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Social Networks and Brexit: Evidence from a Trade Shock[☆]

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ABSTRACT

Regional exposure to Chinese import competition has often been linked to support for the Leave option in the 2016 UK EU membership referendum. Looking at 143 harmonised International Territorial Level 3 (ITL3) regions covering England and Wales, and using data on the density of online social ties between them, I show that regional support for leaving the EU was also associated with exposure in socially connected regions. I first delineate 18 commuting zones based on interregional flows over three Census years. For each region, I then construct a measure of own exposure to Chinese import competition and a measure of exposure in a set of social neighbours located outside its commuting zone. Exploiting variation within commuting zones, and using an instrumental variable approach, I find that the two measures have comparable positive effects on the regional share of the Leave vote. In a series of checks, I do not find evidence that the effect of social neighbours' exposure is driven by an economic channel or a relationship between import competition and social ties. I also corroborate the regional results using survey data on vote choice. I interpret these findings as indicative of social spillovers between local labour markets: information flows from social neighbours are a likely channel behind the estimated spillover effects on voting outcomes.

1. Introduction

The result of the 2016 European Union membership referendum is often said to betray a 'geography of discontent' in the United Kingdom (McCann and Ortega-Argilés, 2021). Motivating this diagnosis is the link between local economic decline and voting to leave the EU (e.g., Becker et al., 2017; Colantone and Stanig, 2018a; Harris and Charlton, 2016)—the option that was formally opposed by the incumbent government before the referendum was held. Looking through the areas where the Leave option prevailed, one can quickly find 'places that don't matter' (Rodríguez-Pose, 2018): former industrial hubs that have been adversely affected by economic globalisation. This observation has revitalised the debate on the political significance of spatial inequality and its policy implications for both the UK and the EU (e.g., Iammarino et al., 2018; Martin et al., 2021; McCann, 2020; Rajan, 2019; Sandbu, 2022). I contribute to this debate by showing that local support for leaving the EU is also likely to have responded to spillovers from exposure to global trade in other local labour markets.

I focus on the rise of China as a major exporter and its effects on the share of the Leave vote in 143 harmonised ITL3 regions covering the whole of England and Wales.[1] This contribution is thus closely related to existing work on the political effects of regional exposure to the 'Chinese import shock' in Great Britain (Ballard-Rosa et al., 2021; Colantone and Stanig, 2018a; Steiner and Harms, 2021). However, rather than only measuring within-region exposure, I also use the Social Connectedness Index (SCI) by Bailey et al. (2020) to construct a weighted measure of exposure in the five most socially connected regions located outside each region's local labour market—its 'social neighbours'. Comparing regions within local labour markets, I find that an increase by one standard deviation in either measure corresponds to an increase in the regional share of the Leave vote by roughly 3 percentage points. Adopting the shift-share instrumental variable approach of Autor et al. (2013), I retrieve supply-driven components of both measures using Chinese imports into eight high-income countries and obtain new estimates, which remain close to the baseline. The estimated spillover effects are only slightly higher when considering all regions outside each region's local labour market, suggesting a pattern of decay as interregional social connectedness decreases. Spillovers from social neighbours still seem to travel a fair geographic distance: on average, these are located between 74 and 102 km away.

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[1] ITL3 refers to the third level of disaggregation of the International Territorial Level classification. Following Brexit, ITL3 replaced the same level of the EU-wide Nomenclature for the Use of Territorial Statistics (NUTS3) in the publication of UK official statistics. The initial version of ITL3, which is the one employed in this paper, mirrors the 2021 version of NUTS3. As I discuss in Appendix A, creating a harmonised ITL3 classification—whereby a small number of ITL3 units are aggregated—allows me to uniformly observe all relevant variables.

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Following the economic literature on the effects of import competition in the US, I define local labour markets as commuting zones derived using the hierarchical clustering approach of Tolbert and Sizer (1996). Specifically, I assign each harmonised ITL3 region to one of 18 commuting zones based on the mean commuting dissimilarity between region-pairs over three Census years. These zones aid me in addressing the problem of 'correlated effects' (Manski, 1993) under the identifying assumption that regional exposure to Chinese import competition is conditionally exogenous and does not affect the interregional social ties considered (see Bramoullé et al., 2020). As regions within the same local labour market are likely to be exposed to a range of common unobserved shocks, commuting zones help me to account for such heterogeneity. In addition, as the Chinese import shock precedes the year in which the SCI is measured, focusing only on social connectedness between commuting zones helps ensure that this is unaffected by past mobility responses within local labour markets.

In principle, social ties between commuting zones could still have formed as a result of processes triggered by the import shock, such as migration between local labour markets (e.g. see Acemoglu et al., 2016). Comparing the social connectedness of each region with all others outside of its commuting zone, I find that the former is significantly, weakly, and negatively associated with import-shock exposure in other regions, with the association disappearing when gross migration flows are held constant. Reassuringly, I also show that the estimated spillover effects from social neighbours' exposure are robust to the inclusion of regional controls for gross migration to and from regions outside of the commuting zone between the year that China ascended to the World Trade Organisation and the year in which social ties are observed. Taken together, these findings suggest that the social connectedness of each region with its social neighbours is unlikely to have formed endogenously due to import-shock exposure. Importantly, I also show that this is not necessarily the case for social connectedness between more weakly connected regions, making the identification of spillovers from all regions more challenging.

I argue that there are two probable channels behind the estimated effects of social neighbours' import-shock exposure on the regional share of the Leave vote: (1) economic spillovers that, in line with the framework of Acemoglu et al. (2016), operate via indirect effects on linked industries, aggregate demand effects, and reallocation effects, and (2) social spillovers operating via information flows over social networks. Consistent with the latter explanation, I find that baseline estimates are robust to the inclusion of regional controls for the start-of-period employment share in manufacturing, relative growth in gross value added, and migration to and from social neighbours leading up to the vote. This is consistent with the expectation that economic spillovers will to a large extent be contained within local labour markets (e.g., see Autor et al. 2016, Dorn and Levell 2021). A further analysis using individual-level data from the British Election Study mirrors the regional results. Importantly, I show that spillover effects are not restricted to voters facing economic difficulty.

In all, the empirical results suggest that social spillovers between local labour markets in England and Wales are likely to have been an important channel through which import competition with China affected voting in the 2016 EU membership referendum. This evidence offers a new perspective on the potential role of spatially heterogeneous economic shocks in national voting outcomes.

2. Background

An extensive literature documents that the growing participation of China in global trade since the early 1990s has had adverse effects on labour market outcomes in many Western regions that used to rely on manufacturing employment (e.g. see Autor et al., 2016; Dorn and Levell, 2021). Aided by the country's status as a major low-wage producer, Chinese imports displaced production in Western import-competing industries, resulting in substantial employment and wage losses in highly exposed local labour markets.[2] Shadowing its economic effects, the political effects of the shock have also been observed in several countries: higher local exposure has been tied to increased support for Eurosceptic candidates in national elections within EU member states (e.g., Barone and Kreuter, 2021; Colantone and Stanig, 2018c; Dippel et al., 2021; Malgouyres, 2017), for Donald Trump in US presidential elections (Autor et al., 2020), and for the Leave option in the 2016 UK EU membership referendum (Colantone and Stanig, 2018a).[3]

A number of studies on the relationship between regional exposure to import competition and voting behaviour point to the presence of neighbourhood effects. For instance, Colantone and Stanig (2018a) measure exposure in Great Britain at the level of NUTS3 regions and find that its positive effect on individual-level support for Brexit persists when accounting for employment status and occupation. Similarly, Steiner and Harms (2021) measure exposure both at the level of NUTS3 regions and different occupations, finding that the negative effect of regional exposure on individual-level support for EU membership persists when holding occupational exposure constant. Looking at individuals in the UK and several EU member states, Colantone and Stanig (2018c) and Hays et al. (2019) also note that exposure at the level of NUTS2 regions corresponds to higher support for nationalist parties irrespective of employment status. As the authors argue, these findings suggest that labour market outcomes are not the only channel through which regional exposure to import competition affects voting behaviour.

It is often argued that one of the reasons that one might observe neighbourhood effects is the high density of social ties among geographically proximate individuals (Cox, 1969; Johnston and Pattie, 2000, 2011, 2014; Miller, 1977). If a group of individuals is closely bound by interpersonal relationships that stimulate the flow of information, then the exposure of some to an economic shock may easily feed into the political preferences of others. Indeed, a nascent empirical literature is consistent with this prospect. Examining the policy preferences of Spanish voters, Liu et al. (2020) find that when almost half of one's friends and acquaintances have experienced economic hardship during the Great Recession, support for staying in the Euro currency is about 10 percentage points lower compared to when no peers are affected. Similarly, looking at the behaviour of Danish voters, Alt et al. (2022) find that a percentage point increase in the share of 2nd degree peers that have recently become unemployed increases the probability of voting for a left-wing party by 3.7 percentage points.[4]

While there is strong evidence that social ties generally decay with geographic distance (Bailey et al., 2020), treating geographic neighbourhoods and the localised social networks they contain as 'social islands' may still conceal spatial dependence in voting behaviour. As Johnston and Pattie anticipate, 'such [localised] social networks are extremely unlikely to be isolated – many members will have links to either or both of other, nonlocal networks (based on workplaces or family/kin, for example) and separate networks in adjacent neighbourhoods: such external links are continual sources of new information to the importing networks, providing stimuli to which they respond, in some cases altering their attitudes and behaviour as a consequence' (2014, 3). That is, residents in any given area are likely to respond to conditions in socially connected areas.

[2] Notably, growth in manufacturing imports from China typically vastly outweighs the growth of exports to China. As shown in Table B.1, between 1991 and 2007, import growth in the UK was nearly three times higher than export growth.

[3] Guriev and Pappaioannou (2022) and Rodrik (2021) provide comprehensive reviews of the literature on the political effects of import competition in various countries.

[4] I refer to n-th degree peers as those separated by an unweighted shortest path of length n along dyadic ties. That is, n-th degree peers share at least one peer of degree $n-1$.

To date, studies on the effect of the Chinese import shock on Brexit have assumed that different regions are independent of each other. This is in line with the expectation that the adverse economic effects of local exposure to the shock will be largely contained within local labour markets, which is a common relaxing assumption in the economic literature. Nonetheless, even if economic spillovers between local labour markets are too modest to bear any substantial political effects, the same may not hold for social spillovers involving the flow of information. This paper therefore asks whether import competition with China is likely to have shaped voting in the referendum via this unexplored channel.

3. Conceptual framework

In this section, I introduce a simple conceptual framework that informs the empirical strategy of this paper. This rests on the intuition that there are two main channels through which exposure to import competition in one region can influence voting outcomes in its social neighbours: (1) 'economic spillovers' operating via indirect effects on linked industries, aggregate demand effects, and reallocation and mobility effects, and (2) 'social spillovers' operating via information flows over social networks. Insofar as more economically integrated regions are likely to have more dense social ties, the two channels will not be readily distinguishable from each other. Further, given that social ties as measured by the SCI are observed at a later time than the Chinese import shock, the latter may affect the former, posing challenges in the identification of spillover effects. As such, a discussion of the kinds of processes that fall under each channel is informative with respect to both the high-level interpretation of empirical results and the ways in which these issues may be addressed. Though as I ground this on relevant theories of voting behaviour, it is important to stress that the empirical analysis is not directly informative about the individual-level mechanisms anticipated by these theories.

3.1. Economic voting and economic spillovers

Studies on the political effects of the Chinese import shock often subscribe to the economic voting hypothesis (Kinder and Kiewiet, 1981). Namely, they anticipate that voting behaviour is influenced by both personal economic circumstances (egotropic voting) and the state of the local economy (sociotropic voting).[5] The former case is exemplified by a voter experiencing a loss of employment, income, or wealth, and then becoming disaffected with incumbents or particular policies. However, even when one suffers no personal economic losses as a result of an import shock, their political preferences and voting behaviour may still sociotropically respond to its salient effects in the area in which they reside, such as deteriorating local public services (Feler and Senses, 2017), closures of local businesses and venues (Bolet, 2021), crime (Che et al., 2018; Dix-Carneiro et al., 2018) and anti-social behaviours such as substance abuse (Pierce and Schott, 2020).

Notably, egotropic and sociotropic voting need not be explicitly motivated by economic concerns.[6] For instance, Colantone and Stanig (2018b) show that local exposure to the Chinese import shock can also activate concerns about the cultural threat posed by immigration—a common issue in Eurosceptic campaigning. Similarly, observing the positive effect of pub closures on voting for the Eurosceptic UKIP party in the UK, Bolet (2021) argues that the socio-cultural degradation induced by local economic shocks can also hurt residents' sense of place-based identity. As such, in the interest of simplicity, I refer to any behaviour that responds to personal economic circumstances as egotropic, and to any behaviour that responds to changes in local economic conditions as sociotropic—irrespective of whether such behaviours are primarily motivated by economic or other concerns.

Regional exposure to import competition can induce egotropic and sociotropic voting responses in other regions via economic spillovers. That is, egotropic voting responses will occur in other regions insofar as personal economic circumstances within them are impacted by interdependencies with the exposed region. Likewise, sociotropic voting responses may also occur if interdependencies with the exposed region affect the overall state of other regional economies. What do such interdependencies look like? Acemoglu et al. (2016) offer a framework for decomposing the employment impact of import competition within a local labour market, which is also informative about possible economic spillovers. Here, the local employment impact is comprised of (a) direct effects on exposed industries, (b) indirect effects on linked industries, (c) reallocation effects, (d) and aggregate demand effects.

The direct effects of exposure to Chinese import competition within a local labour market are the job and wage losses of workers in local industries whose products directly compete with Chinese imports. Though firms operating in these industries are also likely to be in supplier or buyer relationships with other local and non-local firms operating in linked industries. Their direct exposure to the shock may thus also beget indirect effects on workers in those other firms. These may be contractionary 'upstream' effects whereby suppliers are themselves hit by suppressed demand from their buyers, or 'downstream' effects whereby buyers either face supply chain issues or benefit from the availability of cheaper alternatives. While an extensive theoretical and empirical literature on agglomeration economies establishes that firms in linked industries tend to be co-located (e.g., Glaeser 2010), some may not be.[7] As such, direct and indirect effects on local industries within one local labour market may also conceivably bear indirect effects on linked industries in others, in turn affecting voting behaviour.

Operating alongside direct and indirect effects is reallocation—the expansion of industries that seize the freed labour and capital. Notably, this includes displaced workers moving on to different firms. Again, the evidence on labour mobility responses to import competition suggests that this is unlikely to involve substantial flows between local labour markets (e.g., Autor et al., 2016; Dorn and Levell, 2021). Still, mobility may be more likely between certain regions, such as those with strong pre-existing social ties (e.g., see Munshi, 2020); in such cases, reallocation between local labour markets could be strong enough to influence voting outcomes.

Finally, aggregate demand effects relate to changes in consumption and investment. Such is the case when reduced spending on local goods and services results in additional employment losses in non-tradable sectors. Here too, as workers typically buy goods and services from firms that are in proximity to their residences and workplaces, a large component of the aggregate demand effects of a given local shock is likely to be contained within the exposed local labour market (e.g., Mian et al., 2013; Mian and Sufi, 2014). Though there are ways in which spending may be routinely carried out elsewhere, such as travel (e.g., Dunn and Gholizadeh, 2020). As such, insofar as a local shock affects spending in other local labour markets, spillover effects on voting outcomes may be expected to follow.

[5] While Kinder and Kiewiet (1981) first defined sociotropic voting as relating to the state of the national economy, later work recognises that voters often respond to local economic conditions (Kiewiet and Lewis-Beck, 2011). Local conditions have also been found to inform voters' evaluations of the national economy (Ansolabehere et al., 2014; Hansford and Gomez, 2015).

