items, namely Item 2.02 (Results of Operations and Financial Condition), Item 7.01 (Regulation FD Disclosure), and Item 8.01 (Other Events), are considered voluntary disclosures (Lerman and Livnat, 2010; He and Plumlee, 2020). The deadlines for these voluntary items are somewhat flexible. Specifically, Item 2.02 (Operating Results) must be completed and published prior to any associated analyst conference call. Furthermore, Item

7.01 (Regulation Fair Disclosure) filings vary based on the firm's willingness to disclose. If the firm intends to release the information publicly, it must do so concurrently with the event's release. However, if the release is unintentional, it can be done on the subsequent trading day. Lastly, there is no specified deadline for the disclosure of Item 8.01.

In the panorama of disclosure mechanisms, 8-K filings have increasingly garnered the attention of researchers, with a particular focus on those classified under voluntary disclosure. This growing interest is attributed to the observation that different stakeholders accord varying degrees of importance to the filing date, event date, and disclosure information of 8-Ks (Ben-Rephael et al., 2017). For the purposes of this thesis, which centres on firms' voluntary disclosure behaviour, Items 2.02, 7.01, and 8.01 of the 8-K form deserve special attention. Of these, Item 2.02 (Results of Operations and Financial Condition) is less likely to carry information pertaining to the firm's future strategies or investments in ETs and Item 8.01 (Other Events) is not credible due to lack of necessary regulation. Considering this, the data collection for this research is primarily concerned with 8-K reports that include Item 7.01. The particulars of this item will be introduced in the following section.

# 3.2.2 Regulation Fair Disclosure (Item 7.01)

Regulation Fair Disclosure (Reg FD), which was issued by the SEC as part of Exchange Act Release No. 33-7787, came into effect in October 2000, having been promulgated on December 20, 1999 (SEC, 2011). The context of this regulation is embedded in the perceived information asymmetries, which are frequently intensified by agency issues between managers and stakeholders (Duarte et al., 2008). Such agency issues arise from the fact that managers, by virtue of their active involvement in the business operations, inherently possess an informational advantage over shareholders. This informational imbalance has the potential to amplify the agency problems and, hence, further widen the asymmetry of information.

According to SEC (2000), "when an issuer, or person acting on its behalf, discloses material non-public information to certain enumerated persons, it must make public disclosure of that information" (17 CFR 243.100(a)). Thus, the fundamental intent of this regulation is to safeguard a broader stakeholder by preventing firms from engaging in selective disclosure of

material events or information. Under Reg FD, stakeholders can access significant information in a timely manner, which may assist them in their decision-making processes. However, the key issue revolves around the definition of 'material' information. Both Gordon (1933) and Moriarity and Barron (1979) contend that a material fact is one where a false statement or omission significantly influences investor behaviour in holding or disposing of securities.

Despite substantial literature discussing the concept of materiality in the field of corporate disclosure financially or non-financially, the managers' recognition of material event or information is mainly intuitive. If managers believe that an event is likely to have a significant impact, they will promptly disclose it to stakeholders. In other words, managers could still provide material disclosure even if a particular event or corporate strategy is nonmaterial. That is why the Reg FD is recognised as voluntary disclosure by Lerman and Livnat (2010).

This thesis aligns with Lerman and Livnat (2010) and He and Plumlee (2020) in classifying Reg FD as a form of voluntary disclosure. Despite the SEC's mandate for firms to disclose material information under Reg FD, the determination of whether the information is deemed material largely rests on the manager's judgement. This ambiguity arises from the lack of specific provisions clarifying which firm-specific events constitute materiality, thereby allowing managers a certain degree of interpretative latitude in this regard.

Given this framework, this research does not so much contradict Reg FD as it aims to examine the varying market reactions triggered by the disclosure of ETs at different phases of GHC, predicated on the motivation of voluntary disclosure. The rationale for this approach is that firms may often disclose only a vague concept or prospect related to an ET, as opposed to

<sup>&</sup>lt;sup>1</sup> According to the explanation of Reg FD, there is no clear definition of the terms of 'material' and 'non-public' although the regulation requires firms to disclose material non-public information. Instead of discussing what is non-public information, this research focuses on the definition of material information. The regulation highlights that material information is a substantial likelihood important from the perspective of reasonable shareholders (see SEC (2000), II-B-2, Disclosures of Material Non-public Information).

<sup>&</sup>lt;sup>2</sup> To provide greater protection against the possibility of improper liability and to further prevent any chilling effect that this provision may have, Reg FD provides that: "This (Reg FD requirement) will provide additional assurance that issuers will not be second-guessed on close materiality judgments. Neither will we (regulators), nor could we, bring enforcement actions under Reg FD for mistaken materiality determinations that were not reckless." (See SEC (2000) Final Rule: Selective Disclosure and Insider Trading. Available at: https://www.sec.gov/rules/final/33-7881.htm#P12 1307).

a clearly defined investment objective. Thus, even though such disclosure is framed within a mandatory disclosure policy, it can, nonetheless, be construed as a manifestation of voluntary disclosure from managers.

# 3.3 Gartner Hype Cycle

In alignment with the research objectives of my thesis, this section will initially introduce the concept of ETs. Subsequently, I delve into the components, development, and theoretical foundation of the GHC, which serves as the foundation for the 'bag-of-words' approach utilised in the textual analysis. The aim of this thesis is to explore how the market reacts to corporate disclosures of these ETs.

# 3.3.1 Definition of emerging technologies?

Broadly speaking, the term 'emerging technology' is used to denote nascent technologies, but it may also apply to the ongoing development of existing technologies. This term typically refers to technologies that are currently being developed or are projected to be available within the next five to ten years. Especially since the advent of the 21st century, ETs have been thriving in a wide range of industries. These technologies, from their initial conceptual stages to entering the public's purview, engender distinct expectations at each phase of development.

The evolutionary trajectory of a new technology can be summarised by its introduction and subsequent promotion by firms and media, leading to a surge in market enthusiasm. This enthusiasm tends to diverge towards two different outcomes. On the one hand, technical difficulties perceived as insurmountable can lead to disillusionment, resulting in a decline in market and public expectations for this type of new technology. On the other hand, positive outcomes occur when ETs make tangible progress and show promise. Driven by financial support from investors and public expectations, these technologies are often adopted because of their proven feasibility.

# 3.3.2 Hype Cycle components and its theoretical foundation

The Hype Cycle, first introduced by Jackie Fenn and Mark Raskino of Gartner Inc. in 1995, is a graphical representation intended to trace the maturity, adoption, and societal application of various ETs. As depicted in Part A of Figure 3.1, the vertical axis represents the degree of expectations associated with an ET, while the horizontal axis signifies time. Theoretically, the Hype Cycle incorporates two components, or equations, which stem from the interplay between human nature and the nature of innovation (Fenn and Raskino, 2008). Part B of Figure 3.1 restores the Hype Cycle depicted in Part A to its original form. The first component is a bell-like curve, referred to as the hype level curve, demonstrating the relationship between the level of expectations and time. The second component is an S-curve that denotes the trajectory of engineering or business maturity of the technology.

Building on Robert Shiller's concept of 'Irrational Exuberance' (Shiller, 2015), the Hype Cycle can be traced back to the irrational decisions of investors, which are influenced more by psychological factors rather than rational judgments founded on professional knowledge and experience. The bell curve of the Hype Cycle can be explained through three dimensions: novelty preference, social contagion, and decision heuristics (Fenn and Raskino, 2008). The dimension of novelty preference explains that investors typically exhibit enthusiasm for and anticipation of new developments. The dynamic between novelty preference and familiarity preference is a constant tension (Park et al., 2010). On the one hand, some researchers argue that investors feel a greater sense of security and confidence with familiar entities, thereby prioritising them. Investors often have good reasons to select public firms with which they are familiar. On the other hand, the allure of novelty can captivate investors, especially in an era characterised by an overload of information. This novelty preference for breaking the smooth is exciting. The advent of a new technology can generate buzz among investors and media hype, escalating expectations by drawing investor attention.

Moreover, the hype surrounding ETs can also be interpreted through social or behavioural contagion, a concept introduced by Gustave Le Bon in 1896. This phenomenon supposes that individuals tend to imitate the behaviour of those around them or those with whom they are familiar (Le Bon, 1896). A notorious example from capital markets is the spontaneous emergence of a Ponzi scheme, resulting in stock price bubbles and crashes. This situation arises

when investors concentrate excessively on past share prices and the behaviour of others rather than grounding their decisions. Thus, it is plausible that investors exhibit an overreaction when an ET, accompanied by the prospect of widespread popularity and application, comes into the limelight. This collective overreaction fuels the hype associated with these technologies.

The final factor contributing to the hype-driven expectation is decision heuristics, a strategy that influences decision-making processes. As posited by Shah and Oppenheimer (2008), heuristics are based on the utilisation of minimal information to attain satisfactory results. The principal advantage of heuristic decision-making lies in its time-saving attribute. In the context of new technology development, the narrative can be shaped by heuristic decisions. When an ET becomes a focal point, investors may overestimate its prospects by recalling instances of successful technological revolutions from their memory. This is attributable to an inherent bias investors have towards novel and innovative things where the positive aspects outweigh the negatives. This bias leads to higher psychological expectations for ETs (Fenn and Raskino, 2008).

In terms of the engineering or business maturity curve, it forms the right half of the GHC. In this part of the cycle, ETs transition slowly from an initial stage to a rapid enlightenment stage, ultimately reaching maturity. As proposed by Foster (1986), the S-curve serves a crucial role in depicting the trajectory of a technology based on inductively derived theory. The performance of the product, represented on the Y-axis, increases in correlation to the time and engineering efforts depicted on the X-axis. Ultimately, the overlap of the initial hype level curve and the S-curve, which illustrates the technology development trajectory, constitutes the GHC, as depicted in Part B of Figure 3.1.

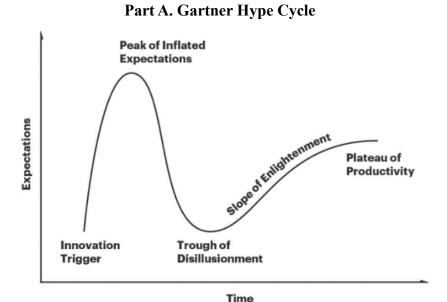
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<sup>&</sup>lt;sup>3</sup> Although scholars have been critically discussing the S-curve of technological development since 1992 (see Christensen, 1992), this research does not discuss its disadvantages because this research focuses on the Gartner Hype Cycle rather than on its parts. The discussion of the components in this section is intended to increase understanding of the logic of Gartner Hype Cycle. Similarly, for another component (hype level), different explanation can be obtained based on different theories.

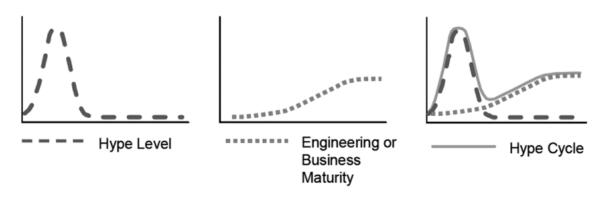
# 3.3.3 Hype Cycle phases

The GHC, as depicted in Part A of Figure 3.1, comprises five distinct phases: Innovation Trigger, Peak of Inflated Expectations, Trough of Disillusionment, Slope of Enlightenment, and Plateau of Productivity. In detail, the Innovation Trigger phase represents the initial stage of a potential technology, often only theoretical or conceptual in nature. Due to media coverage and publicity, technologies at this phase may receive considerable attention, despite the possibility of lacking commercial viability. In the second phase, the Peak of Inflated Expectations, ETs are met with heightened expectations due to the accumulation of early publicity. Many ETs succeed in transitioning from the beginning to this peak. The Trough of Disillusionment phase represents the most challenging time for ETs, mainly due to the continual underperformance against expectations. Producers may face elimination if they fail to attract new investment during this phase. This narrative takes a positive turn in the fourth stage, the Slope of Enlightenment. During this phase, the public gradually warms to the ETs as they begin to appreciate their advantages and benefits. Finally, the Plateau of Productivity is the period during which new technologies become market favourites, having successfully navigated the tumultuous journey of the Hype Cycle.

Figure 3.1 Gartner Hype Cycle and The Two Components of The Hype Cycle



Part B. The two components of the Hype Cycle



Note: This Figure shows the Gartner Hype Cycle and its two components. Part A shows that the vertical axis represents the extent of expectations related to an ET and the horizontal axis is the time. There are five different phases of Gartner Hype Cycle showing in Part A of Figure 3.1, including innovation trigger, peak of inflated expectations, trough of disillusionment, slope of enlightenment, and plateau of productivity. Part B is a restoration of the Part A Hype Cycle to its original form. The first component is the hype level curve like a bell which shows the relationship between the level of expectations and time, and the second component is an S curve of engineering or business maturity.

Source from: Gartner, Inc., 2007.

Available at: https://www.gartner.com/en/research/methodologies/gartner-hype-cycle

# 3.4 The process of textual analysis

# 3.4.1 History and development of textual analysis

Textual or content analysis has gained significant attention in the field of accounting and finance research since the 1950s (Dong et al., 2019). Textual data, abundant in accounting, offers a wealth of valuable insights, delineating various facets of firm characteristics, managerial psychological traits, and behavioural motivations. Drawing inspiration from psychology and sociology, textual analysis is commonly deployed in qualitative research, particularly for analysing interview transcripts. However, in accounting and finance research, the focus often shifts to corporate documents such as annual reports, filings, prospectuses, or director announcements. Traditional research methods, including word count, keywords, and text length, were predominantly used in the early stages of textual analysis (Li, 2008).

As illustrated in Figure 3.2, the scope of accounting text samples extends beyond corporate disclosure, encompassing non-corporate disclosures such as analyst research reports, social media news, and Internet posts (Li, 2010). Relying on the researcher's concentration, for content relevant characteristics, the analysis pays attention to risk, competitive, forward-looking, or false description. Additionally, tone, readability, and repetition are quantified although they are not part of the content of the accounting text. In recent years, many difficulties in analysing accounting texts have been solved effectively with the development of computer language and machine learning. The two most common textual analysis methods are dictionary-based approaches and machine learning algorithms, the latter being further divided into supervised and unsupervised categories (Bao and Datta, 2014).

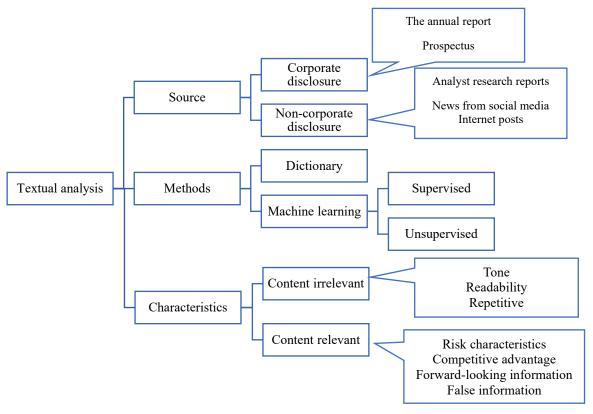


Figure 3.2 The Framework of Textual Analysis

Note: This figure presents the framework of textual analysis in terms of source, methods, and characteristics.

The dictionary-based method of textual analysis operates on the frequency of specific words appearing in the text, matching this against a predetermined word list (Li, 2010). In addition, several software solutions such as General Inquirer (GI), Diction, and Linguistic Inquiry and Word Count (LIWC) facilitate direct text analysis. In the accounting and finance field of research, Henry (2008) and Loughran and McDonald (2011) have created popular versions of dictionaries. However, these dictionaries often lack the ability to recognise specific terminology in the accounting and finance context (Li, 2008). Consequently, researchers often modify the original word list in the dictionary to align with their research topics (Campbell, 2014; You et al., 2018). While dictionary-based methods are appropriate for broad topics such as tone and readability calculation, they are limited by language and subject matter constraints.

Machine learning has significantly enhanced the precision of textual analysis over the last decade. Methods such as Naïve Bayes, cosine similarity, and Latent Dirichlet Allocation (LDA)

have gained popularity in addressing classic questions (Blei et al., 2003). Machine learning can be divided into supervised and unsupervised approaches. Supervised machine learning relies on categorising predefined tags, a technique well-accepted in accounting research (Li, 2010). Despite the unreal assumption of word independence, the accuracy of Naïve Bayes is higher than that of other software and programs (Huang et al., 2014). In contrast, unsupervised learning algorithms do not rely on classification rules. However, owing to its complexity, unsupervised machine learning is still in its nascent stages of development.

# 3.4.2 8-K filings download

This research relies on all Form 8-K filings from 2010 to 2019, sourced from the EDGAR database. Both foreign and domestic firms are obligated to release their 8-K filings publicly available on EDGAR within four business days of the triggering event (SEC, 2012, p.1). Hence, EDGAR is a comprehensive database hosting firm-specific filings of US firms. It allows users to freely access and download firm disclosures in a timely manner. Moreover, the database is designed to facilitate research, enabling bulk downloads of specific types of filings such as 8-K filings or annual 10-K reports.

EDGAR provides full indexes that bridge the gap between quarterly and daily indexes, compiling filings from the start of the current quarter through the preceding business day. At the end of each quarter, the full index is integrated into a static quarterly index. These indices combine diverse reporting types, firm names, CIK numbers, disclosure dates, and filing paths, thus facilitating bulk downloads. Each 8-K filing path consists of a fixed URL path followed by a variable segment.<sup>4 5</sup> All filings can be computationally downloaded via a loop function that seamlessly combines the two parts of the URL path. <sup>6</sup>

To prevent the 8-K filings from becoming excessively long, most firms choose to disclose

<sup>5</sup> Based on individual 8-Ks, such as edgar/data/1000045/0001193125-10-005109.txt

<sup>&</sup>lt;sup>4</sup> Available at: https://www.sec.gov/Archives/.

<sup>&</sup>lt;sup>6</sup> I use the 'request' function of Python to save 8-K filings' contents. To ensure the integrity of the 8-K filings download, I compared the number of text files downloaded to the sum of the number of quarterly indices provided by EDGAR to ensure the data is complete and reliable.

certain information, such as management appointments and resignations, press releases, conference slides, and strategic plans, etc., as appendices in the form of Exhibits. For example,

"On December 11, 2017, the Company issued a press release in connection with the events reported above. A copy of the press release is furnished as Exhibit 99.1."

In this thesis, textual analysis is not confined to the primary content of Item 7.01 of each 8-K filing, but also extends to the Exhibits associated with Item 7.01. These appendices may have rich information, influencing investors in their judgement and decision-making processes. Thus, to ensure that the exhibit is accurately linked to Item 7.01, my textual analysis incorporates both the main content of Item 7.01 and the associated exhibits. The process of 'screening the Item 7.01 and its exhibits' involves searching for both Item 7.01 and the 99.1 exhibit within the 8-K filings collectively.<sup>7</sup>

# 3.4.3 Cleaning the Text

Before proceeding with the analysis, it is essential to clean the text of each 8-K filing. One effective way to improve the accuracy of textual analysis is to streamline filings into a uniform type with minimal noise, prior to searching for keywords. After computationally downloading all 8-K filings, the text format file includes basic information such as the firm name, disclosure date, type of filing, index key, etc., alongside the content related to a specific item. However, due to their HTML format, each 8-K filing contains extraneous elements. For instance, some words representing the text format precede the main item content description. Therefore, as illustrated in Figure 3.3, the first step after screening Item 7.01 and its Exhibits is to remove HTML tags using BeautifulSoup in Python. Additionally, documents like prospectuses, strategic plans, and significant research and development related to ETs are likely to appear in the form of slides or PDF files in the Exhibit. Similar to the main content, this part of the Exhibit is also cleaned to retain words only.

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<sup>&</sup>lt;sup>7</sup> See Appendix D-1 an example of 8-K filing including Item 7.01.

<sup>&</sup>lt;sup>8</sup> E.g. <font size="2" face="Times New Roman">

The next prominent step in text processing is to remove punctuation and symbols. The process of eliminating punctuation ensures each text is treated equally. For instance, the term 'big data' should be treated the same as 'big data!'. While numbers often do not denote explicit meanings, this thesis retains them as certain emerging technologies include numbers, such as '5G'. The final step prior to searching for information related to ETs is 'tokenisation'. Tokenisation splits the raw text into small chunks, including words and sentences (Manning et al., 2014). This thesis utilises the word tokenize function from the Natural Language Toolkit (NLTK) to transform the complete 8-K filing into a pool of words. <sup>10</sup> Given that English alters word letters according to different tense changes, this thesis also conducts lemmatisation using WordNetLemmatizer. For example, the word 'processing' would be returned as 'process'.

Identify all items and exhibits Screening the Item 7.01 and its exhibits Removing HTML tags Removing punctuations and symbols Tokenization (Word segmentation and lemmatization)

Figure 3.3 The Process of Textual Data Cleaning

Note: This figure shows the process of textual data cleaning starting from the identification of all items and exhibits to the tokenization.

# 3.4.4 Emerging technologies-related keywords searching

# 3.4.4.1 Dictionary construction

Every year, Gartner's experts release an updated hype cycle, reflecting the market

<sup>9</sup> Including !"#\$%&\'()\*+,-./:;?@[\\]^\_{|}~`

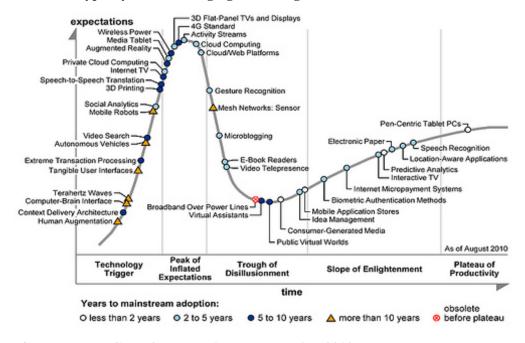
<sup>&</sup>lt;sup>10</sup> Available at: https://www.nltk.org/ modules/nltk/tokenize/punkt.html.

conditions and the status of various ETs. Each phase within this cycle is assigned a specific, professional term. For instance, in 2013, as depicted in Figure 3.4, the 'Innovation Trigger' phase included 14 technologies such as Bioacoustic Sensing, Smart Dust, Quantum Computing, and Quantified Self, among others. In addition to the annual ET curves published by Gartner, its official website categorises all disclosed ETs by degree of market hype. Thus, for this thesis, I collated all the ETs from GHC annually and categorised them under their specific phases. Moreover, the empirical chapters of this thesis do not account for synonyms associated with these ETs. This decision was made under the assumption that for many ETs, especially those in less familiar domains like biology and medicine, investors might not be acquainted with terminological nuances. <sup>11</sup>

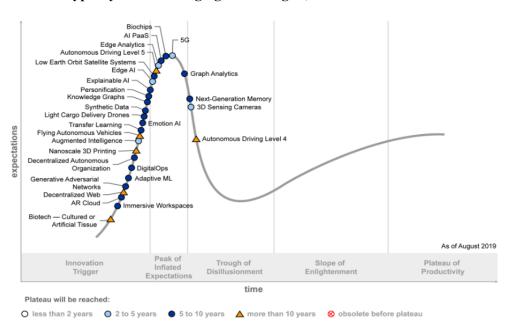
<sup>&</sup>lt;sup>11</sup> For robustness check, this thesis finds unchanged results after considering synonyms. For example, one of the technologies namely brain-computer interface is always known as brain-machine interface, neural-control interface, mind-machine interface, or direct neural interface (Wikipedia) in industries where it is widely used. This thesis conducts keywords searching according to the extended dictionary.

Figure 3.4 Two Example for The Gartner Hype Cycle Emerging Technologies

Panel A. Gartner Hype Cycle for Emerging Technologies, 2010



Panel B. Gartner Hype Cycle for Emerging Technologies, 2019



Source from: https://www.gartner.com/

# 3.4.4.2 The reliability of self-dictionary

The robustness of the bag-of-words (BoW) textual analysis is dependent on the quality of the dictionary (Laver and Garry, 2000). Thus, the first challenge of this thesis is to develop a reliable dictionary. Due to the time-consuming nature of self-dictionary construction, researchers prefer to use available dictionaries. For example, the dictionary of Loughran and McDonald (2014) is well-known for measuring tone. However, existing dictionaries may not meet the particular research objectives which means it is necessary to build a dictionary of ETs to investigate the market reactions to the information disclosure. Although there is no standard for the dictionary building process, researchers use as many texts as possible to expand the dictionary. For example, You et al. (2018) manually read 2,000 randomly selected financial news articles and classified words into positive words, negative words, definite words, and ambiguous words. Bochkay et al. (2020) used the Amazon's Mechanical Turk service to build a linguistic extremity dictionary. Du et al. (2022) used Word2vec to develop a financial sentiment dictionary from 3.1 million Chinese financial news articles.

This thesis employs the GHC as the primary source for selecting ETs-related keywords for three pivotal reasons. Firstly, the model has monitored the innovation of thousands of ETs over the past several decades, proving itself as an effective management tool that extends beyond mere theoretical concepts (Fenn and Raskino, 2008). Secondly, the Hype Cycle aptly depicts investors' heightened enthusiasm during the emergence of a new technological trend. This not only assists firms in making informed decisions regarding the investment or adoption of these technologies but also equips investors with the ability to gauge a firm's commitment to ETs amidst the prevailing fervour. Lastly, the cycle has predominantly been developed and utilised by American researchers, ensuring a plethora of successful studies and reliable precedents. <sup>12</sup>

<sup>&</sup>lt;sup>12</sup> See Appendix D-3. the list of GHC-ET during the thesis sample period.

# 3.4.4.3 The process of keywords searching

The GHC, designed and released annually by Gartner, Inc., typically has an its updated version between the end of July and mid-August. Given this timing, this thesis employs a one-year lag approach when selecting the ETs dictionary for keyword searches within the 8-K filings. This means that, for example, the GHC from 2013 serves as the basis for extracting ETs-related information from the initial 8-K filings of 2014. The textual analysis task is executed using the readWordFile function in Python. <sup>13</sup>

# 3.5 Sample processing

Unlike the regular quarterly 10-Q or annual 10-K filings, the frequency of 8-K filings is considerably higher, leading to a substantial initial sample size. As illustrated in Table 3.1, from 2010 to 2019, a total of 663,897 8-K filings were disclosed by all EDGAR registrants. Nonetheless, this research concentrates solely on those 8-K filings that encompass the voluntary Item 7.01, reducing the sample size to 98,352 filings. Columns (1) and (2) in Table 3.2 indicate that US firms have consistently increased their disclosure frequency related to Item 7.01 each year, even though the overall number of 8-K filings has seen a decline. This could be attributed to firms now having various avenues for communication with investors due to broader access to disclosure mediums. Consequently, the annual count of 8-K filings has been dwindling. Nonetheless, heightened attention from stakeholders (Healy and Palepu, 2001) and the influence of peer pressure (Seo, 2021) has motivated managers towards more voluntary disclosures. As evidence, the number of 8-K filings that include Item 7.01 in 2019 is twice that of 2010.

 $<sup>^{13}</sup>$  See Appendix D-2 an example for the GHC-ET disclosures under Item 7.01.

**Table 3.1 The Process of Sample Selection** 

Process	Sample size
Original 8-K filings of all registrants in EDGAR during 2010 to 2019	663,897
Less: 8-K filings without the Item 7.01	(565,545)
8-K filings including the Item 7.01	98,352
Less: 8-K filings after the initial 8-K filings of each firm in each year	(72,040)
Initial 8-K filings including the Item 7.01	26,312
8-K filings including the Item 7.01 containing GHC-ET	1,414

To study the market reaction to GHC-ET-related disclosures and, in particular, to capture the first wave of shock from investors, I have chosen the 8-K filings that encompass Item 7.01 from each firm's initial disclosure annually following Cheng et al. (2019). This narrows the sample down to 26,312 filings, as indicated in Column (3) of Table 3.2. Post the text data cleansing and conducting a keyword search pertaining to ETs, as highlighted in Column (4), the sample is further refined to 1,414 8-K filings that incorporate information about ETs. 14

<sup>&</sup>lt;sup>14</sup> There may be short two-year disclosure intervals because we focus only on the first 8-K of each year that contains GHC-ET information. For example, a firm discloses the first 8-K on GHC-ET on 1<sup>st</sup> December in 2016 but discloses the first 8-K on GHC-ET on 15<sup>th</sup> January in 2017, so that the interval between two filings belonging to different years is less than 2 months. Therefore, the market reaction may not be accurately estimated. However, a total of three firms in our sample have a disclosure interval of 3 months, while the rest of the sample firms have a disclosure interval of more than 5 months. After excluding these three firms, our regression results do not change substantially.

**Table 3.2 Sample Distribution** 

	(1)	(2)	(3)	(4)
Year	8-K filings	8-Ks including Item 7.01	Initial 8-Ks including Item 7.01	GHC 8-Ks
2010	80,442	6,457	1,867	74
2011	78,824	7,923	2,201	122
2012	77,353	8,713	2,336	91
2013	76,369	9,222	2,462	184
2014	76,930	9,971	2,664	230
2015	76,407	10,468	2,738	76
2016	72,621	10,832	2,862	87
2017	70,785	11,324	2,985	152
2018	68,181	11,662	3,056	225
2019	66,427	11,780	3,141	176
Total	663,897	98,352	26,312	1,414

Note: Table 3.2 shows the firm-year observations distributions. Column (1) shows is the total 8-K filings disclosed by all EDGAR registrants from 2010 to 2019. Column (2) reports how many 8-K filings include Item 7.01. Column (3) indicates the number of firms that disclose 8-K filings containing Item 7.01 for the first time each year. Column (4) indicates the number of the GHC-ET included in all first 8-K filings each year.

## 3.6 Conclusion

This chapter has introduced the institutional context and regulatory framework of corporate disclosure in relation to my thesis, highlighting the SEC's regulation of US firms. It specifically dealt with 8-K filings, a common form of disclosure, with a particular focus on voluntary disclosures under Item 7.01. The chapter also elaborated on the dictionary used in text analysis, the categorisation of emerging technologies, the methodology of textual analysis, and the process of collecting and cleaning 8-K filings. It presented the final sample used in this research after applying certain exclusion conditions and described the sources of the data.

# Chapter 4. An Event-Study of Emerging Technologies Disclosures

## 4.1 Introduction

Globalisation and digitisation have led to a widening and deepening of investors' demands for information about companies, especially in relation to innovations and developments in the field of technology (Verrecchia, 2001). Investors need adequate, accurate and timely information from companies to be able to make informed investment decisions (Healy and Palepu, 2001), especially those that reflect the firm's performance, potential and risks. However, the need for information may vary from investor to investor, with some professional investors wanting more in-depth and detailed business and financial data, while some small investors are more interested in the firm's fundamentals and future outlook including the firm's ability to innovate in science and technology and science and technology strategy (Barber and Odean, 2008).

Driven by technological advances, investors have developed a higher demand for voluntary disclosure of firms' ETs-related information. They want to know the latest progress of companies in emerging technologies such as AI, cloud computing, big data, etc., and how companies are utilising these technological innovations to improve their products or services and enhance their competitiveness (Beyer et al., 2010). Firms are motivated to make voluntary disclosures due to investors' information needs. Past literature suggests that voluntary disclosure can enhance a firm's market value, reduce the cost of financing, and build a firm's social image (Leuz and Wysocki, 2016). There is a very large body of literature that explores the benefits and investor responses associated with firms' voluntary disclosure of non-financial information, including FinTech-related disclosures in specific time periods (e.g., Cahill et al., 2020 and Cheng et al., 2019).

Most of the relevant literature that I have observed focuses on a particular technology hotspot, such as Blockchain (e.g., Cahill et al., 2020 and Cheng et al., 2019), to examine the FinTech-type technology disclosure of firms. However, usually several ETs coexist. If by default all investors are only interested in FinTech, that interest does not reflect the true market reaction. For example, investors with a medical background may look out for medically related

ETs or medical firms, such as artificial skin. Based on my literature search, there is no prior study that broadens the perspective to include all categories of GHC-ET disclosures.

"There was little evidence on the central issues of corporate finance. Now we are overwhelmed with results, mostly from event studies" (Fama, 1991, p.1600). The event study method provides a powerful tool for examining how investors respond to voluntary corporate disclosures. This approach can reveal investor responses by measuring the impact of specific events, such as corporate announcements or press releases, on a firm's stock price (MacKinlay, 1997). This approach is valuable in understanding how investors deal with voluntary corporate disclosures, especially those about technological innovations (Kothari and Warner, 2007).

This chapter examines the following three questions,

- 1) What are investors' immediate reactions to a firm's GHC-ET disclosures?
- 2) Is there a change in investors' delayed reaction to a firm's disclosure of GHC-ET?
- 3) Is there a difference in investor reaction to firm's GHC-ET disclosures at different GHC phases?

Based on the GHC-ET keywords searching in Chapter 3, the event study is carried out on a sample of 1,407 8-K filings with ET-related information from 2010 to 2019. The event study method not only analyses the market reaction from the overall perspective of GHC-ET disclosure, but also innovatively divides ET into five phases according to GHC to explore the difference in market reaction when firms disclose ET at different phases. This chapter finds the immediate market reaction to ET disclosure is positive according to CAR (-3, +3) and BHAR (-3, +3) but is negative in the long term. The immediate and delayed market reactions are varied for firms which disclose ET at different phases. In the short term, only the disclosure of the first three phases of the GHC's ET will result in a positive market reaction. However, in the long term, investors show a negative reaction only to the disclosure of the second phase (those in the peak of inflated expectations of the market). The results are robust after changing event windows and estimation models.

The remainder of this chapter is organised as follows. Section 4.2 provides a theoretical foundation in terms of the definition of efficient market hypothesis, three forms of efficient markets, and how to test the efficient market hypothesis. In addition, this section also presents at the literature review of the event study especially focusing on the market reaction because of mandatory disclosure or voluntary disclosure. Section 4.3 describes the event study method including the estimation process and significant tests. Section 4.4 shows the summary statistics of the whole events collected from textual analysis. Section 4.5 reports the results of the event study based on different event windows. The results can be categorised by event window into short-term and long-term and by sample size for the overall sample and sub-GHCs at different phases of the sample to bring about a market reaction. To verify the robustness, I test the market reaction in the pre-event window, using alternative estimate models and report the results of significant tests. Finally, Section 4.6 concludes the whole chapter.

## 4.2 Theoretical foundation and literature review

This chapter investigates how investors react after the corporate disclosure of ETs-related information in high-frequency reporting. Most of the prior literature, focusing on market reactions of specific events, usually uses the event study to capture the abnormal returns. Therefore, this chapter also uses the simple but direct approach to answer the research question.

This section is organised as follows. Firstly, the definition and assumptions of the efficient market hypothesis will be introduced. Secondly, several key relative papers will be summarised which focus on the use of event studies in terms of corporate mergers and acquisitions, corporate governance and top management team, capital markets and investor characteristics, legal and regulatory events, specific events and periods, and corporate disclosures.

# 4.2.1 Efficient market hypothesis

# 4.2.1.1 The definition of efficient market hypothesis

Tracing the history of the efficient market hypothesis, Fama (1970) and Roberts (1967) proposed a definition of the efficient market hypothesis based on the random walk hypothesis and the uncorrelated price series. They argue that the most efficient market would be one in

which market price movements are completely random and unpredictable. In other words, the price reflects and incorporates not only historical information but also all known information about the firm whose shares are traded. If enough investors in the market have homogeneous information, the market is efficient and excess returns cannot be obtained by analysing existing information (Fama, 1970).

Jensen (1978) redefined the market efficiency hypothesis based on the challenge of simultaneous market efficiency and the non-optimal behaviour of investors. However, normal returns and abnormal returns on risk-taking remain indistinguishable. A widely accepted summary definition is from Malkiel (1992), which is "A capital market is efficient if it adequately and correctly reflects all relevant information in determining the price of a security".

In theory, the efficient market hypothesis includes three dimensions. The first dimension is value of a stock. Efficient markets assume that participants in capital markets are rational economic agents who weigh risk and return to make investment decisions. The second dimension is price. The price of a stock reflects the relationship between supply and demand; in other words, the possibility of arbitrage stems from the difference between those who are short and those who are long. The third dimension is the efficiency of information. When the market is efficient, the price of a stock adequately reflects all available information about the asset, and its price changes in response to changes in information. If a firm discloses news, good or bad, the share price will change.

# 4.2.1.2 Three forms of efficient market hypothesis

The state of market efficiency can be divided into three levels, weak form efficiency, semi-strong form efficiency and strong form, according to the degree of response of information in the stock price. Figure 4.1 shows three forms of efficient markets with different information sets.

Weak form efficiency is that the stock price includes all historical information including trading volume, history price, short selling amounts, etc. Inventors are not able to earn excess returns through the analysis of historical information if the market is weak form efficient. As the second level structure of Figure 4.1, the market will be semi-strong form efficient if the

current stock price not only includes historical information but also public information, such as the earnings announcement, dividend payments, share splits and additions, etc. However, investors are not able to earn excess returns through the analysis of public information. The highest form of efficient market is strong form efficiency which means the stock price includes all information externally and internally. Due to the exposure of all information, no investor including insider traders can gain excess returns if the market is strong form efficient.

Strong form efficiency

Semi-strong form efficiency

Public information

Weak form efficiency

History information

Figure 4.1 Three Forms of Efficient Markets with Different Information Sets

Note: This figure shows three forms of efficient markets with different information sets. The left stacked venn presents three dimensions of market efficiency while the right one presents the information available at different level of market efficiency.

# 4.2.1.3 Testing efficient market hypothesis

Most of the past literature supports weak form efficient and semi-strong form efficient markets while questioning strong form efficient markets. Thus, the literature concentrates on the first two dimensions of the test of the form of market efficiency.

Random walk is the main idea behind the test of a weak form efficient market (Samuelson, 1965). The weak form efficient market assumption will be valid if stock prices are consistent with stochastic movements. Other methods, such as the serial correlation test and the filter rule test, are commonly used to examine weak form efficiency. In addition, the test

for semi-strong form is mainly by using the event study method (Fama et al., 1969). Statistical analysis of stock price performance before and after the release of information on a particular event to see when and how stock prices react to these important events can verify whether the market has reached semi-strong form efficiency. If stock prices are lagging in their response to specific events and there are abnormal returns, then the market should not achieve semi-strong form efficiency. It is not easy to test for strong form efficient markets using quantitative methods. Therefore, strong form efficient markets are not valid if the insider trader interviewed has gained excess returns through inside information.

This thesis agrees that the US market is semi-strong form efficient which means investors will react if they notice public information like corporate disclosure. Therefore, this chapter uses the event study method to capture the short-term and delayed investors' reaction to corporate disclosures (i.e., GHC-ET disclosures).

## 4.2.2 Literature review

# 4.2.2.1 Studies about the event study

MacKinlay (1997) suggests that the earliest event study approach was Dolley (1933), which examined the market's response to nominal price changes in stock splits through a sample of 95 splits from 1921 to 1931. By the 1960s, the event study method had been extended from economics to finance and management and was widely used (e.g., Ashley, 1962; Barker, 1956, 1957, 1958; Myers and Bakay, 1948). According to Corrado (2011), the studies of Modigliani and Miller (1958) and Miller and Modigliani (1961, 1963) propelled the issue of capital structure to the forefront of financial research, which contributes to the emergence of event studies as an important empirical tool for studying financial events.

Kothari and Warner (2005) report that 565 articles use the event study method between 1974 and 2000 in the top five finance journals. The event study has also been applied in accounting, marketing, and politics research areas. Today, the event study method based on Ball and Brown (1968) and Brown and Warner (1980), continues to be widely used to measure the extent to which events affect firm value or market performance.

I search the top three accounting and finance journals using the key word 'event study'

from 2000 to 2022. <sup>15</sup> The search is not only limited to the abstract but also extends to the full text. However, if keywords appeared in the literature review section only then they were not considered. After manual selection, 413 papers used the event study method to explore the market reactions. <sup>16</sup> Overall, finance journals contain about 60% of event study method articles while accounting is 40%. In detail, JF has the largest share (about 30%) with 124 articles using the event study method. TAR has the smallest share (about 5%), with only 19 articles using the event study method over the past 13 years. On the timeline, 2022, 2021, and 2012 had the most event study method papers published (30, 28, and 25, respectively). Although the results based on different search methods and keywords are inconsistent, especially considering other financial and accounting journals, I can conclude that the event study remains the dominant research methodology to examine the market reaction to an event.

Consequently, the event study method is widely used in accounting and finance for a variety of research topics. These include corporate mergers and acquisitions, corporate governance and top management team, capital markets and investor characteristics, legal and regulatory events, specific events and periods, and corporate disclosure. As this chapter of my thesis is not a literature review, I only concentrate on the event study papers from top journals in the accounting and finance fields.

# 4.2.2.2 Corporate disclosures

Based on the nature of corporate disclosure, the use of event study to measure short-term market reactions could be summarised in two dimensions, one is mandatory disclosure and the other is voluntary disclosure. For mandatory disclosure, the prior studies normally start from the financial reporting perspective such as the application of one specific accounting standard. Regarding voluntary disclosure, the non-financial information is always highlighted as CSR or ESG-related information. Apart from this information, firms may disclose innovative

<sup>&</sup>lt;sup>15</sup> Six top journals include: The Journal of Finance, Journal of Financial Economics, Review of Financial Studies, The Accounting Review, Journal of Accounting and Economics, Journal of Accounting Research.

<sup>&</sup>lt;sup>16</sup> Please see Appendix A-1.

investment decision (i.e., R&D), forward-looking information, strategic plan (i.e., M&A), etc. However, after some countries required listed firms to mandatorily disclose CSR or ESG-related information, studies about mandatory disclosure have moved their attention to this field.

# 4.2.2.2.1 Mandatory disclosures

The benefits and costs of mandatory disclosure can be judged in terms of whether the market response to mandatory disclosure of information is positive or negative. First, according to Easley and O'Hara (2004), mandatory disclosure could help investors to predict the future performance of firms (i.e., cash flow or income). Second, the requirement of mandatory disclosure plays the role of monitoring. The disclosure of financial information reduces the possibility of financial fraud (Dimmock and Gerken, 2012). Third, mandatory disclosure requirements induce all firms to disclose information of the same specifications, thereby increasing comparability, which helps investors identify and select information to make investment decisions.

Greenstone et al. (2006) find positive market reactions (3.5%) of the Securities Acts amendments in 1964. The extension of mandatory disclosure requirements to large companies in the OTC prompted management to move closer to the goal of maximising shareholder interest. The mandatory disclosure of financial information of listed firms by securities regulators is also reflected in the requirements for accounting standards. For example, Armstrong et al. (2010) investigate the market reaction to the adoption of IFRS in Europe, suggesting the response is progressively more positive for firms with lower information quality or high information asymmetry prior to IFRS adoption. Wang and Welker (2011) find the market reaction is strong for the difference in net profit arising from the application of IFRS in Australia and Europe. In addition, Khan et al. (2018) and Campbell et al. (2021) focus on FASB's standards or statements.

Some studies move attention to earnings announcement (e.g., Chiang et al., 2019; Cready and Gurun, 2010; DeFond and Zhang, 2009; Kimbrough 2005) or financial statements reporting (e.g., De Franco et al., 2011; Kajüter et al., 2019). There are a number of papers discussing the market reaction to mandatory disclosure if the restrictions on top journals are

lifted; for example, environmental or ESG-related information (e.g., Grewal et al., 2019; Flammer et al., 2021; Peters and Romi, 2013), Because my thesis focuses on the market reaction to disclosure of emerging technologies, a voluntary attribute, I will not go into the details of the literature in this section.

# 4.2.2.2.2 Voluntary disclosures

Voluntary disclosure is the provision of information by a firm to the public or relevant stakeholders on its own initiative, as opposed to mandatory disclosure based on legal or regulatory requirements. Information about emerging technologies is often closely linked to a firm's future investment direction and growth strategy. This information is not disclosure information required by regulatory authorities or financial information required by accounting standards. Voluntary disclosures are also dominated by non-financial information, such as CSR performance, risk-related alerts, customer relationships, and product innovations, etc.

Voluntary disclosure can bring many benefits to firms including increased transparency, avoidance of regulatory issues, and enhanced reputation. Importantly, investors are usually more inclined to invest in firms with transparent disclosures and comprehensive risk disclosures. Dhaliwal et al. (2011) and Gomes et al. (2007) find that voluntary disclosure can attract potential investors and may improve a firm's ability to raise capital. As Chapter 3 mentioned, this thesis agrees with Lerman and Livnat (2010) to regard Reg FD disclosure containing emerging technologies-related information as the voluntary type.

Many studies investigate the market reaction to Reg FD. For example, Bushee et al. (2004) conclude that Reg FD has little effect on managerial disclosure choices and negative investor reactions to disclosure. Different capital market participants (i.e., institutional investors and analysts) react differently to Reg FD. Ke et al. (2008) test the anomalous selling that briefly increased among institutional investors prior to the outbreak of impending bad news following Reg FD. Gintschel and Markov (2004) find that the absolute impact of information disseminated by financial analysts on prices was reduced after the introduction of the FD regulations. Goff et al. (2008) find that stock prices reacted more strongly to changes in recommendations accompanying news events, after analysing the informational content of

changes in stock analysts' recommendations following the passage of Reg FD regulations. Finally, Eng et al. (2015) and Jorion et al. (2004) explore the impact of Reg FD from the perspective of the information environment, suggesting that the informational effects of rating downgrades and upgrades are found to be much larger in the post-FD period, with Reg FD reducing information asymmetries and increasing price efficiency.

# 4.3 Event study method

"An event study is a statistical technique that estimates the stock price impact of occurrences such as mergers, earnings announcements, and so forth. The basic notion is to disentangle the effects of two types of information on stock prices — information that is specific to the firm under question (e.g., dividend announcement) and information that is likely to affect stock prices marketwide (e.g., change in interest rates."

This chapter uses a standard event study approach, following Kothari and Warner (2007), to investigate the market reaction of GHC-ET disclosures by firms through their 8-K filings.

## 4.3.1 The definition of events

Although 8-K filings are a mandatory requirement among US firms to disclose the material events to investors within four business days from the occurrence of this material corporate event (SEC, 2012, p.1), the firm still subjectively determines whether the event is material or not. That is why this thesis focuses on voluntary disclosure items because of the potential for content related to emerging technologies. The EDGAR database of SEC documents all firm-specific 8-K filings of US firms including the firm name, submission date, and CIK number.

To capture the reaction of investors about emerging technologies and avoid the effects of other events, this thesis focuses on the initial 8-K filing containing emerging technologies of each US firm in each year. The event date is the filing date shown on the EDGAR, which is t=0.

## 4.3.2 Event and estimation windows

The event window is the time for examination of the stock price involved in the event. According to SEC, firms have four days to prepare the 8-K filing after the material event happened, but Lerman and Livnat (2010) observed that the vast majority of declarations are made on the same working day as the date of the event or within one or two days of it. Therefore, comparing the disclosure date (t=0), the event window starts from three days before the disclosure date (t=-3) (e.g., Cahill et al. 2020; Carlini et al. 2020; Cheng et al., 2019) to investigate the reaction of investors after emerging technologies-related disclosure. Regarding the delayed market reactions, the event window (+3, +30) is selected to show the change in market reaction after thirty trading days. In order to cover the overall market reaction from before the disclosure occurred to after the disclosure, the event window (-3, +30) is also be discussed. As a placebo test, the CARs and BHARs based on the event window (-20, -3) show the market reactions before the disclosure of emerging technologies-related information.

The estimation window is often difficult to determine because of the balance between estimation accuracy and incorrect calculation parameters. Longer estimation windows provide higher precision because they imply a larger sample of returns. However, too long estimation windows may also mix the effects of other unrelated events. The estimation window is typically 210 trading days to 11 trading days before the event ([-210, -10]), which is the same as this thesis.

# 4.3.3 Normal and abnormal returns

The natural logarithm of returns  $R_{i,t}$  is used to define daily return of firm i in day t. The formula is

$$R_{i,t} = ln(\frac{P_{i,t}}{P_{i,t-1}}) \tag{4-1}$$

where  $P_{i,t}$  is the stock price for firm i at day t and  $P_{i,t-1}$  is the stock price of firm i at day t-1.

The abnormal return is the difference between the actual return and the normal return for

each stock, which is able to reflect the economic impact of emerging technologies-related disclosure. The abnormal return can be calculated by

$$AR_{i,t} = R_{i,t} - E(R_{i,t}) \tag{4-2}$$

where  $AR_{i,t}$  is the abnormal return,  $R_{i,t}$  is abnormal returns, and  $E(R_{i,t})$  is the expected stock return for firm i at day t. This thesis uses the market model to estimate the expected stock return  $E(R_{i,t})$  as follows.

$$E(R_{i,t}) = \alpha_i + \beta_i R_{m,t} + \epsilon_{i,t} \tag{4-3}$$

where  $R_{m,t}$  is the market return on the benchmark index (S&P 500) at day t, respectively.  $\alpha_i$  and  $\beta_i$  are estimated using returns from the pre-event window (-210, -10) of each stock i.  $\epsilon_{i,t}$  is the error term.

#### 4.3.4 Short-term horizon – Cumulative abnormal returns

This thesis uses cumulative abnormal return (CAR) to examine short-term investors' reaction to emerging technologies-related disclosures. The formula is that

$$CAR_{i,t,t+k} = \sum_{t}^{t+k} AR_{i,t} \tag{4-4}$$

where  $CAR_{i,t,t+k}$  is the sum of the average abnormal returns for firm i over a certain period from t to t + k.  $AR_{i,t}$  is the abnormal return for firm i at day t.

# 4.3.5 Long-term horizon - Buy-and-hold abnormal returns

Buy and hold is an investment strategy in which investors may buy stocks and hold them for a long time (Barber and Lyon, 1997). BHARs employ geometric returns rather than arithmetic returns. Based on this principle, BHAR could be calculated by the difference between realised buying and holding returns and normal buying and holding returns as follows,

$$BHAR_{i,t,t+k} = \prod_{t=0}^{t+k} (1+R_{i,t}) - \prod_{t=0}^{t+k} (1+R_{m,t})$$
(4-5)

where  $BHAR_{i,t,t+k}$  is the buy-and-hold abnormal returns for firm i over a certain period from t to t + k.  $R_{i,t}$  and  $R_{m,t}$  are the stock normal return for firm i and the market return at day t.

#### 4.3.6 Alternative estimation models

This thesis also uses the Fama-French three-factor model and the Carhart four-factor model to estimate the expected returns  $(E(R_{i,t}))$ .