[6] Sociotropic voting is also often misrepresented as necessarily altruistic (Kiewiet and Lewis-Beck, 2011). Though local conditions may well shape preferences via one's own economic expectations.

[7] Lavoratori and Castellani (2021) illustrate the agglomeration of UK manufacturing firms.

3.2. Social influence and social spillovers

The economic voting hypothesis anticipates how aggregate economic conditions in the geographic neighbourhood in which voters reside can affect their behaviour. Though it is less informative about the ways in which this can be shaped by the economic circumstances of 1st or n–th degree peers in their social networks who may well reside elsewhere. Theories on the role of social influence in voting behaviour are attentive to two main mechanisms: information diffusion (e.g., Huckfeldt and Sprague, 1995) and conformity (e.g., Berelson et al., 1986). While it can be said that all social influence requires the flow of information in some manner, the latter mechanism is more restrictive in that it presupposes that a particular preference is already held by a 1st degree peer—or indeed a group of 1st degree peers—before it gets passed on to another through persuasion or learned norms. In contrast, simple information diffusion includes cases where preferences respond to information received from others with no regard for their preferences.

The study of Alt et al. (2022) provides an intuitive setting in thinking about how economic circumstances within one's social network may influence voting through either mechanism. As the authors link unemployment shocks in Danish voters' 2nd degree peers with various political preferences, there are two elementary scenarios. Strict information diffusion would involve the focal peer simply becoming aware of the job loss of a 2nd degree peer and then adjusting their preferences in response. On the other hand, a strict conformity scenario would require that a 2nd degree peer adjusts their preferences after becoming unemployed, then compels a 1st degree peer to also adjust their preferences in a similar direction, who in turn compels the focal peer to do the same.[8] Of course, it is possible that the two mechanisms are mixed. For instance, it could be that the preferences of the 1st degree peer simply respond to the information that the 2nd degree peer has become unemployed and then the focal peer is persuaded to conform. It is also not difficult to conceive of more complex cases where the unemployment shock that triggers the information diffusion or conformity pressure that ultimately affects the focal peer's preferences originates from a peer of even higher degree. For simplicity, I thus refer to any combination of information diffusion and conformity pressures involving peers of any degree as information flows. Importantly, I make no distinction with respect to the mode over which information flows are transmitted. This may equally involve peers meeting in-person, visiting each other's neighbourhood, telephone contact, text messaging, or online interactions.[9]

Regional exposure to import competition may affect voting outcomes elsewhere via social spillovers. More specifically, as the shock affects economic conditions and political preferences in one region, information flows relating to these conditions and preferences may plausibly feed into the behaviour of others. A burgeoning literature shows that social influence is often characterised by complex contagion (e.g, Christakis and Fowler, 2007; Sprague and House, 2017; Törnberg, 2018). That is, the probability of an individual changing their behaviour is conditional on the number of peers from which they receive a signal, the frequency in which they receive it, as well as the strength of their relationship with peers. Indeed, Alt et al. (2022) and Liu et al. (2020) respectively associate voter preferences to the shares of 2nd and 1st degree peers experiencing economic adversity, rather than considering a binary treatment. Social spillovers between regions are thus likely to be determined both by the extent of their respective exposure to import competition as well as the density of 1st degree social ties between them.

[8] Alt et al. (2022) suggest that a strict conformity mechanism is unlikely in their study setting.

[9] A growing literature shows that interactions over social media can affect a range of political outcomes (e.g. see Zhuravskaya et al., 2020 and Sabatini, 2023 for reviews). For instance, large-scale experimental evidence suggests that exposure to other users' posts can have significant effects on Facebook users' voting behaviour (Bond et al., 2012; Jones et al., 2017).

4. Data

4.1. Harmonised regions

The data that are required for the empirical objectives of this paper are not all readily available for the same spatial units. As detailed in Appendix A, I address this by drawing on the Office for National Statistics (ONS) Code History Database and Eurostat correspondence tables to produce crosswalks to harmonised regions. Namely, I create a harmonised ITL3 classification comprised of 143 regions covering England and Wales, and a harmonised local authority district (LAD) classification comprised of 366 regions covering England, Scotland and Wales. The latter ensures that most variables, which are available for different versions and variants of LAD, can be uniformly observed over time, while the former ensures that these can be aggregated to the same level as data on social ties, which are available for the NUTS3 2016 classification—a predecessor of ITL3. However, while LAD in England and Wales are nested within ITL3 regions, this does not hold for Scotland, which is necessarily excluded from main empirical specifications. Still, as discussed later in this section, Scotland can still be considered in correcting measures of regional exposure to import competition in England and Wales for measurement error, hence its inclusion in the harmonised LAD classification. Notably, Northern Ireland is wholly excluded from the analysis due to data limitations.

4.2. Mobility

I obtain data on interregional commuting flows measured at the time of each UK Census via the public 'Flow Data' portal operated by the UK Data Service. Importantly, these flows also provide information on the size of the resident workforce, as the data include the number of workers commuting within their region of residence. Apart from commuting, I also obtain data on interregional migration directly from ONS publications on annual internal migration estimates.

4.3. Social ties

The SCI by Bailey et al. (2020) serves as the key measure of interregional social ties. The public release of the SCI used in this paper was accessed via the Humanitarian Data Exchange of the UN Office for the Coordination of Humanitarian Affairs and is based on a snapshot of all active Facebook users (i.e. those who have logged in during the previous 30 days) as of August 2020.

For NUTS3 2016 region-pairs uu', the SCI is defined as follows:[10]

$$SCI_{uu'} = SCI_{u'u} = \frac{FB\_Connections_{uu'}}{FB\_Users_u \times FB\_Users_{u'}} \tag{1}$$

That is, the SCI is the total number of Facebook friendships in both regions over the product of active users in each region. It can therefore be thought of as a measure of the relative probability of Facebook friendship between an active user that resides in region u and an active user that resides in u', or the density of Facebook friendships between the active user populations of each region.

I convert the SCI to the harmonised ITL3 region classification using the approach of Bailey et al. (2021).[11] For the vast majority of units, there is 1-to-1 correspondence between the latter and the NUTS3 2016 classification in which the SCI is available. Other than recoding, the conversion thus effectively involves aggregating SCI values relating

[10] Before release, the SCI is scaled so that the global index has a maximum value of 1,000,000,000 and a minimum of 1. For region-pairs in England and Wales, the maximum is 2,871,114 and the minimum is 1,620, excluding each region's connectedness with itself.

[11] In the absence of data on the regional populations of Facebook users, Bailey et al. (2018) suggest that scaling the SCI using total regional populations should bear similar results.

to the four NUTS3 child regions referenced on Table A.3 into values relating to the two harmonised ITL3 parent regions also shown on the same table. Formally, I recalculate the SCI as follows:

$$SCI_{rr'} = SCI_{r'r} = \sum_{u}\sum_{u'} PopShare_{u} \times PopShare_{u'} \times SCI_{uu'} \tag{2}$$

Here, u and u' are NUTS3 regions respectively mapping into harmonised ITL3 regions r and r', and $PopShare_u$ is the population of u as a share of the population of r based on ONS mid-2020 estimates. Following the conversion, I also set SCI values where $u = u'$ to zero, effectively discarding each region's ties with itself.

As the SCI is based on social media friendships, it is arguably not a perfect representation of the true density of social ties between regional populations. However, as the UK Office for Communications (2020) estimates that approximately 72 per cent of UK adults were social media users in 2020, and that 88 per cent of those had a Facebook account (i.e. over 63 per cent of all UK adults), the SCI likely constitutes a sound proxy for both online and offline social ties among regions.

4.4. Regional exposure to import competition

I obtain data on regional employment by industry from the 1991 ONS Annual Employment Survey (AES) via the public 'Nomis' portal operated by the ONS. Industry breakdowns are accessed at the 3-digit level of the 1992 Standard Industrial Classification (SIC), which is equivalent to the first revision of the Statistical Classification of Economic Activities in the European Community (NACE Rev 1). Notably, regional figures produced by the survey relate to persons employed within the region as opposed to the residents of that region.

Annual data on the value of goods imported from China into the UK are drawn from the UN International Trade Statistics Database (COMTRADE) for product categories of the third revision of the Standard Industrial Trade Classification (SITC Rev.3). Product breakdowns are accessed at the lowest level that is available in both 1991 and 2007, which mark the period over which import growth is observed. As imports are reported in US dollars and current prices, I also use annual currency conversion factors available on COMTRADE along with the ONS Consumer Price Index (CPI) to express them in sterling and in 2015 prices.

Associating imports in different product categories to the corresponding import-competing manufacturing industries is necessary for measuring regional exposure to import competition. In doing so, I use a crosswalk published by the World Integrated Trade Solution (WITS) service of the World Bank, which allows me to match the SITC Rev.3 product categories to 3-digit NACE Rev.1 industries.[12]

Following the approach of Autor et al. (2013), I measure regional exposure to Chinese import competition as follows:

$$ImpShock_{r} = \sum_{d} \frac{Employment_{rd(1991)}}{Employment_{d(1991)}} \times \frac{\Delta Imp_{d(1991,2007)(CN,UK)}}{Employment_{r(1991)}} \tag{3}$$

Here, r indexes the 143 harmonised ITL3 regions and d indexes 95 manufacturing industries at the 3-digit NACE Rev.1 level, and $ImpShock_r$ is expressed in pounds per worker. Exposure to import competition within a national industry will be high if the growth in competing Chinese imports between 1991 and 2007 was also high relative to the number of industry workers across all regions.[13] As such, regional exposure will be high if a large share of regional employment in 1991 was in highly exposed manufacturing industries. Consistent with evidence on the economic effects of the Chinese import shock (e.g., Autor et al., 2016; Dorn and Levell, 2021), this measure reflects the intuition that regions specialising in import-competing manufacturing industries were also the ones most likely to experience adverse labour market outcomes due to the growth of Chinese imports.

Using 1991 as the base year in the import-shock exposure measure is in line with the onset of Chinese import growth in developed economies including the UK. Equally, using 2007 as the year up to which import growth is measured is preferred due to preceding the Great Recession and its confounding effects on trade. As shown in Table B.1, in the UK, the share of imports that came from China increased from just over 0.6 per cent to over 8 per cent over this period.

To the extent that a given region had a substantial number of residents that worked elsewhere in 1991, the regional import-shock exposure measure may misrepresent exposure among residents in that region. In addressing this concern, I follow Malgouyres (2017) and calculate place-of-residence, or 'residential', exposure based on commuting flows in that year. First, I calculate exposure in each Scottish harmonised LAD region h, $ImpShock_h$. I subsequently calculate the residential measure for harmonised ITL3 regions in England and Wales as follows:

$$ResImpShock_{r} = \sum_{r^*} \frac{Commuters_{rr^*(1991)}}{Workers_{r(1991)}} \times ImpShock_{r^*} \tag{4}$$

Here, r indexes harmonised ITL3 regions, whereas r^* indexes harmonised ITL3 regions r' and Scottish harmonised LAD regions h. That is, for each harmonised ITL3 region r, the residential import-shock exposure measure is the weighted sum of the place-of-work measure in each harmonised ITL3 region and Scottish harmonised LAD r^* multiplied by the share of commuting flows from r to r^* relative to the resident labour force of r. Recall that harmonised ITL3 regions only cover England and Wales due to correspondence issues with Scottish harmonised LAD. Still, as import-shock exposure can be obtained for Scottish harmonised LAD, its consideration in the residential exposure of regions in England and Wales accounts for the potential exposure of commuters from these regions to Scotland.

Appendix C presents a detailed comparison of place-of-work and residential exposure to import competition, showing that for the vast majority of regions the two measures are very similar. As I employ the residential rather than the place-of-work measure in all empirical specifications, any subsequent references to import-shock exposure thus allude to the former unless explicitly stated.

4.5. Voting outcomes

Regional voting outcomes are obtained from the UK Electoral Commission, which publishes the official referendum results alongside information on turnout and electoral size. Data on individual voting outcomes are drawn from Wave 9 of the British Electoral Study, which was held between the 24th of June and the 4th of July 2016. As the wave immediately follows the date of the UK EU membership referendum, individual voting outcomes represent self-reported vote choice.

5. Empirical strategy

The main challenge in identifying spillover effects on regional voting outcomes from the exposure of socially connected regions to Chinese import competition is the well-known problem of 'correlated effects' (Manski, 1993). That is, estimates may be biased if there are unobserved similarities between socially connected regions. Not least, similar regions may be more socially connected as a consequence of homophily between their populations (McPherson et al., 2001). As shown by Dieye et al. (2014), given a randomised treatment that does not affect social ties, it is possible to obtain unbiased estimates of spillover effects even in the presence of endogenous network processes. That is, if

[12] For a small number of cases (53 out of 3214 SITC Rev.3), there are 1-to-n matches between SITC Rev.3 and NACE Rev.1. In such cases, I follow Malgouyres (2017) and apportion the value of imports in each SITC product category into NACE industries based on the share of employment in each industry in 1991. I also discard any import data under the 'special transactions' SITC product category (9310) as these cannot be mapped to any given industry.

[13] National employment totals include England, Scotland, and Wales.

both the treatment and social exposure to the treatment are exogenous, their effects can be identified from correlated effects (Bramoullé et al., 2020). While spatial variation in exposure to Chinese import competition might be endogenous, various approaches may be employed in isolating an as-good-as random component of this variation. Then, the key condition to be satisfied for the identification of spillover effects is that interregional social connectedness is unaffected by exposure to import competition. In this section, I describe the adopted empirical strategy and how this works toward satisfying the discussed conditions for identification.

5.1. Delineating commuting zones

If a given local labour market spans multiple regions, the latter are likely to be similarly affected by unobserved factors that are correlated with both regional exposure to Chinese import competition as well as regional voting outcomes. These may range from common shocks affecting the productivity of the local workforce to similarities in culture and political representation. Insofar as such similarities are also shared with socially connected regions, their exposure may too be endogenous. Also, given that social ties as measured by the SCI are observed after the Chinese import shock, the former may be shaped by mobility responses within local labour markets. I address these threats to the identification by focusing on variation within commuting zones, and only considering socially connected regions that are located in different commuting zones. Specifically, I delineate 18 commuting zones using the approach of Tolbert and Sizer (1996) with harmonised ITL3 regions as building blocks. Geographic clusters derived in this manner are often considered as equivalent to local labour markets in the US literature on import competition (e.g. Autor et al., 2013, 2020).[14]

In UK official statistics, the most similar classification to commuting zones is that of Travel-to-Work Areas (TTWA) (Coombes and Bond, 2008). Though commuting zones are still preferred in this paper for at least three reasons. First, there is poor correspondence between ITL3 regions and TTWA. While the clustering approach for TTWA could be in principle applied on harmonised ITL3 regions, the Tolbert–Sizer approach remains preferable as it is more conservative with respect to the level of commuting flows that is tolerated between the clusters.[15] Importantly, the Tolbert–Sizer approach also provides a more straightforward measure for evaluating commuting dissimilarity between region-pairs, which further aids with precluding substantial commuting flows between socially connected regions.

A difference between the approach used in this paper and that of Tolbert and Sizer (1996) is that the latter only uses data for 1991 to measure the commuting dissimilarity between region pairs. Rather, I take the mean commuting dissimilarity across three UK Census years: 1991, 2001, and 2011. Given that harmonised ITL3 regions are comparable to US counties—which form the building blocks used by Tolbert and Sizer (1996)—commuting zones delineated using just 1991 data might be sufficiently stable over time, as is often argued in the US literature.[16]

However, as social ties are observed in 2020, taking the mean dissimilarity across years works towards clustering any region-pairs which may have developed stronger social ties via long-term commuting adjustments to past import-shock exposure. Formally, for every harmonised ITL3 region-pair rr' and Census year t, I calculate the following proportional flow measure:

$$P_{rr't} = P_{r'rt} = \frac{Commuters_{rr't} + Commuters_{r'rt}}{min(Workers_{rt}, Workers_{r't})} \tag{5}$$

The measure thus represents the ratio of gross commuting flows between regions r and r' in Census year t over the minimum of the two regional populations of resident workers in that Census year. Subsequently, I obtain $P_{rr'}$, which is the mean commuting similarity between two regions across the three Census years.[17]

The commuting dissimilarity between two regions is then defined as:

$$D_{rr'} = D_{r'r} = 1 - P_{rr'} \tag{6}$$

In the same manner as Tolbert and Sizer (1996), I use average agglomerative hierarchical clustering to produce a dendrogram of harmonised ITL3 region clusters based on $D_{rr'}$ and select those above the between-cluster commuting dissimilarity cut-off of 0.98. Fig. 1 lists the resulting 18 commuting zones by electorate size and the number of regions spanned, and Fig. 2 maps them.[18] Notably, only three commuting zones overlap with higher levels of the ITL classification: zone Z7 with the North East of England ITL1 region, zone Z17 with the Cumbria ITL2 region, and zone Z13 with the Kent ITL2 region. Overall, it is shown that local labour markets cross administrative geographies and the England–Wales border.

5.2. Creating social weight matrices

I create a modified index, $SCI_{(-c)}$, which is equal to the SCI except where region-pairs belong to the same commuting zone or have a commuting dissimilarity $D_{rr'}$ of less than the between-zone average 0.98, in which case it is equal to zero. That is, I discard connections between regions in the same commuting zone and regions that share substantial pairwise commuting flows. Fig. 3 maps the five most socially connected regions as defined by the SCI and $SCI_{(-c)}$ for regions with the maximum, median, and minimum exposure to Chinese import competition. In all three cases, the five most socially connected regions as per the SCI are in close geographic proximity. In contrast, the regions defined by $SCI_{(-c)}$ are more distant and in some cases lie well beyond the boundaries of the region's commuting zone.

Appendix D reviews the mean characteristics of the k nearest neighbours defined by SCI and $SCI_{(-c)}$. First, it is shown that a given region's respective first and fifth nearest neighbours as defined by $SCI_{(-c)}$ are, on average, 74 and 102 km away, exhibiting limited overlap with neighbours defined on the basis of geographic proximity. Second, it is shown that social connectedness decays rapidly as neighbour rank increases. For neighbours defined by SCI, the social connectedness with the focal region on average decreases by a factor of four between the first and fifth nearest neighbour, and almost halves between the fifth and the tenth. A similar rate of decay is observed in the density of social ties as measured by $SCI_{(-c)}$, which halves between the first and fifth nearest neighbour and levels off thereafter. This has two implications. First, most ITL3 regions in England and Wales are densely connected to only a few others and relatively sparsely connected to most. Second, to discard region-pairs in the same commuting zone or with substantial

[14] With exceptions such as Ballard-Rosa et al. (2021), who employ TTWA, the European literature on the effects of import competition often equates local labour markets to NUTS3 regions (e.g., De Lyon and Pessoa, 2021; Dippel et al., 2021). Though NUTS does not preclude substantial interregional commuting flows as it is based on administrative geographies.

[15] For TTWAs, at least 70 per cent of those living in the area will also work there and 70 per cent of those working in the area will also live there. Commuting zones will, on average, group region-pairs where gross commuters are over 2 per cent of the workforce of the smaller region.

[16] The population of a harmonised ITL3 region is, on average, almost twice as large as that of a US county (417,620 against 207,544 in 2020) but is much less heterogeneous (respective standard deviations of 205,300 and 1,269,953). As there are almost 22 times as many US counties, the two geographies can be considered as comparable in terms of granularity.

[17] Note that, for any given year, the calculation described in (5) is identical to the one employed by Tolbert and Sizer (1996) in measuring commuting similarity between US county pairs.

[18] The clustering algorithm first produces 19 zones with the Isle of Wight forming its own zone. To allow for within-zone variation, the island is grouped with the most proximate zone (Z8).

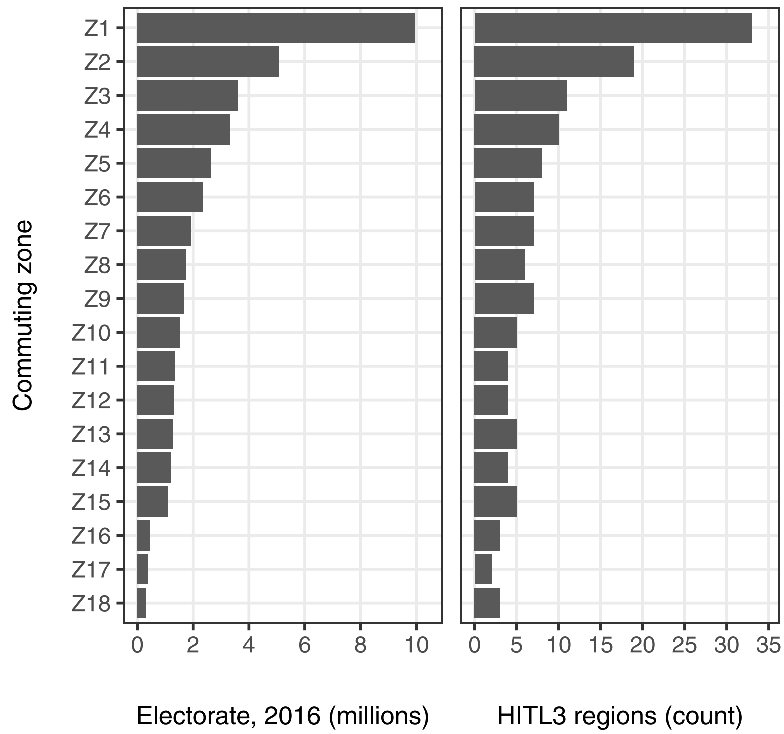

Fig. 1. Commuting zones, by electorate and number of harmonised ITL3 regions.

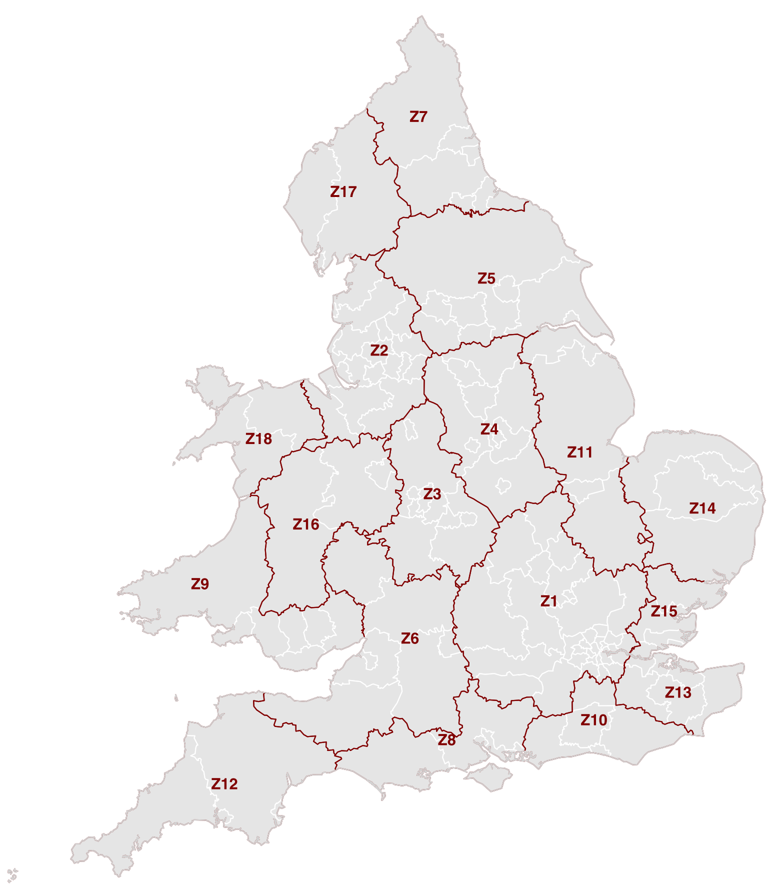

Fig. 2. Commuting zones and harmonised ITL3 regions. *Notes:* Commuting zones are drawn in red, and harmonised ITL3 regions in white. The zones are based on the hierarchical clustering approach of Tolbert and Sizer (1996) using a mean commuting dissimilarity measure computed across three Census years (1991, 2001, 2011). The zone labels are numbered according to 2016 electorate size, in descending order. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

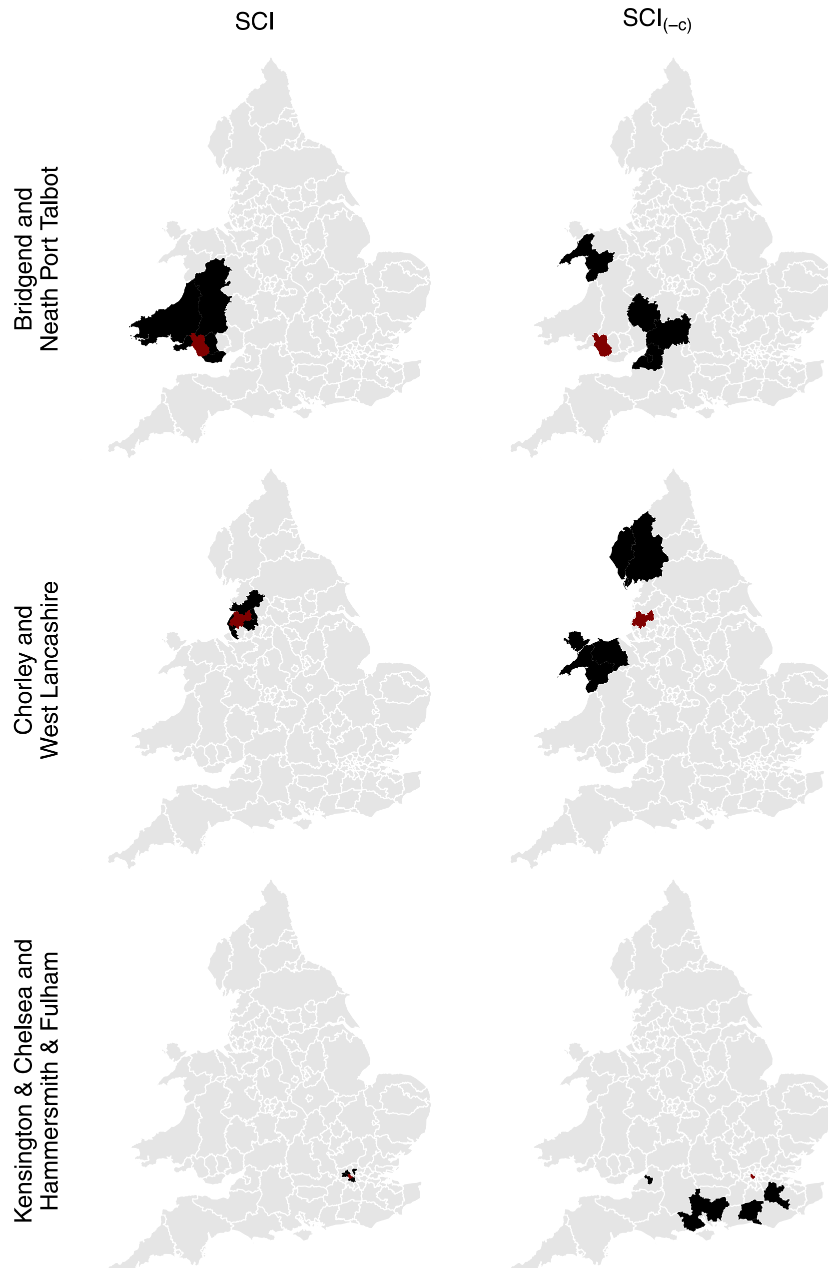

Fig. 3. Five nearest neighbours, by region and measure. *Notes*: The focal region is shaded in red and its neighbours in black. SCI refers to the Social Connectedness Index (Bailey et al., 2020) after discarding the connectedness of each region with itself. $\text{SCI}_{(\text{-c})}$ refers to the latter measure discarding region-pairs in the same commuting zone or with substantial pairwise commuting flows. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

pairwise commuting flows is to discard the most socially connected region-pairs, meaning that only the first few nearest neighbours defined by $\text{SCI}_{(\text{-c})}$ are likely to be substantially socially connected with the focal region. Nonetheless, as the remaining variation in social connectedness is plausibly unrelated to the effects of the Chinese import shock on commuting patterns, it is better suited for the identification of spillover effects from socially connected regions' exposure to the shock.

To investigate spillovers from socially connected regions beyond each region's commuting zone, I create the social neighbour matrix **W** by populating its elements (r, r') with zero except where $SCI_{rr'(\text{-c})}$ is in the five highest values in the row, in which case they contain that value. As such, for each region-row, non-zero cells identify the five most social connected regions that are not in its commuting zone or have substantial pairwise commuting flows with it—what I henceforth refer to as its 'social neighbours'. By storing the SCI values associated with each neighbour, **W** also captures its relative social connectedness with the focal region. Additionally, to investigate potential spillovers from beyond the most socially connected regions, I also construct a matrix **A**, whose elements (r, r') are populated with all respective values of the $SCI_{rr'(\text{-c})}$, capturing the relative social connectedness of each region with all others outside of its commuting zone.

5.3. Social exposure to import competition

Alongside measures of within-region exposure to Chinese import competition I also calculate measures of social neighbours' exposure as follows:

$$SocNeighbExp_r = \hat{\mathbf{w}}_r \cdot \mathbf{ResImpShock} = \sum_{k \in K_r} \frac{SCI_{rk} \times ResImpShock_k}{\sum_{k \in K_r} SCI_{rk}} \quad (7)$$

Here, $\hat{\mathbf{w}}_r$ is a row vector from the row-normalised social weights matrix $\hat{\mathbf{W}}$ identifying the social neighbours of harmonised ITL3 region r and their relative weights in terms of the density of their social ties to r, **ResImpShock** is the column vector of import-shock exposure within each harmonised ITL3 region, and k indexes each of the five social neighbours in the set K_r. That is, exposure in a set of social neighbours is the SCI weighted sum of each of their exposures over the sum of SCI values in the set. This measure can thus be interpreted as the expected exposure of the 1st degree peers of a resident in r who reside in the social neighbours of r outside of its commuting zone. In a similar manner, I also calculate the 'social lag' of exposure to import competition across all regions outside each region's commuting zone, $SocLagExp_r$, as $\hat{\mathbf{a}}_r \cdot \mathbf{ResImpShock}$, where $\hat{\mathbf{a}}_r$ is a row vector from the row-normalised social weights matrix $\hat{\mathbf{A}}$.

For ITL3 regions across England and Wales, Fig. 4 plots social neighbours' exposure to Chinese import competition against the regional share of the Leave vote in the 2016 UK EU membership referendum and within-region exposure, while Fig. 5 maps these measures. In terms of within-region exposure, the map broadly resembles those of previous UK studies (Ballard-Rosa et al., 2021; Colantone and Stanig, 2018a; Steiner and Harms, 2021). The most highly exposed regions are seen in South Wales, the Midlands, and the North of England, which is in line with the historical reliance of these regions on employment in import-competing manufacturing industries. In contrast, the least exposed regions are largely concentrated around London and the South East. However, different patterns emerge when looking at social neighbours' exposure.[19] For instance, Harrow and Hillingdon, North Yorkshire, and Herefordshire, are respectively in the first, third, and fourth deciles for within-region exposure, moving up to the sixth, eighth, and tenth deciles for social neighbours' exposure.