The Fama-French three-factor model which is calculated by

$$E(R_{i,t}) = R_{f,t} + \beta_{m,i}[R_{m,t} - R_{f,t}] + \beta_{s,i}[R_{s,t} - R_{l,t}] + \beta_{v,i}[R_{v,t} - R_{g,t}]$$
(4-6)

where  $R_{m,t}$ ,  $R_{f,t}$ ,  $R_{s,t}$ ,  $R_{l,t}$ ,  $R_{v,t}$ , and  $R_{g,t}$  are the market return, the risk-free rate, the small firm return, the large firm return, the value stock return, and the growth stock return at day t, respectively.  $\beta_{m,i}$  is the sensitivity of stock i to the market factor,  $\beta_{s,i}$  is the sensitivity of stock i to the value factor.

The Carhart four-factor model which is calculated by,

$$E(R_{i,t}) = \beta_{m,i}[R_{m,t} - R_{f,t}] + \beta_{s,i}[R_{s,t} - R_{l,t}] + \beta_{v,i}[R_{v,t} - R_{g,t}] + \beta_{u,i}[R_{u,t}$$
 (4-7)  
-  $R_{d,t}$ ]

where  $R_{m,t}$ ,  $R_{f,t}$ ,  $R_{s,t}$ ,  $R_{l,t}$ ,  $R_{v,t}$ , and  $R_{g,t}$ , are the market return, the risk-free rate, the small firm return, the large firm return, the value stock return, and the growth stock return, at day t, respectively. The  $R_{u,t}$ , and  $R_{d,t}$  are returns of winner stocks and loser stocks.  $\beta_{m,i}$  is the sensitivity of stock i to the market factor,  $\beta_{s,i}$  is the sensitivity of stock i to the size factor,  $\beta_{v,i}$  is the sensitivity of stock i to momentum factor.

## 4.3.7 Significance tests

This thesis uses standard event-study method (Kothari and Warner 2007) which needs to make sure individual event or sample of events is significant different from zero rather than a purely accidental result. Therefore, it is necessary to conduct significant tests whose null hypothesis  $(H_0)$  is no abnormal returns within the event window and the alternative hypothesis  $(H_1)$  is the abnormal returns existing.

According to Brown and Warner (1980) and Dychman et al. (1984), the parametric t-test is well specified under the null hypothesis of no abnormal price performance. For CAR significance test, the null hypothesis is that  $H_0$ :  $E(CAR_{i,t}) = 0$  and the test statistic is given by

$$t_{CAR_{i,t}} = \frac{CAR_{i,t}}{S_{CAR_i}} \tag{4-8}$$

where  $S_{CAR_i}$  is the standard deviation of the cumulative abnormal returns in the estimation window according to

$$S_{CAR_i}^2 = (T_2 - T_1) \frac{1}{M_i - 2} \sum_{t=T_0}^{T_1} (AR_{i,t}^2)$$
 (4-9)

where  $T_1$  is the 'latest' day of the estimation window relative to the event day and  $T_2$  is the 'latest' day of the event window relative to the event day, so  $T_2 - T_1$  is the event window length.

In addition, the buy-and-hold abnormal return (BHAR) is estimated by a characteristic based portfolio matching approach (Ikenberry et al. 1995). The null hypothesis (no event effect which means the expected value of BHAR is zero). According to Lyon et al. (1999), this hypothesis can be tested by

$$t_{BHAR} = \frac{\overline{BHAR}(h)\sqrt{n}}{S_{BHAR}} \tag{4-10}$$

where  $\overline{BHAR}$  is the sample mean and  $S_{BHAR}$  is the sample standard deviation of  $BHAR_{i(\tau_1,\tau_2)}$ .

## 4.4 Summary statistics

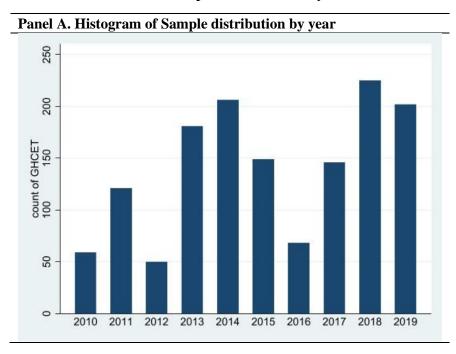
While it was learned in Chapter 3 that the number of US firms disclosing 8-K filings containing Item 7.01 increased each year over the sample period, there was no similar trend in the number of firms disclosing emerging technologies. As Table 4.1 shows, the 2013, 2014, 2018 and 2019 8-K filings contain more information on emerging technologies, while the 2010, 2012 and 2016 filings contain less. During the sample period of this thesis, the first peak of disclosure occurred in 2013 and 2014. By looking at the results after text analysis, the emerging technologies that US firms concentrate on disclosing are the IoT and Big Data. <sup>17</sup> <sup>18</sup> <sup>19</sup> The second peak of disclosures occurred after 2017 when the blockchain and 5G became corporate favourites.

\_\_\_

<sup>&</sup>lt;sup>17</sup> The Internet of Things (IoT) is used for the Internet to connect and exchange data with other devices and systems, and it includes a collection of embedded sensors, software and other technologies.

<sup>&</sup>lt;sup>18</sup> Big data refers to data that is large, fast or complex that is difficult to handle with traditional methods, such as massive customer data analysis or high-frequency transaction data.

<sup>&</sup>lt;sup>19</sup> IoT and Big data are on phase one and phase two of the GHC in 2012, respectively. Both IoT and Big data are on phase two of the GHC in 2013.



**Table 4.1 Sample Distribution by Year** 

Panel B. Sample dis	stribution by year	
Year	Count	Percentage
2010	59	4.19%
2011	121	8.60%
2012	50	3.55%
2013	181	12.86%
2014	206	14.64%
2015	149	10.59%
2016	68	4.83%
2017	146	10.38%
2018	225	15.99%
2019	202	14.36%
Total	1,407	100%

Note: This table shows the sample distribution by year. Panel A presents the histogram of sample distribution which Panel B presents the sample distribution table.

Typically, the GHC updates its emerging technology curve in late July to mid-August each year. According to the sample distribution by month (Table 4.2), the emerging technologies-related disclosures are concentrated on the first quarter which accounts for 31.70%.

Panel A. Histogram of Sample distribution by month 150 count of GHCET 20

**Table 4.2 Sample Distribution by Month** 

Panel B.	Sample	distribution	by	month

Panel B. Sample distribution by month						
Month	Count	Percentage				
1	150	10.66%				
2	159	11.30%				
3	137	9.74%				
4	108	7.68%				
5	140	9.95%				
6	109	7.75%				
7	87	6.18%				
8	88	6.25%				
9	120	8.53%				
10	100	7.11%				
11	110	7.82%				
12	99	7.04%				
Total	1,407	100%				

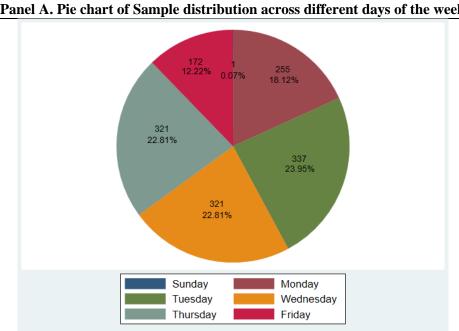
Note: This table shows the sample distribution by month. Panel A presents the histogram of sample distribution which Panel B presents the sample distribution table.

Table 4.3 presents the sample distribution across different days of the week. According to the pie chart, 23.95%, 22.81%, and 22.81% of the sample firms chose to release their 8-K filing containing the GHC-ET on Tuesday, Wednesday, and Thursday, respectively. Approximately

30% of the sample firms chose to disclose GHC-ET information on the first and last day of the weekly trading day. One firm chooses to disclose its 8-K on Sunday, while no firm does so on Saturday.

Table 4.3 Sample Distribution Across Different Days of The Week

Panel A. Pie chart of Sample distribution across different days of the week



Panel B. Sample distribution across different days of the week Day Count Percentage 255 18.12% Monday Tuesday 337 23.95% Wednesday 321 22.81% Thursday 321 22.81% Friday 172 12.22% Saturday 0 0.00% 1 0.07% Sunday Total 1,407 100%

Note: This table shows the sample distribution across different days of the week. Panel A presents the pie chart of sample distribution which Panel B presents the sample distribution table.

Table 4.4 shows the sample distribution by the GHC phase. Based on novelty preference, firms and investors tend to pay more attention to new things. The most disclosed emerging technologies are in the first phase (innovation trigger) which accounts for 39.73%. In addition,

the second phase accounts for 37.81%. In other words, more than two-thirds of the disclosures about emerging technologies originated in the first and second phases of the GHC, before crossing the peak of investor expectations and declining.

Panel A. Histogram of Sample distribution by phase

Table 4.4 Sample Distribution by The Gartner Hype Cycle Phase

Panel B. Sample distribution by phase	Panel B	. Sample	distribution	bv	phase
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Phase	Count	Percentage
1 (Innovation trigger)	559	39.73%
2 (Peak of inflated expectations)	532	37.81%
3 (Trough of disillusionment)	230	16.35%
4 (Slope of enlightenment)	64	4.55%
5 (Plateau of productivity)	22	1.56%
Total	1,407	100%

Note: This table shows the sample distribution by GHC phase (Phase one: Innovation trigger, Phase two: Peak of inflated expectations, Phase three: Trough of disillusionment, Phase four: Slope of enlightenment, Phase five: Plateau of productivity). Panel A presents the histogram of sample distribution which Panel B presents the sample distribution table. See Section 3.3.3 for details on the phases of each ET.

#### 4.5 Results and discussion

#### 4.5.1 Introduction

This section describes the results of event study based on the market models for different event windows. Abnormal returns provide evidence to investors to understand the performance of an individual asset or a portfolio of assets. However, in a short event window, abnormal returns seem to be biased. Cumulative Abnormal Return (CAR) which is the sum of abnormal returns over a given period could avoid this uncertainty. This section also calculates buy-and-hold abnormal return (BHAR) to measure the market reaction to companies' emerging technology 8-Ks disclosure. This is because of the bias of CARs compared with BHARs. Ritter (1991) documents new listing bias when using CARs to measure the market reaction because new listed companies may underperform or outperform market averages leading to CARs being positive or negative separately.

Section 5.2 discusses the short-term investor reactions to GHC-ET disclosures while Section 5.3 focuses on the delayed investor reactions. Section 5.4 shows the placebo tests. Finally, Section 5.5 reports result of significant tests.

#### 4.5.2 Immediate investor reactions

# 4.5.2.1 The disclosure of emerging technologies

Figure 4.2 shows the results of CAR and BHAR for the short-term event window (-3, +3) based on the market model while Table 4.5 shows significant test results. In terms of the trend of the curves, three trading days before the date of the 8-K disclosure containing the information of ET, the firm's disclosure information about ET has been leaked. This is in line with the conjecture of Cheng et al. (2019) that the SEC gives US firms four business days to prepare disclosures for material events, leading to the possibility that relevant information is known to the market in advance. This is why this thesis sets the event window as three trading days before to three trading days after the disclosure of the 8-K filings containing ETs. As a result, the market shows positive feedback. Both CARs and BHARs are gradually increasing and peak on the disclosure date of the 8-K filings containing ET. Specifically, the average event window returns for CAR (-3, +3) is 1.64% based on the estimated results for the firms' initial

ET-related 8-Ks each year (t-statistic of 3.328). Similarly, BHAR (-3, +3) returned 1.80% (t-statistic of 3.502).<sup>20</sup>

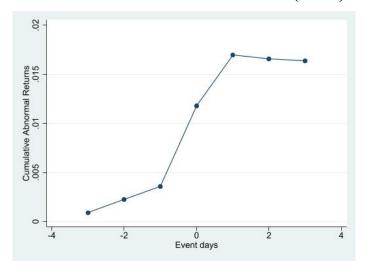
Cheng et al. (2019) find that firms will receive a 5.10% (BHAR (-3, +3)) market return for disclosing information about blockchain in an initial 8-K filing. My thesis extends ET to all industries, so an excess return of about 2% is reasonable. The results of the event study method validate the question posed in this chapter that any ET has the potential to become the next mainstream technology favoured by the market, thus triggering a new technological revolution. Therefore, according to signalling theory, investor's view firms making disclosures related to an ET as positive signals that such firms may be involved in ETs-related projects in the near future.

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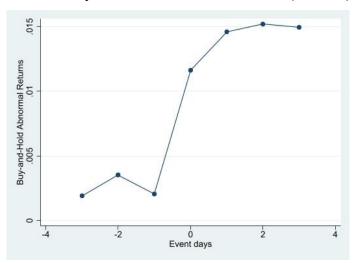
<sup>&</sup>lt;sup>20</sup> All event study results of different event windows based on the Fama-French three-factor model and the Carhart four-factor model are shown in Appendix A2-15. The results of significant tests are reported in each significant test results table together. Both CARs and BHARs are unchanged comparing with the event study results based on the market model.

Figure 4.2 The Cumulative Abnormal Returns (CARs) and the Buy-and-Hold Abnormal Returns (BHARs) over Event Window (-3, +3)

Panel A. Cumulative abnormal returns (CARs)



Panel B. Buy-and-hold abnormal returns (BHARs)



Note: This figure shows the cumulative abnormal returns (CARs) and the buy-and-hold abnormal returns (BHARs) from three trading days before the event date to three trading days after the event date. The event date is the 8-K filing date of US firms shown on the EDGAR. The expected stock returns are estimated by the market model. The estimation window is (-210, -10).

## 4.5.2.2 The difference in market reactions among five phases

The second innovation of this thesis is the division of different ETs into five phases depending on the different market expectations.<sup>21</sup> It is reasonable to estimate and compare the market response of GHC-ET disclosures that are at different phases.<sup>22</sup> In Figure 4.3, there are clear differences in the CARs of market responses generated by firms disclosing different phases of ET, which can be divided into two groups overall. The first group includes those ETs at phase one (Innovation trigger), phase two (Peak of inflated expectations), and phase three (Trough of disillusionment) while the rest of the group includes phase four (Slope of enlightenment) and phase five (Plateau of productivity).

Figure 4.3 shows the results of CAR and BHAR for ETs at different phases of disclosure estimated based on the short-term event window (-3, +3) of the market model. Overall, GHC-ET disclosures in the first four phases of the GHC harvest positive CARs and BHARs on the disclosure date. One exception is the disclosure that the CAR for phase four (Slope of enlightenment) ET reaches its maximum value one trading day before the disclosure date and starts a downward trend after the disclosure date.

In detail, according to the estimation results, the average event window returns of CAR (-3, +3) for disclosing phase one ETs is 2.15% for the firm's initial ET-related 8-Ks (t-statistic = 2.294), which is higher than the overall sample mean of 1.64% (1.80%). Similarly, BHAR (-3, +3) returned 2.59% (t-statistic = 2.509). The average event window returns for CAR (-3, +3) with disclosure of phase two ET is 1.06% (t-statistic is 1.683) and the return for BHAR (-3, +3) is 1.15% (t-statistic = 1.830). The average event window returns for CAR (-3, +3) disclosing the phase three ET is 1.65% (t-statistic = 1.674) and the BHAR (-3, +3) is 1.77% (t-statistic = 1.733). While disclosure of a phase five ET would bring a negative market reaction, the reactions to disclosure of phase four and five ETs are negligible.<sup>23</sup>

<sup>&</sup>lt;sup>21</sup> See Chapter 3 about the five phases of ETs based on the Gartner Hype Cycle.

<sup>&</sup>lt;sup>22</sup> See Table 4.4 the distribution of five phases of the whole sample.

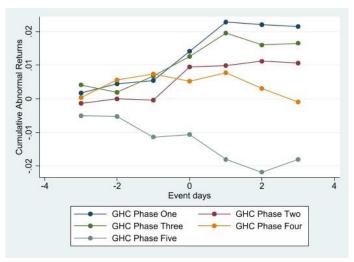
<sup>&</sup>lt;sup>23</sup> All event study results of different event windows based on the Fama-French three-factor model and the Carhart four-factor model are shown in Appendix A. The results of significant tests are reported in

According to Fenn (2007) and Fenn and Raskino (2008, 2009), investors are interested in ETs in their trigger stage because of novelty preference. Therefore, this thesis observes that the CARs of those firms that disclose ETs at the innovation trigger phase are above the mean of the total sample. In addition, although market expectations have peaked in the second phase of ET, excessive market reactions have not been observed. The market reaction is even higher for the disclosure of phase three ETs than for phase two (CARs (-3, +3) are 1.65% and 1.06%, respectively). This phenomenon can be explained by the indifference of investors to the firm's follow-through behaviour after the disclosure of their competitors. Further, risk-averse investors are in a wait-and-see attitude towards ETs that are hyped by the market. Finally, the market reaction is not significant because ETs in the fourth and fifth phase are already familiar to investors.

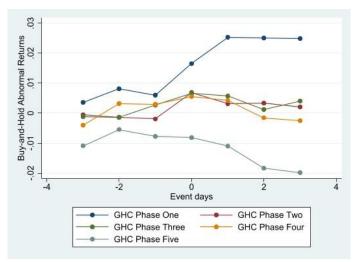
each significant test results table together. Both CARs and BHARs are unchanged comparing with the event study results based on the market model.

Figure 4.3 The Cumulative Abnormal Returns (CARs) and the Buy-and-Hold Abnormal Returns (BHARs) over Event Window (-3, +3) by Phase

Panel A. Cumulative abnormal returns (CARs) by phase



Panel B. Buy-and-hold abnormal returns (BHARs) by phase



Note: This figure shows the cumulative abnormal returns (CARs) and the buy-and-hold abnormal returns (BHARs) by the GHC phase (Phase one: Innovation trigger, Phase two: Peak of inflated expectations, Phase three: Trough of disillusionment, Phase four: Slope of enlightenment, Phase five: Plateau of productivity) from three trading days before the event date to three trading days after the event date. The event date is the 8-K filing date of US firms shown on the EDGAR. The expected stock returns are estimated by the market model. The estimation window is (-210, -10).

Table 4.5 Significant Tests of CARs and BHARs over Event Windows (-3, +3)

Panel A. The w	hole sample					
_	Market	Model	Fama-Frenc	Fama-French three-factor		our-factor
Event windows	CAR	BHAR	CAR	BHAR	CAR	BHAR
_	(1)	(2)	(3)	(4)	(5)	(6)
(-3, +3)	0.0164***	0.018***	0.0155***	0.0178***	0.0158***	0.0181***
t-stats	(3.328)	(3.502)	(3.240)	(3.456)	(3.303)	(3.462)
Panel B. Phase	One					
E	Market	Model	Fama-Frenc	h three-factor	Carhart fo	our-factor
Event windows-	CAR	BHAR	CAR	BHAR	CAR	BHAR
(-3, +3)	0.0215**	0.0259**	0.0188**	0.0231**	0.0190**	0.0233**
t-stats	(2.2936)	(2.509)	(2.046)	(2.357)	(2.075)	(2.362)
Panel C. Phase	Two					
E41	Market	Model	Fama-French three-factor		Carhart four-factor	
Event windows-	CAR	BHAR	CAR	BHAR	CAR	BHAR
(-3, +3)	0.0106*	0.0115*	0.0105*	0.0113*	0.0104*	0.0113*
t-stats	(1.683)	(1.830)	(1.678)	(1.814)	(1.677)	(1.893)
Panel D. Phase	Three					
E411	Market Model		Fama-Frenc	h three-factor	Carhart fo	our-factor
Event windows-	CAR	BHAR	CAR	BHAR	CAR	BHAR
(-3, +3)	0.0165*	0.0177*	0.0170*	0.0182*	0.0183*	0.0194*
t-stats	(1.674)	(1.733)	(1.728)	(1.809)	(1.814)	(1.783)
Panel E. Phase	Four					
F 4 : 1	Market	Model	Fama-French three-factor		Carhart four-factor	
Event windows	CAR	BHAR	CAR	BHAR	CAR	BHAR
(-3, +3)	-0.0009	-0.0002	-0.0011	-0.0004	-0.0010	-0.0004
t-stats	(-0.369)	(-0.491)	(-0.077)	(-0.132)	(-0.073)	(-0.027)
Panel F. Phase	Five					
E	Market	Model	Fama-Frenc	h three-factor	Carhart four-factor	
Event windows-	CAR	BHAR	CAR	BHAR	CAR	BHAR
(-3, +3)	-0.0180	-0.0181	-0.0151	-0.0151	-0.0135	-0.0136
t-stats	(-0.978)	(-0.955)	(-1.279)	(-1.187)	(-1.134)	(-1.138)
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Note: This table shows the CARs and BHARs over event windows (-3, +3) using market, the Fama-French three-factor, and the Carhart four-factor models. Panel A shows results of the whole sample while the rest of panels are five GHC phases. Columns (1) and (2) of each panel report CARs and BHARs using the market model to estimate the expected returns. Columns (3) and (4) report the Fama-French three-factor model. Column (5) and (6) report the Carhart four-factor model. The t-statistics presented in parentheses. The significance levels are: \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

## 4.5.3 Delayed investor reactions

## 4.5.3.1 The disclosure of emerging technologies

Cheng et al. (2019) find that investors' overreaction to blockchain-related disclosures made by firms during the blockchain mania was short-lived. This thesis selects two different windows (-3, +30) and (+3, +30) to examine the change of investors' reaction after GHC-ET disclosures.

## 4.5.3.1.1 Event window (-3, +30)

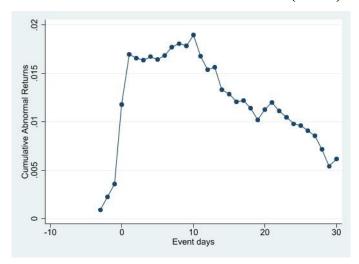
Figure 4.4 provides the combined reactions over the initial and follow-up period (-3, +30) while Table 4.6 shows significant tests results. The CARs and BHARs for GHC-ET disclosures are estimated based on the event window (-3, +30) of the market model. Overall, both CAR and BHAR show an upward trend from three trading days before the GHC-ET disclosure. For CAR, the upward trend continues until the 12th trading day after the disclosure date. In addition, BHAR declined sharply from the 7th trading day and returned to its pre-market disclosure status by the 11th day. The market then reacted negatively, with BHAR at approximately -0.8% on 30th trading day from the disclosure date. Combined with the initial CARs, the average CAR (-3, +30) is 0.57% (t-statistic=3.328), while the average BHAR (-3, +30) is 0.49% (t-statistic=3.502) in the 30 trading days after the ET-related disclosure. The results of these curves indicate that most of the initial positive responses to 8-K containing ET information are reversed within 30 days.<sup>24</sup>

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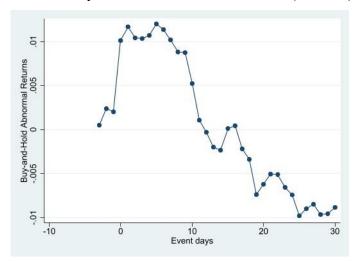
<sup>&</sup>lt;sup>24</sup> All event study results of different event windows based on the Fama-French three-factor model and the Carhart four-factor model are shown in Appendix. The results of significant tests are reported in each significant test results table together. Both CARs and BHARs are unchanged comparing with the event study results based on the market model.

Figure 4.4 The Cumulative Abnormal Returns (CARs) and the Buy-and-Hold Abnormal Returns (BHARs) over Event Window (-3, +30)

Panel A. Cumulative abnormal returns (CARs)



Panel B. Buy-and-hold abnormal returns (BHARs)



Note: This figure shows the cumulative abnormal returns (CARs) and the buy-and-hold abnormal returns (BHARs) from three trading days before the event date to thirty trading days after the event date. The event date is the 8-K filing date of US firms shown on the EDGAR. The expected stock returns are estimated by the market model. The estimation window is (-210, -10).

## 4.5.3.1.2 Event window (+3, +30)

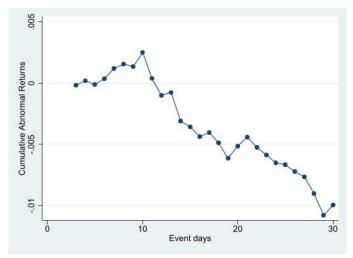
Figure 4.5 provides the delayed market reaction after the 8-K disclosure. The CARs and BHARs for the disclosure of ETs are estimated based on the event window (+3, +30) of the market model. Overall, both CAR and BHAR show a plummeting trend after the GHC-ET related disclosure. For CAR, the upward trend continues until the 10th trading day after the disclosure date while BHAR starts to decline from the 5th trading day. After the three trading days of initial 8-K filing containing ETs, the average CAR (+3, +30) is -1.05% (t-statistic=-2.165), while the average BHAR (+3, +30) is -1.29% (t-statistic=-2.019). The results of these curves suggest that investors react negatively to the delayed response of GHC-ET, in contrast to the immediate response.<sup>25</sup>

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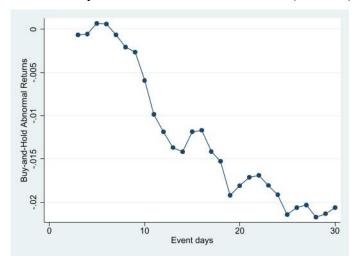
<sup>&</sup>lt;sup>25</sup> All event study results of different event windows based on the Fama-French three-factor model and the Carhart four-factor model are shown in Appendix A2-15. The results of significant tests are reported in each significant test results table together. Both CARs and BHARs are unchanged comparing with the event study results based on the market model.

Figure 4.5 The Cumulative Abnormal Returns (CARs) and the Buy-and-Hold Abnormal Returns (BHARs) over Event Window (+3, +30)

Panel A. Cumulative abnormal returns (CARs)



Panel B. Buy-and-hold abnormal returns (BHARs)



Note: This figure shows the cumulative abnormal returns (CARs) and the buy-and-hold abnormal returns (BHARs) from three trading days after the event date to thirty trading days after the event date. The event date is the 8-K filing date of US firms shown on the EDGAR. The expected stock returns are estimated by the market model. The estimation window is (-210, -10).

Table 4.6 Significant tests of CARs and BHARs over Event Windows (-3, +30) and (+3, +30)

Б	Market	Model	Fama-Frenc	h three-factor	Carhart fo	our-factor
Event windows -	CAR	BHAR	CAR	BHAR	CAR	BHAR
willdows	(1)	(2)	(3)	(4)	(5)	(6)
(-3, +30)	0.0057***	0.0049***	0.0046***	0.0040***	0.0066***	0.0059***
t-stats	(3.328)	(3.502)	(3.289)	(3.456)	(3.293)	(3.462)
(+3, +30)	-0.0105**	-0.0129**	-0.0110**	-0.0135**	-0.0089**	-0.0115**
t-stats	(-2.165)	(-2.019)	(-2.278)	(-2.183)	(-1.851)	(-1.843)

Note: This table shows the CARs and BHARs over event windows (-3, +30) and (+3, +30)) of the whole sample using market, the Fama-French three-factor, and the Carhart four-factor models. Columns (1) and (2) of each panel report CARs and BHARs using the market model to estimate the expected returns. Columns (3) and (4) report the Fama-French three-factor model. Column (5) and (6) report the Carhart four-factor model. The t-statistics presented in parentheses. The significance levels are: \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

## 4.5.3.2 The difference in market reactions among five phases

# 4.5.3.2.1 Event window (-3, +30)

In Figure 4.6, there are clear differences in the CARs of market responses generated by firms disclosing different phases of ET, which can be divided into two groups overall. Different to the short-term reactions, the first group includes those ETs at phase one (Innovation trigger), phase two (Peak of inflated expectations), phase three (Trough of disillusionment), and phase five (Plateau of productivity) while the rest of the group only includes phase four (Slope of enlightenment).

The detailed results are shown in Table 4.7 including CAR and BHAR for ETs at different phases of disclosure estimated based on the event window (-3, +30) of the market model. Overall, the market reactions are negative to GHC-ET disclosures in phase one, two, three, and five of the GHC since the disclosure date. Two phases that should be highlighted are phase one and phase four. For the disclosure of phase one ETs, the average CAR and BHAR are negative and significant in the event window (-3, +30). The disclosure of the CAR for phase four ETs starts an upward trend overall.

In details, according to the estimation results, the average event window returns of CAR (-3, +30) and BHAR (-3, +30) for disclosing phase one ETs is -0.11% and -0.10% for the firm's

initial ET-related 8-Ks (t-statistic = 2.283 and 2.509, respectively), which is lower than the overall sample mean of 0.57% (0.49%). The average event window returns for CAR (-3, +30) with disclosure of phase two ET is 0.78% (t-statistic is 1.820) and the return for BHAR (-3, +30) is 0.53% (t-statistic = 1.830). The average event window returns for CAR (-3, +30) disclosing the phase three ET is 0.91% (t-statistic = 1.766) and the BHAR (-3, +30) is 0.76% (t-statistic = 1.733). While the reactions to disclosure of phase four and five ETs are negligible.<sup>26</sup>

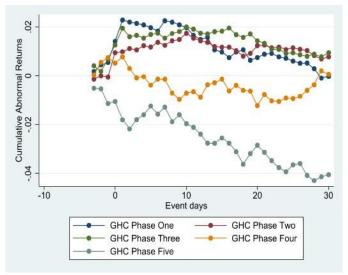
This thesis observes that the market reaction to disclosure of ETs that are in the fourth phase is exceptional although the significance test of the event study method is not significant. In terms of the characteristics of each phase of ET based on the GHC, the first two phases have the highest market expectations, but due to the uncertainty and high failure rate that characterise ETs, there is a high probability that firms involved in the development of such ETs will not be able to reap the rewards of their involvement in a short period. However, ETs in the fourth phase have greater potential and are highly likely to enter the market application stage after making breakthroughs. Compared to the disclosure of ETs in the application phase (phase give in the GHC), the established facts do not attract investors' attention.

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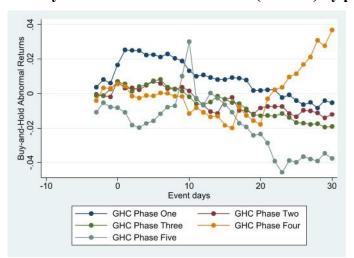
<sup>&</sup>lt;sup>26</sup> All event study results of different event windows based on the Fama-French three-factor model and the Carhart four-factor model are shown in Appendix A2-15. The results of significant tests are reported in each significant test results table together. Both CARs and BHARs are unchanged comparing with the event study results based on the market model.

Figure 4.6 The Cumulative Abnormal Returns (CARs) and the Buy-and-Hold Abnormal Returns (BHARs) over Event Window (-3, +30) by Phase

Panel A. Cumulative abnormal returns (CARs) by phase



Panel B. Buy-and-hold abnormal returns (BHARs) by phase



Note: This figure shows the cumulative abnormal returns (CARs) and the buy-and-hold abnormal returns (BHARs) by the GHC phase (Phase one: Innovation trigger, Phase two: Peak of inflated expectations, Phase three: Trough of disillusionment, Phase four: Slope of enlightenment, Phase five: Plateau of productivity) from three trading days before the event date to thirty trading days after the event date. The event date is the 8-K filing date of US firms shown on the EDGAR. The expected stock returns are estimated by the market model. The estimation window is (-210, -10).

Table 4.7 Significant tests of CARs and BHARs over Event Windows (-3, +30) by Phase

Panel A. P	hase One							
Т.	Market	Model	Fama-Frenc	h three-factor	Carhart fo	our-factor		
Event windows -	CAR	BHAR	CAR	BHAR	CAR	BHAR		
willdows -	(1)	(2)	(3)	(4)	(5)	(6)		
(-3, +30)	-0.0011**	-0.0010**	-0.0058**	-0.0054**	-0.0052**	-0.0052**		
t-stats	(2.283)	(2.509)	(2.129)	(2.340)	(2.149)	(2.362)		
Panel B. F	Phase Two							
Г .	Market	Model	Fama-Frenc	h three-factor	Carhart fo	our-factor		
Event windows -	CAR	BHAR	CAR	BHAR	CAR	BHAR		
willdows -	(1)	(2)	(3)	(4)	(5)	(6)		
(-3, +30)	0.0078*	0.0053*	0.0077*	0.0054*	0.0103*	0.0082*		
t-stats	(1.820)	(1.830)	(1.891)	(1.900)	(1.883)	(1.893)		
Panel C. Phase Three								
Except =	Market	Model	Fama-Frenc	h three-factor	Carhart fo	our-factor		
Event windows -	CAR	BHAR	CAR	BHAR	CAR	BHAR		
windows -	(1)	(2)	(3)	(4)	(5)	(6)		
(-3, +30)	0.0091*	0.0076*	0.0119*	0.0106*	0.0158*	0.0144*		
t-stats	(1.766)	(1.733)	(1.845)	(1.809)	(1.827)	(1.862)		
Panel D. I	Phase Four							
Г .	Market	Model	Fama-Frence	h three-factor	Carhart fo	our-factor		
Event - windows -	CAR	BHAR	CAR	BHAR	CAR	BHAR		
willdows -	(1)	(2)	(3)	(4)	(5)	(6)		
(-3, +30)	0.0006	0.0017	-0.0042	-0.0032	-0.0031	-0.0021		
t-stats	(0.369)	(0.491)	(-0.194)	(-0.132)	(-0.143)	(-0.177)		
Panel E. F	Phase Five							
Б .	Market	Model	Fama-Frenc	h three-factor	Carhart fo	Carhart four-factor		
Event windows -	CAR	BHAR	CAR	BHAR	CAR	BHAR		
willuows -	(1)	(2)	(3)	(4)	(5)	(6)		
(-3, +30)	-0.0405	-0.0438	-0.0272	-0.0298	-0.0223	-0.0248		
t-stats	(-0.978)	(-0.955)	(-1.187)	(-1.321)	(-1.095)	(-1.120)		
Note: This	table shows th	ne CARs and	BHARs over	event windows	(-3, +30) usin	g market, the		

Note: This table shows the CARs and BHARs over event windows (-3, +30) using market, the Fama-French three-factor, and the Carhart four-factor models. Panel A to E show results of five GHC phases. Columns (1) and (2) of each panel report CARs and BHARs using the market model to estimate the expected returns. Columns (3) and (4) report the Fama-French three-factor model. Column (5) and (6) report the Carhart four-factor model. The t-statistics presented in parentheses. The significance levels are: \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

## 4.5.3.2.2 Event window (+3, +30)

In Figure 4.7, there are clear differences in the CARs of market responses generated by firms disclosing different phases of ET, which can be divided into two groups overall. Similar to the event window (-3, +30), the first group includes those ETs at phase one, phase two, phase three, and phase five while the rest of the group only includes phase four.

The detailed results are shown in Table 4.8 including CAR and BHAR for ETs at different phases of disclosure estimated based on the event window (+3, +30) of the market model. Overall, the market reactions are negative to GHC-ET disclosures in five phases after the disclosure date. Specially, disclosure of phase one ETs has the strongest negative market reaction in the long run while disclosure of phase four ETs has the least negative delayed market reaction compared to the other four phases.

In detail, according to the estimation results, the average event window returns of CAR (+3, +30) and BHAR (+3, +30) for disclosing phase one ETs is -2.24% and -2.52% for the firm's initial ET-related 8-Ks (t-statistic = -2.435 and -2.067, respectively), which is lower than the overall sample mean of -1.05% (-1.29%). However, the reactions to disclosure of other ETs phases are negligible.<sup>27</sup>

It makes sense that those firms that disclose phase one ETs in their initial 8-Ks would get negative feedback from the market after the 8-K disclosures. Due to the novelty of phase one ETs, investors naturally expect more. However, if innovative ETs with ahead-of-the-curve concepts are not viable, the negative investor reaction to such ETs will be the strongest.

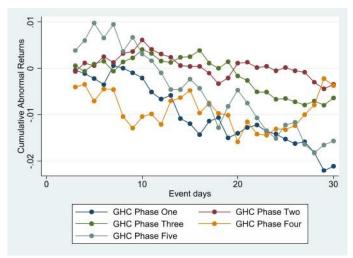
the event study results based on the market model.

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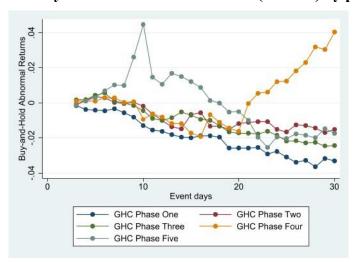
<sup>&</sup>lt;sup>27</sup> All event study results of different event windows based on the Fama-French three-factor model and the Carhart four-factor model are shown in Appendix A2-15. The results of significant tests are reported in each significant test results table together. Both CARs and BHARs are unchanged comparing with

Figure 4.7 The Cumulative Abnormal Returns (CARs) and the Buy-and-Hold Abnormal Returns (BHARs) over Event Window (+3, +30) by Phase

Panel A. Cumulative abnormal returns (CARs) by phase



Panel B. Buy-and-hold abnormal returns (BHARs) by phase



Note: This figure shows the cumulative abnormal returns (CARs) and the buy-and-hold abnormal returns (BHARs) by the GHC phase (Phase one: Innovation trigger, Phase two: Peak of inflated expectations, Phase three: Trough of disillusionment, Phase four: Slope of enlightenment, Phase five: Plateau of productivity) from three trading days after the event date to thirty trading days after the event date. The event date is the 8-K filing date of US firms shown on the EDGAR. The expected stock returns are estimated by the market model. The estimation window is (-210, -10).

Table 4.8 CARs and BHARs over Different Event Windows

Panel A. P	hase One							
П .	Market	Model	Fama-French	n three-factor	Carhart fo	ur-factor		
Event windows -	CAR	BHAR	CAR	BHAR	CAR	BHAR		
willdows -	(1)	(2)	(3)	(4)	(5)	(6)		
$\overline{(+3, +30)}$	-0.0224**	-0.0252**	-0.0252***	-0.0281**	-0.0245***	-0.0275**		
t-stats	(-2.435)	(-2.067)	(-2.762)	(-2.379)	(-2.669)	(-2.339)		
Panel B. P	hase Two							
	Market	Model	Fama-Frencl	n three-factor	Carhart fo	ur-factor		
Event - windows -	CAR	BHAR	CAR	BHAR	CAR	BHAR		
willdows -	(1)	(2)	(3)	(4)	(5)	(6)		
$\overline{(+3, +30)}$	-0.0034	-0.0061	-0.0032	-0.0061	-0.0005	-0.0033		
t-stats	(-0.492)	(-0.442)	(-0.468)	(-0.437)	(-0.365)	(-0.365)		
Panel C. Phase Three								
Г	Market	Model	Fama-French	n three-factor	Carhart fo	ur-factor		
Event - windows -	CAR	BHAR	CAR	BHAR	CAR	BHAR		
windows –	(1)	(2)	(3)	(4)	(5)	(6)		
(+3, +30)	-0.0063	-0.0081	-0.0037	-0.0054	-0.0004	-0.0022		
t-stats	(-0.857)	(-0.734)	(-0.444)	(-0.629)	(-0.048)	(-0.057)		
Panel D. F	Phase Four							
-	Market	Market Model		n three-factor	Carhart fo	ur-factor		
Event - windows -	CAR	BHAR	CAR	BHAR	CAR	BHAR		
willdows -	(1)	(2)	(3)	(4)	(5)	(6)		
(+3, +30)	-0.0036	-0.0052	-0.0083	-0.0101	-0.0073	-0.0091		
t-stats	(-0.122)	(-0.282)	(-0.669)	(-0.925)	(-0.572)	(-0.618)		
Panel E. P	hase Five							
Б ( -	Market	Model	Fama-French	n three-factor	Carhart fo	Carhart four-factor		
Event windows -	CAR	BHAR	CAR	BHAR	CAR	BHAR		
willdows -	(1)	(2)	(3)	(4)	(5)	(6)		
$\overline{(+3, +30)}$	-0.0156	-0.0167	-0.0057	-0.0065	-0.0018	-0.0025		
t-stats	(-0.581)	(-0.622)	(-0.235)	(-0.228)	(-0.070)	(-0.090)		
Note: This t	table shows th	ne CARs and	BHARs over e	vent windows	(+3, +30) usin	g market, th		

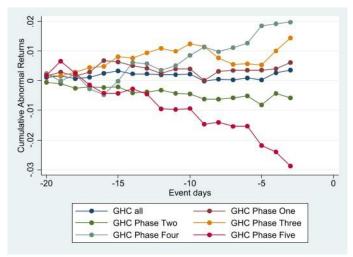
Note: This table shows the CARs and BHARs over event windows (+3, +30) using market, the Fama-French three-factor, and the Carhart four-factor models. Panel A to E show results of five GHC phases. Columns (1) and (2) of each panel report CARs and BHARs using the market model to estimate the expected returns. Columns (3) and (4) report the Fama-French three-factor model. Column (5) and (6) report the Carhart four-factor model. The t-statistics presented in parentheses. The significance levels are: \*\*\* p<0.01, \*\*\* p<0.05, \* p<0.1.

#### 4.5.4 Placebo tests

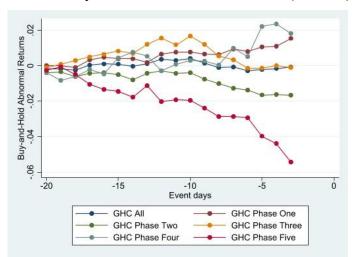
This thesis changes the event window to twenty trading days before to three trading days after the event date (-20, -3) to conduct a placebo test. Figure 4.8 and Table 4.9 report the event study results including CARs and BHARs. The CARs and BHARs of the event study for the overall sample are insignificant (t-statistic = 0.760 and 0.680 for CARs and BHARs, respectively). In addition, for different phases, all CARs and BHARs are also insignificant (t-statistic = 0.603 and 0.964 for CARs and BHARs of Phase one sample, t-statistic = -0.364 and -0.364 for CARs and BHARs of Phase two sample, t-statistic = 1.073 and 1.073 for CARs and BHARs of Phase three sample, t-statistic = 0.645 and 0.522 for CARs and BHARs of Phase four sample, t-statistic = 0.741 and 0.741 for CARs and BHARs of Phase five sample). Therefore, the market reactions because of GHC-ET disclosures of firms' initial 8-Ks are robust.

Figure 4.8 Placebo Tests Using the Event Window (-20, -3)

## Panel A. Cumulative abnormal returns (CARs)



Panel B. Buy-and-hold abnormal returns (BHARs)



Note: This figure shows the cumulative abnormal returns (CARs) and the buy-and-hold abnormal returns (BHARs) of the whole sample and by the GHC phase (Phase one: Innovation trigger, Phase two: Peak of inflated expectations, Phase three: Trough of disillusionment, Phase four: Slope of enlightenment, Phase five: Plateau of productivity) from twenty trading days before the event date to three trading days before the event date. The event date is the 8-K filing date of US firms shown on the EDGAR. The expected stock returns are estimated by the market model. The estimation window is (-210, -10).

Table 4.9 Significant test of CARs and BHARs over Event Windows (-20, -3)

Panel A. The wh	ole sample	,					
	Market		Fama-Frenc	h three-factor	Carhart fo	our-factor	
Event windows	CAR	BHAR	CAR	BHAR	CAR	BHAR	
	(1)	(2)	(3)	(4)	(5)	(6)	
(-20, -3)	0.0037	0.0049	0.0040	0.0053	0.0042	0.0055	
t-stats	(0.760)	(0.680)	(0.825)	(0.998)	(0.859)	(0.857)	
Panel B. Phase	One						
E411	Market	Model	Fama-Frenc	h three-factor	Carhart fo	our-factor	
Event windows—	CAR	BHAR	CAR	BHAR	CAR	BHAR	
(-20, -3)	0.0061	0.0100	0.0065	0.0104	0.0067	0.0107	
t-stats	(0.603)	(0.964)	(1.006)	(1.006)	(1.003)	(1.003)	
Panel C. Phase	Two			, ,		•	
E 4 1 1	Market Model		Fama-French three-factor		Carhart four-factor		
Event windows-	CAR	BHAR	CAR	BHAR	CAR	BHAR	
(-20, -3)	-0.0058	-0.0065	-0.0059	-0.0065	-0.0061	-0.0068	
	(-0.364)	(-0.364)	(-0.688)	(-0.688)	(-0.925)	(-0.925)	
Panel D. Phase	Three		,		,	,	
	Market Model		Fama-Frenc	h three-factor	Carhart fo	our-factor	
Event windows-	CAR	BHAR	CAR	BHAR	CAR	BHAR	
(-20, -3)	0.0145	0.0146	0.0142	0.0144	0.0146	0.0147	
t-stats	(1.073)	(1.073)	(0.888)	(0.888)	(0.874)	(0.874)	
Panel E. Phase	Four						
E 4 1 1	Market	Model	Fama-Frenc	Fama-French three-factor		Carhart four-factor	
Event windows-	CAR	BHAR	CAR	BHAR	CAR	BHAR	
(-20, -3)	0.0198	0.0190	0.0239	0.0233	0.0235	0.0230	
t-stats	(0.645)	(0.522)	(0.680)	(0.680)	(0.4654)	(0.4654)	
Panel F. Phase I	Five		, , , , , ,	, , ,			
	Market	Model	Fama-Frenc	h three-factor	Carhart four-factor		
Event windows-	CAR	BHAR	CAR	BHAR	CAR	BHAR	
(-20, -3)	-0.0288	-0.0307	-0.0259	-0.0278	-0.0237	-0.0255	
t-stats	(0.741)	(0.741)	(1.098)	(1.098)	(0.835)	(0.835)	

Note: This table shows the CARs and BHARs over event windows (-20, -3) using market, the Fama-French three-factor, and the Carhart four-factor models. Panel A shows results of the whole sample while the rest of panels are five GHC phases. Columns (1) and (2) of each panel report CARs and BHARs using the market model to estimate the expected returns. Columns (3) and (4) report the Fama-French three-factor model. Column (5) and (6) report the Carhart four-factor model. The t-statistics presented in parentheses. The significance levels are: \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

#### 4.6 Conclusion

## 4.6.1 Summary of findings

This chapter finds that investors positively react to ETs-related 8-Ks filing disclosure in the initial seven-day event window. Despite the uncertainty associated with the implementation of ETs, GHC-ET disclosures imitative was viewed by investors as a favourable corporate strategy, with strong innovation capabilities, weakening their judgment and tolerance of risk. However, this chapter concludes that this market reaction caused by GHC-ET disclosures is temporary. The market reaction will reverse within 60 trading days after the initial GHC 8-K disclosure. The results are robust over different event windows and using different expected return models.

### 4.6.2 Challenges to the event study approach

Despite that the event study captures market reactions to GHC-ET disclosures, it is difficult to investigate more details and verify its reliability. The reason is mainly due to drawbacks of the event study approach. Therefore, this section summarises the shortcomings of the approach in several dimensions.

First, while in many cases the event study method can be a useful tool for making causal inferences, it is difficult to rule out the influence of hidden variables on causality. This is because event studies usually rely on 'natural experiments', for example, using events (e.g., disclosures made by firms about emerging technologies) as 'treatments' to observe their effects on outcomes. Therefore, except financial characteristics, there are other unobservable variables should be taken into consideration. Also, there are concurrent events that may cause the market to respond, e.g., other events taking place in the firm, its competitors, and its auditors. These hidden variables may lead to results that appear to be causal but are caused by other factors.

Second, some events may have a lagged effect on outcomes. In an event study, it is difficult for this chapter to determine exactly how long the impact of a firm making an ET disclosure lasts and when the short-term positive market reaction is reversed. In addition, this chapter does not exclude the effect of noise, such as when firms make earning announcements or other significant events occur around the date of GHC-ET disclosures. Thus, while the CARs

estimated by the event study method are positive for those firms that disclose ETs, this chapter remains unable to verify what proportion is contributed by such disclosures.

Third, this chapter cannot conclude the reason of the reversal of delayed market reaction. There are two plausible reasons to explain this phenomenon. The first is due to a shift in investor attitudes towards ETs' information. ETs are known to be characterised by high risk, high uncertainty, and high failure rates. Whether investors react positively to information about ETs in the short term due to irrational judgement or novelty preference, in the long term such reactions are temporary. Investors who have time to reasonably estimate the prospects of the ET by reviewing information or asking experts. Their reaction will be reversed once they determine that the ETs potential of the firm's undertaking is not worth investing in and paying attention to. If the manager carries out other behaviours (e.g., selling shares) after GHC-ET disclosures, investors have reason to believe that the true intention of the disclosure is only to raise the stock price.

#### 4.6.3 Further research

The above three major shortcomings deserve further study and discussion. Chapter 5 will focus on answering the following questions. First, in addition to differences in firm financial characteristics, do investor sentiment and 8-K characteristics (i.e., tone or readability) containing information about ETs affect investors' judgement of disclosures and thus responses? Second, if firms have good news to release to the market before including GHC-ET disclosures, then positive market reactions are not caused by, or are not all caused by, investor preferences for ET information. Chapter 5 will answer this question. Finally, the next chapter also explores what causes delayed market reactions to reverse.

# Chapter 5. Financial Market Reactions to Disclosures of Emerging Technologies

#### 5.1 Introduction

A variety of new technologies have emerged from time to time to drive the development of industry and society, such as the internet, Bitcoin, Blockchain, and cloud computing. The Wall Street Journal reports a significant increase in investor interest in Bitcoin and Blockchain technology, as witnessed by the sharp rise in Bitcoin prices in 2017. Firms involved in this type of popular technology grow rapidly and experience increased share prices and attractiveness to investments. For example, the share price of a small firm, Longfin, increased by 1,342% within one trading day after inside news of the acquisition of a cryptocurrency firm with no revenue (Buck, 2017). How do investors react to news about the development and application of such ETs?

An emerging body of literature has begun to answer this question. For example, Cheng et al. (2019) and Cahill et al. (2020) find that investors react positively to blockchain-related announcements even though the firm lacks substantial commitments or follow-through on development plans for blockchain technology. However, such studies have tended to focus on one technology and investors' short-term reactions to disclosures about its development and adoption. Although it can be observed through the event study method in Chapter 4 that firms making GHC-ET disclosures can lead to positive CARs, causality still cannot be accurately determined. The results of the event study in Chapter 4 find that investor reactions to GHC-ET disclosures reverse in the long term, but the exact reason for this is not clear. Further, prior studies have also tended to neglect many details in such disclosures, such as the frequency of disclosure and the market hype phases of the technology. As a result, my understanding of investors' perceptions of and reactions to technological developments is still seriously limited. This chapter aims to address this gap.

In this chapter, I use the GHC, which lists substantial ETs in five development dimensions (see Figure 3.1), to capture ET vocabularies and use them for textual analysis.<sup>28</sup> The GHC sometimes subtly overlaps with other curves. Figure 5.1 shows that the Google Trend of '3D printing' coincides with the GHC between 2010 and 2015 when this kind of technology was put forward and caused strong repercussions in the market. In the GHC, 3D printing technology was in the first phase from 2010 to 2012, reached the peak of investors' expectations from 2012 to 2014, and entered the application stage after a short period of technical bottlenecks. Although the factors influencing stock prices are complex, investors' expectations could be one of the factors because of the direct or indirect effects on their imagination of the enterprise's strategy and future development, which thus change their investment behaviour. Figure 2 also presents the two share-price movements of the two largest firms whose main business is 3D printing during the 3D printing technology mania. The stock prices of these two firms have similarly fluctuated in response to expectations during the 3D printing mania.



Figure 5.1 Gartner Hype Cycle for 3D Printing

Note: This figure plots the similar trend in term of two historical stock prices of two largest firms whose main business is 3D printing, Google trend of 3D printing, and the GHC. The red dotted lines divide different phases of Gartner Hype Cycle, which means the 3D printing technology was in the first phase from 2010 to 2012, reached the peak of investors' expectations gradually from 2012 to 2014, and entered the application stage after a short period of a technical bottleneck.

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<sup>&</sup>lt;sup>28</sup> Five development dimensions are innovation trigger, peak of inflated expectations, trough of disillusionment, slope of enlightenment, and plateau of productivity.

Thus, the first objective of this chapter is to identify market reactions to GHC-ET disclosures based on the event study results after controlling firm-level characteristics. While novelty and speculation can cause a rapid initial rush of enthusiasm from investors to firm disclosures related to GHC-ET, the long-term perspective is uncertain due to a deeper understanding of what the technology could achieve (Fenn, 1995). The findings of this chapter show that investors react positively in the immediate to the initial GHC-ET disclosure each year. However, the delayed market reaction is negative. I wonder whether the shift in investor attitudes is due to a correction of overreactions or to other events. Further investigation in this chapter verifies that insider selling within 60 trading days of the GHC-ET disclosure is responsible for the reversal of investor reaction.

In addition, this chapter investigates whether and how investors react differently to the details of GHC-ET disclosure, such as the disclosure intensity in each 8-K, the frequency of 8-K containing GHC-ET information each year, and the disclosures indicating different technology development phases. Based on the exposure effect (Titchener, 1910), investors tend to trust familiar items and develop a preference for them, which means that the intensity or frequency of a firm's disclosure is influential. However, firms may also be at risk of overselling if they choose to excessively increase the intensity or frequency of disclosure, especially for something that is new. The regression results side with the overselling story, as reflected in the negative market reaction in both the immediate and delayed reactions to the intensity and frequency of GHC-ET disclosures. Regarding the development phases of GHC of each technology, I find that while immediate investors react more positively to GHC-ET disclosures in the 'innovation trigger' and 'peak of inflated expectations' phases, the attitude is negative after the disclosures.

This chapter conducts several robustness checks. First, to exclude the effect of other events on investor reactions, I strictly exclude samples with annual and quarterly earnings announcements in the five trading days prior to the first GHC-ET disclosures, and 8-Ks that

<sup>&</sup>lt;sup>29</sup> Since this research focuses only on the phase when ETs are widely followed and highly expected, the market reactions at the dawn of ETs and their peak are compared (the 'innovation trigger' and 'peak of inflated expectations' phase).

contain mandatory disclosure items.<sup>30</sup> I also re-run the regression after removing the sample with insider selling. The results are unchanged after excluding the effects of other events but insignificant if insider selling is excluded in testing the delayed market reaction. Second, I estimate expected returns using the Fama-French three-factor and the Carhart four-factor models to calculate CARs and verifying whether the market reacts positively before the 8-K filings release period. The results are robust with different estimation models, and I find no significant positive or negative market reactions sixty trading days before the 8-K filings release. Finally, I add three additional control variables, including firm-specific investor sentiment and the tone and readability of each 8-K filing. The results are unchanged.

I run regressions for subsamples to investigate the difference between firms with different institutional holdings and analysts' followings. The immediate market reaction is positive when institutional holdings are low, suggesting that experienced institutional investors have more information and thus are not easily influenced by speculative disclosures. However, institutional investors react negatively over the long horizon. In addition, the immediate market reaction is positive for firms with fewer analysts but the delayed reaction turns to negative for firms with more analysts. This validates my expectations that the management of firms with fewer analysts is bolder in disclosing information even with high uncertainty. I also validate the importance of the information environment. Investors pay more attention to information on ETs when information asymmetry is high. Finally, I conduct additional tests and find that investors are more sensitive to familiar FinTech-type technologies and are interested in choosing technologies that are soon adopted by the market. High-tech firms or firms in high-tech environments are not favoured more than other firms.

The remaining of this chapter is organised as follows. Section 5.2 presents the literature review followed by hypotheses development. In Section 5.3, I describe the data, the variable construction based on an event study and textual analysis, and the econometric models. In Section 5.4, I summarise the regression results, including robustness checks and further

<sup>&</sup>lt;sup>30</sup> According to the SEC (2004), mandatory items include entry into or termination of a material agreement, creation of or increase in an off-balance sheet obligation, exit or disposal activities, material impairments, notice of delisting, and non-reliance on a previously issued report.

analysis. Section 5.5 is the conclusion including summary of findings, limitations, and further suggestions.

# 5.2 Literature review and hypothesis development

Due to the information advantage, managers have more information on whether the firm has good or bad news. In addition to mandatory disclosures, managers can make voluntary disclosures, including nonfinancial information to outsiders. Increasing the amount and timeliness of voluntary disclosure by firms can reduce information asymmetry (Healy and Palepu, 2001) and limit the ability of insiders to use private information for profitable trading (Frankel and Li, 2004). According to signalling theory, good news at the firm level, whether about financial aspects such as satisfied earnings announcements or nonfinancial aspects such as the fulfilment of social responsibilities, gives investors' confidence and increases stock prices. Although managers have incentives to hide information, especially bad news, stock-based compensation plans could prompt them to provide voluntary disclosures to avoid stock price crashes (Beyer et al., 2010). In addition, managers have the flexibility to decide what and how to disclose and may use their disclosure discretion to influence market reactions (Marquardt and Wiedman, 2005). Therefore, managers are motivated to voluntarily disclose ETs either to maximise shareholder value or for self-interest realisation.

Extensive evidence shows that investors react differently to various information. Although a large part of prior studies focused on nonfinancial information disclosure, such as social and environmental information, through CSR reports, the stock price feedback resulting from voluntary disclosure may allow managers to improve their strategic decisions (Dye and Sridhar, 2002). This predictable market response prompts management to increase the degree of voluntary disclosures, especially speculative and temporary disclosures. Cheng et al. (2019) find that investors overreact to blockchain-related information in 8-K filings during the market mania of blockchain even if the firm lacks further investments and substantial applications of the technology. Investors view such information as having the potential for future growth and firm value enhancements (Sarkees, 2011). During the market mania, managers learn the information needs of investors and decide when to disclose what information.

The preference for novelty is used to explain that investors are usually enthusiastic about and look forward to new things (Fenn and Raskino, 2008). The shock of novelty could attract investors' attention, especially in the age of the information explosion. When a new technology comes along, investor buzz and media hype could raise expectations by attracting investors' attention. Furthermore, the hype of ETs could be interpreted as social or behavioural contagion (Le Bon, 1896), which explains investors' herding behaviour, especially retail investors. A well-known example of capital markets is the spontaneous emergence of the Ponzi process, resulting in share price bubbles and crashes. 31 Therefore, it is reasonable to assume that investors are overreacting when an ET is hyped by the market. In addition, the problem of information asymmetry can be reduced through voluntary disclosures. Several prior studies have identified with signalling theory that managers prefer to disclose more information if the firm has positive news (Healy and Palepu, 2001). GHC-ET disclosures can be seen as a positive sign that, on the one hand, investors pay more attention to similar disclosures during a particular ET mania. On the other hand, it is common for firms to make positive disclosures around ETs in terms of investment direction or hiring new executives. Therefore, the first hypothesis is proposed as follows:

**Hypothesis 1**. GHC-ET disclosures are associated with positive immediate market reactions.

Some psychological factors seem temporary, which means that investors probably change their mind after an irrational period. As these ETs further develop and mature, they are finally applied to the market. The expectations and attention of investors are also maximised during the mania phase, such as blockchain in 2017. In addition, the firm may announce its innovation strategy to investors in the early stage when the concept of ET is proposed to demonstrate

<sup>&</sup>lt;sup>31</sup> The process of using new investors' money to pay interest and short-term returns to previous investors to create the illusion of making money and thus scamming them into investing more. Shiller (2000) argues that the naturally occurring Ponzi process can lead to speculative bubbles. In this case, increasing asset prices boosted investor confidence and expectations. The media and institutional investors tend to contribute to the rationalization of rising share prices. Such a cycle plays out like an actual Ponzi scheme until it is recognized.

industry leadership and obtain more investments. When these technologies are to be hyped, the firm's disclosure of ETs that already attracts investor attention may be suspected as only catching the market mania. If investors do not fully recognize the possibility of ET application failure during GHC-ET disclosures in 8-K filings, they react to uncertain information slowly or even negatively. For example, Cheng et al. (2019) find a negative market reaction when investors realize that the firm's disclosures against the Blockchain were simply to gain a market advantage during bitcoin mania. On the other hand, ET investments and applications are commonly characterized by high failure rates. The disclosure of ETs could be regarded as uncertain information that exposes the risks in firms' operations, enhancing the returns for investors (Johnstone, 2021). As a result, I could predict a negative delayed market reaction to GHC-ET disclosures in 8-K filings.

### **Hypothesis 2.** GHC-ET disclosures are associated with negative delayed market reactions.

Disclosure intensity refers to the number of times the ET keyword appears on the firm's first 8-K filing each year that contains the GHC-ET. Disclosure frequency is the number of 8-K reports in the year following this 8-K filing that also contain GHC-ET. There are two possible market reactions, one based on the impression management or self-presentation perspective (Leung et al., 2015) and the other based on the overemphasis perspective (Beyer and Guttman, 2012). Policymakers consistently highlight the importance of narrative disclosures in helping investors learn about firm risks (Leung et al., 2015). The impression management argument interprets management disclosure as opportunistic behaviour in which managers with an information advantage selectively disclose information and manipulate the content and presentation of information in corporate documents with the aim of distorting investors' perceptions of the firm's performance and prospects (Aerts, 2005). Managers may use impression management to hint to investors about the firm's ability and prospects for innovation. Based on this possibility, managers are eager to show investors the firm's strategy for and even applications of ETs. They highlight this information several times in voluntary disclosures to prevent investors from ignoring it. Therefore, the market reaction to the intensity

and frequency of GHC-ET disclosures is positive, i.e., the more times that ETs appears in an 8-K filing, the more positive is the investor reaction.

However, some studies that have focused on the content of corporate disclosures conclude that retail investors benefit from clearer and more concise disclosures (i.e., Hsieh et al., 2016; Lawrence, 2013; Tan et al., 2015). While the disclosure of corporate information by managers can reduce the level of information asymmetry, disclosing too much information not only increases the cost to the firm of disclosures but also reduces credibility. In addition, investors simply observe a firm's disclosures rather than inferring the value of the firm from the information, so information repeated many times by managers can be suspected (Fishman and Hagerty, 2003). Therefore, investors may view management's repeated references to GHC-ET disclosures as over recommendations or an overemphasis, which leads to thinking about their true purpose. I expect to analyse 8-K filings containing GHC-ET disclosures to validate the effect of investor feedback on the intensity and frequency of disclosure. The hypotheses can be put forward as follows.

**Hypothesis 3.** The intensity of GHC-ET disclosures is associated with market reactions.

**Hypothesis 4.** The frequency of GHC-ET disclosures is associated with market reactions.

Finally, I compare the market response of ETs at different GHC phases (see Figure 3.1). Market expectations of ETs are on the rise in phases one and two. However, do investors react differently to ETs in the market before and after the peak of inflated expectations? When these technologies are to be hyped, disclosure by firms of applications of technologies already in the maturity stage may be suspected of being simply an attempt to capture the market frenzy. According to Marks (2011), most investors can easily use first-order thinking to judge a firm's share price trend through positive signals. Such views and opinions are emotional in nature. Second-order thinking is different and requires the successful investor to have more insights than the market and other investors. In other words, investors probably see ET disclosures as a positive signal and react immediately. However, attitudes change as more information about ETs becomes available. Further, there is also a voice that argues that ETs in their infancy are

riskier and that after a period of market hype, investors have more time and opportunity to judge their true viability. Thus, the disclosure of ETs in the second phase of the GHC reaps positive responses from investors, while those in other phases of the GHC struggle to attract investors. I propose a hypothesis to examine the market response to different GHC phases.

**Hypothesis 5**. The market reacts differently to GHC-ET disclosures in different phases.

# **5.3 Data and sample selection**

# 5.3.1 Data description

As mentioned in Chapter 3, all firms – foreign and domestic registrants – are required to disclose 8-K filings to the public through EDGAR within four business days after a material event (SEC, 2012, pp.1). All 8-K filings between 2010 to 2019 are downloaded by web crawling from the SEC's EDGAR, which is a database with the most comprehensive filings of US firms. Although US listed firms were required to complete the 8-K filings in 2004, the sample of this chapter starts in 2010 to avoid the impact of the 2008 financial crisis on markets and managers' behaviour. Furthermore, the sample period stops in 2019 to avoid the effect of the COVID-19 pandemic on estimations.

To investigate the market reaction to GHC-ET disclosures, after removing observations with missing values, I select the 8-K filings containing Item 7.01 from the firm's first disclosure each year for the textual analysis, leaving a sample of 13,268 filings (Column (3) in Table 5.1). As shown in Column (4), after text data cleaning and GHC keyword search, there are finally 582 8-K filings containing information on ETs.<sup>32</sup> The data used in this study are obtained from Wharton Research Data Services (WRDS), i.e., historical stock prices from The Center for Research in Security Prices (CRSP), analysts' data from I/B/E/S, and firm-specific characteristics from Compustat. The institutional shareholder data comes from Bloomberg.

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<sup>&</sup>lt;sup>32</sup> Of these, 175 belong to GHC phase one,177 belong to GHC phase two, 166 belong to GHC phase three, 45 belong to GHC phase four, and only 19 belong to GHC phase five.

**Table 5.1 Sample Distribution** 

Panel A. Data cleaning process	
Original 8-K filings of all registrants in EDGAR during 2010 to 2019	663,897
Less: 8-K filings without the Item 7.01	(565,545)
8-K filings including the Item 7.01 (Column 2 of Panel B)	98,352
Less: 8-K filings after the initial 8-K filings of each firm in each year	(72,040)
Initial 8-K filings including the Item 7.01 (Column 3 of Panel B)	26,312
Less: missing firm-specific controls	(13,044)
Initial 8-K filings including the Item 7.01 firm-year observations (Column 4 of Panel B)	13,268
Less: 8-K filings including the Item 7.01 without GHC-ET	(12,686)
Initial 8-K filings including the Item 7.01 containing GHC-ET (Column 5 of Panel B)	582

Panel B. Sample distribution by year and GHC phase

		8-K			GHC					
	8-K	incl.	Initial 8-K	Firm-year	Initial	Phase	Phase	Phase	Phase	Phase
Year	0-10	7.01	incl. 7.01	observations	8-K incl.	One	Two	Three	Four	Five
		7.01			7.01					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
2010	80,442	6,457	1,867	830	36	7	17	1	11	0
2011	78,824	7,923	2,201	891	38	11	17	1	9	0
2012	77,353	8,713	2,336	1,089	50	6	5	30	1	8
2013	76,369	9,222	2,462	1,175	66	18	7	31	0	10
2014	76,930	9,971	2,664	1,272	103	17	23	60	2	1
2015	76,407	10,468	2,738	1,331	27	18	4	3	2	0
2016	72,621	10,832	2,862	1,495	51	16	14	12	9	0
2017	70,785	11,324	2,985	1,611	67	33	15	8	11	0
2018	68,181	11,662	3,056	1,735	71	20	31	20	0	0
2019	66,427	11,780	3,141	1,839	73	29	44	0	0	0
Total	663,897	98,352	26,312	13,268	582	175	177	166	45	19

Note: Table 5.1 reports the sample distributions. Panel A reports the data cleaning process while Panel B reports the sample distribution by year and GHC phase. Column (1) shows the total 8-K filings disclosed by all EDGAR registrants from 2010 to 2019. Column (2) reports the number of 8-K filings including Item 7.01. Column (3) indicates the number of firms that disclose 8-K filings containing Item 7.01 for the first time each year while Column (4) shows firm-year observations after removing missing firm-level controls. Column (5) indicates the number of the initial 8-K filings containing Item 7.01 and GHC-ET each year. Finally, Columns (6) to (10) show the number of observations which include phase one (innovation trigger), phase two (the peak of inflated expectations), phase three (trough of disillusionment), phase four (slope of enlightenment), and phase five (plateau of productivity), respectively.

Table 5.2 shows the industry distribution using the Global Industry Classification (GIC), which divides all sample firms into 11 sectors.<sup>33</sup> As shown in Column (1), the largest share of the sample is in the health care sector at 15.80%, followed by the industrial sector at 14.60% and the least – utilities – at only 2.90%. The distribution of GHC sample is different from the final sample. The largest share is in the information technology sector (43.80%), which makes sense because the sector has the highest chance of being involved in ETs.

**Table 5.2 Industry Distribution** 

g .	Final sample observations	Percentage	GHC sample	Percentage
Sectors			observations	
	(1)	(2)	(3)	(4)
Utilities	389	2.90%	8	1.40%
<b>Communication Services</b>	516	3.90%	40	6.90%
Real Estate	528	4.00%	2	0.30%
Consumer Staples	595	4.50%	6	1.00%
Materials	706	5.30%	18	3.10%
Energy	1,354	10.20%	23	4.00%
Information Technology	1,660	12.50%	255	43.80%
Financials	1,734	13.10%	32	5.50%
Consumer Discretionary	1,741	13.10%	53	9.10%
Industrials	1,939	14.60%	61	10.50%
Health Care	2,092	15.80%	84	14.40%
Total	13,268	100.0%	582	100.0%

Note: This table presents the distribution of industry by the Global Industry Classification (GIC) industry classification. Columns (1) and (3) report the firm-year observations for the final and GHC sample in different sectors, respectively. Columns (2) and (4) indicate the percentage of observation in each industry to the total firm-year observations and GHC sample observations, respectively.

Figure 5.2 shows the number of firms in different states in the US that disclose GHC-ET 8-K. A total of 3,877 firms in the sample are unevenly distributed across states. Specifically,

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<sup>&</sup>lt;sup>33</sup> Bhojraj et al. (2003) show that the GIC industry classification outperforms other industry classifications. The research replaces other industry classification standards, such as Standard Industrial Classification (SIC) codes, and obtain similar results with no significant changes.

New York (320), California (463) and Texas (487) have the highest number of firms disclosing GHC-ET, which accounts for more than 30% of total sample firms.

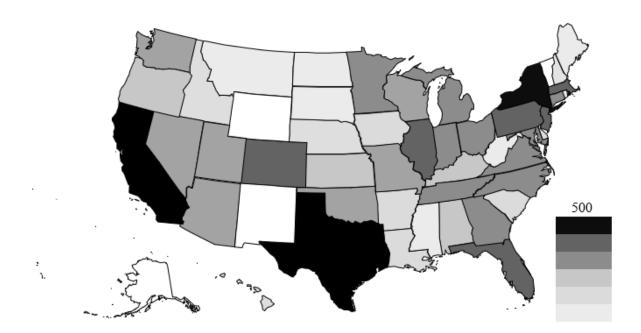


Figure 5.2 The Disclosure of Emerging Technologies in Each US State

Note: This figure shows the number of firms disclosing GHC-ET 8-K filings of each state in the US.

### 5.3.2 Variable construction

## 5.3.2.1 Event study and dependent variable

This chapter investigates whether investors react in the short and long terms to GHC-ET disclosures. Further, this chapter also investigates whether such reactions vary according to the disclosure intensity, frequency, and technology at different phases of market hype. The event study is selected to measure the market's reaction using abnormal returns following GHC-ET disclosures. Lerman and Livnat (2010) observe that the vast majority of declarations are made on the same working day as the date of the event or within one or two days of it although firms have four days to prepare the 8-K filing after the material event happened. Therefore, the event window starts three days before the disclosure date (d = -3) (Cheng et al., 2019). The

possibility of the material event being leaked in advance is not excluded, so this research also chooses (-5, +5) as an alternative event window (Cahill et al., 2020; Carlini et al., 2020). The estimation window is typically 210 trading days to 11 trading days before the event ([-210, -10]).

To investigate the effects of an event on the stock price of all firms, most researchers use cumulative abnormal returns  $(CAR_i(d_1, d_2))$  over a given period. The purpose of this is to adapt to the uncertainty of the exact date of the event or to fully grasp the impact of the event on the stock price. The expected returns are estimated using the market model of Marshall et al. (2019):

$$R_{i,d} = \alpha_i + \beta_i R_{m,d} + \varepsilon_{i,d} \tag{5-1}$$

where  $R_{i,d}$  is the stock returns for firm i on day d.  $R_{m,d}$  is the US market return (S&P 500 index). The abnormal return  $(AR_{i,d})$  because of GHC-ET disclosures of firm i on day d is calculated based on the least squares OLS regressions performed separately for each firm. Once the estimated coefficients  $\widehat{\alpha}_i$  and  $\widehat{\beta}_i$  are obtained,  $AR_{i,d}$  can be calculated using the following formula:

$$AR_{i,d} = R_{i,d} - (\widehat{\alpha}_i + \widehat{\beta}_i R_{m,d}) \tag{5-2}$$

where  $AR_{i,d}$  represents the abnormal return for firm i on day d. To study the impact of the event on overall security pricing, the cumulative abnormal return  $CAR_i(d_1, d_2)$  should be calculated, which is the sum of the average abnormal returns of firm i over a period from  $d_1$  to  $d_2$  (Equation (5-3)). In this study, event windows (-3, +3) (Cheng et al., 2019) and (-5, +5) (Cahill et al., 2020; Carlini et al., 2020) are used to investigate short-term market reactions. The event windows (+4, +60) and (+6, +60) are used for delayed market reactions.

news. Therefore, this research follows Dellavigna and Pollet (2009) and Hirshleifer et al. (2009) and employ the same window to analyse investors' reactions after ETs disclosures – that is 60 trading days

<sup>&</sup>lt;sup>34</sup> Dellavigna and Pollet (2009) argue that the difference in investor responses becomes more pronounced approximately 30 trading days after firms' disclosures and continues to increase over the next 60 trading days. Overlooked information is not incorporated immediately after a disclosure but in a slow process. They believe that investors do not realise they have ignored certain information until they revisit their investment decisions for other reasons, such as insider selling or disclosure-related

$$CAR_{i}(d_{1}, d_{2}) = \sum_{d=d_{1}}^{d_{2}} AR_{i,d}$$
 (5-3)

Finally, I estimate the mean cumulative abnormal return  $(\overline{CAR_l(d_1, d_2)})$  in each event window by calculating the average  $CAR_l(d_1, d_2)$  for each stock N:

$$\overline{CAR_i}(d_1, d_2) = \frac{1}{N} \sum_{d=d_1}^{d_2} CAR_i(d_1, d_2)$$
 (5-4)

# 5.3.2.2 Textual analysis and independent variables

This chapter uses a bag-of-words (dictionary-based) method to conduct GHC-ET keyword searching of firms' 8-K filings based on the GHC. Gartner's experts release an updated hype cycle every year based on market conditions and the status of the development of each technology. Each phase has different ETs with a name.<sup>35</sup> Organising reports to a uniform type with as little noise as possible before searching for keywords is one of the effective ways to improve the accuracy of the textual analysis. Detailed procedures can be seen in Chapter 3. In addition, this research not only conducts textual analysis for the main content of the Item 7.01 in each 8-K filing, but also exhibit the content related to Item 7.01.<sup>36</sup> These appendices may have rich information that also affects investors' judgments and decisions.

Based on the annual GHC, I collect the number of ET terms for each phase for the keyword search including 83 in phase one (innovation trigger), 73 in phase two (peak of inflated expectations), 43 in phase three (trough of disillusionment), 20 in phase four (slope of

<sup>(</sup>approximately three calendar months). All the empirical results remain consistent when the event window is changed to 30 trading days.

<sup>&</sup>lt;sup>35</sup> For example, in 2010, the innovation trigger phase has 12 technologies, such as human augmentation, context delivery architecture, brain-computer interface, etc. See Figure 3.4 an example of the GHC.

<sup>&</sup>lt;sup>36</sup> See Appendices D-1 and D-2 for an example of an 8-K filing, includes GHC-ET, the main content of Item 7.01, the main content of its exhibit, and the slides in the exhibit.

enlightenment), and 4 in phase five (plateau of productivity).<sup>37</sup> The dictionary does not contain synonyms for ETs for two reasons. First, most technologies have proper nouns that are difficult to replace, for example, 5G would not be described as 4G+. Second, not all investors are experts in understanding some ETs, especially the more specialised ones, such as bionic technology. The only way for investors to identify firms making GHC-ET disclosures is through popular specialised reports (i.e., GHC). Therefore, it is reasonable to use only the names of ETs covered on GHC in this research.<sup>38</sup> <sup>39</sup>

As shown in Panel A of Table 5.3, this study counts the twenty ETs that appear most frequently in the 8-K filings (for the year in which that ET appeared). The 'internet of things' appears 178 times, and "5G" was mentioned 167 times. Not every ET word listed by the GHC is found in the 8-K filings. The word cloud chart in Panel B of Table 5.3 shows all ETs that appear, with the size indicating the frequency of occurrence. Therefore, the independent variable is set as a dummy variable ( $GHCET_{i,t}$ ), with one indicating that the 8-K filing contains at least one GHC-ET term and zero otherwise.

In addition, to investigate the market's reaction to GHC-ET disclosures with different intensity and frequency of disclosure, I also design two independent variables ( $Intensity_{i,t}$  and  $Frequency_{i,t}$ ) to represent the disclosure characteristics. To compare the different market reactions between different phases of the GHC,  $GHCET\_phase_{j,i,t}$  is set.

<sup>&</sup>lt;sup>37</sup> This research assumes that firms and investors are based on the ETs list released in the previous year, as the latest GHC ETs list is released in late July or early August each year.

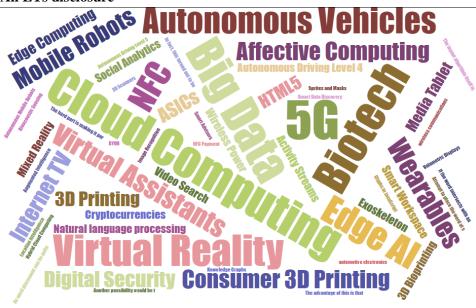
<sup>&</sup>lt;sup>38</sup> This research recognises that GHC is not the only third-party organisation that collects and organises ETs. However, based on our perception, GHC is the most extensive research directory of trends, including ETs, currently used to study the US market.

<sup>&</sup>lt;sup>39</sup> To test my reasoning, I used Wikipedia to look up synonyms for ET where GHC occurs. The regression results are unchanged substantially using the extended version of the ETs dictionary.

Table 5.3 Top 20 ETs Most Frequently Disclosed in the 8-K Filings

Panel A. Top 20 ETs disclosure								
Keywords	Number	Keywords	Number					
Internet of Things	178	Connected Home	42					
5G	167	Computing devices	35					
Cloud Computing	112	Computer-Brain interface	32					
Big Data	106	Edge AI	32					
Brain-computer interface	106	Machine Learning	30					
Biotech	85	tangible user interfaces	28					
Blockchain	67	Autonomous Vehicles	24					
Augmented Reality	57	NFC	24					
Virtual Reality	48	Quantum Computing	22					
Predictive Analytics	43	Wearable User Interfaces	16					

Panel B. All ETs disclosure



Note: This table presents the top 20 keywords of GHC-ET disclosures after conducting textual analysis. The word cloud shows all GHC-ET disclosures by firms in 8-K filings in our full sample.

## 5.3.3 Descriptive statistics

Table 5.4 provides the summary statistics for the merged sample. All variables, except for returns and the characteristics of GHC-ET disclosures, are winsorized at the 1% and 99% percentiles. 40 Panel A presents the characteristics of GHC-ET disclosures in four dimensions,

<sup>40</sup> All empirical results remain consistent when variables are winsorized at 1.5% or 2%.

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including the number of GHC 8-Ks containing GHC-ET discloses by the firm each year (intensity), the frequency of ET words disclosed in the initial 8-K each year, whether disclosure belongs to the fintech category of terms and whether it needs a long time to reach the plateau. Specifically, for firms that disclosed ETs, the average number of ETs in the initial GHC 8-K was two. In other words, managers repeat GHC-ET disclosures two times on average in the initial 8-K filing containing ETs. After the first GHC 8-K, managers issue an average of two additional 8-K filings with ETs each year. Approximately 35% of GHC-ET discloses by firms belong to the fintech category, while only 16.7% (=1 – 0.833) of ETs need more than ten years to be fully adopted. In addition, the descriptive statistics for other variables are shown in Panel B. All financial data are similar to those used in other studies focusing on EDGAR-registered firms. In general, 4.4% of the whole sample disclosed ETs within our sample period. Finally, Panel C of Table 5.4 shows the comparison of market reactions based on different event windows between the non-GHC and GHC groups. The difference in CARs between these groups is significant.

**Table 5.4 Summary Statistics** 

Panel A. Characteristic	Panel A. Characteristics of the GHC-ET disclosures								
Variables	N	Mean	Median	Std. Dev.	Min	Max			
Intensity <sub>i,t</sub>	582	2.536	1.000	5.625	1	105			
Frequency <sub>i,t</sub>	582	1.938	1.000	1.692	1	16			
Fintech <sub>i,t</sub>	582	0.352	0.000	0.478	0	1			
Quick_Adoptionii,t	582	0.833	1.000	0.373	0	1			
Panel B. Variables in m	narket reacti	on regressi	ons						
Variables	N	Mean	Median	Std. Dev.	Min	Max			
CAR_MM (-3, +3)	13,268	0.008	0.002	0.147	-1.419	6.581			
CAR_FF3 (-3, +3)	13,268	0.010	0.004	0.149	-1.257	6.535			
$CAR_C4 (-3, +3)$	13,268	0.010	0.003	0.149	-1.265	6.518			
$CAR\_MM (-5, +5)$	13,268	0.008	0.001	0.165	-1.486	6.516			
CAR_FF3 (-5, +5)	13,268	0.010	0.003	0.168	-1.336	6.620			
$CAR_C4 (-5, +5)$	13,268	0.010	0.003	0.168	-1.324	6.618			
CAR_MM (+4, +60)	13,268	-0.002	-0.003	0.270	-3.127	5.936			
CAR_FF3 (+4, +60)	13,268	0.001	-0.004	0.287	-2.072	5.879			
CAR_C4 (+4, +60)	13,268	0.005	0.002	0.279	-2.085	5.874			
CAR_MM (+6, +60)	13,268	-0.001	-0.004	0.264	-3.021	5.920			
CAR_FF3 (+6, +60)	13,268	0.0004	-0.003	0.281	-2.509	5.813			
CAR_C4 (+6, +60)	13,268	0.005	0.002	0.274	-2.118	5.809			
$GHCET_{i,t}$	13,268	0.044	0.000	0.205	0	1			
GHCET_phase <sub>1,i,t</sub>	13,268	0.013	0.000	0.115	0	1			
GHCET_phase <sub>2,i,t</sub>	13,268	0.013	0.000	0.114	0	1			
GHCET_phase3,i,t	13,268	0.013	0.000	0.111	0	1			
GHCET_phase <sub>4,i,t</sub>	13,268	0.003	0.000	0.058	0	1			
GHCET_phase5,i,t	13,268	0.001	0.000	0.038	0	1			
RET (%)	13,268	0.004	0.001	0.082	-0.669	5.446			
Turnover (%)	13,268	0.213	0.092	0.261	-0.045	1.492			
Log (Firm size)	13,268	7.459	7.552	1.754	3.978	10.634			
ROA	13,268	-0.013	0.019	0.112	-0.421	0.131			
BM	13,268	0.527	0.457	0.352	-0.002	1.173			
Log (Age)	13,268	2.378	2.618	0.789	-1.910	3.932			
FCF	13,268	0.029	-0.002	0.117	-0.120	0.348			
OCF	13,268	0.044	0.061	0.096	-0.197	0.192			
Log (FCI)	13,268	13.985	14.302	2.183	-0.159	21.143			
ANA	13,268	0.520	1	0.500	0	1			
IdioVol	13,268	0.701	1	0.457	0	1			
INSTOWN	13,268	0.585	1	0.493	0	1			

Panel C. Comparison between the Non-GHC and the GHC group								
Non-GHC sample Mean GHC sample Mean Difference								
CAR_MM (-3, +3)	0.007	0.027	-0.019***					
$CAR\_MM (-5, +5)$	0.007	0.028	-0.021***					
CAR_MM (+4, +60)	0.0005	-0.040	0.040***					
CAR_MM (+6, +60)	0.001	-0.041	0.042***					

Note: This table provides the summary statistics for key variables used in this research between 2010 to 2019. Panel A reports the summary statistics on the characteristics of GHC-ET disclosures in terms of the intensity of disclosure, the frequency of disclosure followed by the initial GHC 8-K, the category to which they belong, and the time it takes to reach the plateau. Panel B presents the summary statistics for the variables used in market reaction regressions. CAR\_MM, CAR\_FF3, and CAR\_C4 are the cumulative abnormal returns (CARs) calculated by the market model, the Fama-French three factor model, and the Carhart four factor model, respectively. Panel C shows the comparison means of CARs in each event window between the Non-GHC and the GHC group. This research applies a 99% winsorisation for non-return variables and keep the original frequency data. Definitions for all the other variables are provided in Appendix B-1.

# 5.4 Empirical results

## 5.4.1 Empirical model

To assess the market reaction to GHC-ET disclosures, first, this chapter performs a baseline regression for both immediate and delayed reaction as follows:

$$CAR_{i}(d_{1}, d_{2}) = \alpha + \beta GHCET_{i,t} + \gamma X_{i,t} + Year_{i,t} + Industry_{i,t} + \varepsilon_{i,t}$$
 (5-5)

where  $CAR_i(d_1, d_2)$  is the mean cumulative abnormal return of firm i from  $d_1$  to  $d_2$ .  $GHCET_{i,t}$  is a dummy variable equal to one when the firm's first 8-K filing of the year includes GHC-ET and zero otherwise. To test Hypothesis 1 related to short-term reaction, I choose (-3, +3) and (-5, +5) as event windows. This chapter is interested in the coefficient of  $GHCET_{i,t}$ . If investors can be attracted by GHC-ET information in the short term, I expect  $\beta$  to be positive. Regarding Hypothesis 2 related to delayed reaction, this research chooses (+4, +60) and (+6, +60) as event windows. Based on the assumptions, this overreaction may only be short-lived. If investors treat this type of information with restored rationality in the foreseeable long term, then  $\beta$  is negative, and arguably the market reaction is negative.

 $X_{i,t}$  is a vector of control variables selected based on previous studies (e.g., Cahill et al., 2020; Carlini et al., 2020; Cheng et al., 2019; Loffler et al., 2021; Noh and Zhou, 2022; Pevzner

et al., 2015). These control variables include the annualized variance in daily returns (RET), firm size (Firm Size), profitability (ROA), firm age (Age), book-to-market ratio (BM), average share turnover (Turnover), financing cash flow (FCF), operating cash flow (OCF), and financial constraint index (FCI).  $\varepsilon$  is the residual item of regression. In each regression model,  $Year_{i,t}$  and  $Industry_{i,t}$  are the year and industry (based on the GIC industry classifications) dummies, respectively, used to capture variations across different times and sectors. I also generate clustered standard errors at the firm level that are resistant to heteroskedasticity to account for sample firm similarity.

#### 5.4.2 Market reactions

### 5.4.2.1 Immediate market reaction

To investigate the immediate reaction to GHC-ET disclosures, I use the CARs obtained from the event study as the dependent variable in all regressions. Table 5.5 reports the panel regression results. For both event windows (-3, +3) and (-5, +5), this research chooses the market model to estimate the CARs. Column (1) - with no year and industry fixed effects shows that the disclosure of  $GHCET_{i,i}$  is positively associated with the CARs of the 8-K filings release period. The coefficient of  $GHCET_{i,t}$  is 0.0164 (1.64%), which is significant at the 1% significance level, indicating that the CARs are 1.64% higher for firms that disclosed ETs than for those that did not in their initial 8-K. Controlling for fixed effects by year and industry, shown in Column (2), the coefficient of *GHCET*<sub>i,t</sub> is still positive with the CARs at the 1% significance level, and its magnitude is increased to 0.0181 (1.81%) compared to that from the pooled regression. After controlling for the intensity of GHC-ET disclosures in Column (3), the coefficient of  $GHCET_{i,t}$  is further increased to 0.0641 (6.41%), which is significantly positive at the 1% significance level and associated with the CAR (-3, +3). In addition, after controlling for the frequency of GHC-ET disclosures, the coefficient magnitude of GHCET<sub>i,t</sub> is 0.0285 (2.85%) (Column (4)), which is significantly positive at the 1% significance level and associated with the CAR (-3, +3).

Based on the assumptions of Lerman and Livnat (2010), firms may not wait until the deadline to disclose an 8-K filing after a material event has occurred, although they have four

days to prepare. They select three days before the filing date as the start of the event window. However, for GHC-ET disclosure, this may not be an unpredictable material event, meaning that this type of news may not be a material event that follows the four-day disclosure deadline given by the SEC. Therefore, this study extends the event window to five trading days before the 8-K filing date. Shown in Columns (5) to (8), similar results can be obtained. All coefficients of *GHCET*<sub>i,t</sub> are significantly and positively associated with CARs at the 1% significance level.

Overall, these regression results are supportive of Hypothesis 1, which states that the short-term market reaction to GHC-ET disclosures is positive during the initial 8-K filing release period. In other words, investors tend to react to GHC-ET disclosures positively and immediately in the short term.

To verify Hypotheses 3 and 4, the GHC-ET disclosures intensity (*Intensity<sub>i,t</sub>*) (Equation (5-6)) and the number of 8-Ks disclosed followed by the initial GHC 8-K (*Frequency<sub>i,t</sub>*) (Equation (5-7)) are added as extra explanatory variables as follows.

$$CAR_{i}(d_{1}, d_{2}) = \alpha + \beta_{1}GHCET_{i,t} + \beta_{2}Intensity_{i,t} + \gamma X_{i,t} + Year_{i,t}$$

$$+ Industry_{i,t} + \varepsilon_{i,t}$$
(5-6)

$$\begin{aligned} CAR_{i}(d_{1},d_{2}) &= \alpha + \beta_{1}GHCET_{i,t} + \beta_{2}Frequency_{i,t} + \gamma X_{i,t} + Year_{i,t} \\ &+ Industry_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{5-7}$$

where  $Intensity_{i,t}$  is the number of the same ET-related words in an 8-K filing and  $Frequency_{i,t}$  is how many 8-Ks with GHC-ET disclosed by firms after the initial GHC 8-K.<sup>41</sup> Similar to Equation (5-5), Equations (5-6) to (5-7) also include the same set of control variables in addition to the dummy variables of year and industry. Both  $Intensity_{i,t}$  and  $Frequency_{i,t}$  are

<sup>&</sup>lt;sup>41</sup> For example, the 'Intensity<sub>i,t</sub>' is 5 if 5G mentioned five times in the content of 8-K filing.

negatively and significantly associated with CARs. The findings are consistent with investors' reaction being negative to managers' overselling of GHC-ET information, which consistent with the argument of Hsieh et al. (2016), Lawrence (2013) and Tan et al. (2015) that retail investors prefer clearer and more concise disclosures. Hence, repetitive GHC-ET disclosures can therefore be perceived by investors as over-recommendation, raising suspicions about true intent. The results support Hypotheses 3 and 4.<sup>42</sup>

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<sup>&</sup>lt;sup>42</sup> Appendices B-2 and B-3 show subsample regression for above or below the mean of intensity or frequency. The results support the baseline results that the high intensity or frequency of GHC-ET disclosures lead to negative market reactions.

**Table 5.5 Immediate Reaction of GHC-ET Disclosures** 

Variables	CAR_MM (-3, +3)	CAR_MM (-3, +3)	CAR_MM (-3, +3)	CAR_MM (-3, +3)	CAR_MM (-5, +5)	CAR_MM (-5, +5)	CAR_MM (-5, +5)	CAR_MM (-5, +5)
variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
GHCET <sub>i,t</sub>	0.0164***	0.0181***	0.0641***	0.0285***	0.0175***	0.0193***	0.0650***	0.0299***
	(0.0052)	(0.0053)	(0.0078)	(0.0058)	(0.0060)	(0.0062)	(0.0091)	(0.0067)
Intensity <sub>i,t</sub>			-0.0239***				-0.0238***	
			(0.0030)				(0.0035)	
$Frequency_{i,t}$				-0.0041***				-0.0042***
				(0.0009)				(0.0010)
$RET_{i,t} \\$	1.0115***	1.0117***	1.0107***	1.0108***	1.0360***	1.0358***	1.0349***	1.0349***
	(0.0130)	(0.0130)	(0.0129)	(0.0130)	(0.0150)	(0.0150)	(0.0150)	(0.0150)
$Turnover_{i,t} \\$	-0.0080	-0.0078	-0.0071	-0.0077	-0.0107*	-0.0102*	-0.0095	-0.0100
	(0.0053)	(0.0053)	(0.0053)	(0.0053)	(0.0061)	(0.0062)	(0.0062)	(0.0062)
Firm Size <sub>i,t</sub>	-0.0021***	-0.0024***	-0.0024***	-0.0024***	-0.0021**	-0.0024**	-0.0024**	-0.0024**
	(80000)	(0.0008)	(0.0008)	(0.0008)	(0.0009)	(0.0010)	(0.0010)	(0.0010)
$ROA_{i,t}$	-0.0145	-0.0089	-0.0093	-0.0074	-0.0217	-0.0171	-0.0176	-0.0157
	(0.0155)	(0.0162)	(0.0161)	(0.0162)	(0.0179)	(0.0187)	(0.0187)	(0.0187)
$BM_{i,t}$	-0.0031	-0.0037	-0.0036	-0.0035	-0.0054	-0.0067	-0.0066	-0.0066
	(0.0032)	(0.0036)	(0.0036)	(0.0036)	(0.0037)	(0.0041)	(0.0041)	(0.0041)
$Age_{i,t}$	0.0004	0.0005	0.0005	0.0004	0.0020	0.0020	0.0020	0.0020
	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0016)	(0.0016)	(0.0016)	(0.0016)
$FCF_{i,t}$	0.0087	0.0072	0.0074	0.0068	0.0095	0.0098	0.0100	0.0094
	(0.0113)	(0.0114)	(0.0114)	(0.0114)	(0.0130)	(0.0132)	(0.0132)	(0.0132)
$OCF_{i,t}$	0.0022	0.0016	-0.0001	0.0001	0.0075	0.0069	0.0052	0.0054
	(0.0183)	(0.0194)	(0.0194)	(0.0194)	(0.0212)	(0.0225)	(0.0225)	(0.0225)
$FCI_{i,t}$	0.0005	0.0002	0.0001	0.0001	0.0007	0.0004	0.0003	0.0003
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Constant	0.0142	0.0235**	0.0237**	0.0237**	0.0085	0.0191	0.0192	0.0192
	(0.0098)	(0.0113)	(0.0113)	(0.0113)	(0.0113)	(0.0131)	(0.0131)	(0.0131)
Year FE	NO	YES	YES	YES	NO	YES	YES	YES
Industry FE	NO	YES	YES	YES	NO	YES	YES	YES
Clustered SE	NO	YES	YES	YES	NO	YES	YES	YES
Observations	13,268	13,268	13,268	13,268	13,268	13,268	13,268	13,268
Adj. R-square	0.3165	0.3166	0.3198	0.3176	0.2657	0.2661	0.2686	0.2669

Note: Table 5.5 shows the immediate market reaction of GHC-ET disclosures after 8-K was released. The dependent variables are estimated CARs in the event windows (-3, +3) and (-5, +5) based on market model. Columns (1)-(2) and (5)-(6) show the immediate market reaction to the GHC-ET disclosure according to different event windows. Columns (3) and (7) present the immediate market reaction to the intensity of GHC-ET disclosures in the initial 8-K while Columns (4) and (8) present the immediate market reaction to the number of 8-K filings including ETs each year. Columns (1) and (5) are pooled regressions without fixed effects while other columns include fixed effects by year and industry. The industry fixed effect is based on the GIC industry classifications. The standard errors presented in parentheses are corrected for firm-clustering heteroscedasticity. Definitions for all of variables are provided in Appendix B-1. The significance levels are: \*\*\* p<0.01, \*\*\* p<0.05, \*\* p<0.1.

When ETs are at different phases of GHC, investors' reactions may be different. For example, investor enthusiasm reaches its maximum when ETs are in the second phase of GHC (peak of inflated expectations). Do they react more strongly than when the ET is in its infancy? This study regresses the following equation to investigate the difference in short-term market reactions to different GHC phases.

$$CAR_{i}(d_{1}, d_{2}) = \alpha + \beta_{1}GHCET\_Phase_{j,i,t} + \gamma X_{i,t} + Year_{i,t} + Industry_{i,t}$$

$$+ \varepsilon_{i,t}$$
(5-8)

where  $GHCET\_Phase_{j,i,t}$ , a dummy variable for each phase, represents the phase of the ET in GHC that is disclosed by firms (j from one to five). Table 6 shows that investors only react positively to ETs at phases one and two, suggesting that investors are only interested in ETs hyped by the market. The coefficient of  $GHCET\_Phase_{i,t}$  for phase one is 0.0232 (2.32%), while for phase two, it is 0.0316 (3.16%). While investors also react positively to ETs in their infancy, investors react more strongly to those that are hyped to a fever pitch by the market, showing a CAR of 0.8% more. The results remain unchanged when the event window is changed from (-3, +3) to (-5, +5).

Table 5.6 Immediate Reaction of GHC-ET Disclosures by Phase

	CAR_MM (-3, +3)	CAR_MM (-3, +3)	CAR_MM (-3, +3)	CAR_MM (-3, +3)	CAR_MM (-3, +3)
Variables	Phase One	Phase Two	Phase Three	Phase Four	Phase Five
	(1)	(2)	(3)	(4)	(5)
GHCET_Phase <sub>i,t</sub>	0.0232**	0.0316***	0.0033	-0.0025	-0.0137
	(0.0093)	(0.0094)	(0.0098)	(0.0183)	(0.0281)
Constant	0.0242**	0.0245**	0.0245**	0.0246**	0.0245**
	(0.0113)	(0.0113)	(0.0113)	(0.0114)	(0.0113)
Controls, Year, Industry FE	YES	YES	YES	YES	YES
Clustered SE	YES	YES	YES	YES	YES
Observations	13,268	13,268	13,268	13,268	13,268
Adj. R-square	0.3163	0.3166	0.3160	0.3160	0.3160

Variables	Phase One	Phase Two	Phase Three	Phase Four	Phase Five
variables	(6)	(7)	(8)	(9)	(10)
GHCET_Phase <sub>i,t</sub>	0.0426***	0.0524***	0.0155	0.0054	-0.0074
	(0.0103)	(0.0103)	(0.0105)	(0.0185)	(0.0282)
Intensity <sub>i,t</sub>	-0.0099***	-0.0107***	-0.0071***	-0.0060***	-0.0059***
	(0.0022)	(0.0022)	(0.0022)	(0.0021)	(0.0020)
Constant	0.0251**	0.0258**	0.0250**	0.0251**	0.0252**
	(0.0113)	(0.0113)	(0.0113)	(0.0114)	(0.0113)
Controls, Year, Industry FE	YES	YES	YES	YES	YES
Clustered SE	YES	YES	YES	YES	YES
Observations	13,268	13,268	13,268	13,268	13,268
Adj. R-square	0.3173	0.3177	0.3165	0.3164	0.3164
Variables	Phase One	Phase Two	Phase Three	Phase Four	Phase Five
Variables	(11)	(12)	(13)	(14)	(15)
GHCET_Phase <sub>i,t</sub>	0.0319***	0.0418***	0.0075	0.0006	-0.0112
	(0.0096)	(0.0097)	(0.0099)	(0.0183)	(0.0281)
Frequency <sub>i,t</sub>	-0.0031***	-0.0034***	-0.0025***	-0.0024***	-0.0024***
	(0.0009)	(0.0009)	(0.0008)	(0.0008)	(0.0008)
Constant	0.0246**	0.0251**	0.0248**	0.0249**	0.0250**
	(0.0113)	(0.0113)	(0.0113)	(0.0114)	(0.0113)
Controls, Year, Industry FE	YES	YES	YES	YES	YES
Clustered SE	YES	YES	YES	YES	YES
Observations	13,268	13,268	13,268	13,268	13,268
Adj. R-square	0.3170	0.3173	0.3164	0.3164	0.3164

Note: Table 5.6 shows the immediate market reaction of GHC-ET disclosures by GHC different phases. The dependent variables are estimated CARs in the event windows (-3, +3) based on the market model. Columns (1)-(5) show the immediate market reaction to GHC-ET disclosures according to different GHC phases. Columns (6)-(10) present the immediate market reactions to the intensity of the GHC-ET in the initial 8-Ks while columns (11)-(15) present the immediate market reaction to the frequency of 8-K containing the GHC-ET each year. The results are unchanged when I use CAR (-5, +5) as the dependent variable. All regressions include control variables and fixed effects by year and industry. The industry fixed effect is based on the GIC industry classifications. The standard errors presented in parentheses are corrected for firm-clustering heteroscedasticity. Definitions for all of variables are provided in Appendix B-1. The significance levels are: \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

### 5.4.2.2 Delayed market reaction

Table 5.7 reports the panel regression results to investigate the delayed market reaction to GHC-ET disclosures. For both event windows (+4, +60) and (+6, +60), the market model is selected to estimate the CARs. The short-lived enthusiasm faded, and investors' attitudes toward GHC-ET disclosures shifted. Column (1) – with no year and industry fixed effects -

shows that the disclosure of GHC-ET is negatively associated with CARs 60 trading days after the 8-K filings date. The coefficient of *GHCET*<sub>i,t</sub> is -0.0384 (-3.84%), which is significant at the 1% level, indicating that the CARs are 3.84% lower for firms that disclosed GHC-ET than for those that did not in the long term. Using fixed effects by year and industry, shown in Column (2), the coefficient of *GHCET*<sub>i,t</sub> is still significantly and negatively associated with the CARs at the same level, although its magnitude decreases to -0.0317 (-3.17%). After controlling the intensity and frequency of GHC-ET disclosures, *GHCET*<sub>i,t</sub> and *Intensity*<sub>i,t</sub> are insignificant while only *Frequency*<sub>i,t</sub> is significant and negative.

Overall, the regression results verify Hypothesis 2, which states that investors' overreaction to GHC-ET is temporary and speculative. The gradual reduction in market hype on ETs could restore rationality to investors, which triggers the abandonment of firms that once disclosed GHC-ET. Similar to the short-term market reaction, the change in the event window has no effect on the regression results. The results remain significantly negative between  $GHCET_{i,t}$  and CAR\_MM (+6, +60) as per Columns (5) and (6).