5.4. Baseline specifications

For harmonised ITL3 regions r within commuting zones c, I estimate the following baseline regional specification using ordinary least squares (OLS) regression:

$$Leave_{rc} = \alpha_c + \beta ResImpShock_r + \gamma SocNeighbExp_r + \epsilon_{rc} \quad (8)$$

Here, $Leave_{rc}$ is the share of valid votes cast in region r in support of the Leave option in the 2016 UK EU membership referendum, α_c represents commuting zone fixed effects, $ResImpShock_r$ is the within-region exposure of r to Chinese import competition, and $SocNeighbExp_r$ is exposure in the social neighbours of r. The coefficient of interest is therefore γ, which, following the standardisation of all independent variables to have zero mean and unit variance, is interpreted as the percentage point change in the regional share of the Leave vote for a one standard deviation increase in its social neighbours' exposure to Chinese import competition. For each coefficient, I report heteroscedasticity-robust standard errors clustered at the level of 31 lower commuting zones.[20]

For respondents to Wave 9 of the British Election Study i residing in harmonised ITL3 regions r within commuting zones c, I also estimate the following baseline individual-level specification using probit regression:

$$Leave_{irc} = \alpha_c + \eta ResImpShock_r + \theta SocNeighbExp_r + \mathbf{z}_i + \epsilon_{irc} \quad (9)$$

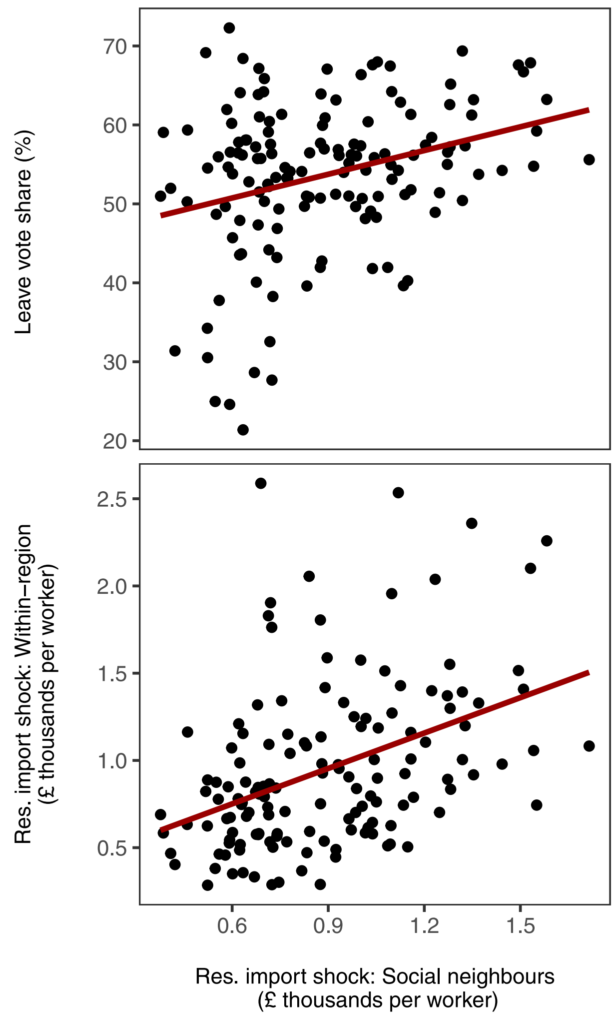

Fig. 4. Import-shock exposure and voting in harmonised ITL3 regions. *Notes:* Social neighbours are the five most socially connected regions as measured by the $SCI_{(\text{-c})}$, which is equal to the SCI (Bailey et al., 2020) after discarding region-pairs in the same commuting zone or with substantial pairwise commuting flows. Import-shock exposure in a set of social neighbours is the $SCI_{(\text{-c})}$ weighted sum of exposure over the sum of $SCI_{(\text{-c})}$ in the set.

Here, $Leave_{irc}$ is a binary variable that is equal to one when an individual has voted in favour of leaving the EU, while $ResImpShock_r$ and $SocNeighbExp_r$ remain the same as in the baseline regional specification. Also included is the vector $\mathbf{z}_i$, containing controls for age and gender, and five education dummies.[21] I also calculate and report the average marginal effect θ' which can be interpreted as the average change in the probability of voting to leave the EU for a standard deviation increase in the five nearest social neighbours' import-shock exposure. As with the regional specifications, I report heteroscedasticity-robust standard errors clustered at the level of lower commuting zones.

Across baseline specifications, the identifying assumption for the coefficients of interest is that the density of social ties between regions and their social neighbours is not affected by their respective exposure to import competition and that regional variation in social neighbours' exposure within commuting zones is as good as random. In alternative regional and individual-level specifications, I also replace the five nearest social neighbours' import-shock exposure, $SocNeighbExp_r$, with

[19] Assuming linearity, social neighbours' exposure to Chinese import competition explains roughly 17 per cent of the variation in within-region exposure. When looking at variation within commuting zones, this figure reduces to 9 per cent.

[20] The 31 lower commuting zones are nested within the 18 commuting zones and are derived in the same way except for setting the between-cluster commuting dissimilarity cut-off to 0.95. That is, lower commuting zones will, on average, group region-pairs where gross commuters are more than 5 per cent, as opposed to 2 per cent, of the workforce of the smaller region.

[21] The five education dummies indicate whether the individual's highest qualification is at the postgraduate, undergraduate, A-level, GCSE A-C, or GCSE D-G level.

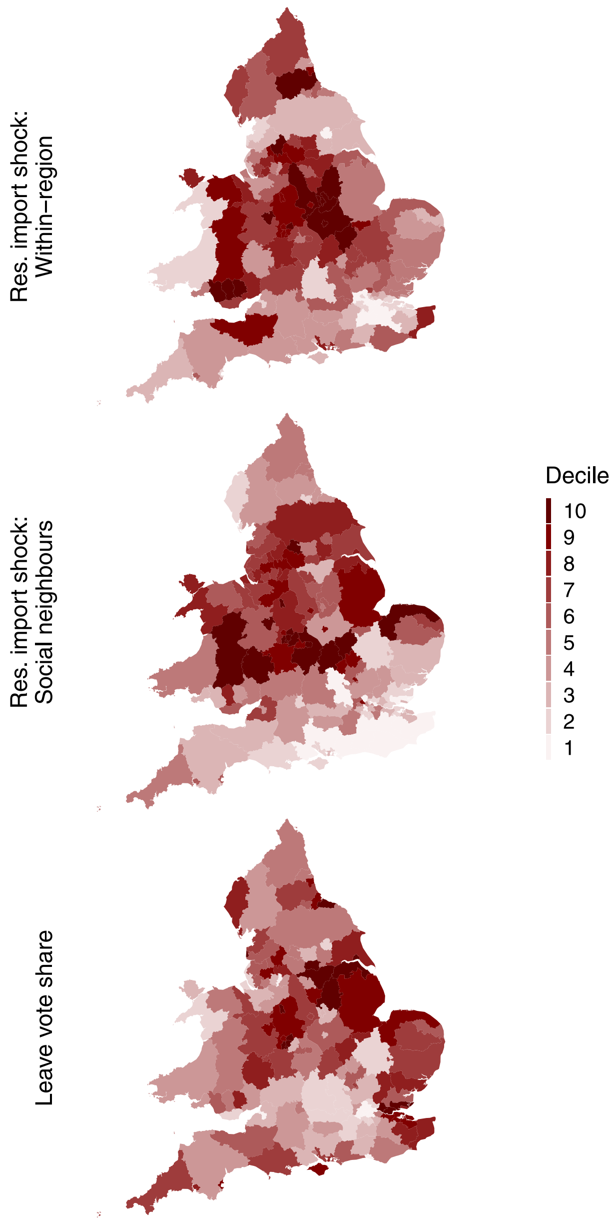

Fig. 5. Import-shock exposure and voting in harmonised ITL3 regions. *Notes:* Social neighbours are the five most socially connected regions as measured by the $\mathrm{SCI}_{(\text{-c})}$, which is equal to the SCI (Bailey et al., 2020) after discarding region-pairs in the same commuting zone or with substantial pairwise commuting flows. Import-shock exposure in a set of social neighbours is the $\mathrm{SCI}_{(\text{-c})}$ weighted sum of exposure over the sum of $\mathrm{SCI}_{(\text{-c})}$ in the set.

the social lag of exposure to import competition across all regions outside of the commuting zone of r, $SocLagExp_r$. Here, the identifying assumption is that the density of social ties between each region and all others outside of their commuting zone is not affected by their respective exposure to import competition and that regional variation in the social lag of exposure within commuting zones is as good as random.

5.5. Instrumental variable estimation

Focusing only on variation within commuting zones in all baseline specifications accounts for potentially endogenous social, economic, and political factors varying at the level of local labour markets. Still, omitted variable bias from regional heterogeneity within local labour markets remains a concern. I address this using an instrumental variable (IV) approach akin to that of Autor et al. (2013). Namely, I isolate the variation in the import-shock exposure measures that relates to supply conditions in China by instrumenting Chinese imports into the UK with Chinese imports into eight high-income countries.[22] This approach rests on the idea that supply-side factors in China, such as productivity growth, will have similarly affected its capacity to export across developed trading partners. As such, insofar as there are no common demand shocks in a given pair of partners, Chinese import growth in the one can be used to retrieve a supply-driven component of import growth in the other that is orthogonal to regional characteristics.

I create instruments for within-region exposure, $ResImpShock_{r(\mathrm{HI})}$, social neighbours' exposure, $SocNeighbExp_{r(\mathrm{HI})}$, and the social lag of exposure $SocLagExp_{r(\mathrm{HI})}$, by first substituting growth in Chinese imports into the UK competing within industry d, $\Delta Imp_{d(1991,2007)(\mathrm{CN,UK})}$, with growth in Chinese imports into the eight high-income countries competing within the same industry, $\Delta Imp_{d(1991,2007)(\mathrm{CN,HI})}$ in (3) and then recalculating the respective measures. Using these instruments, I re-estimate the baseline regional and individual-level specifications using two-stage least squares (2SLS) and IV probit regressions.

6. Results

Table 1 presents estimates from regional-level specifications.[23] As these focus on variation within commuting zones, the estimates are interpretable as comparisons between different regions in the same commuting zone. The first column refers to the most parsimonious OLS specification examining only the effect of within-region exposure to Chinese import competition on the regional share of the Leave vote in the 2016 UK EU membership referendum. Appended in the second column is the effect exposure in the region's social neighbours: the five most socially connected regions that are outside of its commuting zone and with which it does not share substantial commuting flows. In the third column, the latter is replaced with the social lag of exposure in all such regions. The remaining columns present the respective 2SLS estimates based on the shift-share instrumental variable approach discussed in the previous section.

In the first column of Table 1, it is shown that two regions within the same commuting zone that differ in their exposure to Chinese import competition by one standard deviation are estimated to differ by roughly 3.5 percentage points in their Leave vote share.[24] When considering both within-region exposure and social neighbours' exposure as in the second column, it is shown that both measures are associated with similar positive responses in voting in favour of leaving the EU. Comparing regions within the same commuting zone, a one standard deviation increase in either measure is associated with a roughly 2.8 percentage point increase in the regional share of the Leave vote. Further, as seen in the third column, the estimated spillover effects are greater by slightly over 1 percentage point when considering the social lag of exposure in all regions outside each region's commuting zone with which the latter does not share substantial commuting flows. This is a modest increase considering that, for each region, the social

[22] Following Autor et al. (2013), these countries include Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland. I also create alternative instruments for regional exposure to Chinese import competition using imports into the United States as well as imports into both the United States and the aforementioned eight high-income countries.

[23] Table F.1 presents key summary statistics relating to the regional data. Table F.2 also presents equivalent estimates obtained using place-of-work rather than place-of-residence import-shock exposure, which remain very similar.

[24] Note that the estimated effect of within-region exposure is of similar magnitude to that in the study of Colantone and Stanig (2018a), which investigates differences between NUTS3 regions within NUTS1 regions in England, Scotland, and Wales.

Table 1
Regional-level results.

	Leave vote share					
	(1)	(2)	(3)	(4)	(5)	(6)
Import-shock exposure:						
Within-region	3.511[a]	2.809[a]	2.586[b]	4.395[a]	3.435[a]	3.249[b]
	(1.003)	(0.807)	(1.118)	(1.215)	(0.965)	(1.430)
Social neighbours		2.866[b]			3.244[b]	
		(1.142)			(1.208)	
Social lag			4.050[b]			4.314[a]
			(1.500)			(1.512)
Estimation method	OLS	OLS	OLS	2SLS	2SLS	2SLS
Commuting zone FE	✓	✓	✓	✓	✓	✓
Observations	143	143	143	143	143	143
Within-R^2	0.128	0.179	0.201	0.120	0.172	0.196
Kleibergen–Paap F				880.7	473.5	419.9

Notes: Robust standard errors in parentheses are clustered at the level of 31 lower commuting zones. All independent variables are standardised to have zero mean and unit variance. Social neighbours are the five most socially connected regions as measured by the $SCI_{(-c)}$, which is equal to the SCI (Bailey et al., 2020) after discarding region-pairs in the same commuting zone or with substantial pairwise commuting flows. Import-shock exposure in a set of social neighbours is the $SCI_{(-c)}$ weighted sum of exposure over the sum of $SCI_{(-c)}$ in the set. The social lag of import-shock exposure is the $SCI_{(-c)}$ weighted sum of exposure across all regions over the respective $SCI_{(-c)}$ value sum. $^{a}p < 0.01$, $^{b}p < 0.05$.

lag of exposure considers interregional social ties with at least as many as 93 other regions:[25] a substantially higher number than the five most connected social neighbours. In line with the discussion in Appendix D, this is in line with the intuition that as each region is densely socially connected to only a few others, spillovers from more weakly connected regions are likely to be relatively limited.

When comparing OLS estimates in the first, second, and third column to the respective 2SLS estimates in the fourth, fifth, and sixth column it is shown that the latter are generally slightly higher, which is suggestive of a limited downward bias in the OLS estimates.[26] Though in both cases, when considered in tandem, social neighbours' exposure to Chinese import competition is associated with a comparable positive response in the Leave vote share as within-region exposure.[27] In other words, residing in a region that is socially connected to exposed others is seemingly of similar political relevance to residing in a region that is itself exposed.

Given that only variation within commuting zones is considered, I also look at alternative counterfactual shifts to further gauge the substantive significance of these results. Namely, I follow Mummolo and Peterson (2018) and report the mean range within commuting zones and the standard deviation of the within-distribution for each of the standardised import-shock exposure measures. I express these as standard deviations over the full distribution of the respective exposure measure, which is the shift considered thus far. The mean range within commuting zones is 1.97 and 1.53 for standardised exposure to Chinese import competition within a region and its social neighbours respectively, while the standard deviations of the corresponding within-distributions are 0.78 and 0.63.

Based on the fifth column of Table 1, the Leave vote share of the most exposed region to Chinese import competition within a commuting zone will, on average, be larger than that of the least exposed region by $1.97 \times 3.44 = 6.78$ percentage points. Similarly, the Leave vote share of the region with the most exposed social neighbours within a commuting zone will, on average, be larger than that of the region with the least exposed neighbours by $1.53 \times 3.24 = 4.96$ percentage points. When one considers the 'typical' differences between two regions from the same commuting zone, the Leave vote share of the region with higher exposure to import competition is expected to be higher by $0.78 \times 3.44 = 2.68$ percentage points, whilst the Leave vote share of the region with more exposed social neighbours is expected to be higher by $0.63 \times 3.24 = 2.04$ percentage points. Thus, irrespective of the counterfactual shift considered, the estimated effects of social neighbours' exposure on voting outcomes are indeed comparable to those of within-region exposure.[28] Considering that the referendum result was determined by a 4 percentage point margin, the estimated spillover effects are also clearly of substantive significance.

As discussed in the previous section, the identifying assumption for the estimated spillover effects presented on Table 1 is that regional variation in import-shock exposure is conditionally exogenous with respect to unobserved regional characteristics affecting electoral outcomes and unrelated to the considered interregional social ties between commuting zones. The close correspondence between the presented OLS and 2SLS estimates seems consistent with the former assumption.

Spillover effects are similar when only considering a supply-driven component of variation in exposure that is plausibly exogenous to local conditions affecting voting behaviour in the UK—irrespective of whether this is retrieved by instrumenting Chinese imports into the UK with Chinese imports into the eight high-income countries considered by Autor et al. (2013) as in Table 1, into the US as in Table F.3, or into both as in Table F.4.

While the interregional social ties considered are plausibly unrelated to past mobility within local labour markets, in principle, mobility between local labour markets remains a threat to identification to the extent that this both responds to import competition and affects interregional social ties. As seen in the presented conceptual framework, there is some evidence to suggest that this is an unlikely prospect. For instance, Autor et al. (2016) argue that mobility frictions between local labour markets are, to a large extent, what makes spatially uneven exposure to import competition a persistent economic problem. Similarly, using individual-level administrative data on UK workers, De Lyon and Pessoa (2021) do not find evidence that workers exposed to Chinese import competition are more likely to switch the region in which they work. Still, it is possible that regional exposure affects interregional social ties by dissuading rather than encouraging mobility.

Appendix E offers a closer examination of the relationship between regional exposure to Chinese import competition, interregional social ties, and interregional gross migration flows between 2002 and 2020.[29]

[25] This is the within-region minimum number of pairwise observations when discarding region-pairs within the same commuting zone or with substantial pairwise commuting flows.

[26] Tables F.3 and F.4 show that similar 2SLS estimates are obtained when respectively using Chinese imports into the US and Chinese imports into both the US and the eight-high income countries used in the main results as instruments. Note that the former 2SLS estimates are more directly comparable with those of Colantone and Stanig (2018a).

[27] As shown in Table F.5, when considering weighted-least-squares (WLS) estimates obtained by weighting observations by the regional number of votes cast in the referendum, the ratio of the within-region effect over the spillover effect from social neighbours rises from 1.06 to 1.28. Otherwise, estimates remain broadly similar in magnitude and significance.

[28] For the social lag of import-shock exposure, the mean range within commuting zones is 1.43 and the standard deviation of the within-distribution is 0.54. As such, as per the sixth column of Table 1 the Leave vote share of the region with the highest social lag of exposure within a given commuting zone will, on average, be $1.43 \times 4.31 = 6.16$ percentage points higher than that of the region with the lowest social lag of exposure in the commuting zone, while the Leave vote share of a region with a social lag of exposure that is typically higher than that of another in the same commuting zone will be $0.54 \times 4.31 = 2.33$ percentage points higher.

[29] I calculate annual gross migration flows between a given pair of regions as the sum of migrants moving between regions in a given year. Correspondingly, gross migration flows between 2002 and 2020 are the sum of annual gross migration flows spanning that period. Note that the period over which gross migration flows are considered spans from the earliest year for which data is available, which coincides with the ascension of China to the World Trade Organisation, through to the year in which interregional social ties are observed.

Table 2
Regional-level results, robustness to internal migration.

	Leave vote share					
	(1)	(2)	(3)	(4)	(5)	(6)
Import-shock exposure:						
Within-region	2.069[a]	1.473[c]	1.912[c]	2.573[a]	1.740[c]	2.352[c]
	(0.720)	(0.744)	(1.020)	(0.862)	(0.886)	(1.293)
Social neighbours	3.039[a]	3.048[a]		3.244[a]	3.337[a]	
	(0.919)	(0.944)		(0.886)	(0.934)	
Social lag			1.854			2.108
			(1.651)			(1.661)
Gross migr. rate, 2002–20:						
To/fr. social neighbours	−3.556[a]			−3.455[a]		
	(0.766)			(0.745)		
To/fr. all in social lag		−4.662[a]	−4.242[a]		−4.591[a]	−4.083[a]
		(0.903)	(1.116)		(0.875)	(1.067)
Estimation method	OLS	OLS	OLS	2SLS	2SLS	2SLS
Commuting zone FE	✓	✓	✓	✓	✓	✓
Observations	143	143	143	143	143	143
Within-R^2	0.308	0.438	0.395	0.304	0.436	0.392
Kleibergen–Paap F				389.6	408.1	366.7

Notes: Robust standard errors in parentheses are clustered at the level of 31 lower commuting zones. All independent variables are standardised to have zero mean and unit variance. Social neighbours are the five most socially connected regions as measured by the $SCI_{(-c)}$, which is equal to the SCI (Bailey et al., 2020) after discarding region-pairs in the same commuting zone or with substantial pairwise commuting flows. Import-shock exposure in a set of social neighbours is the $SCI_{(-c)}$ weighted sum of exposure over the sum of $SCI_{(-c)}$ in the set. The social lag of import-shock exposure is the $SCI_{(-c)}$ weighted sum of exposure across all regions over the respective $SCI_{(-c)}$ value sum. $^{a}p < 0.01$, $^{c}p < 0.1$.

When comparing regions outside a given focal region's commuting zone, there is a weak negative association between import-shock exposure and the density of social ties with the focal region, which mirrors a similarly weak and negative association between import-shock and gross migration flows to and from the focal region. Further, the former disappears when gross migration flows are held constant, suggesting that, net of its association with interregional migration, import-shock exposure is unrelated to the density of interregional social ties. While these associations are arguably too modest to be concerning for the identification of spillover effects—a one standard deviation increase in import-shock exposure corresponds to a respective 0.12 and 0.06 standard deviation decrease in interregional gross migration and social connectedness—I examine the robustness of the baseline results to the inclusion of controls for interregional migration in Table 2. The first column of Table 2 examines the robustness of the effect of social neighbours' import-shock exposure on the regional Leave vote share when controlling for the rate of gross migration between 2002 and 2020, relative to the regional population as per the 2001 Census, to and from social neighbours. In the second column, the latter is replaced with the rate of gross migration to and from all regions outside each region's commuting zone with which it does not share substantial pairwise commuting flows, while in the third column social neighbours' exposure is also replaced with the social lag of exposure across regions. The remaining columns present the corresponding 2SLS estimates.

Table 2 shows that the spillover effects of social neighbours' exposure to Chinese import competition on the regional Leave vote share remains close to baseline estimates. However, the same does not hold for the social lag of exposure, which reduces more substantially and loses significance when gross migration flows are held constant. As shown in Appendix E, one possible explanation for this result is that the effect of import-shock exposure on interregional migration is more relevant to the formation of social ties between more weakly connected regions, and less relevant for ties between the most strongly connected regions, which are likely to have been shaped by more structural factors. This could mean that identifying the political effects of the social lag of exposure to import competition is more challenging relative to those of social neighbours' exposure, given that the former measure additionally considers the interregional social ties between relatively disconnected regions.[30] Another possibility is that interregional migration is an important channel via which the social lag of exposure shapes local voting behaviour, which is not necessarily problematic for identification; indeed, it appears that this may also be the case for within-region exposure. Yet without historical data on interregional social ties, it is difficult to properly evaluate each of these prospects. As such, whereas a causal interpretation of the estimated effects of social neighbours' exposure on voting behaviour seems plausible, it might be less so in the case of the estimated effects of the social lag of exposure.

Are the estimated spillover effects of social neighbours' import-shock exposure on voting behaviour attributable to economic spillovers between social neighbours? In the first three columns of Table 3, I successively augment the regional 2SLS specification corresponding to the fifth column of Table 1 with a series of regional economic controls.[31] In line with the conceptual framework, these controls attempt to absorb effects on regional voting outcomes arising from indirect effects on linked industries, aggregate demand effects, and reallocation and mobility effects. In the first column, I control for the start-of-period employment share in manufacturing using data from the 1991 UK Census. According to ONS estimates, manufacturing goods accounted for nearly 70 per cent of intermediate consumption in the UK manufacturing sector around that period (1995). This control thus accounts for the fact that indirect effects on linked industries are likely to be largely contained within the sector. In the second column, I again use ONS data to append the change in regional gross value added between 1997 and 2016 relative to the median. This control, which is also considered by Colantone and Stanig (2018a), captures unequal growth in income generated across regional industries between the onset of the Chinese import shock and the EU membership referendum and thus proxies for aggregate demand effects. Lastly, in the third column, I also include the gross migration rate from social neighbours between 2002 and 2016, relative to the regional population as of 2001, proxying for reallocation and mobility effects.[32]

Across the first three columns of Table 3, it is shown that while the inclusion of regional economic controls largely blocks the effects of within-region exposure to import competition on voting outcomes, spillover effects from social neighbours' exposure retain significance and most of their magnitude relative to the respective 2SLS specification without controls. These results suggest that the estimated spillover effects are unlikely to be primarily driven by economic spillovers between social neighbours, and are thus in line with the presence of social spillovers operating via information flows as discussed in the conceptual framework.

In the fourth column of Table 3, I also examine the robustness of regional estimates of the political effects of social neighbours' exposure to import competition to the inclusion of controls for the start-of-period share of the regional population that is aged over 65 and the start-of-period population share that is foreign-born. In the fifth column, I also consider the regional distance to London calculated as the geographic distance from the centroid of the 'Camden, City of London, and Westminster' harmonised ITL3 region. These and similar factors have previously been identified as salient correlates of regional

[30] Table F.6 further shows that similar estimates are obtained for the effects of social neighbours' exposure when the latter is calculated as a simple rather than an SCI weighted average of exposure in the set. This further suggests that there is no bias arising from a relationship between import competition and the relative weighting of each social neighbour.

[31] Table F.7 presents equivalent robustness checks for the social lag of exposure, augmenting the regional 2SLS specification corresponding to the sixth column of Table 1.

[32] Recall that 2002 is the earliest year for which data on interregional migration flows are available and that 2016 is the year in which the UK EU membership referendum was held.

Table 3
Regional-level robustness, social neighbours' import-shock exposure.

	Leave vote share					
	(1)	(2)	(3)	(4)	(5)	(6)
Import-shock exposure:						
Within-region	2.474[c]	2.142	1.379	2.113[a]	3.447[a]	3.422[a]
	(1.358)	(1.387)	(1.226)	(0.725)	(0.773)	(0.948)
Social neighbours	2.810[a]	2.696[a]	2.694[a]	3.084[b]	2.420[b]	2.748[b]
	(1.001)	(0.893)	(0.665)	(1.190)	(1.092)	(1.108)
Manufacturing emp. share, 1991	1.386	0.903	0.834			
	(1.713)	(1.577)	(1.542)			
Δ Relative income, 1997–2016		−2.433[b]	−2.389[a]			
		(0.937)	(0.845)			
Gross migr. rate, 2002–2016			−3.195[a]			
			(0.757)			
Pop. share aged over 65, 1991				0.0534		
				(0.774)		
Pop. share foreign-born, 1991				−6.122[a]		
				(0.459)		
Distance to London					9.067[a]	
					(3.236)	
Pop. share active Internet users, 2016/17						−2.124[b]
						(0.780)
Estimation method	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Commuting zone FE	✓	✓	✓	✓	✓	✓
Observations	143	143	143	143	143	143
Within-R^2	0.196	0.283	0.391	0.495	0.251	0.218
Kleibergen–Paap F	146.1	148.3	128.7	519.6	432.2	485.1

Notes: Robust standard errors in parentheses are clustered at the level of 31 lower commuting zones. All independent variables are standardised to have zero mean and unit variance. Social neighbours are the five most socially connected regions as measured by the $SCI_{(-c)}$, which is equal to the SCI (Bailey et al., 2020) after discarding region-pairs in the same commuting zone or with substantial pairwise commuting flows. Import-shock exposure in a set of social neighbours is the $SCI_{(-c)}$ weighted sum of exposure over the sum of $SCI_{(-c)}$ in the set. The gross migration rate includes migration flows between each region and its social neighbours. Data on active Internet users are available for 2016 for 79 regions and for 2017 for 64 regions.
[a]$p < 0.1$, [b]$p < 0.05$, [c]$p < 0.1$.

voting behaviour in the 2016 UK EU membership referendum (Becker et al., 2017), and could in principle bias estimates insofar as they are correlated with regional variation in social neighbours' import-shock exposure and the adopted instrumental variable approach fails to isolate exogenous variation in the former. However, as shown across columns, the effect of social neighbours' exposure retains its significance and most of its magnitude, thereby assuaging this concern.[33] The sixth column of Table 3 further demonstrates the robustness of estimates to the inclusion of a control for the share of the population that were active Internet users near the time of the EU membership referendum, defined by the ONS as those who reported using the Internet in the previous three months. Given that social ties are observed using data on Facebook users, this control is intended as proxy for any substantial regional variation in usage of the platform that could be affecting results.

Previous work has shown that, other than regional exposure to import competition, support for the Leave option in the 2016 EU UK referendum is likely to have responded to other kinds of shocks, including exposure to immigration (e.g. Colantone and Stanig, 2018a) and austerity policies (e.g. Fetzer, 2019). Spillover effect estimates could be biased to the extent that a region's social exposure to import competition is correlated with its social exposure to immigration and policy shocks. Table F.9 examines the robustness of the 2SLS estimates arising from the specifications corresponding to the fifth and sixth columns of Table 1 when within-region and social exposure to these shocks are held constant. Namely, I calculate exposure to immigration as the growth in the share of the regional foreign-born population share between the 1991 and 2011 Census, while I draw on the district-level dataset of Fetzer (2019) to measure regional exposure to austerity, aggregating at the level of harmonised ITL3 regions using population weights. In a similar way to the import-shock exposure measures, I also calculate social neighbours' exposure and the social lag of exposure to these shocks. As shown across the columns of Table F.9, the inclusion of these controls does not substantially alter the baseline estimates, suggesting that the spillover effects of import-shock exposure on voting behaviour are unlikely to be confounded by the spillover effects of immigration and austerity policy shocks.

In Table F.10, I also present a supplementary analysis of the effect of both measures of social exposure to Chinese import competition on the regional vote share of UK Independence Party (UKIP), the foremost Eurosceptic party in the UK leading up to the EU membership referendum, in European Parliament (EP) elections over time.[34] Interestingly, whereas the effect of within-region exposure to import competition is shown to only become significant in the 2014 election, social exposure as captured by both measures is shown to be significant earlier in the 2009 election. The seemingly delayed effect of within-region exposure is in line with previous evidence suggesting that the associated regional grievances were only translated into support for Eurosceptic platforms when these were activated by the austerity shocks following the Great Recession (Fetzer, 2019). However, the relatively earlier political impact of social spillovers from local exposure could imply that voting

[33] Table F.8 shows that when considering differences between the mean characteristics of the 15 regions with the highest within-region exposure to import competition relative to those of the 15 regions with the highest social neighbours' exposure, the latter group has significantly lower manufacturing employment shares and higher shares of people aged over 65.

[34] Data on EP vote shares are drawn from the study of Fetzer (2019), which presents similar analyses of the effect of local exposure to austerity on voting behaviour over time. Table F.11 also presents 2SLS estimates of the effects of social neighbours' exposure on the shares of other parties and turnout over time.

Table 4
Individual-level results.