Over the long horizon, the intensity of disclosure no longer influences investor reactions. This study believes that in the long term, investors are no longer sensitive to the overselling of GHC-ET information.

**Table 5.7 Delayed Reaction of GHC-ET Disclosures** 

_	CAR_MM							
Variables	(+4, +60)	(+4, +60)	(+4, +60)	(+4, +60)	(+6, +60)	(+6, +60)	(+6, +60)	(+6, +60)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$GHCET_{i,t}$	-0.0384***	-0.0317***	-0.0149	-0.0184	-0.0400***	-0.0331***	-0.0152	-0.0202
	(0.0115)	(0.0117)	(0.0172)	(0.0127)	(0.0113)	(0.0114)	(0.0169)	(0.0124)
$Intensity_{i,t} \\$			-0.0088				-0.0093	
			(0.0066)				(0.0064)	
$Frequency_{i,t}$				-0.0053***				-0.0051***
				(0.0020)				(0.0019)
$RET_{i,t}$	0.0688**	0.0715**	0.0711**	0.0704**	0.0552**	0.0582**	0.0578**	0.0571**
	(0.0287)	(0.0285)	(0.0285)	(0.0285)	(0.0281)	(0.0279)	(0.0279)	(0.0279)
$Turnover_{i,t} \\$	-0.0280**	-0.0259**	-0.0256**	-0.0257**	-0.0241**	-0.0220*	-0.0218*	-0.0219*
	(0.0117)	(0.0117)	(0.0117)	(0.0117)	(0.0115)	(0.0115)	(0.0115)	(0.0115)
Firm Size <sub>i,t</sub>	-0.0017	-0.0025	-0.0025	-0.0025	-0.0018	-0.0025	-0.0025	-0.0025
	(0.0018)	(0.0018)	(0.0018)	(0.0018)	(0.0017)	(0.0018)	(0.0018)	(0.0018)
$ROA_{i,t}$	-0.1110***	-0.0851**	-0.0853**	-0.0833**	-0.1017***	-0.0743**	-0.0744**	-0.0725**
	(0.0343)	(0.0356)	(0.0356)	(0.0356)	(0.0335)	(0.0348)	(0.0348)	(0.0348)
$BM_{i,t}$	-0.0137*	-0.0143*	-0.0143*	-0.0141*	-0.0129*	-0.0133*	-0.0133*	-0.0131*
	(0.0072)	(0.0078)	(0.0078)	(0.0078)	(0.0070)	(0.0077)	(0.0077)	(0.0077)
$Age_{i,t} \\$	0.0004	0.0012	0.0012	0.0011	-0.0015	-0.0006	-0.0006	-0.0006
	(0.0030)	(0.0030)	(0.0030)	(0.0030)	(0.0030)	(0.0030)	(0.0030)	(0.0030)
$FCF_{i,t}$	-0.0911***	-0.0936***	-0.0935***	-0.0941***	-0.0945***	-0.0982***	-0.0981***	-0.0987***
	(0.0249)	(0.0251)	(0.0251)	(0.0251)	(0.0244)	(0.0246)	(0.0246)	(0.0246)
$OCF_{i,t}$	-0.0002	0.0023	0.0017	0.0004	-0.0042	-0.0050	-0.0057	-0.0069
	(0.0405)	(0.0428)	(0.0428)	(0.0428)	(0.0396)	(0.0418)	(0.0418)	(0.0418)
$FCI_{i,t}$	0.0025**	0.0022*	0.0022*	0.0022*	0.0025**	0.0023**	0.0023**	0.0023**
	(0.0011)	(0.0012)	(0.0012)	(0.0012)	(0.0011)	(0.0011)	(0.0011)	(0.0011)
Constant	-0.0085	-0.0213	-0.0212	-0.0211	-0.0048	-0.0150	-0.0149	-0.0148
	(0.0216)	(0.0250)	(0.0250)	(0.0249)	(0.0212)	(0.0244)	(0.0244)	(0.0244)
Year FE	NO	YES	YES	YES	NO	YES	YES	YES
Industry FE	NO	YES	YES	YES	NO	YES	YES	YES
Clustered SE	YES							
Observations	13,268	13,268	13,268	13,268	13,268	13,268	13,268	13,268
Adj. R-square	0.0030	0.0173	0.0174	0.0178	0.0030	0.0173	0.0173	0.0177

Note: Table 5.7 shows the delayed market reaction of GHC-ET disclosures after 8-K was released. The dependent variables are estimated CARs in the event windows (+4, +60) and (+6, +60) based on market model. Columns (1)-(2) and (5)-(6) show the delayed market reaction to GHC-ET disclosures according to different event windows. Columns (3) and (7) present the delayed market reaction to the intensity of the GHC-ET in the initial 8-Ks while Columns (4) and (8) present the delayed market reaction to the frequency of 8-Ks including the GHC-ET each year. Columns (1) and (5) are pooled regressions without fixed effects while other columns include fixed effects by year and industry. The industry fixed effect is based on the GIC industry classifications. The standard errors presented in parentheses are corrected for firm-clustering heteroscedasticity. Definitions for all of variables are provided in Appendix B-1. The significance levels are: \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

Regarding the disclosure phase in a long horizon, the regression results are as expected. Investors react negatively to the GHC-ET in the second phase of the GHC. As shown in Columns (1) to (5) in Table 5.8, only phase two (-0.0542 (-5.42%)) is negatively associated with CARs at the 1% significance level. ETs at the peak of the market hype receive more attention, suggesting that investors are more excited and expectant about this phase of technologies. Firms disclosing ETs at the top of the hype can reap high short-term market returns but also suffer from market disappointment in the long term. Similarly, although the intensity and frequency of GHC-ET disclosures are significant and negative, the main explanatory variable ( $GHCET_{i,t}$ ) is not significant, thus, the results are negligible. The results remain unchanged after the event window is changed from (+4, +60) to (+6, +60).

Table 5.8 Delayed Reaction of GHC-ET Disclosures by Phase

	CAR_MM	CAR_MM	CAR_MM	CAR_MM	CAR_MM
Variables	(+4, +60)	(+4, +60)	(+4, +60)	(+4, +60)	(+4, +60)
variables	Phase One	Phase Two	Phase Three	Phase Four	Phase Five
	(1)	(2)	(3)	(4)	(5)
GHCET_Phase <sub>i,t</sub>	0.0002	-0.0542***	-0.0291	-0.0396	-0.0656
	(0.0204)	(0.0206)	(0.0215)	(0.0402)	(0.0618)
Constant	-0.0231	-0.0231	-0.0224	-0.0222	-0.0230
	(0.0250)	(0.0249)	(0.0250)	(0.0250)	(0.0250)
Controls, Year, Industry FE	YES	YES	YES	YES	YES
Clustered SE	YES	YES	YES	YES	YES
Observations	13,268	13,268	13,268	13,268	13,268
Adj. R-square	0.0168	0.0173	0.0169	0.0169	0.0169
Variables	Phase One	Phase Two	Phase Three	Phase Four	Phase Five
variables	(6)	(7)	(8)	(9)	(10)
GHCET_Phase <sub>i,t</sub>	0.0311	-0.0353	-0.0078	-0.0232	-0.0521
	(0.0226)	(0.0227)	(0.0230)	(0.0407)	(0.0620)
Intensity <sub>i,t</sub>	-0.0158***	-0.0097**	-0.0124***	-0.0126***	-0.0126***
	(0.0049)	(0.0049)	(0.0048)	(0.0045)	(0.0045)
Constant	-0.0217	-0.0220	-0.0215	-0.0211	-0.0216
	(0.0249)	(0.0249)	(0.0250)	(0.0250)	(0.0250)
Controls, Year, Industry FE	YES	YES	YES	YES	YES
Clustered SE	YES	YES	YES	YES	YES
Observations	13,268	13,268	13,268	13,268	13,268
Adj. R-square	0.0175	0.0175	0.0174	0.0174	0.0174

Variables	Phase One	Phase Two	Phase Three	Phase Four	Phase Five
variables	(11)	(12)	(13)	(14)	(15)
GHCET_Phase <sub>i,t</sub>	0.0192	-0.0374*	-0.0188	-0.0315	-0.0590
	(0.0211)	(0.0214)	(0.0217)	(0.0403)	(0.0618)
Frequency <sub>i,t</sub>	-0.0069***	-0.0055***	-0.0062***	-0.0064***	-0.0064***
	(0.0019)	(0.0019)	(0.0018)	(0.0018)	(0.0018)
Constant	-0.0221	-0.0221	-0.0216	-0.0213	-0.0219
	(0.0249)	(0.0249)	(0.0249)	(0.0250)	(0.0249)
Controls, Year, Industry FE	YES	YES	YES	YES	YES
Clustered SE	YES	YES	YES	YES	YES
Observations	13,268	13,268	13,268	13,268	13,268
Adj. R-square	0.0177	0.0179	0.0177	0.0177	0.0177

Note: Table 5.8 shows the delayed market reaction of GHC-ET disclosures after releasing 8-K by different phases. The dependent variables are estimated CARs in the event windows (+4, +60) based on market model. Columns (1)-(5) show the delayed market reaction to GHC-ET disclosures according to different phases. Columns (6)-(10) present the delayed market reaction to the intensity of the GHC-ET in the initial 8-K while Columns (11)-(15) present the delayed market reaction to the frequency of 8-K containing the GHC-ET each year. The results are unchanged when I use CAR (+6, +60) as the dependent variable. All regressions include control variables and fixed effects by year and industry. The industry fixed effect is based on the GIC industry classifications. The standard errors presented in parentheses are corrected for firm-clustering heteroscedasticity. Definitions for all of variables are provided in Appendix B-1. The significance levels are: \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

# 5.4.3 Robustness checks

To verify the robustness of the main results, this study conducts several robustness checks, including controlling for other events and insider selling, estimating the CARs using the Fama-French three-factor and Carhart four-factor models. This chapter tests whether the market reacts before an 8-K release as a placebo test. In addition, the differences in technology support at the state level are also be controlled. Finally, three additional control variables are added into the regression model, including firm-level investor sentiment, 8-K filings' tone, and 8-K filings' readability. The findings remain unchanged.

### 5.4.3.1 Controlling for other events and insider selling

There are two challenges for this chapter to be convincing with the empirical results about investors' immediate and delayed market reactions to GHC-ET disclosures. One is whether other events occurring before initial 8-K filings containing GHC-ET could affect investors'

immediate reaction, while the other is whether the reversal in the long term might be driven by insider selling. This chapter conducts two tests to answer these two questions.

# 5.4.3.1.1 Do other events affect investor reaction?

The impact of quarterly and annual reports on investors' investment decisions is indisputable. Additionally, many prior studies have confirmed the differences in investor reactions to earnings announcements that both exceed and underestimate expectations (i.e., Hotchkiss and Strickland (2003) and Pevzner et al. (2015)). Therefore, those observations with annual and quarterly earnings announcements five trading days prior to the first 8-K filing that includes GHC-ET are excluded. In addition, this study observes that many firms publish 8-K filings containing multiple items at the same time. These items may not only contain Item 7.01, which I look for and contains voluntary disclosures of ET terms but may also contain other SEC-required mandatory disclosure items. Using a keyword search, this chapter excludes the initial 8-K filing containing GHC-ET with one of the other mandatory items.  $^{43}$  Columns (1) to (3) of Panel A in Table 5.9 present the results after removing the noise (9,288 obs.). The  $GHCET_{it}$  is still significantly and positively associated with CAR\_MM (-3, +3), which is unchanged after I use CAR\_MM (-5, +5) as the dependent variable.

## 5.4.3.1.2 *Is insider selling a trigger for changes in investor attitude?*

This study expects that overlooked information (i.e., high uncertainty and failure rate of ETs) is not incorporated immediately after 8-K filings releases but through a slow process. According to Dellavigna and Pollet (2009), investors may not realise that the negative perspective of GHC-ET disclosures is ignored. Although a negative investor reaction 60 trading dates after GHC-ET disclosures can be observed, this study cannot confirm that the change in their attitude is due to the correction of overreactions. Therefore, this study examines whether the negative results still exist after excluding samples with insider selling during the 60 trading

 $<sup>^{43}</sup>$  Include Items 1.01 to 1.04, Items 2.01, 2.03, 2.04, 2.05, 2.06, Items 3.01 to 3.03, Items 4.01 and 4.02, Items 5.01 to 5.08, Items 6.01 to 6.05.

days following GHC-ET disclosures. The data on insider selling is from Thomson Reuters Insider Filings (Form 4). Based on the study of Massa et al. (2015), the final sample excludes private transactions and define insiders as executive insiders because of their active and direct participation in decision making. <sup>44</sup> Columns (1) to (3) of Panel B in Table 5.9 show an insignificant relationship between *GHCET*<sub>i,t</sub> and CAR\_MM (+4, +60). Further, this study finds a significant result if I only regress the sample with insider selling (Column (4) of Panel B in Table 5.9). Overall, this study concludes that managers seem to hype stock prices due to uninformed traders by disclosing the GHC-ET before they sell stocks.

Table 5.9 Robustness Test for Market Reaction – Controlling for Other Events and Insider Selling

Panel A. After removing	Panel A. After removing other events										
Variables	CAR_MM (-3, +3)	CAR_MM (-3, +3)	CAR_MM (-3, +3)								
Variables -	(1)	(2)	(3)								
GHCET <sub>i,t</sub>	0.0408***	0.0843***	0.0572***								
	(0.0068)	(0.0097)	(0.0077)								
Intensity <sub>i,t</sub>		-0.0231***									
		(0.0037)									
Frequency <sub>i,t</sub>			-0.0069***								
			(0.0016)								
Constant	0.0234*	0.0241*	0.0226								
	(0.0139)	(0.0139)	(0.0139)								
Controls, Year, Industry FE	YES	YES	YES								
Clustered SE	YES	YES	YES								
Observations	9,288	9,288	9,288								
Adj. R-square	0.3407	0.3434	0.3420								

Thomson Boutons Inciden Filings (Form 4) BOLECODE1 causal to CI

<sup>&</sup>lt;sup>44</sup> Thomson Reuters Insider Filings (Form 4) ROLECODE1 equal to CEO, CFO, CI, CO, CT, EVP, O, OB, OP, OS, OT, OX, P, S, SVP, VP. Since this research does not primarily study the specifics of insider trading, there are no alternative insider classifications.

Panel B. Controlling for insider selling									
	CAR_MM	CAR_MM	CAR_MM	CAR_MM					
Variables	(+4, +60)	(+4, +60)	(+4, +60)	(+4, +60)					
	(1)	(2)	(3)	(4)					
GHCET <sub>i,t</sub>	-0.0110	0.0024	-0.0099	-0.0490***					
	(0.0144)	(0.0220)	(0.0161)	(0.0174)					
Intensity <sub>i,t</sub>		-0.0075							
		(0.0094)							
Frequency <sub>i,t</sub>			-0.0005						
			(0.0031)						
Constant	0.0274	0.0273	0.0273	-0.0456					
	(0.0355)	(0.0355)	(0.0355)	(0.0351)					
Controls, Year, Industry FE	YES	YES	YES	YES					
Clustered SE	YES	YES	YES	YES					
Observations	5,325	5,325	5,325	7,943					
Adj. R-square	0.0081	0.0081	0.0080	0.0231					

Note: Table 5.9 shows robustness test for market reaction after controlling for other events and insider selling. Columns (1)-(3) of Panel A present the immediate market reaction of GHC-ET disclosures after removing other events before five trading days from the initial 8-K filing. Other events including quarter or annual reports, earnings announcement, and mandatory items in the same 8-K filing. I obtain robust results after removing the noise. The results are unchanged when I use CAR (-5, +5) as the dependent variable. Columns (1)-(3) of Panel B present the delayed market reaction of GHC-ET disclosures after removing samples with insider selling 60 trading days after 8-K filing release. Column (4) of Panel B shows the delayed market reaction of GHC-ET disclosures only for firms with insider selling 60 trading days after 8-K filing release. The results are unchanged when I use CAR (+6, +60) as the dependent variable. All regressions include control variables. The industry fixed effect is based on the GIC industry classifications. The standard errors presented in parentheses are corrected for firm-clustering heteroscedasticity. Definitions for all of variables are provided in Appendix B-1. The significance levels are: \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

# 5.4.3.2 Alternative estimation models

To verify whether the findings are robust to the CARs calculation procedure, this study uses the Fama-French three-factor model and the Carhart four-factor model to estimate the CARs in the same event windows. The expected returns are estimated using the following formulas:

$$R_{i,d} - R_{f,d} = \alpha_i + \beta_1 (R_{m,d} - R_{f,d}) + \beta_2 SMB_d + \beta_3 HML_d + \omega_{i,d}$$
 (5-9)

$$R_{i,d} - R_{f,d} = \alpha_i + \beta_1 (R_{m,d} - R_{f,d}) + \beta_2 SMB_d + \beta_3 HML_d + \beta_4 MOM_d + \omega_{i,d}$$
 (5-10)

The regression results are shown in Table 5.10. Panel A reports the short-term market reaction before and after removing other events based on the CARs obtained from the event study as the dependent variable. Panel B shows the delayed reaction before and after removing insider selling. All regressions include control variables and fixed effects at the year and industry levels. Whether the Fama-French three-factor model or the Carhart four-factor model is used to estimate the expected returns, the market reactions to GHC-ET disclosures are the same as the baseline regression in both the short and long term. Regarding the disclosure intensity, frequency, and phase, the regression results demonstrate the robustness of the baseline regressions. Overall, changing the measure of expected returns caused no change in the regression results, thus validating the hypotheses and the findings obtained.

#### 5.4.3.3 Placebo test

This study changes the event window to (-60, -4) and (-60, -6) to test whether the market reacts significantly before the release of the initial 8-K filing for different firms each year. This study regresses Equations (5-1), (5-3) and (5-4) using three different models to estimate the expected returns to calculate the CARs. Panel C of Table 5.10 shows that the *GHCET<sub>i,i</sub>* of all regressions is not significantly positively associated with the CARs, suggesting that prior to the release of the 8-K filings, there was no significant market reaction. That is, the market reaction during the 8-K filings release period was caused by the release of the 8-K filings.

**Table 5.10 Robustness Tests – Alternative Estimation of Market Reactions** 

Panel A. Short-ter	rm reaction be	efore and afte	r removing o	ther events								
Before removing other events								After removing other events				
	CAR_FF3 (-3, +3)	CAR_FF3 (-3, +3)	CAR_FF3 (-3, +3)	CAR_C4 (-3, +3)	CAR_C4 (-3, +3)	CAR_C4 (-3, +3)	CAR_FF3 (-3, +3)	CAR_FF3 (-3, +3)	CAR_FF3 (-3, +3)	CAR_C4 (-3, +3)	CAR_C4 (-3, +3)	CAR_C4 (-3, +3)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
GHCET <sub>i,t</sub>	0.0211***	0.0658***	0.0304***	0.0226***	0.0677***	0.0323***	0.0441***	0.0872***	0.0605***	0.0447***	0.0887***	0.0620***
	(0.0054)	(0.0079)	(0.0059)	(0.0054)	(0.0080)	(0.0059)	(0.0069)	(0.0099)	(0.0079)	(0.0070)	(0.0100)	(0.0080)
Intensity <sub>i,t</sub>		-0.0232***			-0.0234***			-0.0229***			-0.0234***	
		(0.0030)			(0.0030)			(0.0038)			(0.0038)	
$Frequency_{i,t}$			-0.0037***			-0.0039***			-0.0069***			-0.0073***
			(0.0009)			(0.0009)			(0.0016)			(0.0016)
Constant	0.0067	0.0068	0.0068	0.0103	0.0104	0.0104	0.0070	0.0077	0.0062	0.0108	0.0114	0.0099
	(0.0115)	(0.0115)	(0.0115)	(0.0116)	(0.0115)	(0.0116)	(0.0143)	(0.0142)	(0.0143)	(0.0143)	(0.0143)	(0.0143)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year, Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Clustered SE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	13,268	13,268	13,268	13,268	13,268	13,268	9,288	9,288	9,288	9,288	9,288	9,288
Adj. R-square	0.3095	0.3125	0.3103	0.3073	0.3103	0.3081	0.3265	0.3291	0.3277	0.3235	0.3262	0.3249

Panel B. Delayed	Panel B. Delayed reaction before and after removing insider selling											
		В	efore removing	g insider selling			After removing insider selling					
	CAR_FF3 (+4, +60)	CAR_FF3 (+4, +60)	CAR_FF3 (+4, +60)	CAR_C4 (+4, +60)	CAR_C4 (+4, +60)	CAR_C4 (+4, +60)	CAR_FF3 (+4, +60)	CAR_FF3 (+4, +60)	CAR_FF3 (+4, +60)	CAR_C4 (+4, +60)	CAR_C4 (+4, +60)	CAR_C4 (+4, +60)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
GHCET <sub>i,t</sub>	-0.0325***	-0.0235	-0.0214	-0.0349***	-0.0271	-0.0238*	-0.0245*	-0.0277	-0.0289*	-0.0260*	-0.0330	-0.0313*
	(0.0122)	(0.0180)	(0.0133)	(0.0120)	(0.0177)	(0.0130)	(0.0149)	(0.0227)	(0.0166)	(0.0148)	(0.0227)	(0.0166)
$Intensity_{i,t} \\$		-0.0047			-0.0041			0.0018			0.0040	
		(0.0069)			(0.0068)			(0.0097)			(0.0097)	
Frequency <sub>i,t</sub>			-0.0044**			-0.0044**			0.0019			0.0023
			(0.0021)			(0.0020)			(0.0032)			(0.0032)
Constant	-0.0788***	-0.0653**	-0.0508**	-0.0612**	0.0084	0.0120	-0.0031	0.0036	-0.0794***	-0.0618**	-0.0658**	-0.0513**
	(0.0261)	(0.0256)	(0.0251)	(0.0256)	(0.0115)	(0.0116)	(0.0134)	(0.0135)	(0.0261)	(0.0256)	(0.0256)	(0.0251)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year, Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Clustered SE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	13,268	13,268	13,268	13,268	13,268	13,268	5,325	5,325	5,325	5,325	5,325	5,325
Adj. R-square	0.0476	0.0475	0.0478	0.0325	0.0324	0.0327	0.0371	0.0369	0.0370	0.0272	0.0270	0.0271

Panel C. Placebo	test-Pre-8-K filiı	ng release							
	CAR_MM (-60, -4)	CAR_MM (-60, -4)	CAR_MM (-60, -4)	CAR_ FF3 (-60, -4)	CAR_FF3 (-60, -4)	CAR_FF3 (-60, -4)	CAR_C4 (-60, -4)	CAR_C4 (-60, -4)	CAR_C4 (-60, -4)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
GHCET <sub>i,t</sub>	-0.0002	0.0001	-0.0132	-0.0001	0.0006	0.0005	-0.0005	-0.0001	0.00001
	(0.0014)	(0.0134)	(-0.0098)	(0.0014)	(0.0021)	(0.0015)	(0.0014)	(0.0020)	(0.0015)
Intensity <sub>i,t</sub>		-0.0017			-0.0004			-0.0002	
		(0.0051)			(0.0008)			(0.0008)	
Frequency <sub>i,t</sub>			0.0040***			-0.0002			-0.0002
			(0.0015)			(0.0002)			(0.0002)
Constant	-0.0017	0.0115	0.0115	-0.0025	-0.0025	-0.0025	-0.0017	-0.0017	-0.0017
	(0.0030)	(0.0166)	(0.0166)	(0.0030)	(0.0030)	(0.0030)	(0.0029)	(0.0029)	(0.0029)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year, Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Clustered SE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	13,268	13,268	13,268	13,268	13,268	13,268	13,268	13,268	13,268
Adj. R-square	0.0008	0.0039	0.0044	0.0018	0.0017	0.0018	0.0014	0.0013	0.0014

Note: Table 5.10 shows the results of robustness checks. Panel A reports immediate market reaction to GHC-ET disclosures before and after removing other events. Columns (1)-(6) show immediate market reaction to GHC-ET disclosures before removing other events while Columns (7)-(12) after. The results are unchanged when the event window (-5, +5) is used. Panel B indicates the delayed market reaction to GHC-ET disclosures before and after removing insider selling. Columns (1)-(6) show the delayed market reaction to GHC-ET disclosures before removing insider selling while Columns (7)-(12) after. The results are unchanged when I use the event window (+6, +60). Panel C shows market reaction pre-8K filing release. CARs are estimated by the Fama-French three-factor model in Columns (1)-(3) and (7)-(9) of Panel A and B as well Column (4)-(6) of Panel C. In addition, CARs are estimated by the Carhart four-factor model in Columns (4)-(6) and (10)-(12) of Panel A and B as well Column (7)-(9) of Panel C. Finally, CARs are estimated by the market model in Columns (1)-(3) of Panel C. All regressions include control variables and fixed effects by year and industry. The industry fixed effect is based on the GIC industry classifications. The standard errors presented in parentheses are corrected for firm-clustering heteroscedasticity. Definitions for all of variables are provided in Appendix B-1. The significance levels are: \*\*\* p<0.01, \*\*\* p<0.05, \* p<0.1.

# 5.4.3.4 Differences in technology support at the state level

This research observes that some states in the US provide more support for the development of technology and science, such as Massachusetts, Colorado, and California (top three in the 2020 and 2022 Milken Institute State Technology and Science Index). These states have higher R&D funding and more experts in computer and information science than other states and advanced education systems. Firms in these states are more hyped than those in other states. To control the differences in technology support between different states, this study reruns Equation (5-5) after controlling for state fixed effects as well. As Table 5.11 reports, the market reactions to GHC-ET disclosures are the same as that from the baseline regression in both the short and long term.

**Table 5.11 Robustness Tests - Controlling for State-Level Fixed Effects** 

Panel A. Shor	Panel A. Short-term market reaction									
Variables	CAR_MM (-3, +3)	CAR_MM (-3, +3)	CAR_MM (-3, +3)	CAR_MM (-5, +5)	CAR_MM (-5, +5)	CAR_MM (-5, +5)				
	(1)	(2)	(3)	(4)	(5)	(6)				
GHCET <sub>i,t</sub>	0.0192***	0.0690***	0.0303***	0.0194***	0.0705***	0.0308***				
	(0.0056)	(0.0082)	(0.0061)	(0.0065)	(0.0095)	(0.0070)				
$Intensity_{i,t} \\$		-0.0258***			-0.0264***					
		(0.0031)			(0.0036)					
$Frequency_{i,t}$			-0.0043***			-0.0044***				
			(0.0009)			(0.0011)				
Constant	0.0288	0.0261	0.0281	0.0177	0.0149	0.0170				
	(0.0320)	(0.0320)	(0.0320)	(0.0371)	(0.0371)	(0.0371)				
Controls	YES	YES	YES	YES	YES	YES				
Year FE	YES	YES	YES	YES	YES	YES				
Industry FE	YES	YES	YES	YES	YES	YES				
State FE	YES	YES	YES	YES	YES	YES				
Clustered SE	YES	YES	YES	YES	YES	YES				
Observations	13,268	13,268	13,268	13,268	13,268	13,268				
Adj. R-square	0.3181	0.3218	0.3193	0.2665	0.2696	0.2675				

Panel B. Delay	Panel B. Delayed market reaction									
Variables	CAR_MM (+4, +30)	CAR_MM (+4, +30)	CAR_MM (+4, +30)	CAR_MM (+4, +60)	CAR_MM (+4, +60)	CAR_MM (+4, +60)				
, unius is	(1)	(2)	(3)	(4)	(5)	(6)				
GHCET <sub>i,t</sub>	-0.0276**	-0.0091	-0.0129	-0.0288**	-0.0091	-0.0147				
	(0.0121)	(0.0176)	(0.0131)	(0.0118)	(0.0172)	(0.0128)				
$Intensity_{i,t} \\$		-0.0096			-0.0102					
		(0.0067)			(0.0065)					
$Frequency_{i,t}$			-0.0056***			-0.0054***				
			(0.0020)			(0.0019)				
Constant	-0.0908	-0.0918	-0.0917	-0.0936	-0.0946	-0.0944				
	(0.0691)	(0.0691)	(0.0691)	(0.0675)	(0.0675)	(0.0675)				
Controls	YES	YES	YES	YES	YES	YES				
Year FE	YES	YES	YES	YES	YES	YES				
Industry FE	YES	YES	YES	YES	YES	YES				
State FE	YES	YES	YES	YES	YES	YES				
Clustered SE	YES	YES	YES	YES	YES	YES				
Observations	13,268	13,268	13,268	13,268	13,268	13,268				
Adj. R-square	0.0183	0.0184	0.0189	0.0184	0.0185	0.0190				

Note: Table 5.11 shows the market reaction of GHC-ET disclosures after controlling the differences of technology support at state level. Panel A shows the immediate market reaction. The dependent variables are estimated CARs in the event windows (-3, +3) and (-5, +5) based on market model. Panel B shows the delayed market reaction. The dependent variables are estimated CARs in the event windows (+4, +30) and (+4, +60) based on market model. All columns include fixed effects by year, industry, and state. The industry fixed effect is based on the GIC industry classifications. The standard errors presented in parentheses are corrected for firm-clustering heteroscedasticity. Definitions for all of variables are provided in Appendix B-1. The significance levels are: \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

### 5.4.3.5 Investor sentiment and qualitative characteristics of each 8-K filings

Previous literature has concluded that investor sentiment affects stock prices and expected returns (Baker and Wurgler, 2006, 2007). The positive (negative) effect of short- (long-) term CARs might be partially due to investors' sentiment. Thus, this study adds the monthly investor sentiment as an additional control variable to equations (5-5), (5-6), and (5-7). This study follows Baker and Wurgler (2006) to measure the sentiment of investors based on the first principal component of the five standardized sentiment proxies of value-weighted dividend premium, first-day returns on IPOs, IPO volume, closed-end fund discount, and equity share in new issues.

In addition, the qualitative characteristic of the disclosure content could also affect investors' reactions to such disclosures (Lee, 2012). This study chooses two commonly used characteristics to control for the effect of different 8-K filings' qualitative characteristics on the relationship between GHC-ET disclosures and CARs, including tone and readability. The tone is based on the Loughran and McDonald (2011) dictionary to measure the percentage of positive to negative word differences to the total number of words in each 8-K filing. The degree of readability is measured by the Fog index.

As shown in Table 5.12, GHC-ET disclosures are significantly and positively associated with CAR\_MM (-3, +3) before and after removing other events. *GHCET*<sub>i,t</sub> is significantly and negatively associated with CAR\_MM (+4, +60) before removing the effect of insider selling and insignificant after such removal. All the results are consistent with our baseline results even when event windows and estimation measures of CARs are changed.<sup>45</sup>

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<sup>&</sup>lt;sup>45</sup> To address the concerns of using contemporaneous investor sentiment of each firm and readability and tone of each 8-K filing. I rerun the regressions by adding lagged controls. The results are shown in Appendix B-4. Panel A of B.4 shows the immediate market reaction is unchanged after controlling lagged investor sentiment, readability, and tone separately or all of them, which is consistent with Table 5.12. However, for delayed market reaction (Panel B), the GHCET is insignificant before and after removing insider selling. These results indicate that lagged investor sentiment and qualitative characters of each 8-K affect decision-making of investors after firm's GHC-ET disclosure.

**Table 5.12 Robustness Tests – Additional Control Variables** 

		Before removin	g other events		After removing other events				
Variables	CAR_MM (-3, +3)	CAR_MM (-3, +3)	CAR_MM (-3, +3)	CAR_MM (-3, +3)	CAR_MM (-3, +3)	CAR_MM (-3, +3)	CAR_MM (-3, +3)	CAR_MM (-3, +3)	
	$\frac{(3,13)}{(1)}$	(2)	(3)	(4)	(5)	(6)	(7)	(8)	
GHCET <sub>i,t</sub>	0.0182***	0.0141***	0.0142***	0.0142***	0.0412***	0.0305***	0.0306***	0.0307***	
	(0.0053)	(0.0048)	(0.0048)	(0.0048)	(0.0068)	(0.0058)	(0.0058)	(0.0058)	
$Investor\_sentiment_{i,t}$	-0.0092			-0.0027	-0.0166			-0.0066	
	(0.0096)			(0.0085)	(0.0118)			(0.0099)	
8K_Readability <sub>i,t</sub>		0.0000		0.0000		0.0000		0.0000	
		(0.0001)		(0.0001)		(0.0001)		(0.0001)	
$8K\_Tone_{i,t}$			-0.1348	-0.1305			-0.1258	-0.1233	
			(0.1433)	(0.1438)			(0.1684)	(0.1688)	
Constant	0.0181	0.0174*	0.0181*	0.0159	0.0134	0.0187	0.0193	0.0148	
	(0.0127)	(0.0103)	(0.0103)	(0.0115)	(0.0157)	(0.0120)	(0.0120)	(0.0135)	
Controls	YES	YES	YES	YES	YES	YES	YES	YES	
Year, Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	
Clustered SE	YES	YES	YES	YES	YES	YES	YES	YES	
Observations	13,268	12,226	12,226	12,226	9,288	8,536	8,536	8,536	
Adj. R-square	0.3166	0.3815	0.3815	0.3814	0.3408	0.4359	0.4359	0.4358	

0.0089

0.0082

0.0165

Panel B. Delayed react	ion to GHC-ET dis	closures								
		Before removing	g insider selling		After removing insider selling					
Variables	CAR_MM (+4, +60)	CAR_MM (+4, +60)	CAR_MM (+4, +60)	CAR_MM (+4, +60)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)		
GHCET <sub>i,t</sub>	-0.0332***	-0.0259**	-0.0259**	-0.0275**	-0.0135	-0.0192	-0.0181	-0.0206		
	(0.0117)	(0.0118)	(0.0118)	(0.0118)	(0.0143)	(0.0146)	(0.0146)	(0.0145)		
Investor_sentiment <sub>i,t</sub>	0.1100***			0.1141***	0.1769***			0.1823***		
	(0.0210)			(0.0209)	(0.0287)			(0.0290)		
8K_Readability <sub>i,t</sub>		0.0000		-0.0000		0.0007		-0.0006		
		(0.0002)		(0.0002)		(0.0009)		(0.0009)		
$8K\_Tone_{i,t}$			-0.2339	-0.1996			-0.9172**	-0.9197*		
			(0.3529)	(0.3539)			(0.4573)	(0.4754)		
Constant	0.0441	-0.0051	-0.0046	0.0637**	0.1388***	0.0285	0.0403	0.1695***		
	(0.0279)	(0.0255)	(0.0253)	(0.0284)	(0.0399)	(0.0393)	(0.0359)	(0.0447)		
Controls	YES	YES	YES	YES	YES	YES	YES	YES		
Year, Industry FE	YES	YES	YES	YES	YES	YES	YES	YES		
Clustered SE	YES	YES	YES	YES	YES	YES	YES	YES		
Observations	13,268	12,226	12,226	12,226	5,325	4,916	4,916	4,916		

Note: Table 5.12 shows the results of robustness checks after adding additional control variables. Panel A reports the immediate market reaction to GHC-ET disclosures before and after removing other events before 8-K filings. The results are unchanged when I use the event window (-5, +5) and use the Fama-French three-factor and the Carhart four-factor model to estimate CARs. Panel B indicates the delayed market reaction to GHC-ET disclosures before and after removing insider selling after GHC-ET disclosures. The results are unchanged when I use the event window (+6, +60) and use the Fama-French three-factor and the Carhart four-factor model to estimate CARs. All regressions include control variables and fixed effects by year and industry. The industry fixed effect is based on the GIC industry classifications. The standard errors presented in parentheses are corrected for firm-clustering heteroscedasticity. Definitions for all of variables are provided in Appendix B-1. The significance levels are: \*\*\* p<0.01, \*\*\* p<0.05, \*\* p<0.1.

0.0208

0.0150

0.0186

0.0193

Adj. R-square

0.0185

#### 5.4.4 Further analysis

## 5.4.4.1 Do institutional investors pay attention to GHC-ET disclosures?

During the past few decades, institutional investors have played an increasingly important role in all aspects of financial markets (Chemmanur et al., 2021).<sup>46</sup> According to Bai et al. (2016), the percentage of institutional investors' holdings in common firms increased from 20% in 1980 to 60% in 2014. It is necessary to investigate the effects of institutional holdings on the association between GHC-ET disclosures and market reactions.

Institutional investors in the market who use their information advantage in trading to avoid losses or earn excess profits are often considered sophisticated investors (Ke and Petroni, 2004). Many studies have identified that institutional investors are important in influencing managers to invest in innovation. <sup>47</sup> Disclosures about GHC-ET may be seen as aggressive in the context of the firm's pursuit of innovation. However, excellent information gathering, processing and identification are institutional trading capabilities. It is easier for institutional investors than the average investor to determine the firm's true intent in presenting GHC-ET information through high frequency 8-K filings. Furthermore, institutional investors are normally regarded as rational investors. This study expects that GHC-ET disclosures during the 8-K filing date are not considered valuable information by institutional investors.

Following the procedure of Pevzner et al. (2015), this study uses subsample regressions to explore the role played by institutional investors in GHC-ET disclosures and market reactions. If the percentage of institutional holdings in the sample firms is greater than the sample mean, then the group has high institutional investor holdings; otherwise, the group has low

<sup>&</sup>lt;sup>46</sup> As required by the SEC (1934, available at: <a href="https://www.nyse.com/publicdocs/nyse/regulation/nyse/sea34.pdf">https://www.nyse.com/publicdocs/nyse/regulation/nyse/sea34.pdf</a>) and the rule of 13F-1, institutional investment managers with investment authority over accounts holding Section 13(F) securities with an aggregate fair market value of at least \$100 million are required to report on SEC 13F filings (Form 13F) within 45 days of the last day of the calendar quarter. Both the WRDS database and Bloomberg have access to Form 13F institutional holdings data. This research collects the percentage of institutional holdings from the Bloomberg database. Institutional investors include mutual funds, hedge funds, endowments, retirement or pension funds, insurance firms, sovereign wealth funds, and private equity firms.

<sup>&</sup>lt;sup>47</sup> Wahal and McConnell (2000) find a positive relationship between R&D expenditure and institutional investors. He and Tian (2013) find a positive relationship between patent output (citations) and institutional investors.

institutional investor holdings.<sup>48</sup> As the regression results in Panel A of Table 5.13 show, for the immediate reaction (event window (-3, +3)), GHC-ET disclosures only receive a positive market response if the firm's institutional investor ownership is low. When institutional holding is low, the coefficients of  $GHCET_{i,t}$  are 0.0446 (4.46%) and 0.0500 (5.00%) in Columns (3) and (4) (all significant at the 1% significance level), respectively.<sup>49</sup> Compared to the full sample in which CARs increase by only approximately 2%, the immediate market response to GHC-ET disclosures is stronger among investors in the sample of firms with low institutional investor holdings. For the delayed market reactions,  $GHCET_{i,t}$  is negatively and significantly associated with market reactions (approximately 4% decrease in CARs) in the sample of high institutional holdings.

## 5.4.4.2 Do analysts follow GHC-ET disclosures?

As has been extensively documented, a firm can lose the attention of analysts if it chooses not to disclose information (Arya and Mittendorf, 2007). A few studies have focused on the role of analysts in corporate governance (Yu, 2008), especially how the presence of analysts influence the voluntary disclosure behaviour of managers. Graham et al. (2005) agree that analysts, as one of the most important groups influencing firms' share prices, have a significant impact on investor behaviour. This research attempts to investigate the differences in market reactions to GHC-ET disclosures when firms have different analyst follows.

The prior literature has made two interesting arguments. On the one hand, analysts could play the role as external monitors through interactions with management. They are expected to be professional given their financial training and have extensive background knowledge of the industry. The analyst's role in information intermediation and external monitoring curbs

<sup>&</sup>lt;sup>48</sup> Another important reason for this treatment is to avoid the impact of a sample with the proportion of institutional investors exceeding 100%. In some cases, investors appear to hold far more shares of the firm than actually exist. This may be due to long-term updates or because of short selling among investors. However, this is a flaw in the data itself, so this study reduces the effect on the regression results by grouping them.

<sup>&</sup>lt;sup>49</sup> This study finds similar results of the short-term market reaction using the Fama-French three-factor and Carhart four-factor models.

managerial opportunism. Higher analyst followings could not only help short-term investors monitor managers but also reduce information asymmetry between inside managers and outside investors (Kim et al., 2019). This oversight and endorsement lend credibility to voluntary disclosures, thus prompting the average investor with scarce experience to trust professional judgment. Therefore, investors should tend to believe GHC-ET disclosures for firms with higher analyst followings.

On the other hand, previous research has shown that analysts are particularly important to spreading bad news (Asquith et al., 2005; Huang et al., 2014). Their role is even more pronounced when management is more likely to be forthright with good news (Kim et al., 2019) and hides or delays bad news (Hong et al., 2017; Hutton et al., 2009). GHC-ET disclosures could be regarded as information reflecting high risk. If management does not disclose GHC-ET and hint at the risks and high failure rate characteristics of ETs in terms of inputs and applications, then such disclosure can be considered as hiding bad news. Substantial analyst attention limits management's boldness because they fear that analysts will comment unfavourably on the firm. However, lesser-known firms only receive analysts' attention if a major event occurs. An obsession with low probability occurrences drives speculative investors to focus on firms with fewer analysts.

This study calculates the average analyst following to divide the full sample into high and low analyst following based on the mean of all sample firms. The regression results are shown in Panel B of Table 5.13. For the immediate reaction (event window (-3, +3)), GHC-ET disclosures receive only a positive market response if the firm's analyst following is low regardless of the model used to estimate expected returns. When analyst following is low, the coefficients of *GHCET*<sub>i,t</sub> are 0.0366 (3.66%) and 0.0435 (4.35%) in Columns (3) and (4) (both are significant at 1%), respectively.<sup>51</sup> Compared to the full sample in which CARs increase by only approximately 2%, the immediate market response to GHC-ET disclosures is stronger

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<sup>&</sup>lt;sup>50</sup> Management's forthrightness about good news but long-term or hidden disclosures of bad news is more evident in disclosures of new items (i.e., ET). For example, a firm first discloses its investment in the metaverse to attract investors' attention but then warns them of the risks in a subsequent report.

<sup>&</sup>lt;sup>51</sup> This study finds similar results of the short-term market reaction using the Fama-French three-factor and Carhart four-factor models.

among short-term investors in the sample of firms with a low analyst following. For the delayed market reactions,  $GHCET_{i,t}$  is negatively and significantly correlated with CARs (approximately 4%, see Columns (5) and (6) of Panel B of Table 5.13) when firms' analyst following is low.

#### 5.4.4.3 Does the information environment matter?

This study investigates whether a different disclosure environment affects investors' short-term market reactions to GHC-ET disclosures. Due to information asymmetry, outside investors need to use various information sources to understand the firm and make investment decisions. The idiosyncratic volatility of stock prices is only affected by firm-specific factors (Campbell et al., 2001). Moreover, according to the market efficiency hypothesis, idiosyncratic stock price volatility is essentially influenced by firm information (Ang et al., 2006). This study believes that idiosyncratic volatility leads to greater information asymmetry between inside managers and outside investors. Therefore, this study uses idiosyncratic volatility as a proxy for the information environment.

Idiosyncratic volatility is the standard deviation of the residuals  $(\epsilon_t)$  from the following regression.

$$r_{d} = \alpha + \beta_{1} HML_{d} + \beta_{2} SMB_{d} + \sum_{i=-3}^{3} \gamma_{i} r_{m,d-1} + \epsilon_{d}$$
 (5-11)

where  $r_d$  is the daily stock return,  $r_{m,d}$  is the market return, and  $HML_d$  and  $SMB_d$  are the daily value premium and size factors from the Fama-French three-factor model and take the value of one if firms' idiosyncratic volatility is larger than the mean and zero otherwise. Due to the higher idiosyncratic volatility (information asymmetry), investors do not have access to more new information about the firm. They react more strongly to GHC-ET disclosures. Panel C of Table 5.13 reports the regression results. All regressions include control variables and fixed effects by year and industry.  $GHCET_{i,t}$  is positively associated with CAR\_MM (-3, +3) at the 1% significance level, and the coefficients are 0.0242 (2.42%) and 0.0256 (2.56%), as noted in Columns (3) and (4), respectively. Therefore, investors react positively to GHC-ET disclosures

when information asymmetry (idiosyncratic volatility) is high. However, after the disclosures, investors have more opportunities and access to the information they need. Therefore, their delayed reaction is negative to GHC-ET disclosures (the coefficients of  $GHCET_{i,t}$  are -0.0504 (-5.04%) and -0.0509 (-5.09%) in Columns (7) to (8) of Panel C). This study finds similar results of the immediate market reaction using the Fama-French three-factor and Carhart four-factor models.

Table 5.13 Further Analysis (I) – Institutional Holdings, Analyst Attention and Disclosure Environment

Panel A. Institutional holdings									
	High institutional holdings Low		Low instituti	onal holdings	High instituti	High institutional holdings Low institutional holdings			
Variables	CAR_MM (-3, +3)	CAR_MM (-5, +5)	CAR_MM (-3, +3)	CAR_MM (-5, +5)	CAR_MM (+4, +60)	CAR_MM (+6, +60)	CAR_MM (+4, +60)	CAR_MM (+6, +60)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	
$GHCET_{i,t}$	0.0007	-0.0009	0.0446***	0.0500***	-0.0414***	-0.0419***	-0.0191	-0.0217	
	(0.0040)	(0.0049)	(0.0118)	(0.0135)	(0.0114)	(0.0111)	(0.0238)	(0.0233)	
Constant	0.0014	0.0078	0.0382	0.0266	0.0025	0.0010	-0.0617	-0.0480	
	(0.0097)	(0.0118)	(0.0234)	(0.0268)	(0.0272)	(0.0266)	(0.0471)	(0.0460)	
Controls	YES	YES	YES	YES	YES	YES	YES	YES	
Year, Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	
Clustered SE	YES	YES	YES	YES	YES	YES	YES	YES	
Observations	7,766	7,766	5,502	5,502	7,766	7,766	5,502	5,502	
Adj. R-square	0.4132	0.3290	0.2867	0.2453	0.0217	0.0211	0.0164	0.0166	

Panel B. Analyst attention

	High analy	st attention	Low analy	st attention	tion High analyst attention		Low analyst attention		
Variables	CAR_MM (-3, +3)	CAR_MM (-5, +5)	CAR_MM (-3, +3)	CAR_MM (-5, +5)	CAR_MM (+4, +60)	CAR_MM (+6, +60)	CAR_MM (+4, +60)	CAR_MM (+6, +60)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	
GHCET <sub>i,t</sub>	0.0071	0.0044	0.0366***	0.0435***	-0.0418***	-0.0408***	-0.0131	-0.0181	
	(0.0043)	(0.0051)	(0.0111)	(0.0128)	(0.0111)	(0.0109)	(0.0233)	(0.0227)	
Constant	0.0110	0.0138	0.0429**	0.0354	-0.0253	-0.0226	-0.0491	-0.0403	
	(0.0107)	(0.0127)	(0.0216)	(0.0249)	(0.0274)	(0.0269)	(0.0453)	(0.0442)	
Controls	YES	YES	YES	YES	YES	YES	YES	YES	
Year, Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	
Clustered SE	YES	YES	YES	YES	YES	YES	YES	YES	
Observations	6,893	6,893	6,375	6,375	6,893	6,893	6,375	6,375	
Adj. R-square	0.3484	0.2867	0.3075	0.2604	0.0244	0.0235	0.0181	0.0183	

Panel C. Disclosure environment									
	Good disclosure environment		Bad disclosur	e environment	Good disclosure environment		Bad disclosur	Bad disclosure environment	
Variables	CAR_MM (-3, +3)	CAR_MM (-5, +5)	CAR_MM (-3, +3)	CAR_MM (-5, +5)	CAR_MM (+4, +60)	CAR_MM (+6, +60)	CAR_MM (+4, +60)	CAR_MM (+6, +60)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	
GHCET <sub>i,t</sub>	0.0012	0.0030	0.0242***	0.0256***	0.0190*	0.0148	-0.0504***	-0.0509***	
	(0.0044)	(0.0053)	(0.0072)	(0.0083)	(0.0115)	(0.0112)	(0.0156)	(0.0152)	
Constant	0.0234**	0.0223*	0.0238	0.0203	-0.0566**	-0.0520*	-0.0193	-0.0151	
	(0.0104)	(0.0126)	(0.0152)	(0.0176)	(0.0274)	(0.0266)	(0.0331)	(0.0324)	
Controls	YES	YES	YES	YES	YES	YES	YES	YES	
Year, Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	
Clustered SE	YES	YES	YES	YES	YES	YES	YES	YES	
Observations	3,964	3,964	9,304	9,304	3,964	3,964	9,304	9,304	
Adj. R-square	0.2978	0.2254	0.3171	0.2680	0.0303	0.0290	0.0182	0.0183	

Note: Table 5.13 reports the immediate and delayed market reaction to GHC-ET disclosures of firms with different percentage of institutional investors, analyst attention, and disclosure environment. Panel A shows the market reaction to GHC-ET disclosures of firms with different percentages of institutional investors. Panel B shows the market reaction of GHC-ET disclosures of firms with different analyst attention. Panel C shows the market reaction to GHC-ET disclosures of firms with different disclosure environments. This research uses annualised idiosyncratic volatility to represent the information environment which is the degree of information asymmetry between managers and external shareholders. Columns (1)-(4) of each panel are short-term market reaction based on market model and Columns (5)-(8) of each panel are delayed market reaction based on market model. All regressions include control variables. The industry fixed effect is based on the GIC industry classifications. The standard errors of slope coefficients are clustered by year and industry which are reported in parenthesis. Definitions for all of variables are provided in Appendix B-1. The significance levels are: \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

#### 5.4.4.4 Are investors more sensitive to FinTech ETs?

For FinTech ETs, investors are more likely to receive overwhelming hype from the media. For ETs that belong to the biological category, for example, only investors interested in the biological field may know the extent and prospects of their development. To test this conjecture, this study compares the fintech glossary disclosed by Deloitte to classify all ET terms of the GHC.<sup>52</sup>

Panel A of Table 5.14 reports the results of the short- and delayed market reaction to fintech-type disclosures in 8-K filings. Similar to previous tests, this study uses three different models to estimate the expected returns. All regressions include control variables and control for industry and year fixed effects. In the short term, *FinTech<sub>i,t</sub>* is positively associated with CAR\_MM (-3, +3) and CAR\_MM (-5, +5) at the 1% significance level, and the coefficients are 0.0483 (4.83%) and 0.0449 (4.49%) in Columns (1) and (2), respectively, based on different event windows. The results of the short-term market reaction are unchanged after using the Fama-French three-factor and Carhart four-factor models. In other words, this study learns that investors are more responsive to FinTech-type information. In the long term, consistent with the baseline regression results, investors react negatively to GHC-ET disclosures and, to a greater extent, to FinTech-type information.