	Voted Leave					
	(1)	(2)	(3)	(4)	(5)	(6)
Import-shock exposure:						
Within-region	0.0589^{a}	0.0506^{a}	0.0473^{b}	0.0597^{a}	0.0469^{b}	0.0422^{c}
	(0.0183)	(0.0173)	(0.0210)	(0.0194)	(0.0180)	(0.0226)
Social neighbours		0.0420^{b}			0.0542^{a}	
		(0.0172)			(0.0182)	
Social lag			0.0561^{c}			0.0704^{b}
			(0.0310)			(0.0305)
Estimation method	Probit	Probit	Probit	IV Pr.	IV Pr.	IV Pr.
Commuting zone FE	✓	✓	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓	✓	✓
Observations	22,231	22,231	22,231	22,231	22,231	22,231
Regions	143	143	143	143	143	143
Kleibergen–Paap F				656.8	315.6	289.6

Notes: Robust standard errors in parentheses are clustered at the level of 31 lower commuting zones. All independent variables are standardised to have zero mean and unit variance. Demographic controls include age, gender, and five education dummies. Social neighbours are the five most socially connected regions as measured by the $SCI_{(-c)}$, which is equal to the SCI (Bailey et al., 2020) after discarding region-pairs in the same commuting zone or with substantial pairwise commuting flows. Import-shock exposure in a set of social neighbours is the $SCI_{(-c)}$ weighted sum of exposure over the sum of $SCI_{(-c)}$ in the set. The social lag of import-shock exposure is the $SCI_{(-c)}$ weighted sum of exposure across all regions over the respective $SCI_{(-c)}$ value sum. $^{a}p < 0.01$, $^{b}p < 0.05$.

behaviour in other regions was originally responsive to information flows relating to local conditions rather than conformity.

What kinds of social spillovers might lie behind the estimated spillover effects on regional voting outcomes? Answering this question with any degree of confidence is prohibitive given the absence on data on the nature of information flows between socially connected regions. However, a broad distinction might be made between information transmitted via geographic processes, such as travel, and via processes that are not constrained by geographic distance, such as telecommunication. In Table F.12, I present estimates from alternative specifications looking at spillover effects on the regional share of the Leave vote from the geographic neighbours' exposure to Chinese import competition as well as the spatial lag of exposure. Like the measure relating to the exposure of social neighbours, I define geographic neighbours as the five most geographically proximate regions located outside the focal region's commuting zone that do not share substantial pairwise commuting flows with it, and calculate the inverse distance weighted average of exposure in the set. Mirroring the alternative social lag measure, I also calculate the spatial lag of exposure as the inverse distance weighted average of exposure across all such regions. Across specifications, it is shown that the estimated spillover effects are indistinguishable from zero, which suggests that geographic processes are unlikely to be driving the identified social spillovers.

Table 4 presents estimates from the individual-level specifications using data from Wave 9 of the British Election Study, examining the effect of regional-level social exposure to Chinese import competition on having voted to leave the EU in the referendum, whilst controlling for individual-level demographic characteristics. The first, second, and third columns present baseline probit estimates reflecting the baseline regional OLS estimates on the respective columns of Table 1, while the remaining columns present the corresponding IV probit estimates. To aid interpretation, I also report the average marginal effects for each coefficient in Table F.13. It is shown that the individual-level results are similar to those of the regional analysis, with instrumental variable estimates being slightly higher than the respective baseline estimates. Further, comparing individuals residing in different regions within the same commuting zone, a one standard deviation increase in either within-region or social neighbours' import-shock exposure is associated with a similar increase in the probability of voting Leave by roughly 2

Table 5
Individual-level robustness, social neighbours' import-shock exposure.

	Voted Leave				
	(1)	(2)	(3)	(4)	(5)
Import-shock exposure:					
Within-region	0.0466^{a}	0.0503^{a}	0.0496^{a}	0.0444^{b}	0.0460^{a}
	(0.0168)	(0.0176)	(0.0170)	(0.0173)	(0.0175)
Social neighbours	0.0432^{b}	0.0408^{b}	0.0470^{a}	0.0393^{b}	0.0054
	(0.0189)	(0.0173)	(0.0182)	(0.0189)	(0.0441)
(× At risk of poverty)	−0.0044				
	(0.0274)				
(× Unemployed)		0.0186			
		(0.0678)			
(× Student)			−0.0747		
			(0.1070)		
(× Follows news online)				−0.0090	
				(0.0201)	
(× UK-born parents)					0.0290
					(0.0431)
At risk of poverty	−0.0218				
	(0.0267)				
Unemployed		0.2480^{a}			
		(0.0607)			
Student			-0.6350^{a}		
			(0.0908)		
Follows news online				−0.0080	
				(0.0230)	
UK-born parents					0.1850^{a}
					(0.0602)
Estimation method	Probit	Probit	Probit	Probit	Probit
Commuting zone FE	✓	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓	✓
Observations	20,852	22,231	22,231	21,605	16,658
Regions	143	143	143	143	143

Notes: Robust standard errors in parentheses are clustered at the level of 31 lower commuting zones. All independent variables are standardised to have zero mean and unit variance. Demographic controls include age, gender, and five education dummies. Social neighbours are the five most socially connected regions as measured by the $SCI_{(-c)}$, which is equal to the SCI (Bailey et al., 2020) after discarding region-pairs in the same commuting zone or with substantial pairwise commuting flows. Import-shock exposure in a set of social neighbours is the $SCI_{(-c)}$ weighted sum of exposure over the sum of $SCI_{(-c)}$ in the set. $^{a}p < 0.01$, $^{b}p < 0.05$.

per cent. Again, the effect of the social lag of exposure is estimated to be only moderately higher at roughly 2.6 per cent in line with a likely decay in social spillover effects from exposure beyond the most socially connected regions.

In Table 5, I examine whether spillover effects from social neighbours' exposure to import competition on vote choice in the referendum are restricted to particular categories of voters. In so doing, I augment the probit specification from the second column of Table 4 with a series of dummies which are also interacted with social neighbours' exposure. This includes dummies for individuals that report a moderate to high risk of poverty over the next 12 months, the unemployed, those in full-time education, those who followed political news on the Internet for over 1 hour in the previous 7 days, and those with both parents born in the UK.[35]

Consistent with the regional robustness checks, spillover effects do not appear to be restricted to those facing economic difficulty. As seen in the first two columns of Table 5, spillover effects on vote choice among those at low risk of poverty and those in employment remain close to the baseline, while the corresponding interaction terms are

[35] Table F.14 presents a similar analysis for the effects of the social lag of import-shock exposure. As interactions cannot be accommodated in IV probit specifications, I also present the respective 2SLS estimates in Tables F.15 and F.16.

not significant. Similarly, it does not seem that spillover effects are restricted to those that regularly follow political news on the Internet, suggesting that these are not necessarily restricted to active Internet users. Interestingly, when social neighbours' import-shock exposure is interacted with the dummy variable for both of the individual's parents being born in the UK, the direct effect of the former reduces substantially relative to that of the interaction them. Further, while there is a substantial reduction in the sample of individuals for which this data is available and both effects emerge statistically indistinguishable from zero, the interaction term in the corresponding social lag specification is similar and significant at the 10% level. Taken together, these findings might suggest that voters with UK-born parents have been more responsive to social exposure to import competition in other regions; one potential explanation for this is that recent international migrants are likely to have more geographically concentrated social networks in destination countries (e.g. Schelling, 1971).

7. Conclusion

In this paper, I have shown that local trade-related economic shocks within regions in England and Wales are likely to have had spillovers that boosted support for Brexit in socially connected places lying well beyond their boundaries. The estimated effects on voting behaviour are comparable to those of local exposure and close to the margin that ultimately determined the outcome of the 2016 UK EU membership referendum. Importantly, the results suggest that these spillovers are more likely to be driven by information flows over social networks, rather than industry linkages, spending, and mobility between regions. This evidence offers a new perspective on the role of import competition and 'left-behind' places in voting to the leave EU in the UK. Whereas previous studies have established that the vote benefited from economic and cultural insecurity responding to local economic decline, the evidence presented in this paper suggests that these concerns are likely to have spread more widely and may have even affected the preferences of distant individuals facing relatively little economic difficulty. The results point to a promising avenue of research on the role of social spillovers on voting outcomes from spatially uneven exposure to economic shocks in other national and electoral contexts.

CRediT authorship contribution statement

Andreas Mastrosavvas: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: This work was supported by the UK Economic and Social Research Council (grant number 2272893).

Data availability

Replication materials for this paper are available on GitHub: https://github.com/amastrosavvas/REPL-Social-Networks-and-Brexit.

Appendix A. Delineating harmonised regions

The SCI by Bailey et al. (2020), which is the employed measure of interregional social ties, is reported for NUTS3 regions as of the 2016 version of the classification. Mobility, employment, and voting data are available for local authority districts (LAD), with the exception of commuting flows from the 2011 UK Census, which are in some instances reported for Census Merged LAD (CMLAD). I address the resulting correspondence issues by drawing on the Office for National Statistics (ONS) Code History Database and the Eurostat NUTS correspondence tables to produce crosswalks to harmonised spatial units for which each variable can be uniformly observed over all periods in the dataset. The latter span from 1991, which is the base year of the import-shock exposure measures, to 2020, when the SCI is measured. The earliest LAD version in the data is 2009.

Table A.1
LAD20 to CMLAD11 correspondence.

LAD20 code	LAD20 name	CMLAD11 code	CMLAD11 name
E06000052	Cornwall	E41000052	Cornwall, Isles of Scilly
E06000053	Isles of Scilly	E41000052	Cornwall, Isles of Scilly
E09000001	City of London	E41000324	Westminster, City of London
E09000033	Westminster	E41000324	Westminster, City of London

Notes: Data is drawn from the ONS Code History Database. Only includes CMLAD11 that appear in the dataset.

Table A.2
LAD boundary changes, 2009 to 2020.

LAD code	LAD name	LAD code (previous)	LAD name (previous)	Statutory Instrument
S12000045	E. Dunbartonshire	S12000009	E. Dunbartonshire	353/2010
S12000045	E. Dunbartonshire	S12000043	Glasgow City	353/2010
S12000046	Glasgow City	S12000009	E. Dunbartonshire	353/2010
S12000046	Glasgow City	S12000043	Glasgow City	353/2010
S12000047	Fife	S12000015	Fife	430/2017
S12000047	Fife	S12000024	Perth & Kinross	430/2017
S12000048	Perth & Kinross	S12000015	Fife	430/2017
S12000048	Perth & Kinross	S12000024	Perth & Kinross	430/2017
E08000037	Gateshead	E08000020	Gateshead	595/2013
E06000057	Northumberland	E08000020	Gateshead	595/2013
E07000242	E. Hertfordshire	E07000097	E. Hertfordshire	596/2013
E07000243	Stevenage	E07000097	E. Hertfordshire	596/2013
W06000024	Merthyr Tydfil	W06000007	Powys	889/2009
W06000023	Powys	W06000007	Powys	889/2009

Notes: All codes on the first column except S12000046 were live in December 2020. Data is drawn from the ONS Code History Database. Excludes data for Northern Ireland.

I first create a harmonised LAD classification, which is comprised of 364 LAD as of 2020 and two CMLAD as of 2011, covering England, Scotland, and Wales. As discussed in the main text, Northern Ireland is not considered due to data limitations, while Scotland is excluded from the main empirical specifications due to poor correspondence between Scottish LAD and NUTS3. Though its inclusion in the harmonised LAD classification aids with correcting regional import-shock exposure in England and Wales for measurement error. As shown on Table A.1, the two CMLAD appearing in the dataset are aggregates of two respective pairs of LAD, meaning that any variable that is observed for the latter can be easily aggregated to the former. Nevertheless, as the dataset period spans multiple years, boundary changes cause 1-to-n relations between earlier LAD versions in the dataset and the 2020 version.

Table A.2 presents the ten LAD that are involved in boundary changes as well as indexing the corresponding statutory instruments associated with each change. Statutory instrument documentation is accessible on Legislation.gov.uk.

As detailed in the statutory instrument documentation, the boundary changes only involve a few hundred square metres of land at a time, which largely cover non-residential areas. This is also reflected in the fact that there are no new LAD names arising from the changes. I thus create a crosswalk that ignores these boundary changes by only matching each of the 10 successor LAD codes with the predecessor code corresponding to the same LAD name. This allows me to match units from all LAD versions with a harmonised LAD equivalent or parent.

I next create a harmonised ITL3 classification covering England and Wales, which corresponds with both harmonised LAD and NUTS3 as of 2016. As shown on Table A.3, there are only two instances of mismatching between ITL3 and the latter two classifications: one is due to a NUTS3 region boundary change between the 2016 and 2021 versions, and the other is due to a 1-to-n match between a harmonised

Table A.3
ITL321 to harmonised LAD/NUTS316 correspondence.

ITL321 code	ITL231 name	NUTS316/HLAD code	NUTS316/HLAD name
TLK24	Bournemouth, Christchurch & Poole	UKK22	Dorset CC
TLK25	Dorset	UKK22	Dorset CC
TLI31	Camden, City of London	E41000324	Westminster, City of London
TLI32	Westminster	E41000324	Westminster, City of London

Notes: Data is drawn from the ONS Code History Database and the Eurostat NUTS history tables. Excludes data for Scotland and Northern Ireland.

Table B.1
UK trade with China and world, 1991–2007, in 2015 £billions.

Year	Imports from China	Exports to China	Imports from rest of the world	Exports to rest of the world
1991	0.38	0.15	61.52	53.54
2007	20.17	2.92	225.73	150.95
Growth	5,180 %	1,788 %	267 %	182 %

Notes: Values refer to the trade of manufacturing products. Data are from the COMTRADE database, where they are available in US dollars and at current prices. Currency conversion was performed using factors available on COMTRADE, while the ONS Consumer Price Index (CPI) was used for deflation.

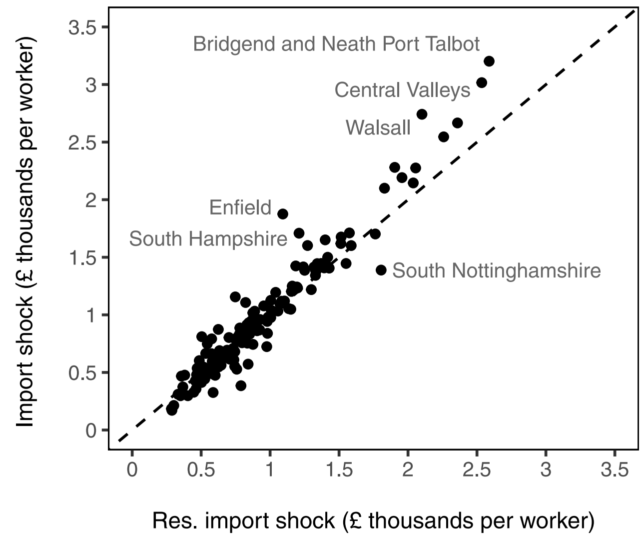

Fig. C.1. Comparison of import-shock measures. *Notes*: Dots represent harmonised ITL3 regions. The two measures are equal for regions on the dashed line. Pounds are in 2015 prices.

LAD and two ITL3 regions. Both instances are resolved by merging the four ITL3 regions into two aggregates. The resulting classification is thus comprised of 141 ITL3 regions and two ITL3 region aggregates.

Appendix B. Trend in UK–China trade

See Table B.1.

Appendix C. Comparing regional import-shock exposure measures

Fig. C.1 compares the place-of-work and residential import-shock exposure measures. It is shown that the two measures are very similar for the vast majority of harmonised ITL3 regions. Mean residential exposure is lower than its place-of-work counterpart by a modest 4 percentage points. Some of the more pronounced differences between the two measures are driven by the smoothing effect of the residential adjustment on extreme values of place-of-work exposure. For instance, Bridgend and Neath Port Talbot—the most affected region by both measures—is shown to move closer to the exposure of other regions as all residents commuting outside the region in 1991 were, as a matter of course, employed in less exposed regions as per the place-of-work measure. There are also cases where switching from place-of-work to residential exposure is associated with a substantial shift in the respective region's position in the distribution. For instance, Enfield moves from being the 11th most exposed region to the 43rd place, betraying its substantial commuting outflows to other regions in Greater London.

Appendix D. Comparing alternative sets of social and geographic neighbours

The top panel of Fig. D.1 plots the mean least-cost geographic distance of the k–th nearest neighbour from the focal region as defined by the SCI and $\mathrm{SCI}_{(\text{-c})}$. I also plot the mean least-cost geographic distance by neighbour rank as defined by inverse least-cost geographic distance before and after discarding region-pairs within the same commuting zone and substantial pairwise commuting flows. Geographic distance is computed between the population weighted centroids of harmonised ITL3 regions, which are derived using 1991 Census enumeration district centroids and populations as building blocks. The least-cost path algorithm is run over a 650 × 550 geographic transition matrix covering England and Wales, allowing for queen moves among cells on land while prohibiting movement along water surfaces. In the underlying raster layer, land buffers are placed around the isles of Wight and Anglesey to connect them to the British mainland.

Across measures, neighbour rank increases with geographic distance. A given region's ten nearest neighbours as defined by the SCI are, on average, about as far away as its respective ten nearest neighbours defined by geographic distance. However, looking at the 'commuting-discounted' measures, neighbours defined on the basis of $\mathrm{SCI}_{(\text{-c})}$ are, on average, further away than their geographic counterparts. The first, fifth, and tenth neighbours based on the former measure are on average 74, 102, and 123 km away from the focal region, while the respective geographic neighbours are 57, 80, and 96 km away. This suggests that there is less overlap in the neighbour ranks emerging from the 'commuting-discounted' measures of social and geographic proximity when compared to the respective raw measures. Indeed, as shown on Fig. D.2, the SCI and the raw geographic distance measure identify the same first nearest neighbour in 65 per cent of cases, up from 37 and 27 per cent for the second and third. In contrast, the respective overlap between $\mathrm{SCI}_{(\text{-c})}$ and the 'commuting-discounted' geographic distance measure is lower at 41, 17, and 10 per cent.

Switching from the SCI to $\mathrm{SCI}_{(\text{-c})}$ does not only alter neighbour ranks, but also the relative density of each neighbour's social ties with the focal region. As shown in the bottom panel of Fig. D.1, within each region, the mean SCI value of the k–th neighbour relative to that of the first neighbour as defined by the SCI declines very sharply. In contrast, the mean relative SCI value of the k–th neighbour as defined by the $\mathrm{SCI}_{(\text{-c})}$ declines more smoothly, meaning there is less variation with respect to the density of their social ties with the focal region. A similar pattern is observed when switching from the raw to the 'commuting-discounted' geographic distance measure. However, in both cases, the relative density of social ties with the focal region is more heterogeneous, suggesting that proximity in social space decays more rapidly than in geographic space.

Appendix E. Import competition and social ties between local labour markets

In order to examine the relationship between import competition and internal migration between ITL3 regions in different local labour

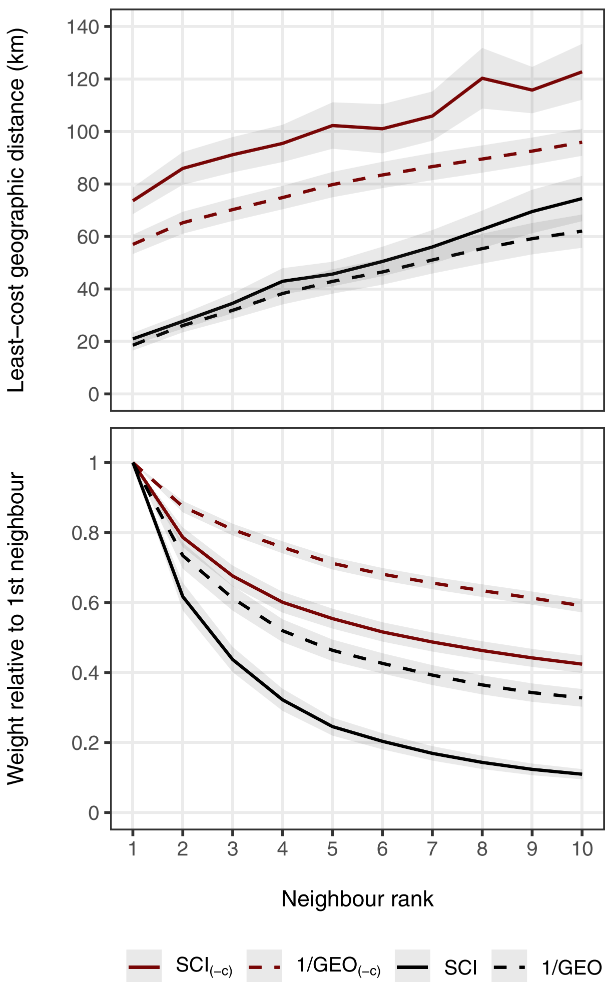

Fig. D.1. Mean distance from and weight of k–th neighbour, by measure. *Notes:* Shaded areas denote 95% confidence intervals. SCI refers to the Social Connectedness Index (Bailey et al., 2020) after discarding the connectedness of each region with itself. $\mathrm{SCI}_{(\text{-c})}$ refers to the latter measure after discarding region-pairs in the same commuting zone or with substantial pairwise commuting flows. Similarly, 1/GEO and $1/\mathrm{GEO}_{(\text{-c})}$ refer to respective measures based on inverse least-cost geographic distance.

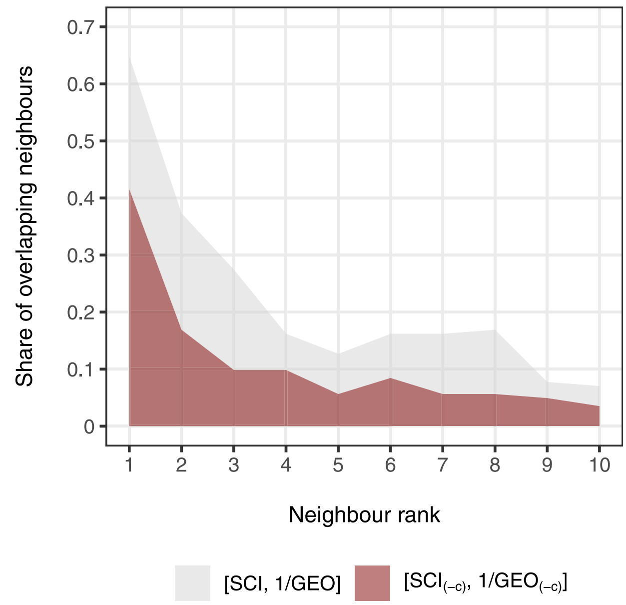

Fig. D.2. Overlapping neighbours, by pairs of measures. *Notes:* SCI refers to the Social Connectedness Index (Bailey et al., 2020) after discarding the connectedness of each region with itself. $\mathrm{SCI}_{(\text{-c})}$ refers to the latter measure discarding region-pairs in the same commuting zone or with substantial pairwise commuting flows. Similarly, 1/GEO and $1/\mathrm{GEO}_{(\text{-c})}$ are respective measures based on inverse least-cost geographic distance.

Table E.1
Effect of import competition on migration flows and social ties.

	Gross migration, 2002–20		$\mathrm{SCI}_{(\text{-c})}$			
	(1)	(2)	(3)	(4)	(5)	(6)
Import-shock exposure:						
Destination region	-0.102^{a}	-0.118^{a}	-0.046^{b}	-0.055^{b}	0.008	0.007
	(0.036)	(0.035)	(0.022)	(0.024)	(0.024)	(0.024)
Gross migration, 2002–20					0.531^{a}	0.531^{a}
					(0.063)	(0.063)
Estimation method	OLS	2SLS	OLS	2SLS	OLS	2SLS
Origin region FE	✓	✓	✓	✓	✓	✓
Observations	18,034	18,034	18,034	18,034	18,034	18,034
Within-R^2	0.013	0.013	0.002	0.002	0.234	0.234

Notes: Observations are ITL3 region-pairs. Robust standard errors in parentheses are two-way clustered at the level of origin regions and destination lower commuting zones. All variables are standardised to have zero mean and unit variance. The $\mathrm{SCI}_{(\text{-c})}$ is equal to the SCI (Bailey et al., 2020) after discarding region-pairs in the same commuting zone or with substantial pairwise commuting flows. $^{a}p < 0.01$, $^{b}p < 0.05$.

markets in England and Wales, I estimate the following specification using both OLS and 2SLS:

$$Mig_{rr'(-c)} = \alpha_r + \psi\, ResImpShock_{r'} + \epsilon_{rr'} \tag{10}$$

Here, $Mig_{rr'(-c)}$ denotes standardised gross migration flows between 2002 and 2020 between ITL3 region pairs rr', disregarding region-pairs that belong to the same commuting zone or share substantial pairwise commuting flows. Further, α_r are 'origin' region fixed effects, $ResImpShock_{r'}$ is the standardised within-region exposure to Chinese import competition in 'destination' region r', and the errors are two-way clustered at the level of origin regions and destination lower commuting zones.[36] The coefficient ψ is thus interpreted as the estimated difference, in standard deviations, in the gross migration flows to and from a given origin region between two destination regions with a one standard deviation difference in exposure to import competition. Note that the period for which gross migration flows are measured starts from the earliest year for which data on interregional migration flows are available—roughly coinciding with the ascension of China to the World Trade Organisation (WTO)—and ends on the year in which interregional social ties in England and Wales are observed.

The first and second column of Table E.1 respectively present OLS and 2SLS estimates based on (10). It is shown that there is a significant and negative relationship between import competition and gross migration flows between local labour markets. Looking at the gross migration flows of a given region to and from two others with a one standard deviation difference in exposure to import competition, it is estimated that gross migration flows to and from the more exposed region will be lower by roughly 0.12 standard deviation relative to those to and from the less exposed region. Consequently, regions that were more exposed to Chinese import competition between 1991 and 2007 are likely to have had slightly lower gross migration flows to and from outside of their local labour market between 2002 and 2020 relative to those less exposed.

Is import competition associated with interregional social ties between local labour markets? In order to examine this, I estimate the

[36] Note that the conventional terms 'origin' and 'destination' here simply refer to the pairwise structure of the data rather than implying directed migration flows. By definition, gross migration flows are undirected: for any given pair of regions, these are the sum of migration flows in both directions.

Table F.1
Key summary statistics.

Variable	Units	N	Mean	SD	Min.	Max.
Import-shock exposure:						
Within-region	£ / worker	143	945	474	285	2,588
Social neighbours	£ / worker	143	887	290	376	1,715
Social lag	£ / worker	143	942	60	790	1,099
Gross migr. rate, 2002–20:						
To/fr. social neighbours	%	143	10.80	5.22	2.45	28.30
To/fr. all in social lag	%	143	76.30	34.00	21.10	20.80
Gross migr. rate, 2002–16:						
To/fr. social neighbours	%	143	8.09	3.94	1.91	22.30
To/fr. all in social lag	%	143	57.20	25.40	15.20	15.05
Manufacturing emp. share, 1991	%	143	17.82	6.20	6.31	34.90
Δ Relative income, 1997–2016	%	143	3.34	10.76	−20.51	48.57
Pop. share over 65, 1991	%	143	16.14	2.72	10.00	25.56
Pop. share foreign-born, 1991	%	143	7.35	7.68	1.42	42.12
Distance to London	km	143	170	114	0	428
Pop.share active Internet users, 2016/17	%	143	88.42	4.30	77.24	96.47

Notes: Measurement is at the level of ITL3 regions. Pounds (£) are in 2015 prices. Migration rates are relative to regional population as of 2001. Data on active Internet users are available for 2016 for 79 regions and for 2017 for 64 regions.

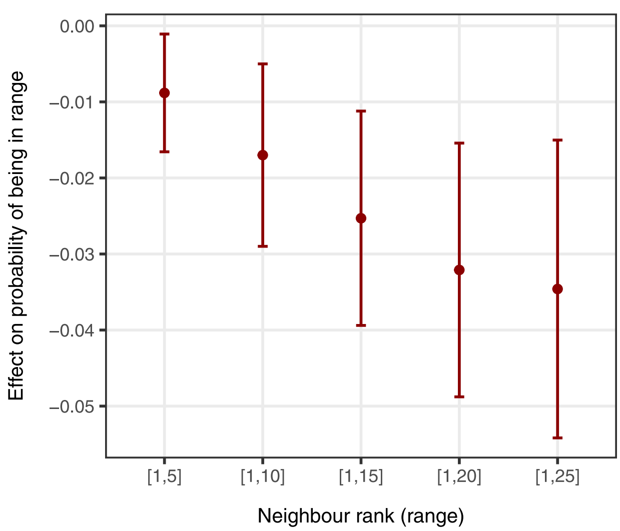

Fig. E.1. Effect of import competition on sets of a social neighbours. *Notes*: Dots represent estimates from separate 2SLS regressions of a binary variable indicating the destination region rank range as defined by the $SCI_{(-c)}$ on destination region import-shock exposure, with observations being region-pairs. All specifications include origin region fixed effects, and robust standard errors two-way clustered at the level of origin regions and destination lower commuting zones. The $SCI_{(-c)}$ is equal to the SCI (Bailey et al., 2020) after discarding region-pairs in the same commuting zone or with substantial pairwise commuting flows.

following specification using both OLS and 2SLS:

$$SCI_{rr'(-c)} = \alpha_r + \xi ResImpShock_{r'} + \epsilon_{rr'} \tag{11}$$

As per the main body of the paper, $SCI_{rr'(-c)}$ denotes the standardised pairwise density of interregional social ties as captured by the SCI by Bailey et al. (2020) after discarding region-pairs in the same commuting zone or with substantial pairwise commuting flows. Similar to (10), α_r represent origin region fixed effects, $ResImpShock_{r'}$ is the standardised within-region exposure to Chinese import competition in destination region r', and the errors are two-way clustered at the level of origin regions and destination lower commuting zones. As such, the coefficient ξ is interpreted as the estimated difference, in standard deviations, in the density of social ties between a given origin region and each of two destination regions with a one standard deviation difference in exposure to import competition.

Table F.2
Regional-level results, place-of-work exposure.

	Leave vote share					
	(1)	(2)	(3)	(4)	(5)	(6)
Import-shock exposure:						
Within-region	2.868^{a}	2.344^{a}	1.812^{a}	3.660^{a}	2.907^{a}	2.335^{b}
	(0.710)	(0.615)	(0.642)	(0.898)	(0.703)	(0.913)
Social neighbours		2.694^{c}			3.227^{c}	
		(1.530)			(1.632)	
Social lag			4.320^{a}			4.808^{a}
			(0.989)			(1.000)
Estimation method	OLS	OLS	OLS	2SLS	2SLS	2SLS
Commuting zone FE	✓	✓	✓	✓	✓	✓
Observations	143	143	143	143	143	143
Within-R^2	0.105	0.156	0.202	0.097	0.148	0.196
Kleibergen–Paap F				1,179	633.1	466.0

Notes: Robust standard errors in parentheses are clustered at the level of 31 lower commuting zones. All independent variables are standardised to have zero mean and unit variance. Social neighbours are the five most socially connected regions as measured by the $SCI_{(-c)}$, which is equal to the SCI (Bailey et al., 2020) after discarding region-pairs in the same commuting zone or with substantial pairwise commuting flows. Import-shock exposure in a set of social neighbours is the $SCI_{(-c)}$ weighted sum of exposure over the sum of $SCI_{(-c)}$ in the set. The social lag of import-shock exposure is the $SCI_{(-c)}$ weighted sum of exposure across all regions over the respective $SCI_{(-c)}$ value sum. $^{a}p < 0.01$, $^{b}p < 0.05$.