## 5.4.4.5 Do investors prefer the quick adoption of ETs?

This study notices that another important piece of information disclosed each year on the GHC is the timing (years) of when ETs become productive.<sup>53</sup> This study divides the sample into short and long term; the long term is defined as ET taking more than 10 years to be applied to the market and short term is defined as otherwise. ETs that can be applied in the short term are more predictable in terms of risk. Compared to ETs that take more than 10 years to reach

<sup>&</sup>lt;sup>52</sup> Available at: https://www.deloitte.com/uk/en/pages/financial-services/articles/fintech-glossary.html

<sup>&</sup>lt;sup>53</sup> There are four main application cycles, including less than 2 years, 2-5 years, 5-10 years and more than 10 years (See Figure 3.4 a GHC example and Appendix D-3 for the list of GHC-ET words).

the plateau, investors can rely on more external information to determine whether the short-term application of the technology can be successful.

Through the comparison of sample GHC years, some of the ETs that require more than 10 years to reach the plateau are likely to be abandoned by the market in subsequent developments and, thus, cannot be found in subsequent GHCs. Thus, this study expects that investors will react positively to GHC-ET, which needs to be applied in the market in the short term. Panel B of Table 5.14 shows the regression results. All regressions include control variables and control for industry and year fixed effects. In the short term, *Quick\_Adoption*<sub>i,t</sub> is positively associated with CAR\_MM (-3, +3) and CAR\_MM (-5, +5) at the 1% significance level, and the coefficients are 0.0306 (3.06%) and 0.0311 (3.11%) in Columns (1) and (2) of Panel B based on different event windows. This study finds similar results of the short-term market reaction using the Fama-French three-factor and Carhart four-factor models. In the long term, *Quick\_Adoption*<sub>i,t</sub> is negatively related to CARs, which means that the delayed market reaction by investors to GHC-ET disclosures with long application periods is negative.

#### 5.4.4.6 Are there any surprises left for firms in high-tech markets or in high-tech environments?

Investors' short-term reaction to ET disclosures has been positive because of their enthusiasm for these technologies. In the long term, this enthusiasm does not appear to be sustainable, especially once investors realize the high level of uncertainty surrounding ETs. Therefore, this study expects those high-tech firms to be more favoured, as their ET disclosures are likely to be for research or investment purposes. This study groups the sample firms into two dimensions to compare the differences in the market's response to GHC-ET disclosure: firms in the Silicon Valley area and firms listed on the NASDAQ exchange.

Panels C and D of Table 5.14 show the regression results. All regressions include control variables and control for industry and year fixed effects. In the short term,  $GHCET_{i,t}$  is only significantly and positively associated with CAR\_MM (-3, +3) and CAR\_MM (-5, +5) for firms in non-Silicon Valley areas or not listed on the NASDAQ exchange. In detail, for firms in non-Silicon Valley areas, the coefficients of  $GHCET_{i,t}$  are 0.0176 (1.76%) and 0.0194 (1.94%) in Columns (3) and (4) of Panel C based on different event windows, respectively.

This study finds similar results using other models to estimate the expected returns. In the long term, regardless of whether firms are in the Silicon Valley area or other areas,  $GHCET_{i,t}$  is negatively related to CARs. In addition, for firms not listed on the NASDAQ exchange, the short-term market reaction is positive and significant. The CARs are stronger than those of other firms (0.0513 (5.13%) and 0.0508 (5.08%)). However, the delayed market reaction is only negative and significant for NASDAQ stocks. The results show that investors are not surprised by GHC-ET disclosures by high-tech firms or firms in high-tech environments.

**Table 5.14 Further Analysis (II) – Technology Type and Environment** 

	CAR_MM	CAR_MM	CAR_MM	CAR_MM
Variables	(-3, +3)	(-5, +5)	(+4, +60)	(+6, +60)
	(1)	(2)	(3)	(4)
FinTech <sub>i,t</sub>	0.0483***	0.0449***	-0.0522***	-0.0538***
	(0.0088)	(0.0101)	(0.0193)	(0.0188)
Constant	0.0237**	0.0193	-0.0221	-0.0159
	(0.0113)	(0.0131)	(0.0249)	(0.0244)
Controls, Year, Industry FE	YES	YES	YES	YES
Observations	13,268	13,268	13,268	13,268
Adj. R-square	0.3176	0.2666	0.0173	0.0172
Panel B. Quick adoption				
Variables	CAR_MM (-3, +3)	CAR_MM (-5, +5)	CAR_MM (+4, +60)	CAR_MM (+6, +60)
	(1)	(2)	(3)	(4)
Quick_Adoption <sub>i,t</sub>	0.0306***	0.0311***	-0.0283**	-0.0287**
	(0.0058)	(0.0067)	(0.0127)	(0.0124)
Constant	0.0227**	0.0183	-0.0213	-0.0151
	(0.0113)	(0.0131)	(0.0250)	(0.0244)
Controls, Year, Industry FE	YES	YES	YES	YES
Observations	13,268	13,268	13,268	13,268
Adj. R-square	0.3174	0.2667	0.0172	0.0170

Panel C.	Techno	logy	cluster
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	Silicon Valley area		Non-Silico	on Valley area	Silicon	Silicon Valley area Non-Silicon Valley ar		
	CAR_MM	CAR_MM	CAR_MM	CAR_MM	CAR_MM	CAR_MM	CAR_MM	CAR_MM
Variables	(-3, +3)	(-5, +5)	(-3, +3)	(-5, +5)	(+4, +60)	(+6, +60)	(+4, +60)	(+6, +60)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
GHCET <sub>i,t</sub>	0.0203	0.0165	0.0176***	0.0194***	-0.0670**	-0.0611*	-0.0293**	-0.0316***
	(0.0186)	(0.0202)	(0.0055)	(0.0065)	(0.0339)	(0.0335)	(0.0125)	(0.0122)
Constant	-0.0179	-0.0020	0.0255**	0.0199	0.1018	0.1039	-0.0130	-0.0050
	(0.0573)	(0.0623)	(0.0117)	(0.0137)	(0.1042)	(0.1031)	(0.0263)	(0.0257)
Controls, Year, Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	1,382	1,382	11,886	11,886	1,382	1,382	11,886	11,886
Adj. R-square	0.2903	0.2559	0.3200	0.2669	0.0094	0.0105	0.0190	0.0189

Panel D. NASDAQ exchange

	Nasdaq firms		Othe	Other firms		Nasdaq firms		firms
Variables	CAR_MM (-3, +3)	CAR_MM (-5, +5)	CAR_MM (-3, +3)	CAR_MM (-5, +5)	CAR_MM (+4, +60)	CAR_MM (+6, +60)	CAR_MM (+4, +60)	CAR_MM (+6, +60)
v dridores	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
GHCET <sub>i,t</sub>	0.0039	0.0059	0.0513***	0.0508***	-0.0328**	-0.0348**	-0.0268	-0.0267
	(0.0059)	(0.0071)	(0.0108)	(0.0119)	(0.0150)	(0.0147)	(0.0186)	(0.0182)
Constant	0.0082	-0.0074	0.0506**	0.0611***	-0.0190	-0.0094	-0.0369	-0.0353
	(0.0135)	(0.0163)	(0.0212)	(0.0233)	(0.0343)	(0.0335)	(0.0365)	(0.0358)
Controls, Year, Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	8,187	8,187	5,081	5,081	8,187	8,187	5,081	5,081
Adj. R-square	0.4183	0.3411	0.1477	0.1331	0.0131	0.0135	0.0263	0.0245

Note: Panel A of Table 5.14 reports the market reaction to whether firms disclose FinTech-type ETs. Panel B shows the market reaction to GHC-ET disclosures in different adoption periods (less than ten years or more than ten years). Panel C shows the difference in market response to whether the firm's headquarter is in the Silicon Valley region while Panel D shows the difference in market response to whether the firm is listed on Nasdaq. All CARs are estimated by the market model. All regressions include control variables. The industry fixed effect is based on the GIC industry classifications. The standard errors of slope coefficients are clustered by year and industry which are reported in parenthesis. Definitions for all of variables are provided in Appendix B-1. The significance levels are: \*\*\* p<0.01, \*\*\* p<0.05, \*\* p<0.1.

#### **5.5 Conclusion**

Based on the GHC, this study conducts textual analysis of all initial 8-K filings each year between 2010 and 2019. Using the CARs calculated through the event study as the dependent variable, this study investigates the immediate and delayed market reaction by investors to GHC-ET disclosures. In detail, this study also investigates the impact of market reactions to GHC-ET disclosure intensity, frequency, and the phase. As further analysis, this study compares firms with different percentages of institutional investors, analyst followings, and information environments. This study also tests the effects of whether investors are more sensitive to FinTech and ET which requires a long period to reach the plateau. Finally, this study verifies whether high-tech firms or firms in high-tech environments could receive more attention from investors. The results are robust after conducting several robustness tests.

## 5.5.1 Summary of findings

This study finds that investors' immediate reaction is positive to GHC-ET disclosures, but the delayed reaction is negative. The reversal in the attitude of investors is due to insider selling and not a correction of immediate overreactions. Regarding disclosure content, the association between GHC-ET disclosure intensity or frequency and the immediate market reaction is significantly negative. Furthermore, investors' immediate reaction is more positive, but the delayed reaction is more negative to GHC-ET in the second phase (the peak of inflated expectations). The association between GHC-ET disclosures and immediate market reactions is positive for firms with fewer institutional investors and less analyst coverage. However, the delayed reaction is negative for firms with more institutional investors and higher analyst coverage. The information environment is important for investors to access corporate disclosures. Thus, investors react positively to GHC-ET disclosures when information asymmetry is high. The findings also show that investors prefer FinTech-type of technologies and those needing a short period to reach the plateau, supporting my expectations. The findings are robust after removing the effects of other events, estimating the expected returns by using different models, and replacing different event windows.

Overall, this research suggests that investors have a small probability of being obsessed and expect that ETs lead to very large gains. However, this phenomenon does not last beyond 60 trading days, indicating that investor enthusiasm is short-lived. Due to novelty preferences and social contagions, investors are attracted by the 'emerging' nature of ETs. While ET disclosure by high-tech firms or firms in a high-tech environment cannot attract additional investor attention, investors are not exactly speculators, preferring the types of FinTech they are familiar with and those that can reach the plateau in the short term.

#### 5.5.2 Limitations

Although this study is extremely detailed in terms of hypothesis formulation and research design, as well as considering multiple robustness tests, there may still be omissions. For example, this study uses CAR to measure investor delayed reaction, although a reversal of investor reaction to GHC-ET disclosures is observed. There may be multiple uncorrelated events that affect asset prices simultaneously. This complicates interpreting CAR values because it is difficult to distinguish which event caused the abnormal returns. Further, this study finds that the reversal in investor reaction is due to the insider selling after initial GHC-ET disclosures, but this may be only one scenario captured in this study. In other words, it is not known whether there were other events that influenced investor reactions.

#### 5.5.3 Further research

Future research could explore whether there are other advantages and disadvantages to firms making GHC-ET disclosures. For example, in the long term, do firms increase their R&D investment and innovation output when they make GHC-ET disclosures? On the other hand, if firms make speculative disclosures, do such disclosures result in an increased risk of stock price crash because managers hide potential risks? Or does it affect the efficiency of the firm's investments?

# Chapter 6. The Disclosure of Emerging Technologies and Stock Price Crash Risk

#### 6.1 Introduction

In an increasingly competitive landscape, firms often pursue growth through innovation, turning to ETs like AI, machine learning, augmented reality, the IoT, and Blockchain to forge core competencies. The advantages of adopting such technologies have been well-established. For instance, the integration of novel switching technologies has consistently been shown to bolster firm performance (i.e., Majumdar, 1995; Uotila et al., 2009). The ascent of technology firms has bolstered investor expectations and confidence, leading to heightened investments. Nonetheless, it is worth noting that technology-driven stock market bubbles are not a surprising phenomenon. The 1920s witnessed a stock market bubble significantly propelled by the technology stocks of that era. This speculative fervour often paralleled moments of intense technological innovation and industrial expansion (DeMarzo et al., 2007).

The capacity for innovation within a firm can often be gauged by indicators like R&D investment or patent outputs (e.g., Bellstam et al., 2021; Bena and Li, 2014; Jaffe, 1986). Yet, this capability can also be discerned through corporate disclosures, serving as a channel of communication between managers and external investors. As the primary source for investors to obtain insights about a firm, voluntary disclosures offer a trove of information, including a firm's focus on and investment in technology. Managers often lean towards voluntary disclosure, driven by the ambition to elevate investor expectations of value, aiming to optimise stock prices (Einhorn, 2007). Given the material nature of information on ETs, firms are inclined to engage in voluntary disclosure to captivate a wider investor audience. Consequently, this chapter focuses on firm-specific voluntary disclosures about GHC-ET.

Grasping the potential risk of a stock price crash is imperative for safeguarding investor value (Habib et al., 2018). Previous studies have mostly tackled the causes behind stock price crashes from two dimensions. The first is the information asymmetry between corporate insiders and external stakeholders (i.e., An et al., 2015; Jin and Myers, 2006; Kim and Zhang, 2016b). The second centres around the conflicting interests between managers and

shareholders, evident in the withholding of unfavourable news (i.e., Benmelech et al., 2010; Bleck and Liu, 2007; Callen and Fang, 2015). While GHC-ET disclosures can bridge the gap in information asymmetry, the inherent uncertainty tied to ETs often remains underemphasised and obscured. If an ET falters, failing to find its footing in the market, firms linked to that technology face a pronounced risk of a stock price crash.

While existing literature delves extensively into the connection between voluntary disclosure and stock price crashes, particularly in the area of CSR-related information (Kim et al., 2014), some studies confirm the link between firm innovation and stock price crashes, as evidenced by Jia (2018) and Zaman et al. (2021). However, to the best of my understanding, no current literature contemplates the relationship between the disclosure of ETs and the risk of a stock price crash. Currently, given their varied cycles in which they have been hyped by the market, ETs inherently exhibit diverse risks and uncertainties. Therefore, the research objective of this chapter is, first, to investigate the relationship between GHC-ET disclosures and the stock price crash risk. Further, depending on the different phase of market hype in ETs, this study also compares the difference between the disclosure of ETs at different phase and the stock price crash risk.

This chapter examines the relationship between GHC-ET disclosures and the stock price crash risk by US firms for the period 2010 to 2019. To capture the high-frequency voluntary disclosure, this chapter (like Chapter 4 and 5) only focuses on 8-K filings containing the Item 7.01 Reg FD. The disclosure of ETs is also measured by textual analysis based on the GHC dictionary. This curve is released annually in late July or early August. As can be observed from Figure 6.1, there is a spike in Google searches for GHC in the period following the release. A dummy variable to indicate whether the firm's initial 8-K filing of each year containing the Item 7.01 includes the information related to ETs that appeared in the GHC in the previous year. <sup>54</sup>

<sup>&</sup>lt;sup>54</sup> This research anticipates that managers will consult the GHC-ET list from the preceding year, given that the most recent GHC is typically released in the third quarter annually. Consequently, this study introduces a one-year lag for the GHC, facilitating an examination of how the annual initial 8-K filing, referencing GHC-ET information, influences the potential for a stock price crash. Additional tests were

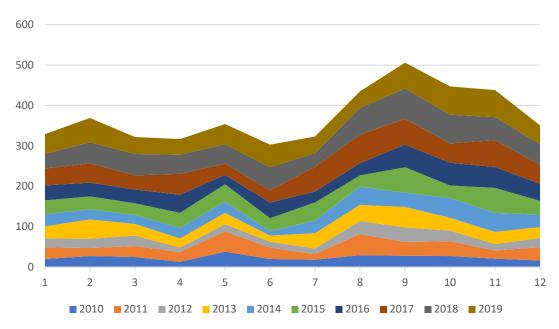


Figure 6.1 Google Trend of Gartner Hype Cycle Search

Note: This figure shows the google trend of Gartner Hype Cycle search from 2010 to 2019. The Gartner Hype Cycle is normally published in late July or early August each year. It corresponds to the rise in Google searches for Gartner Hype Cycle during the publishment period.

Adopting the approach of Chen et al. (2001), this study employs the negative conditional skewness of firm-specific weekly returns (NCSKEW) and the natural logarithm of the down and up volatility ratio of returns (DUVOL) to measure the firm-specific stock price crash risk. To validate the robustness of these findings, a dummy variable (CRASH) is crafted to signify the potential for crashes, as indicated by the average weekly firm-specific return minus 3.09 standard deviations.

Preliminary regression results identify that the disclosure of ETs increases the firm-specific stock price crash risk over a span of one year. Interpreting the standardised coefficient, should a firm disclose ETs information in its initial 8-K filing, the crash risk of the stock price escalates by 3.64% (2.62%) for NCSKEW (DUVOL). Moreover, a differentiation is made regarding the disclosure of ETs at various phases of market hype. Specifically, firms disclosing

carried out on firms' 8-K filings for the fourth quarter; however, these tests produced insignificant sample sizes.

ETs at the 'innovation trigger' (phase one) and 'trough of disillusionment' (phase three) of the GHC exhibit higher stock price crash risks. Conversely, a decline in stock price crash risk is observed when firms disclose GHC-ET at the 'plateau of productivity' (phase five).

A primary challenge encountered in this study stems from the potential influence of unobservable factors associated with both GHC-ET disclosures and crash risk, which could influence the observed positive relationship between the disclosure of ETs and stock price crash risk. To address this, supplementary control variables are incorporated into the analysis. These can be categorised into two distinct dimensions: qualitative attributes of each 8-K filing (such as tone, readability, and information capacity) and firm-level characteristics like the proportion of institutional investors and the count of analyst followers. Incorporating additional control variables serves to account for variations in the information acquisition process attributed to the qualitative attributes of 8-K filings, including aspects like tone, readability, and information content. Moreover, external oversight mechanisms, represented by institutional investors and analysts, can influence a firm's voluntary disclosure practices. Consequently, the analysis also integrates controls for the proportion of institutional investors and the tally of analyst followers. The outcomes remain in line with the primary regression findings, whether these variables are introduced individually or collectively.

Endogeneity poses a second challenge. To mitigate this concern, an instrumental variable is selected: the percentage of internet users (IV\_Internet\_users). This variable is then applied in two-stage-least-square tests. Additionally, to diminish selection bias, propensity score matching (PSM) is employed. The outcomes from these two analytical techniques consistently corroborate the study's primary findings. Further, this study conducts a placebo test. The results are insignificant when the disclosure year is replaced with t+1 and t+2 years. Finally, to track the disclosure effect, this study follows Bertrand and Mullainathan (2003) by replacing the main independent variable with year dummies. The significant effect of disclosure on the stock price crash risk persists until year 2.

This study provides extra evidence through two channels. The first channel is the short-term reaction of investors to the disclosure of ETs. The other channel is CEO overconfidence. The positive relationship between the disclosure of ETs and stock price crash risk is pronounced when the short-term investors' reaction or CEO overconfidence is higher. Using the principal

component analysis (Chung and Hribar, 2021 and Zhang, 2006), this study also investigates the role of information uncertainty and CEO power. The results suggest that above-average uncertainty aggravates the positive and significant relationship between GHC-ET disclosures and stock price crash risk. In addition, the relationship between GHC-ET disclosures and stock price crash risk is stronger when a firm's CEO power is above the mean value, supporting that voluntary disclosures are more likely to be manipulated by powerful CEOs (Aboody and Kasznik, 2000; Gul and Leung, 2004).

To bolster the primary findings concerning the relationship between the disclosure of ETs and stock price crash risk, four additional tests are conducted. These are aimed at understanding the intricacies of speculative behaviour, the concealment of risk-associated information, the influence of governmental innovation policies, and the dynamics of regional innovation environments. The results indicate that disclosing ETs heightened stock price crash risk exclusively during the tenure of a Republican President and outside the Silicon Valley ecosystem. Moreover, significant outcomes emerge for firms that disclosed ETs only once and concurrently concealed risk-oriented narratives.

This research enriches the academic discourse by offering an innovative perspective on evaluating voluntary corporate disclosures for stakeholders. Existing literature on voluntary disclosure has predominantly delved into the ramifications of disseminating information about social responsibility (Kim et al., 2014) or environmental concerns (Zaman et al., 2021) on stock price crash risk. To the best of current knowledge, the impact of voluntary disclosure concerning ET-related information on stock price crash risk remains an underexplored domain.

Secondly, this study diverges from prior research, such as Jia (2018), which probes the relationship between corporate innovation and stock price crash risk. Jia's research posits that firms with an exploratory bent are more susceptible to share price crashes due to elevated project failure rates and a hesitancy to broadcast sporadic adverse innovation news. The present study, rather than confirming the actual investments or applications of the referenced ETs in disclosures, pivots around the behaviour of disclosure itself.

Furthermore, it is observed that not all disclosures related to ETs invariably escalate the future stock price crash risk. GHC-ET disclosures in their nascent stages seem to carry elevated concealment risks. However, for mature, highly productive technologies, their disclosure

serves as a supplementary data source for investors, effectively bridging information gaps. Interestingly, no uptick in the stock price crash risk was detected when firms provided hints about potential risks subsequent to their ETs-related disclosures.

The remainder of this chapter is organised as follows. Section 6.2 reviews the related studies and proposes three hypotheses. Section 6.3 describes the sample, data, and variables as well as showing the descriptive statistics. Section 6.4 presents empirical results including the results of baseline regressions, robustness checks, channels, and additional analysis. Section 6.5 concludes this chapter.

## 6.2 Literature and hypothesis development

#### 6.2.1 Literature review

The crash risk of stock price presents the possibility of the stock price crash, which always reflects the phenomenon of skyrocketing and tumbling (Hutton et al., 2009). According to Jin and Myers (2006), information asymmetry is the 'blasting fuse' of a stock price crash. Insiders, typically managers, may be motivated to suppress adverse news, amplifying information asymmetry. Firms cannot cover bad news for a long period. Ultimately, when accumulated suppressed information reaches a critical point and is suddenly released into the market, stock prices crash (Kim et al., 2014).

Traditional agency theory delineates the motives managers might have for withholding detrimental news or inflating financial results. Managers, acting as agents for a firm, weigh their immediate compensation contracts against long-term career objectives (Ball, 2009; Graham et al., 2005). They hope to overstate the description to hide bad financial results such as floundering earnings or reduced dividend by releasing good news acceleratingly (Kim and Zhang, 2016b). On the other hand, it is typical that managers can possess more private information than any other stakeholders especially investors, thus, they could be motivated to withhold inside information whether good or bad (Healy and Palepu, 2001). If managers are also shareholders, they may unveil positive news before any negative revelations. However, Aboody and Kasznik (2000) suggest that managers might withhold bad news unless they need to release this information to reduce the price of the options.

Numerous studies have pinpointed factors influencing firm-specific stock price crash risk. For example, from a financial performance and market perspective, the stock liquidity (Chang et al., 2017), information transparency (Jin and Myers, 2006), tax avoidance (Kim et al., 2011), accounting conservatism (Kim and Zhang, 2016a), and opaque financial reports (Kim and Zhang, 2014) affect firm-specific stock price crash risk. Corporate governance elements like CEO overconfidence (Kim et al. 2016b), stability of institutional investors (Callen and Fang, 2013), the influence of specialist auditors (Robin and Zhang, 2014), robust internal controls (Chen et al., 2016), and the breadth of analyst coverage (Xu et al., 2013) also have implications.

Finally, some factors at society level can also be investigated including religion (Callen and Fang, 2015), social trust (Li et al., 2017b), and corruption (Chen et al., 2018). Notably, much of the existing discourse on voluntary disclosures centres on non-financial firm declarations like CSR (Kim et al., 2014). Specifically, Jia (2018) offers a relevant analysis, establishing a link between corporate innovation strategies and stock price crash risks. The finding of Jia (2018)'s study is that exploration-oriented firms have higher stock price crash risk than exploitation-oriented ones.

## 6.2.2 Hypothesis development

The future stock price crashes due to information asymmetry (Jin and Myers, 2006). Reducing the information asymmetry between information publishers and information users will effectively reduce the risk of a firm's future stock price crashes. As a regulator, the SEC implemented Reg FD in 2000 to prevent public firms from selectively disclosing information to the market. Firms are required to make full disclosure to reduce the likelihood that managers hide bad news. In addition, many studies argue that the main purpose of voluntary disclosure is to reduce the information asymmetry between retail and institutional investors (Balakrishnan et al., 2014) or between insiders and external investors (Core, 2001). Thus, whether a firm's disclosure is proactive or required, the lower the level of information asymmetry, the more information an investor can capture, making it less likely that bad news will be concealed and accumulated.

However, firms' voluntary disclosures may have reduced the information asymmetry inherent in the offering but that increased disclosure may have been used to 'hype the stock' (Lang and Lundholm, 2000). Although voluntary disclosures concerning ETs offer investors deeper insights into a firm, the inherent unpredictability and elevated failure rates associated with such technologies might be overlooked and hidden by managers. On the other hand, Lerman and Livnat (2010) regard corporate disclosure based on Reg FD as semi-voluntary or voluntary purpose. This is because of the vague definition about those material nonpublic information that the SEC requires firms to disclose. Managers have the autonomy to judge whether information is material or not based on preferences. On the other hand, Huang et al. (2021) find that Reg FD has the effect of reducing the firm's perceived litigation risk, leading to managers hide bad news when they perceive litigation risk decreases. Consequently, speculative ETs-related information could precipitate a stock price crash when managers can no longer perpetuate overstated narratives or conceal ETs-related risks.

Based on these considerations, the study proposes the following hypothesis:

**H:** GHC-ET disclosures are associated with future stock price crash risk.

# 6.3 Sample selection and variables measurement

#### 6.3.1 Sample and data

To investigate the implications of ET disclosures on stock price crash risk, this research selects US firms that included the Item 7.01 Reg FD in their 8-K filings between 2010 and 2019. The focus remains solely on the initial 8-K filing for each firm annually to circumvent potential noise from events such as earnings announcements, corporate adjustments, or other significant developments subsequent to the initial ET disclosures in the 8-K filings. Moreover, in alignment with existing literature (e.g., Jin and Myers, 2006; Kim et al., 2014; Li et al., 2017b), the sample excludes: 1) financial service firms (where GIC sector is 40), 2) firms with a negative book value of equity, 3) firms with stock prices below \$1 at the end of the fiscal year, 4) firms with trading days fewer than thirty weeks, and 5) firm-year observations lacking requisite control variables.

Panel A of Table 6.1 delineates the specifics of sample processing and its distribution by

year. There is a noticeable decline in the total number of 8-K filings disclosed by US firms; however, there is an uptick in the filings containing the Item 7.01. This trend aligns with findings from He and Plumlee (2020), highlighting the significance of studying this item. Specifically, out of the 663,897 8-K filings disclosed during the study period, only 98,352 include the Item 7.01. After data refinement, the final firm-year observations are 9,734. A detailed examination, following a textual analysis based on ETs from the yearly GHC, reveals 401 firm-year observations containing ETs-related information. This includes 150 in phase one, 147 in phase two, 73 in phase three, 16 in phase four, and 15 in phase five. Panel B provides a breakdown of the sample by industry, with industrials and healthcare sectors dominating, accounting for 18.94% and 18.15% of the total sample, respectively.

**Table 6.1 Sample Distribution** 

Panel A. Data cleaning process	
Original 8-K filings of all registrants in EDGAR during 2010 to 2019	663,897
Less: 8-K filings without the Item 7.01	(565,545)
8-K filings including the Item 7.01 (Column 2 of Panel B)	98,352
Less: 8-K filings after the initial 8-K filings of each firm in each year	(72,040)
Initial 8-K filings including the Item 7.01 (Column 3 of Panel B)	26,312
Less: missing firm-specific controls	(16,578)
Initial 8-K filings including the Item 7.01 firm-year observations (Column 4 of Panel B)	9,734
Less: 8-K filings including the Item 7.01 without GHC-ET	(9,333)
Initial 8-K filings including the Item 7.01 containing GHC-ET (Column 5 of Panel B)	401

Panel B. F	Tull samp	ole distrib	oution	by year
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	p	oution by	Jear		~~~~					
Year	8-K	8-K incl. 7.01	Initial 8-K incl. 7.01	Firm-year observations	GHC Initial 8-K incl. 7.01	Phase One	Phase Two	Phase Three	Phase Four	Phase Five
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
2010	80,442	6,457	1,867	621	28	15	7	1	4	1
2011	78,824	7,923	2,201	659	30	16	9	1	4	0
2012	77,353	8,713	2,336	808	30	5	4	13	2	6
2013	76,369	9,222	2,462	859	43	7	15	16	0	5
2014	76,930	9,971	2,664	918	61	21	15	24	1	0
2015	76,407	10,468	2,738	977	19	1	15	2	0	1
2016	72,621	10,832	2,862	1,105	30	10	14	4	0	2
2017	70,785	11,324	2,985	1,178	46	12	25	5	4	0
2018	68,181	11,662	3,056	1,277	57	30	19	7	1	0
2019	66,427	11,780	3,141	1,332	57	33	24	0	0	0
Total	663,897	98,352	26,312	9,734	401	150	147	73	16	15

Panel B. Full sample distribution l	oy industry		
GIC Industry	N	Percentage	
Energy	1,149	11.80%	
Materials	634	6.51%	
Industrials	1,844	18.94%	
Consume Discretionary	1,623	16.67%	
Consumer Staples	572	5.88%	
Health Care	1,767	18.15%	
Information Technology	1,460	15.00%	
Communication Services	484	4.97%	
Utilities	60	0.62%	
Real Estate	141	1.45%	
Total	9,734	100.00%	

Note: Table 6.1 shows the sample distributions by year and industry based on the global industry classification (GIC). Panel A reports the data cleaning process while Panel B reports the sample distribution by year and GHC phase. Column (1) shows the total 8-K filings disclosed by all EDGAR registrants from 2010 to 2019. Column (2) reports the number of 8-K filings including Item 7.01. Column (3) indicates the number of firms that disclose 8-K filings containing Item 7.01 for the first time each year while Column (4) shows firm-year observations after removing missing firm-level controls. Column (5) indicates the number of the initial 8-K filings containing Item 7.01 and GHC-ET each year. Finally, Columns (6) to (10) show the number of observations which include phase one (innovation trigger), phase two (the peak of inflated expectations), phase three (trough of disillusionment), phase four (slope of enlightenment), and phase five (plateau of productivity), respectively. Panel C reports the industry distribution based on GIC. N is the number of observations while % is the percentage of that industry accounted for the whole sample.

The source for the 8-K filings of US firms is the EDGAR database. All keywords pertaining to ETs are extracted from the annual GHCs published by Gartner. Data for stock trading, crucial for measuring stock price crash risk, is sourced from the CRSP database. Relevant firm-specific control variables are derived from the Compustat fundamentals. Analyst information is extracted from I/B/E/S Guidance, while data on institutional investors' percentage comes from the SEC 13F Holdings. Additional variables used for the principal component analysis are obtained from Risk Metrics.

#### 6.3.2 Variables

## 6.3.2.1 Measuring the disclosure of emerging technologies

The GHC offers an exhaustive overview of ETs, illustrating their journey from inception to societal integration through a graphical trajectory (refer to Figure 3.1). This trajectory

encompasses five salient stages: the innovation trigger, peak of inflated expectations, trough of disillusionment, slope of enlightenment, and plateau of productivity. Together, these stages chart the life cycle of each ET, mapping its acceptance and anticipation in the market. The reliability of the GHC in curating a dictionary for textual analysis is affirmed by its comprehensive inventory of ETs across a spectrum of industries. Moreover, its annual issuance guarantees the assimilation of the most contemporary technological innovations.

For this study, a bag-of-words method is utilised to detect references to ETs within every initial 8-K filing. To improve the accuracy of the textual analysis, the present analysis was limited to the original terms specified annually in the GHC, avoiding synonyms. Considering the nascent nature of several ETs, it is posited that investors may not intuitively identify or relate them to similar or derivative terminologies owing to unfamiliarity. Moreover, accounting for the GH's customary release window, which spans from late July to early August, a lag of a year is instituted for every dictionary used in the textual analysis. As an illustration, the GHC from 2009 serves as the basis for sifting through all initial 8-K filings of 2010.

The independent variable of this study is the disclosure of ETs ( $GHCET_t$ ), which is represented as a dummy variable. This study also sets a variable namely  $Phase\_j_t$  (j from one to five) based on the clear border of each phase in the GHC to compare the difference of the relationship between  $GHCET_t$  and stock price crash risk.

## 6.3.2.2 Measuring stock price crash risk

The dependent variable of this study is stock price crash risk. The calculation of the firm-specific weekly return based on Hutton et al.'s (2009) expanded index model. As prior literature shows that, model (1) considers the lag and advance terms of the market yield when reinvesting the cash dividend to reflect firm-specific factors.

$$r_{j,t} = \alpha_j + \beta_{1,j} r_{m,t-2} + \beta_{2,j} r_{m,t-1} + \beta_{3,j} r_{m,t} + \beta_{4,j} r_{m,t+1} + \beta_{5,j} r_{m,t+2} + \varepsilon_{j,t}$$
 (6-1)

where  $r_{j,t}$  means the  $stock_j$  return and  $r_{m,t}$  is the value-weighted market index for the CRSP in  $week_t$ . In addition, the firm-specific return of  $stock_j$  in  $week_t$  is calculated by the natural logarithm of 1 and the residual  $\varepsilon_{j,t}$  ( $W_{j,t} = \ln (1 + \varepsilon_{j,t})$ ). According to Dimson (1979), nonsynchronous trading can be accounted for by the lead and lag terms for the market index

return.

Equations (6-2) is the first measurement of stock price crash risk. It is the negative conditional skewness of firm-specific weekly returns (NCSKEW) (Kim et al. 2014).

$$NCSKEW_{j,t} = -\left[n(n-1)^{3/2} \sum_{j,t} W_{j,t}^{3}\right] / \left[(n-1)(n-2)(\sum_{j,t} W_{j,t}^{2})^{3/2}\right]$$
(6-2)

As equation (6-2) shows that, for each  $stock_j$  in  $year_t$ , NCSKEW can be calculated by the third moment of the firm-specific weekly returns to the third power of the standard deviation of the firm-specific weekly returns.  $W_{j,t}$  is the firm-specific weekly return and n represents the number of trading weeks of  $stock_j$  in  $year_t$ . The higher the negative skewness represents the higher stock price crash risk.

The second measurement of stock price crash risk is the natural logarithm of the down and up volatility ratio of returns (DUVOL). For each  $stock_j$  in  $year_t$ , there are two situations of firm-specific return that above or below the annual mean of the returns. It can be regarded as 'up' if above and 'down' if below. The equation of DUVOL is as follows,

$$DUVOL_{i,t} = log\{(n_u - 1)\sum_{Down} W_{i,t}^2 / (n_d - 1)\sum_{Un} W_{i,t}^2\}$$
(6-3)

where  $n_u$  is the number of 'up' weeks and the  $n_d$  is the number of 'down' weeks. The higher the value of DUVOL, the higher stock price crash risk.

#### 6.3.2.3 Control variables selection

This study selects some variables that might affect the future stock price crash risk for a firm following the prior studies (i.e., Chen et al., 2001; Ji et al., 2021; Kim et al., 2014). Firstly, to control for potential serial correlation, the lagged crash risk measure ( $NCSKEW_t$  or  $DUVOL_t$ ) is added into regressions. Secondly, Chen et al. (2001) find firms have higher stock price crash risk when their stock turnovers are high. The detrended stock trading volume ( $Dturnover_t$ ) is included to represent the investor heterogeneity which is calculated by the difference between the average monthly share turnover in year t and t-1. They also find that past returns are associated with the stock crash because bubbles built from past gains usually follow a crash in prices. This study controls the return ( $RET_t$ ) using the mean of weekly returns of firms. In

addition, according to Jia (2018) and Kim et al. (2014), the stock volatility ( $SIGMA_t$ ) is calculated using the standard deviation of firm-specific weekly returns.

Thirdly, this study selects some control variables in the financial and fundamental dimension. Many studies highlight the influence of firm size, the leverage level, and the profitability on stock price crash risk (e.g., Chen et al., 2001; Harvey and Siddique, 2000; Jia, 2018). Therefore, these three factors are controlled into regressions. The firm size is the natural logarithm of total assets ( $SIZE_t$ ). The level of leverage is calculated by total long-term debts to total assets ( $LEV_t$ ) and the profitability is return on assets ( $ROA_t$ ). Finally, I use residuals from the modified Jones model to measure abnormal accruals ( $ABACC_t$ ) which considers the effects of earnings management on the future crash risk (Hutton et al., 2009). <sup>55</sup> Detailed variable definitions are shown in Appendix C-1.

## 6.3.3 Summary statistics

Panel A of Table 6.2 shows summary statistics of all variables used in regressions. This study winsorizes the continuous variables at the 1% and 99% levels to mitigate the influence of outliers. The sample firms, on average, have a crash risk of 0.069 ( $NCSKEW_{t+1}$ ) and 0.060 ( $DUVOL_{t+1}$ ). There are 4.1% (mean value of  $GHCET_t$ ) of the sample firms that disclose ETs-related information in their initial 8-K filing. In detail, more than 70% of those firms are interested in ETs in phase one (innovation trigger) and two (peak of inflated expectations) of the GHC. In addition, the sample firms have an average change in monthly trading volume ( $Dturnover_t$ ) of 0.058. The average firm-specific weekly return is 0.2% ( $RET_t$ ) with the highest return at 2.7% and the lowest return -2.5%. The mean value of weekly return volatility ( $SIGMA_t$ ) is 0.062. In addition, Panel B reports the comparison of mean value between the non-GHC sample and GHC sample, supporting the existence of significant differences of crash risk (p-values are 0.002 and 0.031, respectively).

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<sup>&</sup>lt;sup>55</sup> The calculation of ABACC can be found in Appendix C-2.

**Table 6.2 Summary Descriptive** 

Panel A. Descr	iptive statistic	s of the final	sample			
	N	Mean	Median	SD	Max	Min
Dependent varia	ables					
NCSKEW <sub>t+1</sub>	9,734	0.069	0.027	1.039	6.729	-5.362
$DUVOL_{t^{+}1} \\$	9,734	0.060	0.033	0.601	4.458	-2.953
Independent var	riables					
GHCET <sub>t</sub>	9,734	0.041	0.000	0.199	1	0
Phase_One <sub>t</sub>	9,734	0.015	0.000	0.123	1	0
$Phase\_Two_t$	9,734	0.015	0.000	0.122	1	0
Phase_Three <sub>t</sub>	9,734	0.007	0.000	0.086	1	0
Phase_Fourt	9,734	0.002	0.000	0.041	1	0
Phase_Five <sub>t</sub>	9,734	0.002	0.000	0.039	1	0
Control variable	es					
NCSKEW <sub>t</sub>	9,734	0.106	0.041	0.957	3.257	-2.812
$DUVOL_t$	9,734	0.075	0.046	0.567	1.667	-1.371
$RET_t$	9,734	0.002	0.003	0.009	0.027	-0.025
$SIGMA_t$	9,734	0.062	0.054	0.034	0.195	0.015
Dturnover <sub>t</sub>	9,734	0.058	-0.010	1.306	6.920	-4.548
$SIZE_t$	9,734	6.783	6.879	2.074	11.865	2.125
$ROA_t$	9,734	-0.052	0.028	0.287	0.325	-1.697
$LEV_t$	9,734	0.269	0.238	0.238	1.118	0.000
$MB_t$	9,734	3.327	2.249	6.359	36.829	-21.553
$ABACC_t$	9,734	0.176	0.127	0.168	0.908	0.002
Panel B. Comp	arison of non-	GHC sample	e and GHC san	nple		
Variables	ETRID=0	Mean	ETRID=1	Mean	Diff	P-value
NCSKEW <sub>t+1</sub>	9,333	0.062	401	0.230	-0.168	0.002***

VariablesETRID=0MeanETRID=1MeanDiffP-valueNCSKEW $_{t+1}$ 9,3330.0624010.230-0.1680.002\*\*\*DUVOL $_{t+1}$ 9,3330.0584010.124-0.0660.031\*\*Note: Table 6.2 reports the summary statistics for variables used in this study. There are 9,734 firm-

Note: Table 6.2 reports the summary statistics for variables used in this study. There are 9,734 firm-year observations during 2010 to 2019. Panel A shows the summary statistics in three dimensions including dependent variables, independent variables, and control variables. Panel B shows the comparison of T-tests between non-GHC sample (9,333) and GHC sample (401). Detailed definition of variables is presented in Appendix C-1.

Table 6.3 presents the Person correlation matrix among all variables. The coefficient between  $NCSKEW_{t+1}$  and  $DUVOL_{t+1}$  is 0.910 and their correlation is significantly positive. This result is comparable to the prior studies (e.g., Chen et al., 2001; Ji et al., 2021; Kim et al., 2014). Interestingly, the two measures of crash risk are significantly positively related with the explanatory variable  $GHCET_t$ , which means the stock price crash risk will increase when firms disclose the information related to ETs. In addition, these two variables are also significantly

positively related with *Phase\_One<sub>t</sub>* and *Phase\_Three<sub>t</sub>* but negatively related with *Phase\_Five<sub>t</sub>*. The problem of multicollinearity between control variables is not observed.

**Table 6.3 Correlation Matrix** 

	Variables	1	2	3	4	5	6	7	8	9
1	NCSKEW <sub>t+1</sub>	1.000					0	,	0	
2	$DUVOL_{t+1}$	0.910***	1.000							
3	GHCET <sub>t</sub>	0.032***	0.022**	1.000						
4	Phase_One <sub>t</sub>	0.029***	0.025**	0.604***	1.000					
5	Phase_Two <sub>t</sub>	0.013	0.003	0.597***	-0.015	1.000				
6	Phase_Three <sub>t</sub>	0.023**	0.020**	0.419***	-0.011	-0.011	1.000			
7	Phase_Four <sub>t</sub>	0.009	0.004	0.196***	-0.005	-0.005	-0.004	1.000		
8	Phase_Five <sub>t</sub>	-0.029***	-0.024**	0.190***	-0.005	-0.005	-0.003	-0.002	1.000	
9	$NCSKEW_t$	0.036***	0.034***	-0.007	0.004	-0.011	-0.001	-0.009	-0.003	1.000
10	$DUVOL_t$	0.038***	0.039***	-0.001	0.008	-0.010	0.009	-0.010	-0.010	0.908***
11	$RET_t$	0.033***	0.035***	-0.003	-0.010	0.005	0.002	-0.006	0.003	-0.357***
12	$SIGMA_t$	-0.023**	-0.008	0.047***	0.057***	0.045***	-0.028***	-0.014	-0.004	-0.022**
13	Dturnover <sub>t</sub>	0.014	0.022**	0.032***	0.018*	0.046***	-0.005	-0.003	-0.027***	0.034***
14	$SIZE_t$	0.060***	0.058***	-0.011	-0.026**	-0.013	0.031***	0.002	-0.005	0.049***
15	$ROA_t$	0.004	0.000	-0.019*	-0.026**	-0.031***	0.027***	0.010	0.008	-0.053***
16	$LEV_t$	0.017*	0.020*	-0.052***	-0.033***	-0.023**	-0.025**	-0.011	-0.023**	0.037***
17	$MB_t$	0.030***	0.036***	0.004	0.007	-0.001	0.008	-0.014	-0.003	-0.025**
18	$ABACC_t$	-0.001	0.013	-0.032***	-0.027***	-0.010	-0.016	-0.016	0.006	-0.049***
	Variables	10	11	12	13	14	15	16	17	18
10	$DUVOL_t$	1.000								
11	$RET_t$	-0.376***	1.000							
12	$SIGMA_t$	0.007	-0.024**	1.000						
13	Dturnover <sub>t</sub>	0.053***	0.029***	0.317***	1.000					
14	$SIZE_t$	0.047***	0.048***	-0.516***	-0.083***	1.000				
15	$ROA_t$	-0.061***	0.201***	-0.544***	-0.111***	0.456***	1.000			
16	$LEV_t$	0.036***	-0.041***	-0.039***	0.021**	0.325***	0.017*	1.000		
17	$MB_t$	-0.026**	0.151***	-0.069***	0.000	0.009	0.027***	-0.062***	1.000	
18	$ABACC_t$	-0.038***	-0.036***	0.156***	0.056***	-0.102***	-0.078***	0.091***	-0.046***	1.000

Note: This table shows pairwise correlations for the explanatory variables used in market reactions regressions. Definitions for all of variables are provided in Appendix C-1. The significance levels are: \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

## 6.4 Empirical results

## 6.4.1 Empirical model

To investigate the effect of GHC-ET disclosures on stock price crash risk, the following regressions are estimated,

$$\begin{aligned} CrashRisk_{i,t+1} &= \beta_0 + \beta_1 GHCET_{i,t} + \beta_2 CrashRisk_{i,t} + \beta_3 RET_{i,t} + \beta_4 SIGMA_{i,t} + \\ \beta_5 Dturnover_{i,t} + \beta_6 SIZE_{i,t} + \beta_7 ROA_{i,t} + \beta_8 LEV_{i,t} + \beta_9 MB_{i,t} + \beta_{10} ABACC_{i,t} + FE_{Year} + \\ FE_{Industry} + \varepsilon \end{aligned} \tag{6-4}$$

$$\begin{aligned} CrashRisk_{i,t+1} &= \beta_0 + \beta_1 Phase\_j_{i,t} + \beta_2 CrashRisk_{i,t} + \beta_3 RET_{i,t} + \beta_4 SIGMA_{i,t} + \\ \beta_5 Dturnover_{i,t} + \beta_6 SIZE_{i,t} + \beta_7 ROA_{i,t} + \beta_8 LEV_{i,t} + \beta_9 MB_{i,t} + \beta_{10} ABACC_{i,t} + FE_{Year} + \\ FE_{Industry} + \varepsilon \end{aligned} \tag{6-5}$$

where  $CrashRisk_{i,t+1}$  is measured by either  $NCSKEW_{i,t+1}$  or  $DUVOL_{i,t+1}$ . The primary independent variable  $GHCET_{i,t}$  is a dummy variable to represent whether the initial 8-K filing of firm i in year t includes ETs-related information. Phase\_j<sub>i,t</sub> is also a dummy variable to represent the GHC phase, j from one to five. All control variables are used the value of one-year lag including  $GHCET_{i,t}$  and  $Phase_j_{i,t}$  from the dependent variable CrashRisk<sub>i,t+1</sub> to examine whether the disclosure of firm i in year t can predict the future stock price crash risk in year t+1. Year and industry fixed effects are included in regressions. This study also clusters the standard errors at firm level to reduce the effects of potential time-series dependence.

## 6.4.2 Baseline regression results

Table 6.4 shows the baseline regression results based on equation (6-4). The measure of stock price crash risk in Columns (1) and (2) is NCSKEW. The regression results suggest that the relationship between the GHC-ET disclosures and stock price crash risk is significantly positive. Similarly, the measure of stock price crash risk is DUVOL in Columns (3) and (4). The disclosure of ETs is still significantly and positively related to the future stock price crash

risk. In other words, the crash risk will be increased for those firms that have ETs-related information in their initial 8-K filing. All regressions in Columns (1) to (4) include fixed effects by year and industry but Columns (1) and (3) without control variables. The results are also economically significant. In detail, the standardised coefficient of  $GHCET_t$  is 0.0364 (0.1899×0.199/1.039) (Column (1)) (0.3599 (Column (2)), which means that the disclosure of ETs is associated with a 3.64% (3.60%) increase in average stock price crash risk. When the crash risk is measured by DUVOL, shown in Columns (3) and (4), the standardised coefficient of  $GHCET_t$  is 0.0262 (0.0739×0.199/0.601) (Column (3)) (0.0245 (Column (4)). The standardised coefficient suggests that the increase in average stock price crash risk is 2.62% (2.45%). Overall, the regression results in Table 6.4 support our Hypothesis one that the disclosure of ETs is more pronounced to future stock price crash risk.

Table 6.4 GHC-ET Disclosures and Stock Price Crash Risk

Variables	NCSKEW <sub>t+1</sub>	NCSKEW <sub>t+1</sub>	DUVOL t+1	DUVOL t+1
Variables	(1)	(2)	(3)	(4)
GHCET <sub>t</sub>	0.1899***	0.1879***	0.0790**	0.0739**
	(3.53)	(3.50)	(2.55)	(2.38)
NCSKEW <sub>t</sub>		0.0548***		
		(4.61)		
$DUVOL_t$		, ,		0.0575***
				(4.92)
$RET_t$		7.1830***		4.3662***
		(5.20)		(5.44)
$SIGMA_t$		-0.2437		0.2285
		(-0.55)		(0.90)
Dturnover <sub>t</sub>		0.0064		0.0037
		(0.75)		(0.75)
$SIZE_t$		0.0379***		0.0239***
		(5.61)		(6.14)
$ROA_t$		-0.1162**		-0.0582**
		(-2.40)		(-2.08)
$LEV_t$		-0.013		-0.0123
		(-0.27)		(-0.43)
$MB_t$		0.0027		0.0022**
		(1.61)		(2.27)
$ABACC_t$		0.0546		0.0663*
		(0.79)		(1.67)
Constant	0.0615***	-0.2233***	0.0572***	-0.1518***
	(5.74)	(-3.59)	(9.25)	(-4.23)
Year, Industry FE	YES	YES	YES	YES
Observations	9,734	9,734	9,734	9,734
Adj. R-square	0.008	0.016	0.011	0.021

Note: This table presents the estimates of regressions of GHC-ET disclosures (GHCET<sub>t</sub>) and stock price crash risk. The first measure of dependent variable is the negative coefficient of skewness (NCSKEW) and the second one is the down-to-up volatility (DUVOL). All independent variables are lagged by one year. All regressions include fixed effects by year and industry. Each parenthesis reports the t-statistic which is based on the standard errors clustered by firms. \*, \*\*, and \*\*\* indicate significance at the 10%, 5%, and 1% levels, respectively. Detailed definition of variables is presented in Appendix C-1.

Table 6.5 reports the regression results of the disclosure of ETs of different GHC phase and stock price crash risk. The dependent variable of Panel A is NCSKEW while DUVOL for Panel B. All regressions include control variables and fixed effects by year and industry. In general, there is a significant and positive relationship between the disclosure of ETs in GHC's

phase one (innovation trigger) and three (trough of disillusionment) and the stock price crash risk. However, the relationship becomes significantly negative when the disclosure belongs to GHC's phase five (plateau of productivity). The disclosure of the other phases (two and four) is insignificant.

Specifically, the standardised coefficient of  $Phase\_One_t$  is 0.0316 (0.2667×0.123/1.039) when the measure of crash risk is NCSKEW (0.0264 (0.1292×0.123/0.601) when crash risk is measured by DUVOL), which means the disclosure of ETs in GHC's phase one is associated with a 3.16% (2.64%) increase in average stock price crash risk. In addition, the standardised coefficient of  $Phase\_Three_t$  is 0.0120 (0.1449×0.086/1.039) when the measure of crash risk is NCSKEW (0.0207 (0.1449×0.086/0.601) when crash risk is measured by DUVOL), which means the disclosure of ETs in GHC's phase three is associated with a 1.20% (2.07%) increase in average stock price crash risk. More interestingly, it is observed that the only negative result exists when firms disclose ETs-related information in GHC's phase five which is the adoption stage of one ET. The standardised coefficient of  $Phase\_Five_t$  is -0.0252 (0.6717×0.039/1.039) when the crash risk is measured by NCSKEW and -0.0436 (0.6717×0.039/0.601) for DUVOL. It means that the stock price crash risk will decrease 2.52% (4.36%) if firms disclose those ETs at the productivity stage.

Table 6.5 GHC-ET Disclosures by Phase and Stock Price Crash Risk

Panel A.					
Variables	$NCSKEW_{t+1}$	$NCSKEW_{t+1}$	$NCSKEW_{t+1}$	$NCSKEW_{t+1}$	NCSKEW <sub>t+1</sub>
variables	(1)	(2)	(3)	(4)	(5)
Phase_One <sub>t</sub>	0.2667***				
	(3.12)				
Phase_Two <sub>t</sub>		0.1116			
		(1.29)			
Phase_Three <sub>t</sub>			0.2906**		
			(2.37)		
Phase_Four <sub>t</sub>				0.2523	
				(0.98)	
Phase_Five <sub>t</sub>					-0.6717**
					(-2.51)
Constant	-0.2260***	-0.2265***	-0.2252***	-0.2286***	-0.2281***
	(-3.63)	(-3.64)	(-3.62)	(-3.67)	(-3.67)
Controls, Year, Industry FE	YES	YES	YES	YES	YES
Observations	9,734	9,734	9,734	9,734	9,734
Adj. R-square	0.016	0.015	0.016	0.015	0.016
Panel B.					
Variables	DUVOL t+1	$DUVOL_{t+1}$	$DUVOL_{t+1}$	$DUVOL_{t+1}$	$DUVOL_{t+1}$
v arrables	(1)	(2)	(3)	(4)	(5)
Phase_Onet	0.1292***				
	(2.62)				
Phase_Twot		0.0103			
		(0.21)			
Phase_Threet			0.1449**		
			(2.05)		
Phase_Fourt				0.0776	
				(0.52)	
Phase_Fivet					-0.3049**
					(-1.98)
Constant	-0.1528***	-0.1535***	-0.1524***	-0.1539***	-0.1538***
	(-4.26)	(-4.28)	(-4.25)	(-4.29)	(-4.29)
Controls, Year, Industry FE	YES	YES	YES	YES	YES
Observations	9,734	9,734	9,734	9,734	9,734
Adj. R-square	0.021	0.020	0.021	0.020	0.021

Note: This table presents the estimates of regressions of GHC-ET disclosures by different GHC phase (Phase\_jt, j from one to five) and stock price crash risk. The dependent variable is the negative coefficient of skewness (NCSKEW) of Panel A and the down-to-up volatility (DUVOL) of Panel B. All independent variables are lagged by one year. All regressions include control variables and fixed effects by year and industry. Each parenthesis reports the t-statistic which is based on the standard errors clustered by firms. \*, \*\*, and \*\*\* indicate significance at the 10%, 5%, and 1% levels, respectively. Detailed definition of variables is presented in Appendix C-1.

#### 6.4.3 Robustness checks

Some robustness tests are necessary to identify the reliability of baseline regressions. Although this study uses one-year lag of all control variables including  $GHCET_t$  and  $Phase\_j_t$  from the dependent variable to alleviate the effects of potential reverse causality, the problems of endogeneity are still worth discussing in this section. At first, this study uses alternative crash risk measure to re-run the equation (6-4). Further, some additional controls are added into regressions including the characters of each 8-K filing, institutional holding, and analysts following. In addition, one instrumental variable is selected to dispel concerns about the influence of unobservable factors. Propensity score matching is used to address the selection bias. Finally, two tests are conducted to verify the veracity as well as the dynamic effects of the disclosure of ETs on the increased risk of stock price crashes.

### 6.4.3.1 Alternative crash risk measures

A dummy variable (CRASH) is conducted to represent the likelihood of crashes. It can define the crash risk of stock price where equal to one means the stock has more than one crash week in year t while zero means the opposite. The formula is shown as follows.

$$W_{j,t} \le Average(W_{j,t}) - 3.09\sigma_{j,t} \tag{6-6}$$

where the crash week is recognised by the average weekly firm-specific return minus 3.09 standard deviations. Hutton et al. (2009) and Chen et al. (2019) have identified the robust of figure 3.09 which represents in the normal distribution at 10% level.

Table 6.6 shows the logistic regression results using the alternative measure of crash risk. The relationship between GHC-ET disclosures and stock price crash risk is still significantly positive whether or not all control variables are included. The standardised coefficient of *GHCET*<sub>t</sub> is 0.0264 (0.0588×0.199/0.443) (Column (1)) (0.0262 (0.0583×0.199/0.443) (Column (2)), which means the stock price crash risk will increase 2.64% (2.62%) when firms disclose ETs in their initial 8-K filing. The results are consistent with Table 6.4 as well as supporting the hypothesis.

**Table 6.6 Alternative Measures of Stock Price Crash Risk** 

Variables	Crash t+1	Crash <sub>t+1</sub>	Crash <sub>t+1</sub>
Variables	(1)	(2)	(3)
GHCET <sub>t</sub>	0.0588**	0.0583**	0.0466*
	(2.57)	(2.55)	(1.89)
$Crash_t$		0.0453***	0.0454***
		(4.37)	(4.38)
$RET_t$		1.1433**	1.1374**
		(2.03)	(2.02)
$SIGMA_t$		-0.3529*	-0.3587*
		(-1.87)	(-1.90)
Dturnovert		0.0076**	0.0077**
		(2.08)	(2.10)
$SIZE_t$		0.0078***	0.0078***
		(2.73)	(2.72)
$ROA_t$		-0.0326	-0.0331
		(-1.58)	(-1.60)
$LEV_t$		-0.0038	-0.0036
		(-0.18)	(-0.17)
$MB_t$		-0.0005	-0.0005
		(-0.69)	(-0.68)
$ABACC_t$		-0.0186	-0.0194
		(-0.63)	(-0.66)
Constant	0.2658***	0.2233***	0.2238***
	(58.37)	(8.43)	(8.45)
Year, Industry FE	YES	YES	YES
Observations	9,734	9,734	9,734
Adj. R-square	0.016	0.019	0.019

Note: This table presents the robustness check on the relationship between GHC-ET disclosures (GHCET<sub>t</sub>) and stock price crash risk. I use alternative measures of crash risk as described in Section 4.4.1. All independent variables are lagged by one year. Year and industry fixed effects are included. Each parenthesis reports the t-statistic which is based on the standard errors clustered by firms. \*, \*\*, and \*\*\* indicate significance at the 10%, 5%, and 1% levels, respectively. Detailed definition of variables is presented in Appendix C-1.

### 6.4.3.2 Additional control variables

In this section, some additional control variables are chosen in two dimensions, one is the characteristics of each 8-K filing and the other is the effects of external monitoring. Based on prior studies, all variables may also affect stock price crash risk of firms. Therefore, this section

re-runs equation (6-4) by controlling for these additional control variables to identify the reliability of baseline regression results.

# 6.4.3.2.1 The characteristics of 8-K filings' content

Arslan-Ayaydin et al. (2016) highlight the importance and low credibility of qualitative information in voluntary disclosures. Quantitative information communicates only the firm's performance, while qualitative information completes the quantitative information and provides incremental information to investors. Prior studies conclude several qualitative characteristics of disclosure on stock price crash risk (i.e., tone (Fu et al., 2021) and readability (Kim et al., 2019)). This study measures the tone, readability, and file size of each 8-K filing to control for the potential effects of these qualitative characteristics on stock price crash risk.

Managers may use a positive tone to convey information thereby exaggerating investor perceptions (Huang et al., 2014). For ETs information with high uncertainty, it is reasonable to believe that investors will use a more positive tone to present the disclosure. This study uses Loughran and McDonald (2011)'s sentiment dictionary to count the number of positive words and negative words of each 8-K filing after removing symbols and stop words. The formula is as follows,

$$Tone_{t} = \frac{Positive\ word\ count-Negative\ word\ count}{Positive\ word\ count+Negative\ word\ count}$$
(6-7)

In addition, this study considers complex forms of expression to confuse the disclosure. The easier the information is to understand, the more useful the information the investor will get. Many studies find managers tend to use complex words to obfuscate unfavourable information (Li, 2008; Li and Zhang, 2015), which leads to an accumulation of bad news that eventually causes an information explosion and stock price collapse (Kim et al., 2019). The Gunning Fog Readability Index is used to measure the readability extent of each 8-K filing. The index can be calculated by the following formula,

$$Readability_t = 0.4 \times \left[ \left( \frac{{}^{Total\ words}}{{}^{Total\ sentences}} \right) + 100 \times \left( \frac{{}^{Complex\ words}}{{}^{Total\ words}} \right) \right] \tag{6-8}$$

Finally, the file size (Filingsize<sub>t</sub>) (bytes) is controlled for in each filing as a proxy variable for ease of access to information by investors. Larger files mean that investors need more time for web caching, although the difference is negligible. In other words, 8-K filings with larger file sizes have much content, and investors need more time to capture ETs' information.

Panel A of Table 6.7 presents the regression results after adding additional control variables for each 8-K filing's characteristics. Each regression includes control variables from the baseline and fixed effects by year and industry. The coefficients of  $GHCET_t$  are significantly and positively related to stock price crash risk, which mean the baseline results are unchanged.

### 6.4.3.2.2 The role of external monitoring

Many studies emphasise that the external monitoring role of institutional shareholders and analysts should not be overlooked. Examining whether external monitoring can mitigate the increased risk of stock price crash due to emerging technology disclosure is not the main research objective of this paper. This study only includes the percentage of institutional investors, and the number of analysts follows as a control variable to reduce the effects of omitted variables to the baseline regression results.

Institutional investors are informed traders in the market due to their greater ability to gather information compared to individual investors. The study of Shleifer and Vishny (1997) concludes that institutional shareholders have an incentive to gather information and monitor management due to their large equity holdings. In addition, Callen and Fang (2013) identify that institutional investors can reduce the stock price crash risk by limiting a manager's hoarding of bad news or delayed release of good news as the external monitoring. Therefore, the percentage of institutional investors of firms is added into equation (6-4).

The ability of managers to hide and accumulate bad news can lead to a decrease in the transparency of information thereby increasing the risk of stock crashes (Jin and Myers, 2006). If analysts disclose firm-specific information (especially bad news) to investors, then the

transparency of the information at firm level will increase, thus the crash risk decreases. However, according to Beyer et al. (2010), analysts may not report all private information to investors especially those on the sell-side part. The bad news will be accumulated if analysts report optimistic forecasts earnings, leading to higher crash risk in the future. Although there is no uniform conclusion on the external monitoring role of analysts, it is possible to determine their impact on the risk of stock price crash based on the literature. Therefore, the number of analysts is also added as an additional control variable.

Panel A of Table 6.7 presents the regression results after adding additional control variables of the percentage of institutional investors and the number of analysts following. Each regression includes control variables from the baseline and fixed effects by year and industry. Similarly, whether the two variables are added individually to equation (6-4) or together, the coefficients of  $GHCET_t$  are significantly and positively related to stock price crash risk, which mean the baseline results are unchanged.

**Table 6.7 Additional Control Variables of 8-K Filings' Characteristics** 

Panel A. Additional controls of 8-K filings characteristics								
Variables	NCSKEW <sub>t+1</sub>	DUVOL t+1	NCSKEW <sub>t+1</sub>	DUVOL <sub>t+1</sub>	NCSKEW <sub>t+1</sub>	DUVOL <sub>t+1</sub>	NCSKEW <sub>t+1</sub>	DUVOL t+1
variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
GHCET <sub>t</sub>	0.2268***	0.0989**	0.2198***	0.0952**	0.2206***	0.0980**	0.2278***	0.1015***
	(3.40)	(2.57)	(3.32)	(2.49)	(3.32)	(2.56)	(3.40)	(2.63)
Tonet	-0.0039	-0.0095					-0.0046	-0.0085
	(-0.21)	(-0.91)					(-0.24)	(-0.77)
Readabilityt			-0.0003	0.0008			-0.0003	0.0005
			(-0.12)	(0.51)			(-0.12)	(0.34)
Filingsizet					-0.0012	-0.0028	-0.0011	-0.0032
					(-0.21)	(-0.86)	(-0.19)	(-0.95)
Constant	-0.2207***	-0.1521***	-0.2261***	-0.1744***	-0.2188**	-0.1277**	-0.2012*	-0.1230**
	(-3.21)	(-3.83)	(-2.78)	(-3.71)	(-2.25)	(-2.28)	(-1.88)	(-1.99)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Year, Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	8,214	8,214	8,214	8,214	8,214	8,214	8,214	8,214
Adj. R-square	0.016	0.020	0.015	0.020	0.015	0.020	0.015	0.020

Panel B. Additional controls of external monitoring							
Variables	$NCSKEW_{t+1}$	DUVOL t+1	$NCSKEW_{t+1}$	DUVOL t+1	$NCSKEW_{t+1}$	DUVOL t+1	
variables	(1)	(2)	(3)	(4)	(5)	(6)	
GHCET <sub>t</sub>	0.1824***	0.0691**	0.1772***	0.0664**	0.1828***	0.0713**	
	(3.46)	(2.28)	(3.36)	(2.18)	(3.41)	(2.31)	
Institutional <sub>t</sub>	0.2782***	0.1558***			0.2779***	0.1555***	
	(6.47)	(6.29)			(6.42)	(6.23)	
Analystst			0.0233	0.0143	0.0197	0.0121	
			(1.45)	(1.55)	(1.23)	(1.31)	
Constant	-0.3158***	-0.2046***	-0.2139***	-0.1475***	-0.3061***	-0.1987***	
	(-4.99)	(-5.61)	(-3.45)	(-4.12)	(-4.78)	(-5.38)	
Controls	YES	YES	YES	YES	YES	YES	
Year, Industry FE	YES	YES	YES	YES	YES	YES	
Observations	9,734	9,734	9,734	9,734	9,734	9,734	
Adj. R-square	0.021	0.025	0.016	0.021	0.020	0.025	

Note: This table presents the robustness check on the relationship between GHC-ET disclosures (GHCET<sub>t</sub>) and stock price crash risk after added additional control variables including 8-K filings characteristics (Panel A) and external monitoring (Panel B). All independent variables are lagged by one year. Control variables and year and industry fixed effects are included. Each parenthesis reports the t-statistic which is based on the standard errors clustered by firms. \*, \*\*, and \*\*\* indicate significance at the 10%, 5%, and 1% levels, respectively. Detailed definition of variables is presented in Appendix C-1.

# 6.4.3.3 Endogenous problems

### 6.4.3.3.1 Instrumental variable approach

To reduce the impact of endogeneity problems caused by unobservable factors or simultaneity bias on the estimation results, this study chooses a two-stage-least-square (2SLS) estimation. Based on the conditions of appropriate instrumental variables (IVs), one IV is selected for the 2SLS estimation.

The IV used in this study is the percentage of internet users including whether the household is connected to broadband and smartphone users by state in the US. According to agency theory, corporate disclosure, especially voluntary disclosure, requires motivation both at the individual management level and from the corporate perspective (Healy and Palepu, 2001). Any disclosure has a cost which means it will become meaningless if the firm discloses the information and then only a few investors and other stakeholders have access to it. In other words, the more investors pay attention, or the more investors have timely access to the information, the more likely the firm is to make the disclosure, given that I do not consider the consequences of disclosure. Therefore, the higher the network coverage in those states, the more likely the firms are to disclose time-sensitive information about ETs. The accessibility of the internet also means more opportunities for investors to learn about different ETs news. However, there is no potentially plausible causal relationship between the percentage of network users and the crash risk of stock prices at the firm level.

Panel A of Table 6.8 reports the 2SLS estimation results. Column (1) contains the first-stage regression results using *GHCET<sub>t</sub>* as the dependent variable and the IV (*IV\_Internet\_Users<sub>t</sub>*) as the main independent variable. The relationship between *IV\_Internet\_Users<sub>t</sub>* and *GHCET<sub>t</sub>* is significantly positive, suggesting that firms are more likely to disclose ETs-related information when the percentage of internet users is high. Column (2) presents the second-stage regression results. The *IV\_Internet\_Users<sub>t</sub>* is significantly and positively related to stock price crash risk, which is measured by NCSKEW and DUVOL, respectively. The 2SLS estimation results support the hypothesis that GHC-ET disclosures increases the stock price crash risk.

Panel B of Table 6.8 reports the results of IV validity tests. Firstly, the Durbin-Wu-

Hausman (DWH) test is a statistical test that is used to test whether the explanatory variables in a model have endogeneity problems. According to DWH tests, for both crash risk measures (NCSKEW and DUVOL), all P ( $\chi^2$ ) are lower than 0.1 (0.0909 and 0.0283, respectively). Therefore, the null hypothesis is rejected, indicating that the coefficients estimated by OLS are significantly different from those obtained using the IV approach. This implies that the explanatory variable ( $GHCET_t$ ) may have endogeneity problems and that the use of IV methods (i.e., 2SLS) is appropriate. In addition, the F-statistic in the first stage is used to assess the strength of the correlation between the IV ( $IV\_Internet\_users_t$ ) and the endogenous explanatory variable ( $GHCET_t$ ). The F-statistic for the first stage is 7.98, which means that there is some degree of correlation between the  $IV\_Internet\_users_t$  and  $GHCET_t$ . To further verity the IV is not weak, the Stock-Yogo Weak IV test is conducted. Because the F-statistic is greater than 6.66 (Critical values 20%), the IV of this study is considered strong enough to avoid the weak IV problem at the looser bias rate criterion (20%).

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<sup>&</sup>lt;sup>56</sup> The common criterion of F-statistics is 10 (Davidson and MacKinnon, 1981).

**Table 6.8 Instrumental Variable Approach** 

Panel A. IV (2SLS) estimation	GHCET <sub>t</sub>	NCSKEW <sub>t+1</sub>	GHCET <sub>t</sub>	DUVOL t+1
Variables	First stage	Second stage	First stage	Second stage
variables	$\frac{\text{Thist stage}}{(1)}$	(2)	(3)	(4)
GHCET <sub>t</sub>	(1)	1.9240**	(3)	1.5372***
GHCE1 <sub>t</sub>		(2.11)		(2.80)
IV_Internet_users <sub>t</sub>	0.0012***	(2.11)	0.0012***	(2.00)
Iv_Internet_users <sub>t</sub>	(5.04)		(5.03)	
NCSKEW <sub>t</sub>	-0.0025	0.0542***	(3.03)	
NCSKE W <sub>t</sub>	(-0.97)	(3.87)		
$DUVOL_t$	(-0.97)	(3.67)	-0.0019	0.0562***
DU V OLt			(-0.45)	(4.07)
$RET_t$	-0.1538	6.0846***	-0.1030	3.6720***
KL1 <sub>t</sub>	(-0.57)	(4.17)	(-0.38)	(4.12)
SIGMA <sub>t</sub>	0.3775***	-1.3124**	0.3788***	-0.5633
SIOMAt	(3.92)	(-2.31)	(3.93)	(-1.63)
Dturnovert	0.0019	0.0091	0.0019	0.0040
Diamovert	(0.88)	(0.80)	(0.86)	(0.59)
SIZE <sub>t</sub>	0.0038***	0.0281***	0.0038***	0.0163***
SIZE	(2.83)	(3.74)	(2.81)	(3.47)
$ROA_t$	0.0027	-0.1648***	0.0028	-0.0779**
KOA <sub>t</sub>	(0.24)	(-2.76)	(0.25)	(-2.21)
$LEV_t$	-0.0510***	0.0510	-0.0511***	0.0511
LE V t	(-6.07)	(0.77)	(-6.07)	(1.27)
$MB_t$	0.0002	0.0031*	0.0002	0.0023**
IVID <sub>t</sub>	(0.55)	(1.77)	(0.53)	(2.06)
ABACC <sub>t</sub>	-0.0248**	0.1780**	-0.0243**	0.1637***
ABACCI	(-2.07)	(2.33)	(-2.02)	(3.44)
Constant	-0.1105***	-0.1975***	-0.1105***	-0.1414***
Constant	(-4.67)	(-3.01)	(-4.66)	(-3.49)
All controls	(-4.07) YES	YES	(-4.00) YES	YES
Year, Industry FE	YES	YES	YES	YES
Observations	8,891	8,891	8,891	8,891
Adj. R-square	0.010	0,071	0.010	0,071

Panel B. IV validity tests		
Durbin-Wu-Hausman Test P (χ²)	0.0909	0.0283
Fist-stage F-statistic	7.98	7.98
Stock-Yogo Weak IV test		
Critical values 15%	8.96	8.96
Critical values 20%	6.66	6.66

Note: This table presents the two-stage-least-square (2SLS) tests for GHCETt and crash risk. The instrumental variable is the internet users (IV\_Internet\_users<sub>t</sub>) which is the percentage of people who can access internet of each state. Panel A reports IV (2SLS) estimation result while Panel B reports IV validity tests. All independent variables are lagged by one year. Year and industry fixed effects included. Each parenthesis reports the t-statistic which is based on the standard errors clustered by firms. \*, \*\*, and \*\*\* indicate significance at the 10%, 5%, and 1% levels, respectively. Detailed definition of variables is presented in Appendix C-1.

### 6.4.3.3.2 Propensity score matching

According to Rosenbaum and Rubin (1983), this study conducts propensity score matching (PSM) to address the selection bias because of firm-specific characteristics and functional misspecification. This study compares the risk of stock price crashes between firms that disclose information related to ETs in their initial 8-K filings (the GHC group) and firms that do not disclose such information but have similar characteristics to the GHC group (non-GHC group). To maintain the comparability, this study chooses the nearest neighbour with replacement to conduct PSM. The comparison, Panel A of Table 6.9 shows that there is a significant difference of  $NCSKEW_{t+1}$  and  $DUVOL_{t+1}$  (p-values are 0.014 and 0.042, respectively) but an insignificant difference between other control variables. This study regresses equation (6-4) with all control variables and fixed effects by year and industry to identify that the baseline regression results are reliable. Panel B of Table 6.9 reports the regression results after PSM which are unchanged across all regressions. In detail, the disclosure of ETs-related information increases the stock price crash risk of firms.

Table 6.9 Propensity Score Matching Analysis of GHC-ET Disclosures and Stock Price Crash Risk

Panel A. Comparison of Treatment and Control Firms							
	non-	non-GHC-sample		GHC-sample	— Diff	P-value	
	N	Mean	N	Mean	— Dili	P-value	
$NCSKEW_{t+1}$	401	0.042	401	0.236	-0.194	0.014**	
$DUVOL_{t+1}$	401	0.035	401	0.125	-0.090	0.042**	
NCSKEW	401	0.081	401	0.080	0.001	0.996	
DUVOL	401	0.089	401	0.071	0.018	0.659	
$RET_t$	401	0.002	401	0.002	0.000	0.700	
$SIGMA_t$	401	0.070	401	0.069	0.001	0.718	
Dturnover <sub>t</sub>	401	0.218	401	0.249	-0.031	0.800	
$SIZE_t$	401	6.747	401	6.748	0.001	0.998	
$ROA_t$	401	-0.073	401	-0.075	0.003	0.898	
$LEV_t$	401	0.214	401	0.213	0.001	0.941	
$MB_t$	401	3.498	401	3.403	0.095	0.805	
$ABACC_t$	401	0.163	401	0.155	0.008	0.525	

Panel B. PSM regression of GHCET and stock price crash risk

	<u>-</u>		
Variables —	$NCSKEW_{t+1}$	$\mathrm{DUVOL}_{\mathrm{t+1}}$	
variables	(1)	(2)	
GHCET <sub>t</sub>	0.2322***	0.1002**	
	(2.72)	(2.09)	
Constant	-0.6108***	-0.3882***	
	(-2.71)	(-3.07)	
Controls	YES	YES	
Year, Industry FE	YES	YES	
Observations	802	802	
Adj. R-square	0.037	0.033	

Note: This table presents the propensity score matching tests for GHC-ET disclosures (GHCETt) and stock price crash risk. Panel A shows the comparison of treatment and control groups while Columns (1) and (2) of panel B report the regression results after propensity score matching. All independent variables are lagged by one year. Year and industry fixed effects are included. Each parenthesis reports the t-statistic which is based on the standard errors clustered by firms. \*, \*\*, and \*\*\* indicate significance at the 10%, 5%, and 1% levels, respectively. Detailed definition of variables is presented in Appendix C-1.

# 6.4.3.4 Dynamic effects of GHC-ET disclosures and placebo tests

To assess the dynamic effects of the disclosure of ETs, this study conducts two tests. First, two pseudo disclosure years (Year t+1 and Year t+2) are conducted to replace the true disclosure year of ETs. As Panel A of Table 6.10 presents, the coefficients of both  $GHCET\_Year\ t+1$  and  $GHCET\ Year\ t+2$  are insignificant, supporting the increase of stock price crash risk due to the

disclosure of ETs. Second, this study follows Bertrand and Mullainathan (2003) to replace the  $GHCET_t$  dummy with year dummy variables that track the dynamic effects of the disclosure of ETs before and after they become effective.

This test includes the following dummy variables: Year -3, Year -2, and Year -1, which equal one for the three years before the disclosure becomes effective, the two years before the disclosure becomes effective, and the year before the disclosure becomes effective, respectively, and zero otherwise. Year 0, which equals one for the year in which the disclosure becomes effective, and zero otherwise. Year 1, Year 2, Year 3, Year 4, and Year 5 which equal one for the year and subsequent years after the disclosure becomes effective, and zero otherwise.

If the disclosure is passed because of changes in other conditions, the positive effect due to the disclosure of ETs on stock price crash risk could be observed before the disclosure. However, as shown in Panel B of Table 6.10, the coefficients of Year -3, Year -2, and Year -1 are insignificant. After the disclosure becomes effective, the coefficients of Year 0, Year 1, and Year 2 are positive and significant, suggesting that the increase in crash risk materialised after GHC-ET disclosures becomes effective.

**Table 6.10. Placebo Tests** 

Panel A. Pseudo disclosure years						
Variables	$NCSKEW_{t+1}$	$DUVOL_{t+1} \\$	$NCSKEW_{t+1} \\$	$DUVOL_{t+1}$		
variables	(1)	(2)	(3)	(4)		
GHCET_Year t+1	0.0165	0.1047				
	(0.15)	(1.13)				
GHCET_Year t+2			-0.0301	-0.0566		
			(-0.23)	(-0.54)		
Constant	-0.2024	-1.5754***	-0.1731	-1.5439***		
	(-1.56)	(-6.83)	(-1.33)	(-6.65)		
Controls	YES	YES	YES	YES		
Year, Industry FE	YES	YES	YES	YES		
Observations	5,082	4,494	5,023	4,443		
Adj. R-square	0.019	0.096	0.019	0.096		

Panel B. Dynamic effect of ETs' disclosure

V-3-11-	$NCSKEW_{t+1}$	$\mathrm{DUVOL}_{t+1}$
Variables —	(1)	(2)
Year -3	0.0989	0.0296
	(1.40)	(0.71)
Year -2	-0.0355	-0.0439
	(-0.55)	(-1.16)
Year -1	-0.0753	-0.0144
	(-1.25)	(-0.41)
Year 0	0.1349*	0.0819*
	(1.82)	(1.87)
Year 1 (first effective year)	0.2221***	0.1366***
	(3.76)	(3.92)
Year 2	0.2402***	0.1514***
	(3.41)	(3.64)
Year 3	0.0711	0.0532
	(0.92)	(1.17)
Year 4	-0.0607	-0.0506
	(-0.71)	(-1.00)
Year 5	0.0302	0.0199
	(0.32)	(0.36)
Constant	0.1262***	0.0794***
	(3.09)	(3.29)
Controls	YES	YES
Year, Industry FE	YES	YES
Observations	15,567	15,567
Adj. R-square	0.008	0.012

Note: This table presents the results of placebo tests. Panel A shows the results after the true disclosure year is replaced by two pseudo disclosure years while Panel B reports the results of dynamic effect of ETs' disclosure. All independent variables are lagged by one year. Year and industry fixed effects are included. Each parenthesis reports the t-statistic which is based on the standard errors clustered by firms. \*, \*\*, and \*\*\* indicate significance at the 10%, 5%, and 1% levels, respectively. Detailed definition of variables is presented in Appendix C-1.

### 6.4.4 Potential channels

#### 6.4.4.1 Investors' short-term reaction

When firms voluntarily make ETs disclosures, investors may overreact, which could lead to a short-term spike in the stock price. Investors may overreact to the disclosure of ETs based on their emotional and behavioural biases. This may result in the stock price deviating from its true value in the short term (Daniel et al., 1998; De Bondt and Thaler, 1985). However, if these expectations are not realised, or if news subsequently emerges that contradicts these positive disclosures, then this may lead to a rapid fall in the stock price, increasing the risk of a share price crash. Many studies identify the role investors play in stock price crashes; for example, investor attention (Cui et al., 2022; Wen et al., 2019), over-optimistic investor sentiment (Cui et al., 2022; Fu et al., 2021; Zouaoui et al., 2011), and investor confidence (Gottesman and Morey, 2023).

Thus, the more strongly investors overreact to ETs disclosure in the short term, the more pronounced the increased risk of a firm's share price crash due to disclosure of ETs. To test this conjecture, the short-term investor reaction is measured by the cumulative abnormal returns (CAR) around the event window (-3, +3) (event date is the 8-K filing containing ETs release date). The formula is,

$$\overline{CAR_{l}}(d_{1}, d_{2}) = \frac{1}{N} \sum_{d=d_{1}}^{d_{2}} R_{i,d} - (\widehat{\alpha}_{l} + \widehat{\beta}_{l} R_{m,d})$$
(6-9)

where  $\overline{CAR_i(d_1, d_2)}$  is the mean CAR in the event window by calculating the average  $CAR_i(d_1, d_2)$  for each stock N.  $R_{i,d}$  is the stock returns for firm i on day d, which equals  $\alpha_i + \beta_i R_{m,d} + \varepsilon_{i,d}$ .  $R_{m,d}$  is the US market return (S&P 500 index). The regression results for this test are provided in Table 6.11. The stock price crash risk is measured by NCSKEW for both Columns (1) and (3) while DUVOL for both Columns (2) and (4). As expected, the coefficient on the interaction term ( $GHCET_t*Investor\_reactiont_t$ ) is positive and significant, suggesting

that stock price crash risk is higher when short-term investor reaction increases.

### 6.4.4.2 CEO overconfidence

CEO overconfidence may lead to a series of biased corporate decisions that can affect the firm's operations and financial position, which in turn may increase the risk of a share price crash. Malmendier and Tate (2005) find that overconfident CEOs may over-assess the returns on some projects, leading to over-investment. For example, for ETs that are at the peak of market hype, if the CEO does not assess the risks in depth and blindly follows other firms to make investments, the actual returns may be lower than the market expectations, thus increasing the risk of a share price crash. Further, overconfident CEOs may choose to delay the reporting of bad news (Chowdhury et al., 2020; Ge and Lennox, 2011; Hirshleifer et al., 2012). Thus, the stock price may suddenly plummet as the issues continue to fester and eventually become public knowledge.

CEO overconfidence is an abstract concept not easily and directly measurable. This study follows Campbell et al. (2011) and Hirshleifer et al. (2012) to use the executive options holding decisions to measure CEO overconfidence. First, the average exercise price is estimated using a CEO's aggregated options data from Standard & Poor's ExecuComp. Then, the average realisable value is calculated by the estimated value of the unexercised exercisable options divided by the number of unexercised exercisable options. The average realisable value less the stock price at the end of the financial year is then the average exercise price of the exercisable options held by the CEO. The average percentage monetisation of options held by the CEO is the average realisable value divided by the average exercise price of exercisable options. CEOs are categorised as overconfident if they hold options that are over 67% in money, otherwise, not.

The regression results for this test are provided in Table 6.11. The stock price crash risk is measured by NCSKEW for both Columns (1) and (3) while DUVOL for both Columns (2) and (4). As expected, the coefficient on the interaction term ( $GHCET_t*CEO\_overcon_t$ ) is positive and significant, suggesting that stock price crash risk is higher when CEO overconfidence increases.

**Table 6.11. Potential Channels** 

Variables	$NCSKEW_{t+1}$	DUVOL <sub>t+1</sub>	NCSKEW <sub>t+1</sub>	$DUVOL_{t+1}$
Variables	(1)	(2)	(3)	(4)
GHCET <sub>t</sub>	0.2619***	0.1063**	0.4110***	0.2016***
	(3.22)	(2.24)	(4.13)	(3.48)
Investor_reaction <sub>t</sub>	-0.2967**	-0.1790**		
	(-2.40)	(-2.48)		
GHCET <sub>t</sub> *Investor_reaction <sub>t</sub>	1.7980***	0.8124**		
	(3.27)	(2.54)		
CEO_overcon <sub>t</sub>			0.1007**	0.0662***
			(2.46)	(2.77)
GHCET <sub>t</sub> *CEO_overcon <sub>t</sub>			0.5676**	0.3613**
			(2.33)	(2.55)
$NCSKEW_t$	-0.1366***		-0.1340***	
	(-8.91)		(-8.72)	
$DUVOL_t$		-0.1308***		-0.1282***
		(-8.67)		(-8.47)
$RET_t$	7.4188***	4.6482***	5.7901***	3.6405***
	(4.00)	(4.26)	(3.15)	(3.37)
SIGMAt	-2.9076***	-1.4530***	-2.5446***	-1.2448***
	(-3.81)	(-3.26)	(-3.33)	(-2.79)
Dturnovert	0.0141	0.0052	0.0123	0.0041
	(1.26)	(0.79)	(1.10)	(0.63)
$SIZE_t$	0.2600***	0.1501***	0.2614***	0.1503***
	(6.52)	(6.45)	(6.52)	(6.44)
$ROA_t$	-0.1300	-0.0428	-0.1048	-0.0334
	(-1.42)	(-0.80)	(-1.15)	(-0.63)
$LEV_t$	-0.0861	-0.0816	-0.0778	-0.0782
	(-0.73)	(-1.18)	(-0.65)	(-1.13)
$MB_t$	0.0041*	0.0029**	0.0038	0.0029**
	(1.65)	(2.05)	(1.55)	(2.01)
$ABACC_t$	0.1113	0.1380**	0.1142	0.1408**
	(0.95)	(2.03)	(0.98)	(2.07)
Constant	-1.7576***	-1.0204***	-1.7970***	-1.0327***
	(-5.92)	(-5.89)	(-6.03)	(-5.95)
Year, Industry FE	YES	YES	YES	YES
Observations	7,499	7,499	7,385	7,385
Adj. R-square	0.106	0.094	0.101	0.093

Note: This table shows the results of channels. All independent variables are lagged by one year. Year and industry fixed effects are included. Each parenthesis reports the t-statistic which is based on the standard errors clustered by firms. \*, \*\*, and \*\*\* indicate significance at the 10%, 5%, and 1% levels, respectively. Detailed definition of variables is presented in Appendix C-1.

### 6.4.5 Does the information uncertainty and CEO power matter?

The baseline regression illustrates that firms that disclose information related to ETs face a higher risk of stock price crash. This section performs mechanistic tests in two moderating effect analyses: uncertainty about the firm's future performance and CEO power.

### 6.4.5.1 The effect of uncertainty on disclosures of GHC-ET

The motivation for a firm's voluntary disclosure is often thought to be motivated by the manager's desire to increase investors' expectations of the firm's value and thus maximise the price (Einhorn, 2007). In other words, firms are more likely to increase the frequency and extent of voluntary disclosure if uncertainty about future performance increases. To examine whether the increase of stock price crash risk due to the disclosure of ETs is higher when a firm has a greater performance uncertainty, this study uses principal component analysis to measure the extent of uncertainty. Based on the studies of Chung and Hribar (2021) and Zhang (2006), this study chooses five components including stock return volatility, earnings volatility, bid-ask spread, cash flow volatility, and high-tech industry.

In detail, this study measures stock return volatility based on Lim (2001) which is the standard deviation of firm-specific weekly return. Bid-ask spread is measured using firm-specific daily trading data while earnings volatility is based on quarterly balance. Following Zhang (2006), this study measures cash flow volatility using the standard deviation of the difference between cash flow from operating activities before extraordinary items and total accruals to total assets. The standard deviation is based on the previous five years (starting from 2005). Firms are removed where fundamental data is less than three years. Finally, firms which have SIC codes 2833-2836, 3570-3577, 3600-3674, 7371-7379, or 8731-8734 belong to high-tech industries (Chung and Hribar 2021). This study uses a dummy variable to represent whether a firm is in a high-tech industry. The variable *Uncertainty*<sub>t</sub> is a dummy variable which means the value is one if the firm-specific uncertainty is larger than the mean of the whole sample.

Table 6.12 reports the results that include variables of GHC-ET disclosures ( $GHCET_t$ ), uncertainty ( $Uncertainty_t$ ), and the interaction of uncertainty ( $GHCET_t*Uncertainty_t$ ). The

coefficient of the interaction ( $GHCET_t*Uncertainty_t$ ) is significantly and positively related to stock price crash risk, suggesting that greater uncertainty increases the crash risk because of emerging technologies-related information disclosure. All regressions include year and industry fixed effects. The p-value of the Bartlett test of sphericity is 0.000 which rejects that all variables are not intercorrelated. In addition, the KMO value (0.554) is larger than 0.5, supporting that the components have sufficient correlation for using principal component analysis.

# 6.4.5.2 The effect of CEO power on disclosures of GHC-ET

It is reasonable to discuss the relationship between a firm's ETs disclosure and the risk of stock price crash from an agency theory perspective. Previous research has shown that managers' success in withholding bad news depends critically on their ability to influence decisions (Al Mamun et al., 2020). Along with a weaker internal regulatory environment, high-powered CEOs have more freedom to make selective disclosures, leading to an accumulation of bad news and an eventual stock price crash. This study believes powerful CEOs are more likely to disclose information about ETs, whether out of a short-term stock price boost to increase personal wealth (Andreou et al., 2017) or because of overconfidence (Kim et al., 2016).

There are a very large number of factors that can be used to measure the amount of power a CEO has. This study also uses the principal component analysis to construct an index of CEO power. The first dimension is CEO personal characteristics such as age (i.e., Andreou et al. 2017; Li et al. 2017a; Serfling 2014) and gender (e.g., Li and Zeng 2019; Schopohl et al. 2021; Usman et al. 2018). The second dimension is about the position of the CEO based on Krause et al. (2014) including the percentage of stock holdings, CEO duality, and the number of other major firms' boards. Finally, this study also chooses whether the CEO is a member or chair of three key committees (Compensation Committee, the Audit Committee, and the Corporate Governance Committee). The value of each variable is at the end of each fiscal year. The variable CEO\_Powert is a dummy variable which means the value is one if the CEO power of a firm is larger than the mean of the whole sample.

Table 6.12 reports the results that include variables of ETs-related information disclosure

( $CEO\ Power_t$ ),  $(GHCET_t)$ , CEO power and the interaction uncertainty of (GHCET<sub>t</sub>\*CEO Power<sub>t</sub>). The coefficient of the interaction (GHCET<sub>t</sub>\*CEO Power<sub>t</sub>) is significantly and positively related to stock price crash risk, suggesting that greater CEO power increases the crash risk because of GHC-ET disclosures. All regressions include year and industry fixed effects. Similarly, the p-value of Bartlett test of sphericity is 0.000 which rejects that all variables are not intercorrelated and the KMO value (0.681) is larger than 0.5, supporting that the components have sufficient correlation for using principal component analysis.

Table 6.12 The Effect of Uncertainty and CEO Power on GHC-ET Disclosures

	Uncer	tainty	CEO Po	ower
Variables	NCSKEW <sub>t+1</sub>	DUVOL t+1	NCSKEW <sub>t+1</sub>	DUVOL t+1
	(1)	(2)	(3)	(4)
GHCET <sub>t</sub>	0.0835	0.0015	-0.6818*	-0.3003
	(1.05)	(0.03)	(-1.66)	(-1.25)
GHCET <sub>t</sub> *Uncertainty <sub>t</sub>	0.0086**	0.0059***		
	(2.29)	(2.73)		
GHCET <sub>t</sub> *CEO_Power <sub>t</sub>			0.0559**	0.0259*
			(2.12)	(1.68)
Uncertainty <sub>t</sub>	-0.0004***	-0.0003***		
	(-3.02)	(-3.65)		
CEO_Power <sub>t</sub>			0.0002	-0.0034
			(0.02)	(-0.64)
$NCSKEW_t$	0.0546***		0.0740***	
	(4.37)		(3.76)	
$DUVOL_t$		0.0584***		0.0818***
		(4.75)		(4.22)
Constant	-0.2930***	-0.2059***	0.0527	0.0367
	(-4.11)	(-5.01)	(0.28)	(0.33)
Bartlett test p-value	0.0	000	0.00	0
Kaiser-Meyer-Olkin Measure	0.5	554	0.68	1
Year, Industry FE	YES	YES	YES	YES
Controls	YES	YES	YES	YES
Observations	8,794	8,794	3,511	3,511
Adj. R-square	0.018	0.022	0.017	0.023

Note: This table presents the effects of uncertainty and CEO power of the relationship between GHC-ET disclosures (GHCET<sub>t</sub>) and stock price crash risk. This study adds two interactions using principal component analysis as described in Section 6.4.5. All independent variables are lagged by one year. Year and industry fixed effects are included. Each parenthesis reports the t-statistic which is based on the standard errors clustered by firms. \*, \*\*, and \*\*\* indicate significance at the 10%, 5%, and 1% levels, respectively. Detailed definition of variables is presented in Appendix C-1.

# 6.4.6 Additional analysis

The performance of a firm's financial markets is often influenced by the environment in which the firm operates and the interaction with that environment (Callen and Fang, 2015; Hilary and Hui, 2009). This study looks at the differences in the political and innovation environments to explore what impact GHC-ET disclosures by firms in different environments can have on stock prices. In addition, the different disclosure motives of companies may also

cause changes in the relationship between ETs-related information disclosure and stock price crash risk.

# 6.4.6.1 Political leadership ideology

The baseline regression results suggest that GHC-ET disclosures increases the risk of future stock price crash of the firm. This study finds that the sample interval of this study covers the period when it was governed by Democrats (2010-2016) and Republicans (2017-2019) respectively, which provides the possibility to explore the effect of political ideology.

The prior studies identify the voluntary disclosures of firms in part to obtain government support (e.g., tax incentives, government contracts or subsidies), to reduce social and political pressure, to compete, etc (Goh et al., 2020). Although both Obama and Trump attach importance to the development of technology, in terms of willingness to invest in science and technology, Obama was willing to devote more financial resources to support research and development (Office of Science and Technology Policy (OSTP)); in addition the American Innovation Strategy since 2009, which systematically deploys and plans for the U.S. science and technology innovation base, corporate innovation, and key areas. However, the OSTP director's vacancy lasted for 2 years, after Trump took office. Therefore, during the Trump administration, GHC-ET disclosures may not bring more government attention and thus may not have the desired effect.

Panel A of Table 6.13 shows the effects of political leadership ideology between Democrat president and Republican president. This study uses a dummy variable to distinguish the different periods, if one it is the period of the Republican administration, i.e., 2017-2019. After including control variables and fixed effects by year and industry, the ETs-related information disclosure is significantly and positively related to stock price crash risk during the Republican administration period (Columns (2) and (4)). However, during the Democrat administration period, the coefficient of  $GHCET_t$  is insignificant (Columns (1) and (3)).

#### 4.6.6.2 Innovation environment

Environment characteristics could be the market in which the firms operate or

geographical conditions including cultural and societal influence (Wejnert, 2002). Silicon Valley is a region in Northern California and a global base for high technology and innovation. When it comes to this vocabulary, investors are often associated with innovation, which contains both the most novel ideas and the most cutting-edge technology. Many scholars have also discussed the positive influence of the external environment on innovation (e.g., Baregheh et al., 2009; Damanpour and Schneider, 2006). At the same time, the superior external technology and innovation environment may also prompt firms to disclose ETs-related information to enhance competition with regional firms. Therefore, I believe that in regions with high levels of technological innovation, firms are more likely to disclose information on ETs because of the information advantage.

In the past 20 years, some of the most disruptive innovations were produced from Silicon Valley. On the one hand, only tech giants are likely to locate their firms in the highly competitive Silicon Valley region. On the other hand, the abundance of resources and innovative environment make investors more willing to trust the success rate of GHC-ET disclosures by these firms. This reduces the potential risk of the high failure rate of ETs as well as reduces the stock price crash risk.

This study sets the firm headquarters in the Silicon Valley area to one and the rest to zero to compare the difference of stock price crash risk between firms in the Silicon Valley area and other areas. Panel B of Table 6.13 shows the effects of innovation environment. After including control variables and fixed effects by year and industry, the emerging technologies-related information disclosure is insignificant for firms in the Silicon Valley area (Columns (1) and (3)). However, the coefficient of  $GHCET_t$  is significantly and positively related to stock price crash risk for firms in other areas (Columns (2) and (4)).

### 6.4.6.3 Speculative disclosure

Next, this study considers the impact of differences in disclosure frequency on the relationship between GHC-ET disclosures and the risk of stock price crash. Lang and Lundholm (2000) find firms significantly increase, especially the most discretionary, disclosure activities prior to issue equity thereby 'hype the stock'. This suggests that the perverse

disclosure behaviour is motivated. Firms have an incentive to use speculative disclosures to achieve objectives, such as hiding bad news (Verrecchia, 1983). This results in different disclosures being perceived by investors as different signals.

While this study has not explored in depth whether the disclosure of information related to the firm's ETs is speculative, the process of applying ETs is not transient. Therefore, this study considers firms that appear only once in our sample as speculative disclosures; in other words, GHC-ET disclosures that occur more than once are considered non-speculative. This study uses a dummy variable to represent whether GHC-ET disclosures are speculative, which means one is speculative disclosure and zero is regular disclosure. Panel C of Table 6.13 shows the effects of speculative disclosure. After including control variables and fixed effects by year and industry, GHC-ET disclosures (GHCET\_Speculative<sub>t</sub>) is significantly and positively related to stock price crash risk for firms with speculative disclosure (Columns (2) and (4)). However, the coefficient of *GHCET\_Regular<sub>t</sub>* is insignificantly related to stock price crash risk for firms with regular disclosure of such information (Columns (1) and (3)).

#### 6.4.6.4 Risk-related information

Finally, this study explores whether the firm discloses information related to ETs along with risk warnings in their initial 8-K filing. If a firm chooses to add a risk description for ETs, then the uncertainty and high risk of ETs is not hidden in its entirety. To answer such a query, this study divides all samples that GHC-ET disclosures into two groups, one with only ETs information but lacking risk-related information, and the other with risk-related descriptions. After risk-related term searching through textual analysis, I manually read each 8-K filing that contains both ETs-related information and risk-related information.<sup>57</sup>

This study uses a dummy variable to represent whether the risk-related information is followed by ETs-related disclosure, which means one is that the firm discloses ETs-related and risk-related information, otherwise zero. Panel D of Table 6.13 shows the comparison between

<sup>&</sup>lt;sup>57</sup> This study uses bag-of-words to search 'risk', 'risky', 'risks', 'failure', 'uncertainty' of each 8-K filing containing GHC ETs-related information.

8-K filings with and without risk-related information. After including control variables and fixed effects by year and industry, GHC-ET disclosures without risk-related information  $(GHCET\_NRisk_t)$  is significantly and positively related to stock price crash risk (Columns (2) and (4)). However, the coefficient of  $GHCET\_YRisk_t$  is insignificantly related to stock price crash risk for firms with risk-related information (Columns (1) and (3)).

Table 6.13 Additional Tests of GHC-ET Disclosures and Stock Price Crash Risk

	$NCSKEW_{t+1}$	NCSKEW <sub>t+1</sub>	DUVOL t+1	DUVOL t+1
Variables	Democrat	Republican	Dama and Duasidant	Republican
	President	President	Democrat President	President
	(1)	(2)	(3)	(4)
GHCET <sub>t</sub>	0.0890	0.3190***	0.0385	0.1182**
	(1.27)	(3.79)	(0.95)	(2.43)
Constant	-0.2655***	-0.1754*	-0.1945***	-0.0972*
	(-3.32)	(-1.75)	(-4.23)	(-1.68)
Controls	YES	YES	YES	YES
Year, Industry FE	YES	YES	YES	YES
Observations	5,947	3,787	5,947	3,787
Adj. R-square	0.014	0.021	0.018	0.022
Panel B. The effects of im	novation environment			
Variables	$NCSKEW_{t+1}$	NCSKEW <sub>t+1</sub>	DUVOL t+1	DUVOL t+1
	Silicon Valley area	Other areas	Silicon Valley area	Other areas
	(1)	(2)	(3)	(4)
GHCET <sub>t</sub>	0.0041	0.2143***	0.0020	0.0819**
	(0.03)	(3.69)	(0.02)	(2.44)
Constant	-0.1770	-0.2261***	-0.2013*	-0.1436***
	(-0.88)	(-3.44)	(-1.77)	(-3.78)
Controls	YES	YES	YES	YES
Year, Industry FE	YES	YES	YES	YES
Observations	1,040	8,694	1,040	8,694
Adj. R-square	0.001	0.017	0.004	0.023
Panel C. The effects of sp	eculative disclosure (Speci	ulative: N=51)		
Variables	NCSKEW <sub>t+1</sub>	NCSKEW <sub>t+1</sub>	DUVOL <sub>t+1</sub>	DUVOL <sub>t+1</sub>
	Regular	Speculative	Regular	Speculative
	disclosure	disclosure	disclosure	disclosure
	(1)	(2)	(3)	(4)
GHCET_Regular <sub>t</sub>	0.1577		0.0288	
	(0.90)		(0.29)	
GHCET_Speculative <sub>t</sub>		0.1973***		0.0842**
		(3.40)		(2.51)
Constant	-0.7151***	-0.1678**	-0.4479***	-0.1214***
	(-2.78)	(-2.56)	(-3.06)	(-3.20)
Controls	YES	YES	YES	YES
Year, Industry FE	YES	YES	YES	YES
Observations	9,734	9,734	9,734	9,734
Adj. R-square	0.007	0.017	0.012	0.020

Panel D. The disclosure of ETs with risk-related words (YRisk: N=35)							
Variables	$NCSKEW_{t+1}$	$NCSKEW_{t+1}$	DUVOL t+1	$DUVOL_{t+1}$			
	With risk-related	No risk-related	With risk-	No risk-related			
	words	words	related words	words			
	(1)	(2)	(3)	(4)			
GHCET_YRisk <sub>t</sub>	-0.1820		-0.1057				
	(-1.04)		(-1.05)				
GHCET_NRisk <sub>t</sub>		0.2227***		0.0911***			
		(3.98)		(2.82)			
Constant	-0.2281***	-0.2228***	-0.1538***	-0.1516***			
	(-3.66)	(-3.58)	(-4.29)	(-4.22)			
Controls	YES	YES	YES	YES			
Year, Industry FE	YES	YES	YES	YES			
Observations	9,734	9,734	9,734	9,734			
Adj. R-square	0.015	0.017	0.020	0.021			

Note: This table presents the subsample analysis of the relationship between GHC-ET disclosures (GHCETt) and stock price crash risk. The details of each subsample analysis as described in Section 6.4.6. Panel A shows the effect of political leadership ideology. Panel B shows the effects of innovation environment and Panel C shows the effects of speculative disclosure and Panel D shows the difference of GHC-ET disclosures and stock price crash risk when firms' initial GHC 8-K filings have risk-related words. All independent variables are lagged by one year. Control variables and year and industry fixed effects are included. Each parenthesis reports the t-statistic which is based on the standard errors clustered by firms. \*, \*\*, and \*\*\* indicate significance at the 10%, 5%, and 1% levels, respectively. Detailed definition of variables is presented in Appendix C-1.

#### 6.5 Conclusion

This study examines the relationship between GHC-ET disclosures and stock price crash risk. Using the initial 8-K filing containing item 7.01 of US firms during 2010 to 2019, this study finds that firms disclose GHC-ET with higher stock price crash risk. The significant and positive relationships are only observed when firms disclose ETs in phase one (innovation trigger) and three (trough of disillusionment) but reverse if the ETs belong to phase five (plateau of productivity) of the GHC. The findings are consistent after several robustness checks including an alternative measure of crash risk, added additional controls, addressed endogeneity problems, and the investigation of dynamic effects. Two channels show that the relationship between the disclosure of ETs and stock price crash risk is pronounced when the short-term investor reaction or CEO overconfidence increases. This study also finds that the relationship between GHC-ET disclosures and stock price crash risk is pronounced when the firm-specific uncertainty of future performance is higher, or CEO power is stronger.

This study has implications for the literature of voluntary disclosure and its effects for a firm's performance in the capital market. Specifically, the research cautions managers to not overlook the uncertainty and high risk associated with ETs while using information about them to attract investors. In addition, the findings also extend knowledge of stock price crash risk and its determinants. Opportunity often comes with risk. The conclusion of this study provides new insights for investors to analyse firms' voluntary disclosures for investment decisions.

# **Chapter 7. Conclusion**

#### 7.1 Introduction

This chapter concludes the whole thesis. Section 7.2 summaries the research findings, especially for the three empirical chapters. Section 7.3 shows the implications for investors and managers. Section 7.4 discusses some research limitations while Section 7.5 provides further research recommendations.

### 7.2 Research findings

This thesis investigates the market reactions to corporate disclosure of GHC-ET. Whether investors will overreact to such information immediately and whether their attitudes will change after the disclosures are the main research questions. This thesis further explores the reasons for the change in investors' attitudes towards ETs and the role of ETs disclosure by firms on the risk of stock price crashes. The sample includes all firms registered on EDGAR during 2010 to 2019. Based on textual analysis, this thesis searches 663,897 8-K filings to find GHC-ET disclosures. The GHC provides an annual target-oriented dataset of ETs, which is a source for the dictionary in this thesis. The research findings are summarised in six dimensions.

### 7.2.1 Voluntary disclosure of emerging technologies

While the number of high-frequency Form 8-K disclosures has declined as the firm's communication channels with investors have increased, the number and percentage of voluntary disclosure items disclosed has been increasing each year. This thesis, firstly, finds that US firms have increased the extent of voluntary disclosures regardless of what they contain (Column (2) in Table 3.2). Compared to 2010, the number of 8-K filings by all US firms that included Item 7.01 nearly doubled in 2019. However, by searching the main content and appendices of each 8-K filing, I find that firms' focus on, and GHC-ET disclosures are not similarly characterised. In other words, firms have not increased their disclosure of information related to ETs in response to technological advances or the advancing wave of ETs. Therefore,

the fact that firms make GHC-ET disclosures is not due to the external environment, which provides the basis for this thesis to explore market responses.

### 7.2.2 Market reactions to disclosures of emerging technologies

Using event study, I first investigate the immediate market reaction to ETs disclosure. During the sample period of this thesis, the firm's disclosure of GHC-ET information causes investor overreaction, reflecting in the 1.64% of CAR (-3, +3) and 1.80% of BHAR (-3, +3). The results obtained by the event study are intuitive, but the causality of market reaction caused by the disclosure of ETs is worth confirming. After controlling for firm financial characteristics, I find significant and positive results by regressing the immediate market reaction (measured by CAR (-3, +3) (or CAR (-5, +5)) and the GHC-ET disclosure (measured by a dummy variable). To reduce the effect of noise, I remove other events around the event windows. The results are also robust when I use the Fama-French three-factor model and the Carhart Fourfactor model to estimate the expected returns. The event study method and empirical results validate investors' novelty preference. In other words, investors ignore the disadvantages of ETs that are inherently high-risk and high-failure rates and view such disclosures as positive signals. However, the investor overreaction was short-lived. I examine CAR and BHAR 30 trading days after the disclosure date using the event study method and find a significant negative reaction.

I also examine the differences between firms with different institutional holdings and analyst attention. When institutional ownership is low, the market reacts positively immediately, suggesting that experienced institutional investors have more information and are therefore less susceptible to ETs disclosures. However, the delayed reaction of institutional investors is negative. Moreover, firms with fewer analysts have a positive immediate market reaction, while firms with more analysts have a negative delayed market reaction. This validates my expectation that the managers of firms with fewer analysts is bolder in disclosing information even in highly uncertain situations. I also validate the importance of the information environment. When information asymmetry is high, investors pay more attention to information about ETs.

# 7.2.3 Market reaction reversal due to insider selling

Similar to Cheng et al. (2019) who examine the market reaction to firms' blockchain-related disclosure during the bitcoin mania period, I also notice a reversal in the delayed market reaction within 30 trading days after the ETs disclosure. However, there is no in-depth exploration of what causes the reversal of market reaction in the study of Cheng et al. (2019). Two perspectives can explain the change in investor reaction after ETs disclosure, one is the correction of overreaction behaviour and the other is due to the impact of other events. Marks (2011) argues that most investors judge a firm's share price movement by positive signals and that this use of first order thinking to make investment decisions is emotional. Therefore, it is reasonable for investors to react negatively to high uncertainty ETs-related information in the long term if they have enough information and time to judge the purpose of corporate disclosures. If investors discover a lack of follow-through or insider selling by firms that make ETs disclosures, then investors may question the true purpose of the GHC-ET disclosures.

To explore the reason of market reaction reversal, I rerun the regression using a sample without insider selling within 60 trading days after the GHC-ET disclosures. The results are insignificant while the results are significant and negative when regressing only those samples that had insider selling.

### 7.2.4 Market reactions to disclosures of emerging technologies at different phases

Based on the differences in the characteristics of ETs that are at different market expectations, I examine how investors react differently to firms disclosing that they are at different GHC phases. There is a voice that suggests that technologies in their infancy are riskier, and that after a period of market speculation, investors have more time and opportunity to judge their true viability. For example, the firm's disclosure in its 8-K filing that it will use 5G or 7G to boost productivity will bring very different results.

To compare the difference of the market reactions, I estimate the CARs and BHARs separately for each phase of ETs disclosure. Although I receive positive and significant immediate market reaction for the disclosure ETs of GHC phase one, two, and three (negative and significant delayed market reaction for GHC phase one and two), the rest of the results are

negligible. For disclosures in ETs at phase one, the CAR (-3, +3) is 2.15 % (BHAR (-3, +3) is 2.59%) higher than the overall sample CAR (-3, +3) (1.64%) (BHAR (-3, +3) (1.80%)). In the long-term, for disclosures in ETs at phase two, the CAR (+3, +30) is -2.24 % (BHAR (+3, +30) is -2.52%) higher than the overall sample CAR (+3, +30) (-1.05%) (BHAR (+3, +30) (-1.29%)).

After controlling for firm financial characteristics, I find significant and positive results by regressing the immediate market reaction (measured by CAR (-3, +3) (or CAR (-5, +5)) and the ETs disclosure (measured by a dummy variable) only for ETs disclosure of GHC phase one and two. Further, the negative results are only found for the ETs disclosure of GHC phase two. Overall, the results show that investors only overreact to ETs at the phase of innovation trigger (Phase one) and the phase of the peak of inflated expectation (Phase two).

# 7.2.5 Overselling the emerging technologies-related information

My thesis investigates whether and how investors react differently to GHC-ET disclosures details (e.g., the intensity of disclosures in each 8-K, the frequency of 8-Ks containing ETs per year, and disclosures indicating different stages of technological development). The exposure effect explains that investors tend to trust and prefer familiar items (Titchener, 1910), implying that the intensity or frequency of a firm's disclosures can have an impact. Therefore, if firms choose to excessively increase the intensity or frequency of disclosure, although it will reduce information asymmetry, it may also be at risk of overselling for novelty ETs.

The results of the immediate negative market reaction to the intensity and frequency of ETs disclosure support the overselling argument. While investors show an overly positive reaction to ETs disclosures in the short-term, this reaction is only captured when firms make low-intensity and low-frequency GHC-ET disclosures. With respect to the phase of GHC development for each technology, this thesis finds that investors react more positively to ETs-related information in the short-term, but negatively after the disclosures, during the 'innovation trigger' and 'peak expectation inflation' phases.

# 7.2.6 The disclosure of emerging technologies and stock price crash risk

This thesis follows Kim et al. (2014) to explore whether ETs-related information, disclosed as voluntary, affects a firm's stock price crash risk. The baseline regression results indicate that the GHC-ET disclosure increases a firm's stock price crash risk one year later. Firms increase their stock price crash risk by 3.64% (2.62%) (NCSKEW (DUVOL)) if they disclose ETs-related information in their initial 8-K filing. In addition, I compare the differences in firms' GHC-ET disclosures at different phases of GHC. Specifically, firms that disclose ETs in GHC phase one (Innovation Trigger) and phase three (Disillusionment Trough) have a higher risk of stock price crash. However, if firms disclose these ETs in phase five (Productivity Plateau), the risk of a stock price crash is reduced. I also find that the positive relationship between the GHC-ET disclosures and the risk of stock price crashes is pronounced when the level of CEO overconfidence is high, and investors present an overreaction in the short term to this type of information.

### 7.3 Implications

### 7.3.1 For managers

My thesis implies that understanding and focusing on ETs can help managers to make better decisions, enhance the firm's competitiveness, address potential risks, and satisfy the needs of stakeholders. In detail, ETs may have a significant impact on the firm's future growth. Management needs to be aware of these impacts and make informed investment decisions based on the needs of stakeholders, especially shareholders. If managers fail to realise the opportunities and challenges brought by the development of ETs in a timely manner, firms will not only miss the opportunities to develop but may also be eliminated from the market. In addition, my thesis identifies the ETs-related information needed from investors but their enthusiasm is temporary if the firm lacks subsequent disclosure or substantive action on ETs. Further, managers need to consider disclosure costs while assessing and managing ETs risks. If the cost of disclosure outweighs the benefits derived from the GHC-ET disclosures, then such disclosures need to be carefully considered.

#### 7.3.2 For investors

For investors, information related to ETs can assess a firm's ability to innovate and its value, as well as provide a better understanding of the firm's operations. ETs can have a significant impact on a firm's operations, competitive position, and future growth. Understanding how firms are utilising or responding to ETs can help investors make more informed investment decisions. If a firm is able to successfully utilise ETs to improve efficiency and develop new products or services, then this may increase the value of the firm. In addition, understanding how a firm applies ETs can help investors predict industry trends. However, any ET is characterised by high risk and a high failure rate. Investors obtaining corporate disclosure about GHC-ET should assess whether the firm's GHC-ET disclosures are speculative because of the consequent potential for a stock price crash.

#### 7.4 Limitations

### 7.4.1 Effectiveness of event study

The event study method is a method used in financial economics to assess the impact of a particular event on a firm's stock return. However, like all research methods, event study has its limitations. Firstly, the event study method is based on the strong efficient market hypothesis, which states that all information (both public and unpublished) is immediately and completely reflected in stock prices. However, this assumption does not always hold true in the US capital markets. For example, some information may not be immediately reflected in stock prices, or there may be heterogeneity in how market participants interpret information, which may affect the results of the event study methodology.

Second, in many cases, it may be difficult to determine precisely when an event occurs. For example, a firm may have used other avenues to express that the firm will apply an ET or a business that involves an ET prior to the release of an 8-K filing containing ET-related information, or the market may have anticipated that the firm was going to make GHC-ET disclosures (e.g., a firm may have made a Blockchain-related disclosure during the Bitcoin mania period), which would complicate defining the event period and may lead to inaccurate results.

### 7.4.2 Information needs and concerns of investors

Investors need access to a variety of information about their investment objectives in order to make informed investment decisions. The main sources of this information include public company reports, news articles, analyst reports, and reports from independent research organisations. Prior research has confirmed that investors need detailed financial information to help them understand a firm's financial condition, profitability, liquidity and financial risk. They also need information about the firm's management, strategic objectives, competitive environment, and the firm's long-term growth plans. Market and macroeconomic information are also essential. Further, with the theme of sustainability, social responsibility and corporate ethics information is also part of investors' focus. The study in this thesis is based on the fact that investors pay enough attention to the voluntary disclosures made by firms. I attempted to use the information provided by the EDGAR log file dataset about Internet search traffic through SEC.gov for the purpose of inferring user access statistics. However, the only way to confirm that investors are paying attention to the firm's 8-K filings is also unavailable due to missing data from the EDGAR log files for 2017 through 2020. Therefore, whether and what types of investors pay attention to the high frequency of voluntary disclosures (i.e., GHC-ET disclosures) are difficult to answer clearly.

#### 7.5 Further research

Cheng et al. (2019) categorise firms that disclose blockchain-related information into speculative firms and existing firms. The main difference between the two groups is the disclosures indicate whether the firm has a significant commitment to blockchain technology or a meaningful track record in blockchain technology. My thesis extends the scope of ETs beyond the fintech sector. It should be interesting to track firms' behaviour after the GHC-ET disclosures. For example, there are two possibilities for firms to describe ETs. On the one hand, after textual analysis, the information related to ETs could be that the firm is going to acquire or merge with firms involved in that ET business. This type of information tends to contain more details about the ET. On the other hand, the firm may be describing the uncertainty that a certain ET development brings to the industry in which it operates. This type of information tends to be vague.

The story after GHC-ET disclosures could be explored to compare the difference of market reactions in the long-term between firms with detailed and vague ETs-related information. What actions related to ETs have the firm carried out after making GHC-ET disclosures, e.g., has it increased disclosure of details, has it increased R&D investment, has it convened a general meeting of shareholders to discuss investments and financing related to the disclosed GHC-ET? The follow-up research may provide a clearer picture of why firms make ETs disclosures. In addition, future research could explore what types of firms (at what stage) are more inclined to the GHC-ET disclosures, or what personality traits make managers ET fanatics.

Investors can be categorised into different types based on their investment objectives, investment strategy, risk tolerance, capital size and investment timeframe. There are significant differences between retail investors and institutional investors in terms of investment size, investment strategy, ability to access information and decision-making. Retail investors' investment strategies are usually relatively simple, based primarily on fundamental analysis, technical analysis, or personal experience and intuition. Institutional investors, on the other hand, have more complex and diversified investment strategies. While my thesis explores the relationship between the proportion of firms' institutional investors affecting GHC-ET disclosures and market reactions in a grouped regression, it does not provide a detailed comparison of the differences in the reactions of different types of investors to GHC-ET disclosures. Future research could explore how different types of investors' attitudes towards information related to ETs and reactions to corporate disclosures differ in the short and long term.

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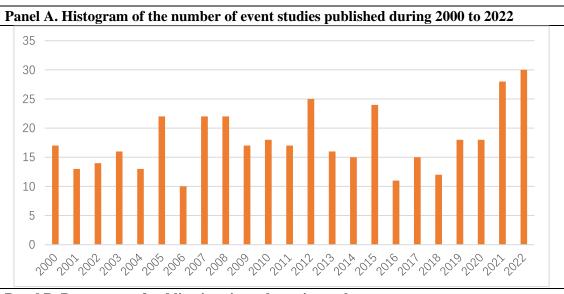
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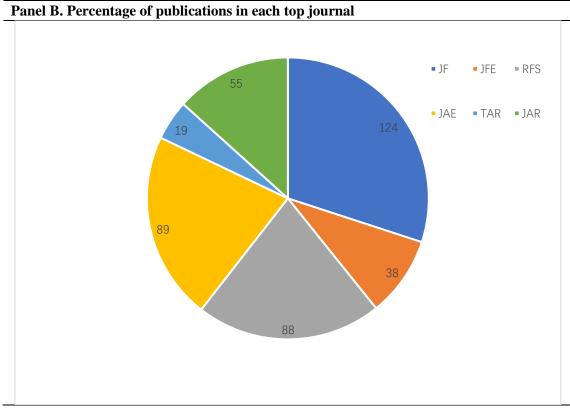
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## **Appendices**

### A-1. Number of Event Studies Published in The Top Major Finance and Accounting Journals During 2000 to 2022





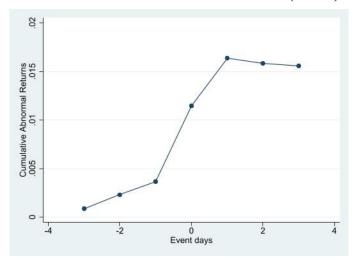
Panel C. The number of event studies published in each top journal by year							
Year	JF	JFE	RFS	TAR	JAE	JAR	Total
2000	6	2	2	3	1	3	17
2001	6	1	3	1	0	2	13
2002	5	0	1	4	1	3	14
2003	11	0	2	2	0	1	16
2004	8	0	0	2	0	3	13
2005	12	4	0	3	0	3	22
2006	7	1	0	1	0	1	10
2007	11	2	6	0	2	1	22
2008	7	1	4	3	4	3	22
2009	2	1	7	4	2	1	17
2010	6	3	5	3	0	1	18
2011	0	4	4	4	2	3	17
2012	7	3	6	6	0	3	25
2013	6	0	3	5	0	2	16
2014	3	2	4	6	0	0	15
2015	2	3	8	8	1	2	24
2016	4	1	3	1	0	2	11
2017	0	2	5	4	1	3	15
2018	4	1	2	3	1	1	12
2019	3	1	5	7	0	2	18
2020	6	1	4	2	1	4	18
2021	6	2	8	6	2	4	28
2022	2	3	6	11	1	7	30
Total	124	38	88	89	19	55	413

Panel D. Main research themes and papers in top journals					
Research themes	Papers in top journals				
Corporate mergers and acquisitions	Bargeron et al. (2008), Custódio and Metzger (2013), El-Khatib et al. (2015), Kang et al. (2000), Kilian and				
	Schindler (2014), Mitchell et al. (2004), Serdar Dinc and Erel (2013)				
Corporate governance and	Cuñat et al. (2012), Falato et al. (2014), Fich and				
top management team	Shivdasani (2006), Field et al. (2013), Hoechle et al.				
	(2012), Kalyta (2009), Morgan and Poulsen (2001),				
	Yermack (2006)				
Capital markets and	Bradley et al. (2003), Brav (2000), Corwin et al.,				
investor characteristics	(2004), Datta et al. (2000), Drake et al. (2012), Falato et				
	al. (2021), Fischer and Stocken (2014), Hsu et al.				
	(2010), Kaplan et al. (2013), Kecskes (2007),				
	Malmendier and Shanthikumar (2017), Mian and				
	Sankaraguruswamy (2012), Shue and Townsend (2021)				
Legal and regulatory	Ali and Kallapur (2001), Bailey et al., (2003), Blouin et				
events	al. (2011), Chakrabarti and Pattison, (2019), Carnes et				
	al. (2019), Gopalan et al. (2014), Khurana and Wang				
	(2019), Kim and Klein (2017), Larcker et al. (2011),				
	Siegel (2005), Silvers (2016)				
Specific events and	Acemoglu et al. (2016), Black and Kim (2012), Dyck et				
periods	al. (2021), Gao (2011), Haddad et al. (2021), Hochberg				
	et al. (2009), Nguyen and Nielsen (2010), Piotroski and				
	Srinivasan (2008), Shkilko and Sokolov (2020)				

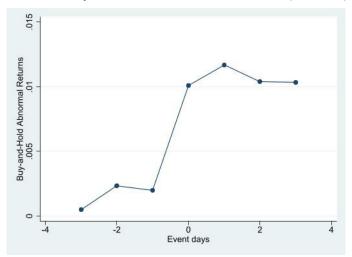
Note: This table reports the number of event studies published in the top major finance (The Journal of Finance, Journal of Financial Economics, Review of Financial Studies) and accounting (The Accounting Review, Journal of Accounting and Economics, Journal of Accounting Research) journals during 2000 to 2022. Panel A shows the histogram of the number of event studies published during 2000 to 2022, Panel B shows the percentage of publications in each top journal. Panel C shows the number of event studies published in each top journal by year while Panel D presents the five research themes which most frequently use event study methods and the main papers published in top journals.

#### A-2. CAR and BHAR over Event Window (-3, +3) Based on the Fama-French Three-Factor Model

Panel A. Cumulative abnormal returns (CARs)



Panel B. Buy-and-hold abnormal returns (BHARs)



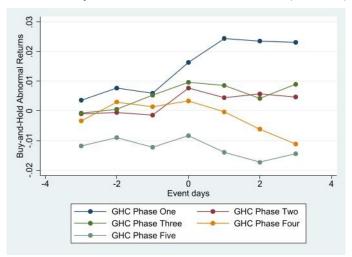
Note: This figure shows the cumulative abnormal returns (CARs) and the buy-and-hold abnormal returns (BHARs) from three trading days before the event date to three trading days after the event date. The event date is the 8-K filing date of US firms shown on the EDGAR. The expected stock returns are estimated by the Fama-French three-factor model. The estimation window is (-210, -10).

#### A-3. CAR and BHAR over Event Window (-3, +3) Based on the Fama-French Three-Factor Model by Phase

Solution of the control of the contr

Panel A. Cumulative abnormal returns (CARs)

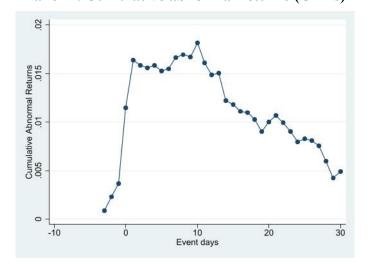
Panel B. Buy-and-hold abnormal returns (BHARs)



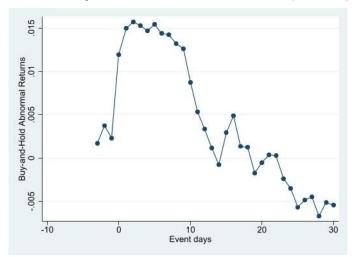
Note: This figure shows the cumulative abnormal returns (CARs) and the buy-and-hold abnormal returns (BHARs) by the GHC phase (Phase one: Innovation trigger, Phase two: Peak of inflated expectations, Phase three: Trough of disillusionment, Phase four: Slope of enlightenment, Phase five: Plateau of productivity) from three trading days before the event date to three trading days after the event date. The event date is the 8-K filing date of US firms shown on the EDGAR. The expected stock returns are estimated by the Fama-French three-factor model. The estimation window is (-210, -10).

#### A-4. CAR and BHAR over Event Window (-3, +30) Based on the Fama-French Three-Factor Model

Panel A. Cumulative abnormal returns (CARs)



Panel B. Buy-and-hold abnormal returns (BHARs)



Note: This figure shows the cumulative abnormal returns (CARs) and the buy-and-hold abnormal returns (BHARs) from three trading days before the event date to thirty trading days after the event date. The event date is the 8-K filing date of US firms shown on the EDGAR. The expected stock returns are estimated by the Fama-French three-factor model. The estimation window is (-210, -10).

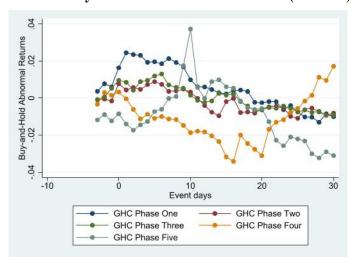
#### A-5. CAR and BHAR over Event Window (-3, +30) Based on the Fama-French Three-Factor Model by Phase

SO. SO. So. For the following state of the fo

Panel A. Cumulative abnormal returns (CARs)

Panel B. Buy-and-hold abnormal returns (BHARs)

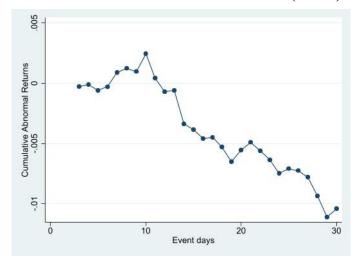
GHC Phase Five



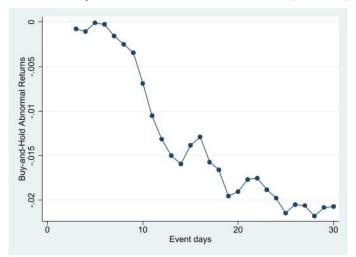
Note: This figure shows the cumulative abnormal returns (CARs) and the buy-and-hold abnormal returns (BHARs) by the GHC phase (Phase one: Innovation trigger, Phase two: Peak of inflated expectations, Phase three: Trough of disillusionment, Phase four: Slope of enlightenment, Phase five: Plateau of productivity) from three trading days before the event date to thirty trading days after the event date. The event date is the 8-K filing date of US firms shown on the EDGAR. The expected stock returns are estimated by the Fama-French three-factor model. The estimation window is (-210, -10).

#### A-6. CAR and BHAR over Event Window (+3, +30) Based on the Fama-French Three-Factor Model

Panel A. Cumulative abnormal returns (CARs)



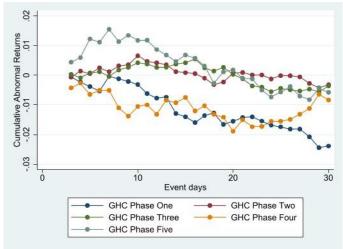
Panel B. Buy-and-hold abnormal returns (BHARs)



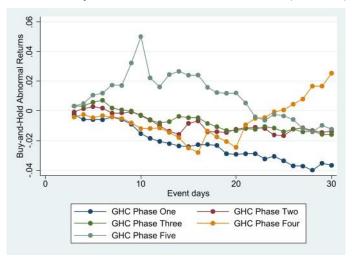
Note: This figure shows the cumulative abnormal returns (CARs) and the buy-and-hold abnormal returns (BHARs) from three trading days after the event date to thirty trading days after the event date. The event date is the 8-K filing date of US firms shown on the EDGAR. The expected stock returns are estimated by the Fama-French three-factor model. The estimation window is (-210, -10).

#### A-7. CAR and BHAR over Event Window (+3, +30) Based on the Fama-French Three-Factor Model by Phase

Panel A. Cumulative abnormal returns (CARs)



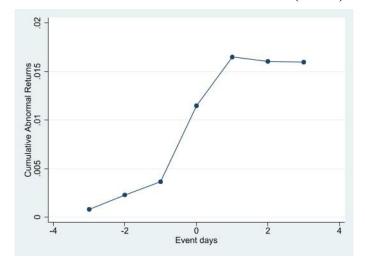
Panel B. Buy-and-hold abnormal returns (BHARs)



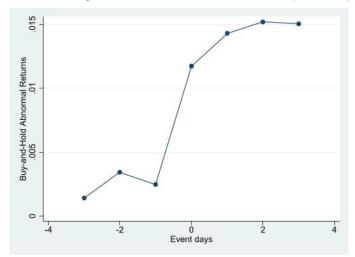
Note: This figure shows the cumulative abnormal returns (CARs) and the buy-and-hold abnormal returns (BHARs) by the GHC phase (Phase one: Innovation trigger, Phase two: Peak of inflated expectations, Phase three: Trough of disillusionment, Phase four: Slope of enlightenment, Phase five: Plateau of productivity) from three trading days after the event date to thirty trading days after the event date. The event date is the 8-K filing date of US firms shown on the EDGAR. The expected stock returns are estimated by the Fama-French three-factor model. The estimation window is (-210, -10).

# A-8. CAR and BHAR over Event Window (-3, +3) Based on the Carhart Four-Factor Model

Panel A. Cumulative abnormal returns (CARs)



Panel B. Buy-and-hold abnormal returns (BHARs)



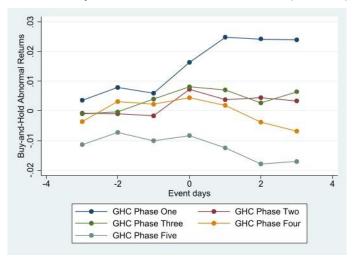
Note: This figure shows the cumulative abnormal returns (CARs) and the buy-and-hold abnormal returns (BHARs) from three trading days before the event date to three trading days after the event date. The event date is the 8-K filing date of US firms shown on the EDGAR. The expected stock returns are estimated by the Carhart four-factor model. The estimation window is (-210, -10).

## A-9. CAR and BHAR over Event Window (-3, +3) Based on the Carhart Four-Factor Model by Phase

SO. Sunning Medium Setting Set

Panel A. Cumulative abnormal returns (CARs)

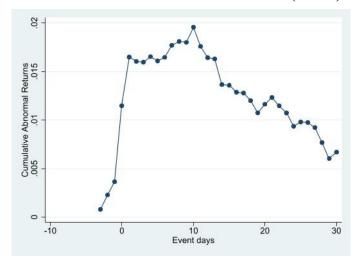
Panel B. Buy-and-hold abnormal returns (BHARs)



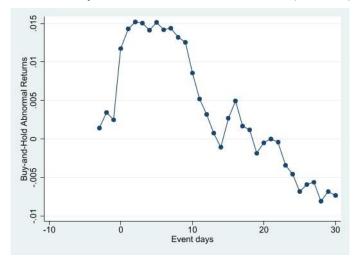
Note: This figure shows the cumulative abnormal returns (CARs) and the buy-and-hold abnormal returns (BHARs) by the GHC phase (Phase one: Innovation trigger, Phase two: Peak of inflated expectations, Phase three: Trough of disillusionment, Phase four: Slope of enlightenment, Phase five: Plateau of productivity) from three trading days before the event date to three trading days after the event date. The event date is the 8-K filing date of US firms shown on the EDGAR. The expected stock returns are estimated by the Carhart four-factor model. The estimation window is (-210, -10).

# A-10. CAR and BHAR over Event Window (-3, +30) Based on the Carhart Four-Factor Model

Panel A. Cumulative abnormal returns (CARs)



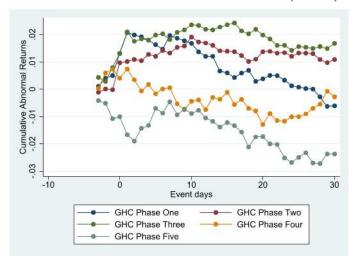
Panel B. Buy-and-hold abnormal returns (BHARs)



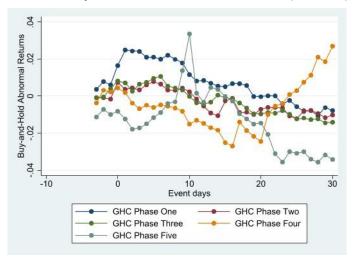
Note: This figure shows the cumulative abnormal returns (CARs) and the buy-and-hold abnormal returns (BHARs) from three trading days before the event date to thirty trading days after the event date. The event date is the 8-K filing date of US firms shown on the EDGAR. The expected stock returns are estimated by the Carhart four-factor model. The estimation window is (-210, -10).

# A-11. CAR and BHAR over Event Window (-3, +30) Based on the Carhart Four-Factor Model by Phase

Panel A. Cumulative abnormal returns (CARs)



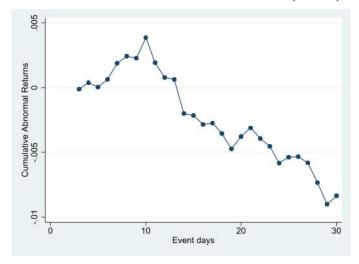
Panel B. Buy-and-hold abnormal returns (BHARs)



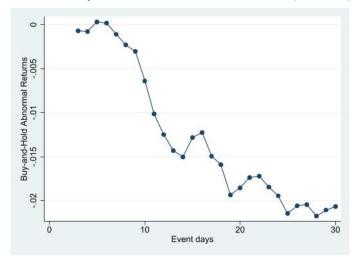
Note: This figure shows the cumulative abnormal returns (CARs) and the buy-and-hold abnormal returns (BHARs) by the GHC phase (Phase one: Innovation trigger, Phase two: Peak of inflated expectations, Phase three: Trough of disillusionment, Phase four: Slope of enlightenment, Phase five: Plateau of productivity) from three trading days before the event date to thirty trading days after the event date. The event date is the 8-K filing date of US firms shown on the EDGAR. The expected stock returns are estimated by the Carhart four-factor model. The estimation window is (-210, -10).

## A-12. CAR and BHAR over Event Window (+3, +30) Based on the Carhart Four-Factor Model

Panel A. Cumulative abnormal returns (CARs)



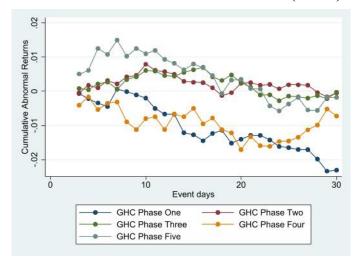
Panel B. Buy-and-hold abnormal returns (BHARs)



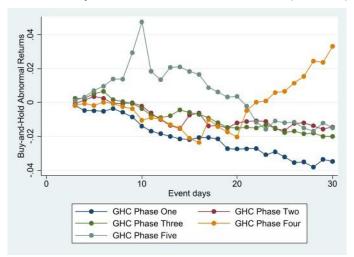
Note: This figure shows the cumulative abnormal returns (CARs) and the buy-and-hold abnormal returns (BHARs) from three trading days after the event date to thirty trading days after the event date. The event date is the 8-K filing date of US firms shown on the EDGAR. The expected stock returns are estimated by the Carhart four-factor model. The estimation window is (-210, -10).

# A-13. CAR and BHAR over Event Window (+3, +30) Based on the Carhart Four-Factor Model by Phase

Panel A. Cumulative abnormal returns (CARs)

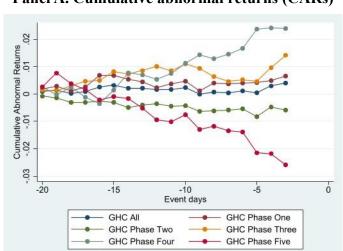


Panel B. Buy-and-hold abnormal returns (BHARs)



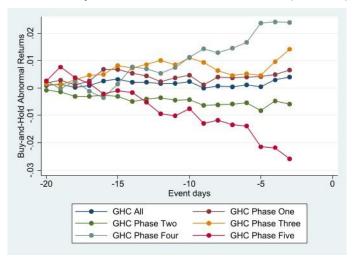
Note: This figure shows the cumulative abnormal returns (CARs) and the buy-and-hold abnormal returns (BHARs) by the GHC phase (Phase one: Innovation trigger, Phase two: Peak of inflated expectations, Phase three: Trough of disillusionment, Phase four: Slope of enlightenment, Phase five: Plateau of productivity) from three trading days after the event date to thirty trading days after the event date. The event date is the 8-K filing date of US firms shown on the EDGAR. The expected stock returns are estimated by the Carhart four-factor model. The estimation window is (-210, -10).

### A-14. CAR and BHAR over Event Window (-20, -3) Based on the Fama-French Three-Factor Model



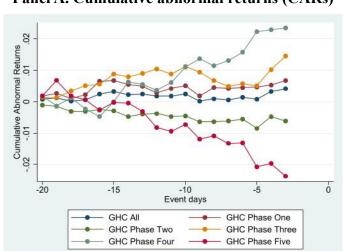
Panel A. Cumulative abnormal returns (CARs)

Panel B. Buy-and-hold abnormal returns (BHARs)



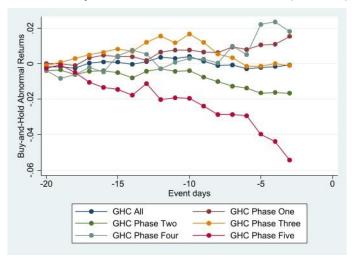
Note: This figure shows the cumulative abnormal returns (CARs) and the buy-and-hold abnormal returns (BHARs) of the whole sample and by the GHC phase (Phase one: Innovation trigger, Phase two: Peak of inflated expectations, Phase three: Trough of disillusionment, Phase four: Slope of enlightenment, Phase five: Plateau of productivity) from twenty trading days before the event date to three trading days before the event date. The event date is the 8-K filing date of US firms shown on the EDGAR. The expected stock returns are estimated by the Fama-French three-factor model. The estimation window is (-210, -10).

## A-15. CAR and BHAR over Event Window (-20, -3) Based on the Carhart Four-Factor Model



Panel A. Cumulative abnormal returns (CARs)

Panel B. Buy-and-hold abnormal returns (BHARs)



Note: This figure shows the cumulative abnormal returns (CARs) and the buy-and-hold abnormal returns (BHARs) of the whole sample and by the GHC phase (Phase one: Innovation trigger, Phase two: Peak of inflated expectations, Phase three: Trough of disillusionment, Phase four: Slope of enlightenment, Phase five: Plateau of productivity) from twenty trading days before the event date to three trading days before the event date. The event date is the 8-K filing date of US firms shown on the EDGAR. The expected stock returns are estimated by the Carhart four-factor model. The estimation window is (-210, -10).

### **B-1.** Variables Definition of Chapter 5

Variables	Definitions
<b>Dependent Variables</b>	
CAR_MM $(d_1, d_2)$	Cumulative abnormal returns are calculated based on the Market Model. I have used several periods and each period represents different days. The short-term periods are (-3, +3) and (-5, +5) while long-term periods are (+4, +60) and (+6, +60) where + (-) indicates the number of days after (before) the initial 8-K containing Item 7.01 disclosure.
CAR_FF3 $(d_1, d_2)$	Cumulative abnormal returns calculated based on the Fama-French three factor model. I have used several periods and each period represents different days. The short-term periods are $(-3, +3)$ and $(-5, +5)$ while long-term periods are $(+4, +60)$ and $(+6, +60)$ where $+$ (-) indicates the number of days after (before) the initial 8-K containing Item 7.01 disclosure.
$CAR\_C4 (d_1, d_2)$	Cumulative abnormal returns calculated based on the Carhart four-factor model. I have used several periods and each period represents different days. The short-term periods are (-3, +3) and (-5, +5) while long-term periods are (+4, +60) and (+6, +60) where + (-) indicates the number of days after (before) the initial 8-K containing Item 7.01 disclosure.
<b>Independent Variable</b>	S
$GHCET_{i,t}$	Dummy variable: one if firm $i$ discloses GHC in the initial 8-K containing Item 7.01 in year $t$ , 0 otherwise.
GHCET_Phase <sub>j</sub> ,i,t	A dummy variable for each phase, represents which phase $j$ (from one to five) of the ET in GHC disclosed by firms $i$ in year $t$ .
Intensity <sub>i,t</sub>	The number of ET-related words in the initial 8-K filling containing the Item 7.01 of firm $i$ in year $t$ .
Frequency <sub>i,t</sub>	The number of 8-Ks containing GHC-ET followed by the initial GHC 8-K for firms <i>i</i> in year <i>t</i> .
<b>Control Variables</b>	<u> </u>
RET <sub>i,t</sub>	The annualized variance of daily returns in the preceding month.
$Turnover_{i,t}$	The average daily share turnover, which is the number of traded shares divided by the total number of shares outstanding.
Firm Size <sub>i,t</sub>	The logarithm of the value of market equity, which is defined as the number of shares outstanding times the stock price from the end of previous year.
$ROA_{i,t}$	The profitability of firms, which is defined as the net income divided by total assets.
$BM_{i,t}$	The logarithm of book-to-market ratio from the end of the previous year. The book value from the firm's annual report known as the end of the previous fiscal year and the market value from the end of the previous year are used.
$Age_{i,t}$	The years of the firm's IPO is calculated by subtracting the IPO year from the current year.
$FCF_{i,t}$	The firm's net cash flow from financing activities scaled by total assets.

The firm's net cash flow from operating activities scaled by total assets. OCF<sub>i,t</sub>  $FCI_{i,t}$ 

The firm's financial constraint index developed by Hadlock and Pierce

(2010).

I follow Baker and Wurgler (2006; 2007) to measure the investor Investor\_sentiment<sub>i.t</sub>

sentiment using principal component of the five standardized sentiment

8K\_Readability<sub>i,t</sub> The readability is measured by the Fog index.

8K\_Tone<sub>i,t</sub> The ratio of Loughran-McDonald positive words minus negative words

to Loughran-McDonald positive words plus negative words.

ANA<sub>i,t</sub> Dummy variable: one if the number of analysts that issue earnings

forecast, in a given year, is larger than the sample mean, zero otherwise.

Dummy variable: one if the firms' institutional investors ownership, in INSTOWN<sub>i,t</sub>

a given year, is larger than the sample mean, zero otherwise.

Idiosyncratic volatility is the standard deviation of the residuals  $(\epsilon_t)$ IdioV<sub>i,t</sub>

the following regression  $r_t = \alpha + \beta_1 HML_t + \beta_2 SMB_t +$  $\sum_{i=-3}^{3} \gamma_i r_{m,t-1} + \epsilon_t$  (Ang et al. (2006)), where  $r_t$  is the daily stock return,  $r_{m,t}$  is the market return, and  $HML_t$  and  $SMB_t$  are the daily value premium and size factors from the Fama-French three-factor model. One if the firms' idiosyncratic volatility, in a given year, is larger

than the sample mean, zero otherwise.

Dummy variable: one if the disclosure of GHC GHC-ET words belong Fintech<sub>i,t</sub>

to fintech firms, zero otherwise.

Quick Adoption<sub>i,t</sub> Dummy variable: one for firms that need less than ten years to mass

adoption from the date of GHC ETs' disclosure, zero otherwise.

**B-2.** Market Reactions to GHC-ET Disclosures – High VS Low Intensity of Disclosures

	minime drate in	arket reaction	Delayed market reaction				
High Iı	ntensity	Low In	ntensity	High Ir	itensity	Low Ir	itensity
CAR_MM	CAR_MM	CAR_MM	CAR_MM	CAR_MM	CAR_MM	CAR_MM	CAR_MM
(-3, +3)	(-5, +5)	(-3, +3)	(-5, +5)	(+4, +60)	(+6, +60)	(+4, +60)	(+6, +60)
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
-0.0493***	-0.0444***	0.0582***	0.0570***	-0.0371**	-0.0415**	-0.0260*	-0.0254*
(0.0084)	(0.0097)	(0.0066)	(0.0076)	(0.0185)	(0.0181)	(0.0145)	(0.0142)
1.0109***	1.0352***	1.0106***	1.0348***	0.0708**	0.0574**	0.0719**	0.0585**
(0.0130)	(0.0150)	(0.0129)	(0.0150)	(0.0285)	(0.0279)	(0.0285)	(0.0279)
-0.0075	-0.0099	-0.0083	-0.0106*	-0.0263**	-0.0225*	-0.0260**	-0.0222*
(0.0053)	(0.0062)	(0.0053)	(0.0062)	(0.0117)	(0.0115)	(0.0117)	(0.0115)
-0.0023***	-0.0022**	-0.0026***	-0.0025***	-0.0026	-0.0026	-0.0025	-0.0025
(0.0008)	(0.0010)	(0.0008)	(0.0010)	(0.0018)	(0.0018)	(0.0018)	(0.0018)
-0.0113	-0.0195	-0.0070	-0.0154	-0.0834**	-0.0726**	-0.0841**	-0.0732**
(0.0162)	(0.0187)	(0.0161)	(0.0187)	(0.0356)	(0.0348)	(0.0356)	(0.0348)
-0.0037	-0.0068	-0.0034	-0.0065	-0.0141*	-0.0131*	-0.0143*	-0.0133*
(0.0036)	(0.0041)	(0.0036)	(0.0041)	(0.0078)	(0.0077)	(0.0078)	(0.0077)
0.0005	0.0020	0.0005	0.0020	0.0012	-0.0006	0.0012	-0.0006
(0.0014)	(0.0016)	(0.0014)	(0.0016)	(0.0030)	(0.0030)	(0.0030)	(0.0030)
0.0098	0.0122	0.0073	0.0099	-0.0939***	-0.0984***	-0.0947***	-0.0994***
(0.0114)	(0.0132)	(0.0114)	(0.0132)	(0.0251)	(0.0246)	(0.0251)	(0.0246)
0.0034	0.0087	-0.0001	0.0054	0.0009	-0.0065	0.0016	-0.0059
(0.0194)	(0.0225)	(0.0194)	(0.0225)	(0.0428)	(0.0418)	(0.0428)	(0.0419)
-0.0000	0.0002	0.0003	0.0005	0.0024**	0.0025**	0.0023**	0.0024**
(0.0005)	(0.0006)	(0.0005)	(0.0006)	(0.0011)	(0.0011)	(0.0012)	(0.0011)
0.0249**	` '	,	` ′	` '	` ′	` '	-0.0156
(0.0113)	(0.0131)	(0.0113)	(0.0131)	(0.0249)	(0.0244)	(0.0250)	(0.0244)
	CAR_MM (-3, +3) (1) -0.0493*** (0.0084) 1.0109*** (0.0130) -0.0075 (0.0053) -0.0023*** (0.0008) -0.0113 (0.0162) -0.0037 (0.0036) 0.0005 (0.0014) 0.0098 (0.0114) 0.0098 (0.0114) -0.0000 (0.0005) 0.0249**	(-3, +3)         (-5, +5)           (1)         (2)           -0.0493***         -0.0444***           (0.0084)         (0.0097)           1.0109***         1.0352***           (0.0130)         (0.0150)           -0.0075         -0.0099           (0.0053)         (0.0062)           -0.0023***         -0.0022**           (0.0008)         (0.0010)           -0.0113         -0.0195           (0.0162)         (0.0187)           -0.0037         -0.0068           (0.0036)         (0.0041)           0.0005         0.0020           (0.0014)         (0.0016)           0.0098         0.0122           (0.0114)         (0.0132)           0.0034         0.0087           (0.0194)         (0.0225)           -0.0000         0.0002           (0.0005)         (0.0006)           0.0249**         0.0205	CAR_MM (-3, +3)         CAR_MM (-5, +5)         CAR_MM (-3, +3)           (1)         (2)         (3)           -0.0493***         -0.0444***         0.0582***           (0.0084)         (0.0097)         (0.0066)           1.0109***         1.0352***         1.0106***           (0.0130)         (0.0150)         (0.0129)           -0.0075         -0.0099         -0.0083           (0.0053)         (0.0062)         (0.0053)           -0.0023***         -0.0022**         -0.0026***           (0.0008)         (0.0010)         (0.0008)           -0.0113         -0.0195         -0.0070           (0.0162)         (0.0187)         (0.0161)           -0.0037         -0.0068         -0.0034           (0.0036)         (0.0041)         (0.0036)           (0.0014)         (0.0016)         (0.0014)           0.0098         0.0122         0.0073           (0.0114)         (0.0132)         (0.0114)           0.0034         (0.0087         -0.0001           (0.0194)         (0.0225)         (0.0194)           -0.0000         0.0002         0.0003           (0.0005)         (0.0006)         (0.0005)	CAR_MM         CO.0760         CO.0150         CO.00160         CO.00160         CO.00160         CO.00160         CO.00160         CO.00160         CO.00160         CO.00160         CO.00161         CO.00161         CO.00161         CO.00161         CO.00161         CO.00161         CO.00161         CO.00161         CO.00161         CO.00161	CAR_MM         CAR_MA         CAR_MA         CAR_MA         C.0.0371         C.0.0371***         C.0.0371***         C.0.0371***         C.0.0708***         C.0.0708***         C.0.0708***         C.0.0706**         C.0.0706**         C.0.0706**         C.0.0706**         C.0.0706**         C.0.0706**         C.0.0706**         C.0.0706**         C.0.0714**         C.0.0356**         C.0.0141**         C.0.0356**         C.0.0141**         C.0.0356**         C.0.0141**         C.0.0141**<	CAR_MM         CAO.0151         -0.00115         -0.00151         -	CAR_MM         CAR_MA         CAO260*         CAO260*         CAO260*         CAO2

Year FE	YES							
Industry FE	YES							
Clustered SE	YES							
Observations	13,268	13,268	13,268	13,268	13,268	13,268	13,268	13,268
Adj. R-square	0.3178	0.2667	0.3200	0.2686	0.0171	0.0170	0.0170	0.0169

This table shows the immediate and delayed market reaction of GHC-ET disclosures after 8-K was released. The dependent variables are estimated CARs in the event windows (-3, +3) and (-5, +5) based on market model. Columns (1) to (4) report the immediate market reaction while columns (5) to (8) report delayed market reaction. Columns (1)-(2) and (5)-(6) show the market reactions to high GHC-ET disclosure intensity while columns (3)-(4) and (7)-(8) present the market reactions to low GHC-ET disclosure intensity. All regressions include fixed effects by year and industry. The industry fixed effect is based on the GIC industry classifications. The standard errors presented in parentheses are corrected for firm-clustering heteroscedasticity. Definitions for all of variables are provided in Appendix B.1. The significance levels are: \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

**B-3.** Market Reactions to GHC-ET Disclosures – High VS Low Frequency of Disclosures

		Immediate m	arket reaction		Delayed market reaction			
	High Fr	equency	Low Fr	equency	High Fr	equency	Low Fr	equency
Variables	CAR_MM (-3, +3)	CAR_MM (-5, +5)	CAR_MM (-3, +3)	CAR_MM (-5, +5)	CAR_MM (+4, +60)	CAR_MM (+6, +60)	CAR_MM (+4, +60)	CAR_MM (+6, +60)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
GHCET <sub>i,t</sub>	-0.0780***	-0.0778***	0.0468***	0.0482***	-0.0421*	-0.0460**	-0.0270**	-0.0275**
	(0.0107)	(0.0124)	(0.0060)	(0.0069)	(0.0237)	(0.0231)	(0.0131)	(0.0128)
$RET_{i,t}$	1.0105***	1.0347***	1.0108***	1.0350***	0.0707**	0.0573**	0.0719**	0.0586**
	(0.0130)	(0.0150)	(0.0129)	(0.0150)	(0.0285)	(0.0279)	(0.0285)	(0.0279)
Turnover <sub>i,t</sub>	-0.0072	-0.0095	-0.0080	-0.0103*	-0.0261**	-0.0223*	-0.0261**	-0.0223*
	(0.0053)	(0.0062)	(0.0053)	(0.0062)	(0.0117)	(0.0115)	(0.0117)	(0.0115)
Firm Size <sub>i,t</sub>	-0.0023***	-0.0022**	-0.0026***	-0.0025***	-0.0026	-0.0026	-0.0025	-0.0025
	(0.0008)	(0.0010)	(0.0008)	(0.0010)	(0.0018)	(0.0018)	(0.0018)	(0.0018)
$ROA_{i,t}$	-0.0115	-0.0199	-0.0074	-0.0157	-0.0833**	-0.0725**	-0.0843**	-0.0734**
	(0.0162)	(0.0187)	(0.0161)	(0.0187)	(0.0356)	(0.0348)	(0.0356)	(0.0348)
$BM_{i,t}$	-0.0038	-0.0069*	-0.0036	-0.0066	-0.0142*	-0.0132*	-0.0142*	-0.0132*
	(0.0036)	(0.0041)	(0.0036)	(0.0041)	(0.0078)	(0.0077)	(0.0078)	(0.0077)
$Age_{i,t}$	0.0005	0.0020	0.0005	0.0020	0.0012	-0.0006	0.0012	-0.0006
	(0.0014)	(0.0016)	(0.0014)	(0.0016)	(0.0030)	(0.0030)	(0.0030)	(0.0030)
$FCF_{i,t}$	0.0091	0.0118	0.0064	0.0090	-0.0946***	-0.0992***	-0.0942***	-0.0988***
	(0.0114)	(0.0132)	(0.0114)	(0.0132)	(0.0251)	(0.0246)	(0.0251)	(0.0246)
$OCF_{i,t}$	0.0022	0.0076	-0.0005	0.0048	0.0002	-0.0073	0.0022	-0.0052
	(0.0194)	(0.0225)	(0.0194)	(0.0225)	(0.0428)	(0.0418)	(0.0428)	(0.0419)
$FCI_{i,t}$	-0.0001	0.0001	0.0003	0.0005	0.0024**	0.0025**	0.0023**	0.0024**
	(0.0005)	(0.0006)	(0.0005)	(0.0006)	(0.0011)	(0.0011)	(0.0012)	(0.0011)
Constant	0.0254**	0.0210	0.0224**	0.0180	-0.0226	-0.0164	-0.0218	-0.0156
	(0.0113)	(0.0131)	(0.0113)	(0.0131)	(0.0250)	(0.0244)	(0.0250)	(0.0244)

Year FE	YES							
Industry FE	YES							
Clustered SE	YES							
Observations	13,268	13,268	13,268	13,268	13,268	13,268	13,268	13,268
Adj. R-square	0.3187	0.2677	0.3192	0.2682	0.0170	0.0169	0.0171	0.0170

Note: This table shows the immediate and delayed market reaction of GHC-ET disclosures after 8-K was released. The dependent variables are estimated CARs in the event windows (-3, +3) and (-5, +5) based on market model. Columns (1) to (4) report the immediate market reaction while columns (5) to (8) report delayed market reaction. Columns (1)-(2) and (5)-(6) show the market reactions to high GHC-ET disclosure frequency while columns (3)-(4) and (7)-(8) present the market reactions to low GHC-ET disclosure frequency. All regressions include fixed effects by year and industry. The industry fixed effect is based on the GIC industry classifications. The standard errors presented in parentheses are corrected for firm-clustering heteroscedasticity. Definitions for all of variables are provided in Appendix B.1. The significance levels are: \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

### **B-4.** Robustness Tests – Using Lagged Control Variables

Panel A. Immediate reactions to GHC-ET disclosures before and after removing other events  Before removing other events  After removing other events								
		After removing other events						
Variables	CAR_MM	CAR_MM	CAR_MM	CAR_MM CAR_MM (-3, +3) (-3, +3)	CAR_MM (-3, +3)	CAR_MM	CAR_MM	CAR_MM
v arrabios	(-3, +3)	(-3, +3)	(-3, +3)			(-3, +3)	(-3, +3)	(-3, +3)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$GHCET_{i,t}$	0.0194**	0.0234***	0.0245***	0.0244***	0.0530***	0.0595***	0.0615***	0.0612***
	(0.0081)	(0.0086)	(0.0087)	(0.0087)	(0.0107)	(0.0113)	(0.0115)	(0.0115)
$L.Investor\_sentiment_{i,t}$	0.0123			0.0096	0.0137			0.0130
	(0.0128)			(0.0136)	(0.0163)			(0.0172)
$L.8K\_Readability_{i,t}$		0.0001		0.0003		0.0001		0.0004
		(0.0004)		(0.0007)		(0.0004)		(0.0010)
$L.8K\_Tone_{i,t}$			0.0000	0.0005			-0.0006	0.0001
			(0.0025)	(0.0027)			(0.0032)	(0.0035)
Constant	0.0150	0.0015	0.0031	0.0053	0.0326	0.0149	0.0185	0.0214
	(0.0180)	(0.0175)	(0.0169)	(0.0233)	(0.0228)	(0.0219)	(0.0214)	(0.0295)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Year, Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Clustered SE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	7,494	6,913	6,796	6,796	5,331	4,925	4,837	4,837
Adj. R-square	0.2122	0.1893	0.1888	0.1886	0.1686	0.1398	0.1395	0.1392

Panel B. Delayed reaction to GHC-ET disclosures								
		Before removii	ng insider selling		After removing insider selling			
Variables	CAR_MM (+4, +60)	CAR_MM (+4, +60)	CAR_MM (+4, +60)	CAR_MM (+4, +60)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
GHCET <sub>i,t</sub>	-0.0240	-0.0187	-0.0176	-0.0176	-0.0291	-0.0383	-0.0368	-0.0367
	(0.0169)	(0.0174)	(0.0175)	(0.0175)	(0.0263)	(0.0272)	(0.0275)	(0.0275)
$Investor\_sentiment_{i,t}$	-0.0239			-0.0277	-0.0082			-0.0154
	(0.0268)			(0.0273)	(0.0394)			(0.0403)
$8K_Readability_{i,t}$		-0.0006		0.0004	(0.2897)	(0.2847)	(0.2858)	(0.2859)
		(0.0008)		(0.0015)		-0.0006		0.0002
$8K\_Tone_{i,t}$			0.0070	0.0074		(0.0009)		(0.0022)
			(0.0050)	(0.0055)			0.0036	0.0038
Constant	-0.0094	0.0297	0.0191	-0.0056			(0.0074)	(0.0081)
	(0.0375)	(0.0354)	(0.0341)	(0.0468)	-0.0275	0.0015	-0.0065	-0.0196
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Year, Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Clustered SE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	7,494	6,913	6,796	6,796	4,349	3,985	3,918	3,918
Adj. R-square	0.0293	0.0328	0.0329	0.0327	0.0379	0.0435	0.0433	0.0428

Note: This table shows the results of robustness checks after adding lagged control variables including investor sentiment, readability, and tone of each 8-K filing. Panel A reports the immediate market reaction to GHC-ET disclosures before and after removing other events before 8-K filings. The results are unchanged when using the event window (-5, +5) and use the Fama-French three-factor and the Carhart four-factor model to estimate CARs. Panel B indicates the delayed market reaction to GHC-ET disclosures before and after removing insider selling after GHC-ET disclosures. The results are unchanged when using the event window (+6, +60) and use the Fama-French three-factor and the Carhart four-factor model to estimate CARs. All regressions include control variables and fixed effects by year and industry. The industry fixed effect is based on the GIC industry classifications. The standard errors presented in parentheses are corrected for firm-clustering heteroscedasticity. Definitions for all of variables are provided in Appendix B.1. The significance levels are: \*\*\* p<0.01, \*\*\* p<0.05, \*\* p<0.1.

### C-1. Variables Definition of Chapter 6

Variables	Definitions
Dependent variables	
NCSKEW <sub>t+1</sub>	The variable of stock price crash risk which is the negative coefficient of skewness. This is calculated by taking the negative third moment of the firm-specific weekly return for each sample year, dividing it by the standard deviation of the firm-specific weekly return, and raising it to the third power. The formula can be found in Eq. (3).
$DUVOL_{t+1}$	The variable of stock price crash risk which is the down-to-up volatility. This is calculated by the log of the ratio of the standard deviation of firm-specific returns on the down weeks to the standard deviation of firm-specific returns on the up weeks. The formula can be found in Eq. (4).
$Crash_{t+1}$	A dummy variable represents the crash risk of stock price. One means that the firm experiences at least one crash week during year t+1, and zero otherwise. The crash week is defined if the firm-specific weekly return falls by 3.09 or more standard deviations below the mean firm-specific weekly returns over year t+1.
Independent variables	
GHCET <sub>t</sub>	A dummy variable represents whether the firm disclose GHC ETs-related information. One means that firm i discloses GHC emerging technologies-related information in the initial 8-K containing Item 7.01 in year t, and zero otherwise.
Phase_j <sub>t</sub>	A dummy variable for each phase, represents which phase j (from one to five) of the ETs in GHC disclosed by firm i in year t.
Control variables	· · · · · · · · · · · · · · · · · · ·
NCSKEW <sub>t</sub>	The lagged value of NCSKEW <sub>t+1</sub> .
$DUVOL_t$	The lagged value of DUVOL <sub>t+1</sub> .
Crash <sub>t</sub>	The lagged value of Crash <sub>t+1</sub> .
$RET_t$	The mean of firm-specific weekly returns over a year t.
$SIGMA_t$	The standard deviation of firm-specific weekly return over a year t.
Dturnovert	The detrended average monthly stock turnover over a year t. This is calculated by the average monthly share turnover in the year minus the average monthly share turnover in the previous year.
$SIZE_t$	The natural logarithm of the book value of total assets over a year t.
$ROA_t$	The ratio of net income to total assets at the fiscal year t end.
$LEV_t$	The ratio of total debts to total assets at the fiscal year t end.
$MB_t$	The ratio of market value of equity to book value of equity at the fiscal year t end.

$ABACC_t$	The absolute value of discretionary accruals estimated from the
	adjusted Jones model over the year t. The detailed estimation
	procedure can be found in Appendix B.3.
IV_Internet_Users <sub>t</sub>	The percentage of internet users of each US state over a year t.
Tone <sub>t</sub>	The ratio of Loughran-McDonald positive words minus negative
	words to Loughran-McDonald positive words plus negative words.
	The formula is Positive word count-Negative word count Positive word count+Negative word count.
Readability <sub>t</sub>	A readability metric from 0 to 20 that uses word and sentence
Readability	length to determine how difficult a text is to read. The formula is
	$0.4 \times \left[ \left( \frac{\text{Total words}}{\text{Total sentences}} \right) + 100 \times \left( \frac{\text{Complex words}}{\text{Total words}} \right) \right]$ where complex
	words are those containing three or more syllables.
Filingsizet	Complete Report File Size (bytes) to represent the extent to which
	8-K filings are more accessible to users.
Institutional <sub>t</sub>	The percentage of institutional investors of firm i in year t.
Analysts <sub>t</sub>	The percentage of analysts follows of firm i in year t.
Investor_reaction <sub>t</sub>	The cumulative abnormal returns around the event window (-3,
	+3).
CEO_overcon <sub>t</sub>	This research follows Campbell et al. (2011) and Hirshleifer et al.
	(2012) to use the executive options holding decisions to measure
	CEO overconfidence.
Additional variables for pr	incipal component analysis
Bid-ask spread <sub>t</sub>	The standard deviation of the spread between bid and ask is the
r r	The standard deviation of the spread between sid and ask is the
	difference between the monthly closing bid and ask quotes for a
r	difference between the monthly closing bid and ask quotes for a firm i in the previous year t-1.
Earnings volatility <sub>t</sub>	difference between the monthly closing bid and ask quotes for a
•	difference between the monthly closing bid and ask quotes for a firm i in the previous year t-1.  The standard deviation of quarterly returned earnings of firm i in the previous year t-1.
•	difference between the monthly closing bid and ask quotes for a firm i in the previous year t-1.  The standard deviation of quarterly returned earnings of firm i in the previous year t-1.  The standard deviation of quarterly increase/decrease of cash and
Earnings volatility <sub>t</sub>	difference between the monthly closing bid and ask quotes for a firm i in the previous year t-1.  The standard deviation of quarterly returned earnings of firm i in the previous year t-1.  The standard deviation of quarterly increase/decrease of cash and cash Equivalents of firm i in the previous year t-1.
Earnings volatility <sub>t</sub>	difference between the monthly closing bid and ask quotes for a firm i in the previous year t-1.  The standard deviation of quarterly returned earnings of firm i in the previous year t-1.  The standard deviation of quarterly increase/decrease of cash and cash Equivalents of firm i in the previous year t-1.  A dummy variable represents whether the firm belongs to a high-
Earnings volatility <sub>t</sub> Cash flow volatility <sub>t</sub>	difference between the monthly closing bid and ask quotes for a firm i in the previous year t-1.  The standard deviation of quarterly returned earnings of firm i in the previous year t-1.  The standard deviation of quarterly increase/decrease of cash and cash Equivalents of firm i in the previous year t-1.  A dummy variable represents whether the firm belongs to a high-tech industry (SIC codes 2833-2836, 3570-3577, 3600-3674, 7371-
Earnings volatility <sub>t</sub> Cash flow volatility <sub>t</sub>	difference between the monthly closing bid and ask quotes for a firm i in the previous year t-1.  The standard deviation of quarterly returned earnings of firm i in the previous year t-1.  The standard deviation of quarterly increase/decrease of cash and cash Equivalents of firm i in the previous year t-1.  A dummy variable represents whether the firm belongs to a high-tech industry (SIC codes 2833-2836, 3570-3577, 3600-3674, 7371-7379, or 8731-8734) (Chung and Hribar 2021).
Earnings volatility <sub>t</sub> Cash flow volatility <sub>t</sub>	difference between the monthly closing bid and ask quotes for a firm i in the previous year t-1.  The standard deviation of quarterly returned earnings of firm i in the previous year t-1.  The standard deviation of quarterly increase/decrease of cash and cash Equivalents of firm i in the previous year t-1.  A dummy variable represents whether the firm belongs to a high-tech industry (SIC codes 2833-2836, 3570-3577, 3600-3674, 7371-
Earnings volatility <sub>t</sub> Cash flow volatility <sub>t</sub> High-tech industries <sub>t</sub>	difference between the monthly closing bid and ask quotes for a firm i in the previous year t-1.  The standard deviation of quarterly returned earnings of firm i in the previous year t-1.  The standard deviation of quarterly increase/decrease of cash and cash Equivalents of firm i in the previous year t-1.  A dummy variable represents whether the firm belongs to a high-tech industry (SIC codes 2833-2836, 3570-3577, 3600-3674, 7371-7379, or 8731-8734) (Chung and Hribar 2021).
Earnings volatility <sub>t</sub> Cash flow volatility <sub>t</sub> High-tech industries <sub>t</sub> CEO_age <sub>t</sub>	difference between the monthly closing bid and ask quotes for a firm i in the previous year t-1.  The standard deviation of quarterly returned earnings of firm i in the previous year t-1.  The standard deviation of quarterly increase/decrease of cash and cash Equivalents of firm i in the previous year t-1.  A dummy variable represents whether the firm belongs to a high-tech industry (SIC codes 2833-2836, 3570-3577, 3600-3674, 7371-7379, or 8731-8734) (Chung and Hribar 2021).  The natural logarithm of the CEO age.
Earnings volatility <sub>t</sub> Cash flow volatility <sub>t</sub> High-tech industries <sub>t</sub> CEO_age <sub>t</sub>	difference between the monthly closing bid and ask quotes for a firm i in the previous year t-1.  The standard deviation of quarterly returned earnings of firm i in the previous year t-1.  The standard deviation of quarterly increase/decrease of cash and cash Equivalents of firm i in the previous year t-1.  A dummy variable represents whether the firm belongs to a high-tech industry (SIC codes 2833-2836, 3570-3577, 3600-3674, 7371-7379, or 8731-8734) (Chung and Hribar 2021).  The natural logarithm of the CEO age.  A dummy variable represents the CEO gender, one is male while zero is female.  A dummy variable represents whether the CEO also serve as
Earnings volatility <sub>t</sub> Cash flow volatility <sub>t</sub> High-tech industries <sub>t</sub> CEO_age <sub>t</sub> CEO_gender <sub>t</sub>	difference between the monthly closing bid and ask quotes for a firm i in the previous year t-1.  The standard deviation of quarterly returned earnings of firm i in the previous year t-1.  The standard deviation of quarterly increase/decrease of cash and cash Equivalents of firm i in the previous year t-1.  A dummy variable represents whether the firm belongs to a high-tech industry (SIC codes 2833-2836, 3570-3577, 3600-3674, 7371-7379, or 8731-8734) (Chung and Hribar 2021).  The natural logarithm of the CEO age.  A dummy variable represents the CEO gender, one is male while zero is female.  A dummy variable represents whether the CEO also serve as chairman, one is yes while zero is no.
Earnings volatility <sub>t</sub> Cash flow volatility <sub>t</sub> High-tech industries <sub>t</sub> CEO_age <sub>t</sub> CEO_gender <sub>t</sub>	difference between the monthly closing bid and ask quotes for a firm i in the previous year t-1.  The standard deviation of quarterly returned earnings of firm i in the previous year t-1.  The standard deviation of quarterly increase/decrease of cash and cash Equivalents of firm i in the previous year t-1.  A dummy variable represents whether the firm belongs to a high-tech industry (SIC codes 2833-2836, 3570-3577, 3600-3674, 7371-7379, or 8731-8734) (Chung and Hribar 2021).  The natural logarithm of the CEO age.  A dummy variable represents the CEO gender, one is male while zero is female.  A dummy variable represents whether the CEO also serve as chairman, one is yes while zero is no.  A dummy variable represents whether the CEO's share holding is
Earnings volatility <sub>t</sub> Cash flow volatility <sub>t</sub> High-tech industries <sub>t</sub> CEO_age <sub>t</sub> CEO_gender <sub>t</sub> Duality <sub>t</sub>	difference between the monthly closing bid and ask quotes for a firm i in the previous year t-1.  The standard deviation of quarterly returned earnings of firm i in the previous year t-1.  The standard deviation of quarterly increase/decrease of cash and cash Equivalents of firm i in the previous year t-1.  A dummy variable represents whether the firm belongs to a high-tech industry (SIC codes 2833-2836, 3570-3577, 3600-3674, 7371-7379, or 8731-8734) (Chung and Hribar 2021).  The natural logarithm of the CEO age.  A dummy variable represents the CEO gender, one is male while zero is female.  A dummy variable represents whether the CEO also serve as chairman, one is yes while zero is no.  A dummy variable represents whether the CEO's share holding is large than 1%, one is yes while zero is no.
Earnings volatility <sub>t</sub> Cash flow volatility <sub>t</sub> High-tech industries <sub>t</sub> CEO_age <sub>t</sub> CEO_gender <sub>t</sub> Duality <sub>t</sub>	difference between the monthly closing bid and ask quotes for a firm i in the previous year t-1.  The standard deviation of quarterly returned earnings of firm i in the previous year t-1.  The standard deviation of quarterly increase/decrease of cash and cash Equivalents of firm i in the previous year t-1.  A dummy variable represents whether the firm belongs to a high-tech industry (SIC codes 2833-2836, 3570-3577, 3600-3674, 7371-7379, or 8731-8734) (Chung and Hribar 2021).  The natural logarithm of the CEO age.  A dummy variable represents the CEO gender, one is male while zero is female.  A dummy variable represents whether the CEO also serve as chairman, one is yes while zero is no.  A dummy variable represents whether the CEO's share holding is
Earnings volatility <sub>t</sub> Cash flow volatility <sub>t</sub> High-tech industries <sub>t</sub> CEO_age <sub>t</sub> CEO_gender <sub>t</sub> Duality <sub>t</sub> CEO_holdings <sub>t</sub>	difference between the monthly closing bid and ask quotes for a firm i in the previous year t-1.  The standard deviation of quarterly returned earnings of firm i in the previous year t-1.  The standard deviation of quarterly increase/decrease of cash and cash Equivalents of firm i in the previous year t-1.  A dummy variable represents whether the firm belongs to a high-tech industry (SIC codes 2833-2836, 3570-3577, 3600-3674, 7371-7379, or 8731-8734) (Chung and Hribar 2021).  The natural logarithm of the CEO age.  A dummy variable represents the CEO gender, one is male while zero is female.  A dummy variable represents whether the CEO also serve as chairman, one is yes while zero is no.  A dummy variable represents whether the CEO's share holding is large than 1%, one is yes while zero is no.  Number of other major company boards.  A dummy variable represents whether the CEO also serve as a
Earnings volatility <sub>t</sub> Cash flow volatility <sub>t</sub> High-tech industries <sub>t</sub> CEO_age <sub>t</sub> CEO_gender <sub>t</sub> Duality <sub>t</sub> CEO_holdings <sub>t</sub> Outside_Public_Boards <sub>t</sub>	difference between the monthly closing bid and ask quotes for a firm i in the previous year t-1.  The standard deviation of quarterly returned earnings of firm i in the previous year t-1.  The standard deviation of quarterly increase/decrease of cash and cash Equivalents of firm i in the previous year t-1.  A dummy variable represents whether the firm belongs to a high-tech industry (SIC codes 2833-2836, 3570-3577, 3600-3674, 7371-7379, or 8731-8734) (Chung and Hribar 2021).  The natural logarithm of the CEO age.  A dummy variable represents the CEO gender, one is male while zero is female.  A dummy variable represents whether the CEO also serve as chairman, one is yes while zero is no.  A dummy variable represents whether the CEO's share holding is large than 1%, one is yes while zero is no.  Number of other major company boards.  A dummy variable represents whether the CEO also serve as a member of the audit committee.
Earnings volatility <sub>t</sub> Cash flow volatility <sub>t</sub> High-tech industries <sub>t</sub> CEO_age <sub>t</sub> CEO_gender <sub>t</sub> Duality <sub>t</sub> CEO_holdings <sub>t</sub> Outside_Public_Boards <sub>t</sub>	difference between the monthly closing bid and ask quotes for a firm i in the previous year t-1.  The standard deviation of quarterly returned earnings of firm i in the previous year t-1.  The standard deviation of quarterly increase/decrease of cash and cash Equivalents of firm i in the previous year t-1.  A dummy variable represents whether the firm belongs to a high-tech industry (SIC codes 2833-2836, 3570-3577, 3600-3674, 7371-7379, or 8731-8734) (Chung and Hribar 2021).  The natural logarithm of the CEO age.  A dummy variable represents the CEO gender, one is male while zero is female.  A dummy variable represents whether the CEO also serve as chairman, one is yes while zero is no.  A dummy variable represents whether the CEO's share holding is large than 1%, one is yes while zero is no.  Number of other major company boards.  A dummy variable represents whether the CEO also serve as a member of the audit committee.  A dummy variable represents whether the CEO also serve as a
Earnings volatility <sub>t</sub> Cash flow volatility <sub>t</sub> High-tech industries <sub>t</sub> CEO_age <sub>t</sub> CEO_gender <sub>t</sub> Duality <sub>t</sub> CEO_holdings <sub>t</sub> Outside_Public_Boards <sub>t</sub> Audit_co_member <sub>t</sub> Compensation_co_member <sub>t</sub>	difference between the monthly closing bid and ask quotes for a firm i in the previous year t-1.  The standard deviation of quarterly returned earnings of firm i in the previous year t-1.  The standard deviation of quarterly increase/decrease of cash and cash Equivalents of firm i in the previous year t-1.  A dummy variable represents whether the firm belongs to a high-tech industry (SIC codes 2833-2836, 3570-3577, 3600-3674, 7371-7379, or 8731-8734) (Chung and Hribar 2021).  The natural logarithm of the CEO age.  A dummy variable represents the CEO gender, one is male while zero is female.  A dummy variable represents whether the CEO also serve as chairman, one is yes while zero is no.  A dummy variable represents whether the CEO's share holding is large than 1%, one is yes while zero is no.  Number of other major company boards.  A dummy variable represents whether the CEO also serve as a member of the audit committee.  A dummy variable represents whether the CEO also serve as a member of the compensation committee.
Earnings volatility <sub>t</sub> Cash flow volatility <sub>t</sub> High-tech industries <sub>t</sub> CEO_age <sub>t</sub> CEO_gender <sub>t</sub> Duality <sub>t</sub> CEO_holdings <sub>t</sub> Outside_Public_Boards <sub>t</sub> Audit_co_member <sub>t</sub>	difference between the monthly closing bid and ask quotes for a firm i in the previous year t-1.  The standard deviation of quarterly returned earnings of firm i in the previous year t-1.  The standard deviation of quarterly increase/decrease of cash and cash Equivalents of firm i in the previous year t-1.  A dummy variable represents whether the firm belongs to a high-tech industry (SIC codes 2833-2836, 3570-3577, 3600-3674, 7371-7379, or 8731-8734) (Chung and Hribar 2021).  The natural logarithm of the CEO age.  A dummy variable represents the CEO gender, one is male while zero is female.  A dummy variable represents whether the CEO also serve as chairman, one is yes while zero is no.  A dummy variable represents whether the CEO's share holding is large than 1%, one is yes while zero is no.  Number of other major company boards.  A dummy variable represents whether the CEO also serve as a member of the audit committee.  A dummy variable represents whether the CEO also serve as a

member of the corporate government committee.

#### C-2. Procedures for Estimating ABACC

According to Dechow et al. (1995), this study employs the modified Jones model to calculate discretionary accruals. The following cross-sectional regression for each industry and fiscal year are estimated.

$$\frac{TA_{i,t}}{Asset_{i,t-1}} = \alpha_0 \times \frac{1}{Asset_{i,t-1}} + \alpha_1 \times \frac{\Delta Sales_{i,t}}{Asset_{i,t-1}} + \alpha_2 \times \frac{PPE_{i,t}}{Asset_{i,t-1}} + \varepsilon_{i,t}$$
 Eq. (B.3-1)

The discretionary accruals ( $DisaAcc_{i,t}$ ) are calculated based on the estimated coefficients from Eq. (B.3-1). The formula is shown as follows,

$$DisaAcc_{i,t} = \frac{{}^{TA_{i,t}}}{{}^{Asset_{i,t-1}}} - (\widehat{\alpha_0} \times \frac{1}{{}^{Asset_{i,t-1}}} + \widehat{\alpha_1} \times \frac{{}^{\Delta Sales_{i,t}-\Delta Rec_{i,t}}}{{}^{Asset_{i,t-1}}} + \widehat{\alpha_2} \times \frac{{}^{PPE_{i,t}}}{{}^{Asset_{i,t-1}}}) \quad \text{Eq. (B.3-2)}$$

where  $TA_{i,t}$  is total accruals for firm i over a year t;  $Asset_{i,t-1}$  is the book value of total assets for firm i over a year t-1;  $\Delta Sales_{i,t}$  is the change of total revenue of firm i over a year t;  $\Delta Rec_{i,t}$  is the change of accounts receivable for firm i over a year t and  $PPE_{i,t}$  is the gross amount of fixed assets for firm i at the end of fiscal year t. The  $ABACC_{i,t}$  is the absolute value of variable  $DisaAcc_{i,t}$ .

#### D-1. An Example of 8-K Filing Including Item 7.01

# UNITED STATES SECURITIES AND EXCHANGE COMMISSION XXXX

#### FORM 8-K

## CURRENT REPORT Pursuant to Section 13 or 15(d) of the Securities Exchange Act of 1934

Date of Report (Date of Earliest Event Reported): September 10, 2013 (September 10, 2013)

### XXX LLC

(Exact name of registrant as specified in its charter)

XXXXX (State or other jurisdiction of incorporation) XXXXX (Commission File Number) XXXXX (I.R.S. Employer Identification No.)

XXXXX (Address of principal executive offices) XXXXX (Zip Code)

Registrant's telephone number, including area code: XXXXX

Not Applicable (Former name or former address, if changed since last report)

Check the appropriate box below if the Form 8-K filing is intended to simultaneously satisfy the filing obligation of the registrant under any of the following provisions (*see* General Instruction A.2 below):

□ Written communications pursuant to Rule 425 under the Securities Act (17 CFR 230.425)

□ Soliciting material pursuant to Rule 14a-12 under the Exchange Act (17 CFR 240.14a-12)

□ Pre-commencement communications pursuant to Rule 13e-4(c) under the Exchange Act (17 CFR 240.13e-4(c))

☐ Pre-commencement communications pursuant to Rule 14d-2(b) under the Exchange Act (17 CFR 240.14d-

#### Item 7.01 Regulation FD Disclosure.

2(b)

On September 10, 2013, XXX Inc. (the "Company") announced that its indirect parent, XXX Holdings LLC, a Delaware limited liability company ("Parent"), intends to offer \$250.0 million aggregate principal amount of senior unsecured notes due 2018 (the "Notes"), subject to market conditions, in a private placement to qualified institutional buyers under Rule 144A and to non-U.S. persons under Regulation S of the Securities Act of 1933, as amended (the "Offering"). In connection with the Offering, Parent disclosed certain information to prospective investors in a preliminary offering memorandum dated September 10, 2013 (the

"Preliminary Offering Memorandum"). Pursuant to Regulation FD, XXX LLC (the "Registrant") is furnishing as Exhibits 99.1 and 99.2 the following information: (i) portions of the section of the Preliminary Offering Memorandum entitled "Summary" and (ii) the section of the Preliminary Offering Memorandum entitled "Risk Factors".

The information in this Item 7.01, including Exhibits 99.1 and 99.2, shall not be deemed "filed" for purposes of Section 18 of the Securities Exchange Act of 1934, as amended (the "Exchange Act"), or incorporated by reference in any filing under the Securities Act of 1933, as amended, or the Exchange Act, except as expressly set forth by specific reference in such a filing. The furnishing of this information pursuant to Item 7.01 shall not be deemed an admission by the Company as to the materiality of such information.

#### Item 8.01. Other Events.

As described in Item 7.01, on September 10, 2013, the Company announced the commencement of the Offering. The Parent intends to use the net proceeds from the sale of the Notes to pay cash dividends on, and/or make other payments in respect of, the Parent's equity interests. A copy of the press release issued by the Company is attached to this Current Report on Form 8-K as Exhibit 99.3 and incorporated by reference herein.

#### Item 9.01. Financial Statements and Exhibits.

#### (d) Exhibits.

The following material is filed as an exhibit to this Current Report on Form 8-K:

Exhibit <u>Number</u>	Description of Exhibit
99.1	Certain portions of the "Summary" section of the Preliminary Offering Memorandum
99.2	"Risk Factors" section of the Preliminary Offering Memorandum
99.3	Press release issued by the Company on September 10, 2013.
	SIGNATURES

Pursuant to the requirements of the Securities Exchange Act of 1934, Registrant has duly caused this report to be signed on its behalf by the undersigned hereunto duly authorized.

XXX LLC (Registrant)		
By:		

Date: September 10, 2013

#### D-2. An Example for the GHC-ET Disclosure Under the Item 7.01

#### Panel A. In the content of Item 7.01

The following chart provides our total addressable market by segment (in millions):

We believe the size of our total addressable market provides an opportunity to grow our subscriber base in the United States and around the world by offering a superior value proposition. Our proprietary online platform, extensive digital historical record collection and easy-to-use technology allow subscribers from the most committed family historians to those taking their first steps to begin to understand who they are and from where they came.

#### Proprietary Content Asset with Growing Network Effects

The foundation of our service is our extensive global content offering, which includes a growing collection of birth records, marriage records and death records, census records, immigration documents, photographs, maps, military records, personal narratives, newspapers and other collections that are accumulated in our database. We add content for our subscribers through our proprietary digitization process for traditional institutional content as well as through web-crawling techniques for other content.

We have digitized and indexed the largest online collection of family history records in the world, with collections from countries such as the United States, the United Kingdom, Australia, Canada, Sweden, Germany, France, Italy and Ireland. Our content process manages an average flow of millions of records per week as data is normalized from thousands of distinct formats. Our technology uses pattern recognition, classification algorithms and natural language processing to index names, dates, places and relationships. This creates structured, searchable records from unstructured content.

We continue to acquire or license, digitize, index and publish additional records for our subscribers. For example, we have partnered with and maintained key relationships with both the United States National Archives and Records Administration and The National Archives of the United Kingdom over the past ten years. In 2011, we added more than 1.7 billion records, in 2012, we added more than 3.1 billion records and for the six months ended June 30, 2013 we added approximately 0.5 billion records. As of June 30, 2013, our collections contained over 11 billion records.

In addition to the content we add to our websites, our users have created over 5 billion family tree nodes and uploaded more than 176 million items, including photographs, scanned documents and written stories.

#### Panel B. In the content of the exhibit of Item 7.01

These substantial opportunities drive governments and wireless carriers to expedite investments and regulations for **5G**.

- In June, the Chinese government announced that it would invest over \$400Bn in <u>5G</u> deployments over the next 10 years.
- In the US, the FCC has been working to free up millimeter-wave spectrum for carriers to enable faster <u>5G</u> networks. In this respect, Verizon and AT&T have announced <u>5G</u> services at 28 and 39Ghz spectrum for the last mile delivery. It enables a much cheaper alternative for home broadband internet services, compared to fiber routing.
- South Korea is planning a commercial **5G** network in time for the 2018 Winter Olympics.
- Last, the approval by the Department of Justice of the pending acquisition of Time Warner by AT&T and Verizon's acquisition of AOL and Yahoo set the stage for video streaming services over <u>5G</u>.

Our new advanced DSP platform, the XC12, has already been licensed to three of the top five base station OEMs who are intensively working on in-house chip solutions for  $\underline{\mathbf{5G}}$ . We are also making progress with a few other key

players in the space, which we have not had business relationships with in the past. Furthermore, we have a number of customers designing  $\underline{\mathbf{5G}}$  mobile broadband chips for Smartphones and home routers based on our CEVA-X and XC platforms. Overall,  $\underline{\mathbf{5G}}$  is a technology breakpoint, requiring new expertise and product offerings. We foresaw these needs and invested ahead of the market, enabling us to offer our customers a head start as the  $\underline{\mathbf{5G}}$  market takes off.

Panel C. In the slides of exhibit of Item 7.01

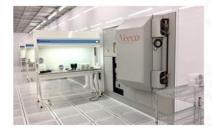
### **II-VI**

#### MATERIALS THAT MATTER

### **Acquisition of Kaiam Laser Limited**







#### **Background**

- 300,000 sq.ft facility with a 100,000 sq.ft clean room
- Located in near Newcastle U.K.
- 6" wafer fab for GaAs, SiC and InP devices capabilities
- Now known as II-VI Compound Semiconductor
  - Part of the Laser Solutions segment

#### **Strategic Rationale**

- Multi-purpose fab to further penetrate of markets driven by:
  - · 3D sensing, expected need for additional capacity
  - 5G wireless
  - The electrification of the car
  - · Data center communications
- Pro Forma Expectations:
  - Purchase price of the acquisition was \$80 million in cash
  - EBITDA breakeven by end of FY18
  - \$0.03 to 0.05 dilutive to EPS quarterly

12

Appendices

### D-3. A List of Gartner Hype Cycle Emerging Technologies

Quick Adoption Technologies						
Technologies	Year	Phase				
3D Bioprinting	2013	Phase 1				
3D Bioprinting Systems	2014	Phase 1				
3D Bioprinting Systems for Organ Transplant	2015	Phase 1				
3-D Flat-Panel Displays	2009	Phase 1				
3D Printing	2009, 2010	Phase 1				
3D Scanners	2012	Phase 1				
5G	2017, 2018	Phase 1				
802.11ax	2016	Phase 1				
Affective Computing	2013, 2014, 2015, 2016	Phase 1				
Augmented Reality	2009	Phase 1				
Automatic Content Recognition	2012	Phase 1				
Autonomous Vehicles	2012, 2013	Phase 1				
Big Data	2011	Phase 1				
Biochips	2014, 2015	Phase 1				
Blockchain for Data Security	2018	Phase 1				
Citizen Data Science	2015	Phase 1				
Commercial UAVs (Drones)	2016	Phase 1				
Connected Home	2014, 2015	Phase 1				
Context Brokering	2016	Phase 1				
Context Delivery Architecture	2009	Phase 1				
Conversational AI Platform	2018	Phase 1				
Conversational User Interfaces	2016, 2017	Phase 1				
Data Broker PaaS (dbrPaaS)	2016	Phase 1				
Deep Reinforcement Learning	2017	Phase 1				
Digital Security	2014, 2015	Phase 1				
Digital Twin	2017	Phase 1				
Edge AI	2018	Phase 1				
Electrovibration	2013	Phase 1				
Extreme Transaction Processing	2010	Phase 1				
Internet of Things	2011	Phase 1				
IoT Platform	2015, 2016	Phase 1				
Knowledge Graphs	2018	Phase 1				
Natural Language Question Answering	2011	Phase 1				
Neuromorphic Hardware	2017, 2018	Phase 1				
People-Literate Technology	2015	Phase 1				
Personal Analytics	2016	Phase 1				
Prescriptive Analytics	2013, 2014	Phase 1				
Quantified Self	2013, 2014	Phase 1				
Quantum Computing	2018	Phase 1				
Self-Healing System Technology	2018	Phase 1				

Serverless PaaS         2017         Phase I           Smart Data Discovery         2016         Phase I           Smart Robots         2014, 2015         Phase I           Smart Workspace         2014, 2016, 2017         Phase I           Social Analytics         2010         Phase I           Software-Defined Anything         2014         Phase I           Software-Defined Security         2015         Phase I           Speech-to-Speech Translation         2010, 2011         Phase I           Surface Computers         2009         Phase I           Video Analytics for Customer Service         2011         Phase I           Video Search         2009, 2010         Phase I           Video Search         2009, 2010         Phase I           Virtual Personal Assistants         2011, 2012         Phase I           Virtual Personal Assistants         2010         Phase 2           3D Flat-Panel TVs and Displays         2010         Phase 2           3D Flat-Banel TVs and Displays         2010         Phase 2           3D Flat-Banel TVs and Displays         2010         Phase 2           3D Flat-Banel TVs and Displays         2010         Phase 2           3D Scanners         2013         Phase 2 <th></th> <th></th> <th>Appendices</th>			Appendices
Smart Robots         2014, 2015, 2017         Phase 1           Smart Workspace         2014, 2016, 2017         Phase 1           Social Analytics         2010         Phase 1           Social TV         2011         Phase 1           Software-Defined Anything         2014         Phase 1           Software-Defined Security         2015         Phase 1           Speech-to-Speech Translation         2010, 2011         Phase 1           Surface Computers         2009         Phase 1           Video Analytics for Customer Service         2011         Phase 1           Video Search         2009, 2010         Phase 1           Video Search         2010         Phase 2           Video Search         2010         Phase 1           Video Search         2010         Phase 1           Video Search         2010         Phase 2           Video Search         2010         Phase 2           3D Finting         2011, 2015         Phase 2           3D Finting         2011, 2015         Phase 2 <td>Serverless PaaS</td> <td>2017</td> <td>Phase 1</td>	Serverless PaaS	2017	Phase 1
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Augmented Reality       2010, 2011, 2012       Phase 2         Autonomous Mobile Robots       2018       Phase 2         Autonomous Vehicles       2014, 2015       Phase 2         Big Data       2012, 2013       Phase 2         Biochips       2018       Phase 2         Blockchain       2016, 2017, 2018       Phase 2         BYOD       2012       Phase 2         Carbon Nanotube       2018       Phase 2         Cloud Computing       2009, 2010, 2011       Phase 2         Cloud/Web Platforms       2010       Phase 2         Cognitive Computing       2017       Phase 2         Cognitive Expert Advisors       2016       Phase 2         Commercial UAVs (Drones)       2017       Phase 2         Complex-Event Processing       2012, 2013, 2014       Phase 2         Connected Home       2016, 2017       Phase 2         Consumer 3D Printing       2013, 2014       Phase 2         Context-Enriched Services       2011       Phase 2         Crowdsourcing       2012       Phase 2         Cryptocurrencies       2014, 2015       Phase 2         Deep Learning       2017       Phase 2         Deep Neural Nets (Deep Learning)       <	Application Stores	2012	Phase 2
Autonomous Mobile Robots       2018       Phase 2         Autonomous Vehicles       2014, 2015       Phase 2         Big Data       2012, 2013       Phase 2         Biochips       2018       Phase 2         Blockchain       2016, 2017, 2018       Phase 2         BYOD       2012       Phase 2         Carbon Nanotube       2018       Phase 2         Cloud Computing       2009, 2010, 2011       Phase 2         Cloud/Web Platforms       2010       Phase 2         Cognitive Computing       2017       Phase 2         Cognitive Expert Advisors       2016       Phase 2         Commercial UAVs (Drones)       2017       Phase 2         Complex-Event Processing       2012, 2013, 2014       Phase 2         Connected Home       2016, 2017       Phase 2         Consumer 3D Printing       2013, 2014       Phase 2         Context-Enriched Services       2011       Phase 2         Context-Enriched Services       2011       Phase 2         Crowdsourcing       2012       Phase 2         Cryptocurrencies       2014       Phase 2         Deep Learning       2017       Phase 2         Deep Neural Network ASICs       2018	Augmented Data Discovery	2017	Phase 2
Autonomous Vehicles       2014, 2015       Phase 2         Big Data       2012, 2013       Phase 2         Biochips       2018       Phase 2         Blockchain       2016, 2017, 2018       Phase 2         BYOD       2012       Phase 2         Carbon Nanotube       2018       Phase 2         Cloud Computing       2009, 2010, 2011       Phase 2         Cloud/Web Platforms       2010       Phase 2         Cognitive Computing       2017       Phase 2         Cognitive Expert Advisors       2016       Phase 2         Commercial UAVs (Drones)       2017       Phase 2         Complex-Event Processing       2012, 2013, 2014       Phase 2         Connected Home       2016, 2017       Phase 2         Consumer 3D Printing       2013, 2014       Phase 2         Context-Enriched Services       2011       Phase 2         Context-Enriched Services       2011       Phase 2         Crowdsourcing       2012       Phase 2         Cryptocurrencies       2014, 2015       Phase 2         Deep Learning       2017       Phase 2         Deep Neural Nets (Deep Learning)       2018       Phase 2         Deep Neural Network ASICs	Augmented Reality	2010, 2011, 2012	Phase 2
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<u> </u>	Deep Neural Nets (Deep Learning)	2018	Phase 2
Digital Dexterity 2015 Phase 2	Deep Neural Network ASICs	2018	Phase 2
	Digital Dexterity	2015	Phase 2

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Digital Twin	2018	Phase 2
E-Book Readers	2009	Phase 2
Edge Computing	2017	Phase 2
Gamification	2011, 2012, 2013	Phase 2
Gesture Control Devices	2016	Phase 2
Group Buying	2011	Phase 2
HTML5	2012	Phase 2
Hybrid Cloud Computing	2012	Phase 2
Image Recognition	2011	Phase 2
In-Memory Database Management Systems	2011, 2012, 2013	Phase 2
Internet of Things	2014, 2015	Phase 2
Internet TV	2009, 2010, 2011	Phase 2
IoT Platform	2017, 2018	Phase 2
Machine Learning	2015, 2016, 2017	Phase 2
Media Tablet	2010, 2011	Phase 2
Micro Data Centers	2015, 2016	Phase 2
Microblogging	2009	Phase 2
Mobile Robots	2013	Phase 2
Nanotube Electronics	2016, 2017	Phase 2
Natural-Language Question Answering	2012, 2013, 2014	Phase 2
NFC Payment	2011, 2012	Phase 2
Private Cloud Computing	2010, 2011, 2012	Phase 2
Silicon Anode Batteries	2012, 2018	Phase 2
Smart Advisors	2014, 2015	Phase 2
Smart Robots	2016, 2017, 2018	Phase 2
Smart Workspace	2018	Phase 2
Social Analytics	2011, 2012	Phase 2
Social Software Suites	2009	Phase 2
Software-Defined Anything (SDx)	2016	Phase 2
Software-Defined Security	2016	Phase 2
•	2012, 2013, 2014,	
Speech-to-Speech Translation	2015	Phase 2
77' 4 1 A ' 4 4	2011, 2013, 2017,	D1 2
Virtual Assistants	2018	Phase 2
Wearable User Interfaces	2013, 2014	Phase 2
Wearables	2015	Phase 2
Window Down	2009, 2010, 2011,	Dl 2
Wireless Power	2012	Phase 2
Audio Mining/Speech Analytics	2012	Phase 3
Augmented Reality	2013, 2014, 2015, 2016, 2017, 2018	Phase 3
Autonomous Field Vehicles	2010, 2017, 2018	Phase 3
Big Data	2014	Phase 3
Cloud Computing	2012, 2013, 2014	Phase 3
Cloud/Web Platforms	2012, 2013, 2011	Phase 3
Cognitive Expert Advisors	2017	Phase 3
Connected Home	2018	Phase 3
	2010	1111000

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Consumer 3D Printing	2015	Phase 3
Consumer-Generated Media	2010	Phase 3
Cryptocurrency Exchange	2015	Phase 3
E-Book Readers	2010, 2011	Phase 3
Enterprise Taxonomy and Ontology Management	2017	Phase 3
Gamification	2014	Phase 3
Gesture Control	2012, 2013	Phase 3
Gesture Recognition	2010, 2011	Phase 3
Green IT	2009	Phase 3
Home Health Monitoring	2009, 2012	Phase 3
Hosted Virtual Desktops	2011, 2012	Phase 3
Hybrid Cloud Computing	2014, 2015	Phase 3
Idea Management	2009, 2010	Phase 3
In-Memory Analytics	2012, 2013	Phase 3
In-Memory Database Management Systems	2014	Phase 3
Internet TV	2012	Phase 3
	2011, 2012, 2013,	_
Machine-to-Machine Communication Services	2014	Phase 3
Microblogging	2010	Phase 3
Mixed Reality	2018	Phase 3
Mobile Application Stores	2010	Phase 3
Mobile Health Monitoring	2013, 2014	Phase 3
Mobile OTA Payment	2012	Phase 3
Natural-Language Question Answering	2015, 2016	Phase 3
NFC	2012, 2013, 2014	Phase 3
Online Video	2009	Phase 3
Over-the-Air Mobile Phone Payment		
Systems, Developed Markets	2009	Phase 3
Public Virtual Worlds	2009, 2010	Phase 3
RFID (Case/Pallet)	2009	Phase 3
Smart Fabrics	2018	Phase 3
Social Network Analysis	2009	Phase 3
Software-Defined Security	2017	Phase 3
Text Analytics	2012	Phase 3
Video Telepresence	2009, 2010	Phase 3
Virtual Assistants	2010	Phase 3
Virtual Reality	2013, 2014	Phase 3
3D Scanners	2014	Phase 4
Activity Streams	2013, 2014	Phase 4
·	2010, 2011, 2012,	
Biometric Authentication Methods	2013	Phase 4
Consumer Telematics	2012, 2013, 2014	Phase 4
Consumerization	2011, 2012	Phase 4
Corporate Blogging	2009	Phase 4
Electronic Paper	2009, 2010	Phase 4
Enterprise 3D Printing	2013, 2014, 2015	Phase 4
Gesture Control	2014, 2015	Phase 4

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Idea Management	2011, 2012	Phase 4
In-Memory Analytics	2014	Phase 4
Interactive TV	2010	Phase 4
Internet Micropayment Systems	2010	Phase 4
Location Intelligence	2013	Phase 4
Location-Aware Applications	2009, 2010	Phase 4
Media Tablets	2012	Phase 4
Mobile Application Stores	2011	Phase 4
Predictive Analytics	2010, 2011	Phase 4
QR/Color Code	2011	Phase 4
SOA	2009	Phase 4
Speech Recognition	2009, 2010, 2011, 2012	Phase 4
Tablet PC	2009	Phase 4
Virtual Reality	2016, 2017	Phase 4
Wikis	2009	Phase 4
Location-Aware Applications	2011	Phase 5
Pen-Centric Tablet PCs	2010	Phase 5
Predictive Analytics	2012, 2013	Phase 5
Speech Recognition	2013, 2014	Phase 5

Slow Adoption Technologies		
Technologies	Year	Phase
3D Bioprinting	2011, 2012	Phase 1
4D Printing	2016, 2017, 2018	Phase 1
Artificial General Intelligence	2017, 2018	Phase 1
Autonomous Driving Level 5	2018	Phase 1
Autonomous Vehicles	2010	Phase 1
Behavioral Economics	2009	Phase 1
Bioacoustic Sensing	2013, 2014, 2015	Phase 1
Biochips	2013	Phase 1
Biotech-Cultured or Artificial Tissue	2018	Phase 1
Brain-Computer Interface	2013, 2014, 2015,	Phase 1
Brain-Computer interface	2016, 2017	
Computer-Brain Interface	2010, 2011	Phase 1
Context Delivery Architecture	2010	Phase 1
Exoskeleton	2018	Phase 1
Flying Autonomous Vehicles	2018	Phase 1
General-Purpose Machine Intelligence	2016	Phase 1
	2009, 2010, 2011,	
Human Augmentation	2012, 2013, 2014,	Phase 1
	2015, 2016, 2017	
Internet of Things	2012	Phase 1
Mobile Robots	2009, 2010, 2011,	Phase 1
Moone Roots	2012	I Hase I

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Neurobusiness	2013, 2014, 2015	Phase 1
Neuromorphic Hardware	2016	Phase 1
Quantum Computing	2009, 2011, 2012, 2013, 2014, 2015, 2016, 2017	Phase 1
Smart Dust	2013, 2015, 2016, 2017, 2018	Phase 1
Tangible User Interfaces	2010	Phase 1
Terahertz Waves	2010	Phase 1
Volumetric and Holographic Displays	2012, 2013, 2014	Phase 1
Volumetric Displays	2015, 2016, 2017, 2018	Phase 1
Autonomous Vehicles	2016, 2017	Phase 2
Brain-Computer Interface	2018	Phase 2
Internet of Things	2013	Phase 2
Autonomous Driving Level 4	2018	Phase 3
Enterprise Taxonomy and Ontology Management	2016	Phase 3
Mesh Networks: Sensor	2009, 2010, 2011, 2012, 2013	Phase 3