The third and fourth column of Table E.1 present the respective OLS and 2SLS estimates based on (11). These suggest that, when considering the density of social ties of a given region with each of two others that are outside of each local labour market and differ in their exposure to import competition by one standard deviation, social connectedness with the more exposed region will be lower by roughly 0.05 standard deviation relative to social connectedness with the less exposed region. Interestingly, the estimate is of the same direction and of a similar magnitude to that of the effect of import-shock exposure on gross migration flows between local labour markets. Indeed, in the fifth and sixth column of Table E.1 it is shown that the relationship between import-shock exposure on social ties disappears when gross migration flows are held constant. Overall, the estimates presented on Table E.1 suggest that import-shock exposure is weakly and negatively associated with interregional social ties, and that, net of regional differences in gross migration patterns, more exposed regions are, on average, no more or less socially connected to others outside of their local labour markets.

Table F.3
Regional-level results, US imports as instrument.

	Leave vote share					
	(1)	(2)	(3)	(4)	(5)	(6)
Import-shock exposure:						
Within-region	3.511[a]	2.809[a]	2.586[b]	3.815[a]	2.993[a]	3.023[b]
	(1.003)	(0.807)	(1.118)	(1.174)	(0.858)	(1.261)
Social neighbours		2.866[b]			3.031[b]	
		(1.142)			(1.298)	
Social lag			4.050[b]			4.228[a]
			(1.500)			(1.231)
Estimation method	OLS	OLS	OLS	2SLS	2SLS	2SLS
Commuting zone FE	✓	✓	✓	✓	✓	✓
Observations	143	143	143	143	143	143
Within-R^2	0.128	0.179	0.201	0.127	0.178	0.199
Kleibergen–Paap F				383.6	236.6	129.6

Notes: Robust standard errors in parentheses are clustered at the level of 31 lower commuting zones. All independent variables are standardised to have zero mean and unit variance. Social neighbours are the five most socially connected regions as measured by the $SCI_{(-c)}$, which is equal to the SCI (Bailey et al., 2020) after discarding region-pairs in the same commuting zone or with substantial pairwise commuting flows. Import-shock exposure in a set of social neighbours is the $SCI_{(-c)}$ weighted sum of exposure over the sum of $SCI_{(-c)}$ in the set. The social lag of import-shock exposure is the $SCI_{(-c)}$ weighted sum of exposure across all regions over the respective $SCI_{(-c)}$ value sum. $^{a}p < 0.01$, $^{b}p < 0.05$.

Table F.4
Regional-level results, US and original high-income country imports as instrument.

	Leave vote share					
	(1)	(2)	(3)	(4)	(5)	(6)
Import-shock exposure:						
Within-region	3.511[a]	2.809[a]	2.586[b]	4.060[a]	3.179[a]	3.118[b]
	(1.003)	(0.807)	(1.118)	(1.180)	(0.890)	(1.322)
Social neighbours		2.866[b]			3.129[b]	
		(1.142)			(1.238)	
Social lag			4.050[b]			4.276[a]
			(1.500)			(1.333)
Estimation method	OLS	OLS	OLS	2SLS	2SLS	2SLS
Commuting zone FE	✓	✓	✓	✓	✓	✓
Observations	143	143	143	143	143	143
Within-R^2	0.128	0.179	0.201	0.125	0.176	0.198
Kleibergen–Paap F				591.7	376.8	294.9

Notes: Robust standard errors in parentheses are clustered at the level of 31 lower commuting zones. All independent variables are standardised to have zero mean and unit variance. Social neighbours are the five most socially connected regions as measured by the $SCI_{(-c)}$, which is equal to the SCI (Bailey et al., 2020) after discarding region-pairs in the same commuting zone or with substantial pairwise commuting flows. Import-shock exposure in a set of social neighbours is the $SCI_{(-c)}$ weighted sum of exposure over the sum of $SCI_{(-c)}$ in the set. The social lag of import-shock exposure is the $SCI_{(-c)}$ weighted sum of exposure across all regions over the respective $SCI_{(-c)}$ value sum. $^{a}p < 0.01$, $^{b}p < 0.05$.

Fig. E.1 further presents 2SLS estimates from a series specifications akin to (11) where the outcome is a binary variable indicating whether the destination region is in different ranges of the origin region's nearest neighbours as defined by the $SCI_{(-c)}$. It is shown that the relationship between regional exposure to import competition and the probability of being in another region's set of k nearest neighbours as defined by the $SCI_{(-c)}$ weakens as k increases. Comparing two regions that differ by one standard deviation in their import-shock exposure, the more exposed one is, on average, only 0.8 per cent less likely to be in another's set of five most socially connected regions, with this probability increasing as the set expands to include more weakly connected regions. This suggests that the density of interregional social ties between the most socially connected regions is less likely to be related to import competition relative to that between others.

Appendix F. Additional tables

See Tables F.1–F.16.

Table F.5
Regional-level results, weighted by votes cast.

	Leave vote share					
	(1)	(2)	(3)	(4)	(5)	(6)
Import-shock exposure:						
Within-region	3.563[a]	3.049[a]	2.695[b]	4.449[a]	3.745[a]	3.360[b]
	(0.989)	(0.877)	(1.110)	(1.171)	(1.023)	(1.412)
Social neighbours		2.544[c]			2.934[b]	
		(1.279)			(1.405)	
Social lag			4.020[b]			4.274[a]
			(1.569)			(1.543)
Estimation method	OLS	OLS	OLS	2SLS	2SLS	2SLS
Commuting zone FE	✓	✓	✓	✓	✓	✓
Observations	143	143	143	143	143	143
Within-R^2	0.128	0.169	0.199	0.120	0.162	0.194
Kleibergen–Paap F				652.9	323.6	285.0

Notes: Robust standard errors in parentheses are clustered at the level of 31 lower commuting zones. All independent variables are standardised to have zero mean and unit variance. Social neighbours are the five most socially connected regions as measured by the $SCI_{(-c)}$, which is equal to the SCI (Bailey et al., 2020) after discarding region-pairs in the same commuting zone or with substantial pairwise commuting flows. Import-shock exposure in a set of social neighbours is the $SCI_{(-c)}$ weighted sum of exposure over the sum of $SCI_{(-c)}$ in the set. The social lag of import-shock exposure is the $SCI_{(-c)}$ weighted sum of exposure across all regions over the respective $SCI_{(-c)}$ value sum. $^{a}p < 0.01$, $^{b}p < 0.05$, $^{c}p < 0.1$.

Table F.6
Regional-level results, equal neighbour weights.

	Leave vote share			
	(1)	(2)	(3)	(4)
Import-shock exposure:				
Within-region	3.511[a]	2.975[a]	4.395[a]	3.606[a]
	(1.003)	(0.852)	(1.215)	(1.004)
Social neighbours		2.781[a]		3.094[a]
		(0.976)		(1.008)
Estimation method	OLS	OLS	2SLS	2SLS
Commuting zone FE	✓	✓	✓	✓
Observations	143	143	143	143
Within-R^2	0.128	0.180	0.120	0.174
Kleibergen–Paap F			880.7	464.2

Notes: Robust standard errors in parentheses are clustered at the level of 31 lower commuting zones. All independent variables are standardised to have zero mean and unit variance. Social neighbours are the five most socially connected regions as measured by the $SCI_{(-c)}$, which is equal to the SCI (Bailey et al., 2020) after discarding region-pairs in the same commuting zone or with substantial pairwise commuting flows. Import-shock exposure in a set of social neighbours is the mean exposure in the set. $^{a}p < 0.01$.

Table F.7
Regional-level robustness, social lag of import-shock exposure.

	Leave vote share					
	(1)	(2)	(3)	(4)	(5)	(6)
Import-shock exposure:						
Within-region	1.714	1.370	0.169	1.780[b]	3.275[a]	3.298[b]
	(1.081)	(1.130)	(0.996)	(0.681)	(1.136)	(1.422)
Social lag	4.001[b]	4.008[a]	1.926	4.885[a]	3.368[b]	3.586[b]
	(1.709)	(1.279)	(1.317)	(0.968)	(1.645)	(1.755)
Manufacturing emp. share, 1991	2.059	1.507	1.944			
	(1.877)	(1.580)	(1.515)			
Δ Relative income, 1997–2016		−2.532[b]	−2.383[a]			
		(1.079)	(0.817)			
Gross migr. rate, 2002–2016			−3.912[a]			
			(0.894)			
Pop. share aged over 65, 1991				0.447		
				(0.757)		
Pop. share foreign-born, 1991				−6.302[a]		
				(0.434)		
Distance to London					8.818[b]	
					(3.820)	
Pop. share active Internet users, 2016/17						−1.928[b]
						(0.812)
Estimation method	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Commuting zone FE	✓	✓	✓	✓	✓	✓
Observations	143	143	143	143	143	143
Within-R^2	0.234	0.326	0.501	0.541	0.269	0.232
Kleibergen–Paap F	150.6	152.8	138.8	432.1	408.5	416.1

Notes: Robust standard errors in parentheses are clustered at the level of 31 lower commuting zones. All independent variables are standardised to have zero mean and unit variance. The social lag of import-shock exposure is the $SCI_{(-c)}$ weighted sum of exposure across all regions over the respective $SCI_{(-c)}$ value sum. The $SCI_{(-c)}$ is equal to the SCI (Bailey et al., 2020) after discarding region-pairs in the same commuting zone or with substantial pairwise commuting flows. Data on active Internet users are available for 2016 for 79 regions and for 2017 for 64 regions. [a]$p < 0.1$, [b]$p < 0.05$.

Table F.8
Mean differences, 15 most directly and indirectly exposed regions.

	Most directly exposed	Most indirectly exposed	Adj. p-value
Import-shock exposure:			
Within-region	£ 1,994 / worker	£ 1,122 / worker	$p < 0.01$
Social neighbours	£ 1,044 / worker	£ 1,436 / worker	$p < 0.01$
Social lag	£ 952 / worker	£ 1,001 / worker	$p < 0.05$
Manufacturing emp. share, 1991	27.32 %	22.59 %	$p < 0.05$
Δ Relative income, 1997–2015	−2.24 %	−2.39 %	$p > 0.1$
Pop. share over 65, 1991	15.46 %	16.76 %	$p < 0.05$
Pop. share foreign-born, 1991	5.11 %	6.12 %	$p > 0.1$
Distance to London	203 km	177 km	$p > 0.1$
Pop. share active Internet users, 2016/17	86.65 %	86.30 %	$p > 0.1$

Notes: The most directly exposed regions are the regions with the 15 highest values for within-region exposure and the most indirectly exposed regions are the regions with the 15 highest values for social neighbours' exposure. P-values from pairwise t-tests for mean differences are adjusted for multiple comparisons using the false discovery rate (FDR) criterion.

Table F.9
Regional-level robustness, social exposure to other shocks.

	Leave vote share					
	(1)	(2)	(3)	(4)	(5)	(6)
Import-shock exposure:						
Within-region	4.299[a]	4.064[a]	3.744[b]	3.342[a]	3.291[a]	3.142[b]
	(1.057)	(1.019)	(1.364)	(1.016)	(0.925)	(1.322)
Social neighbours	2.432[b]	2.747[b]		4.083[a]	3.058[c]	
	(1.177)	(1.224)		(1.415)	(1.591)	
Social lag			4.159[a]			4.375[a]
			(1.204)			(1.383)

(*continued on next page*)

Table F.9 (*continued*).

	Leave vote share					
	(1)	(2)	(3)	(4)	(5)	(6)
Immigration-shock exposure:						
Within-region	2.435	2.402[c]	2.462			
	(1.448)	(1.363)	(1.476)			
Social neighbours	2.178[b]					
	(0.996)					
Social lag		1.226	0.548			
		(1.517)	(1.305)			
Austerity-shock exposure:						
Within-region				0.184	−0.785	−0.851
				(1.129)	(1.226)	(1.230)
Social neighbours				−2.364[b]		
				(1.106)		
Social lag					1.471	0.752
					(2.103)	(2.005)
Estimation method	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Commuting zone FE	✓	✓	✓	✓	✓	✓
Observations	143	143	143	143	143	143
Within-R^2	0.284	0.253	0.276	0.202	0.183	0.203
Kleibergen–Paap F	334.8	400.1	403.9	586.2	593.0	499.8

Notes: Robust standard errors in parentheses are clustered at the level of 31 lower commuting zones. All independent variables are standardised to have zero mean and unit variance. Social neighbours are the five most socially connected regions as measured by the $SCI_{(-c)}$, which is equal to the SCI (Bailey et al., 2020) after discarding region-pairs in the same commuting zone or with substantial pairwise commuting flows. Import-shock exposure in a set of social neighbours is the $SCI_{(-c)}$ weighted sum of exposure over the sum of $SCI_{(-c)}$ in the set. The social lag of import-shock exposure is the $SCI_{(-c)}$ weighted sum of exposure across all regions over the respective $SCI_{(-c)}$ value sum. $^{a}p < 0.01$, $^{c}p < 0.1$.

Table F.10
Regional-level results, UKIP EP vote share over time.

	UKIP EP election vote share					
	(1)	(2)	(3)	(4)	(5)	(6)
Import-shock exposure:						
Within-region × $d2009$	0.702	0.315	0.340	1.175[c]	0.676	0.740
	(0.576)	(0.471)	(0.541)	(0.626)	(0.514)	(0.695)
Social neighbours × $d2009$		1.312[c]			1.458[b]	
		(0.667)			(0.624)	
Social lag × $d2009$			1.699[c]			1.824[b]
			(0.854)			(0.892)
Within-region × $d2014$	2.031[b]	1.967[b]	1.958[c]	2.665[b]	2.562[b]	2.541[c]
	(0.923)	(0.769)	(1.036)	(1.148)	(0.998)	(1.321)
Social neighbours × $d2014$		0.531			0.580	
		(0.962)			(0.861)	
Social lag × $d2014$			0.205			0.280
			(1.180)			(1.239)
Estimation method	OLS	OLS	OLS	2SLS	2SLS	2SLS
Commuting zone FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Observations	286	286	286	286	286	286
Within-R^2	0.060	0.077	0.090	0.053	0.070	0.083
Kleibergen–Paap F				468.9	252.2	223.7

Notes: Robust standard errors in parentheses are two-way clustered at the level of 31 lower commuting zones and years. All independent variables are standardised to have zero mean and unit variance. The dummies $d2009$ and $d2014$ are equal to one when the observation is in the corresponding year and zero otherwise. Social neighbours are the five most socially connected regions as measured by the $SCI_{(-c)}$, which is equal to the SCI (Bailey et al., 2020) after discarding region-pairs in the same commuting zone or with substantial pairwise commuting flows. Import-shock exposure in a set of social neighbours is the $SCI_{(-c)}$ weighted sum of exposure over the sum of $SCI_{(-c)}$ in the set. The social lag of import-shock exposure is the $SCI_{(-c)}$ weighted sum of exposure across all regions over the respective $SCI_{(-c)}$ value sum. $^{a}p < 0.01$, $^{b}p < 0.05$, $^{c}p < 0.1$.

Table F.11
Regional-level results, EP vote shares and turnout over time.

	Conservative Party (1)	Labour Party (2)	Liberal Democrats (3)	Green Party (4)	Turnout (5)
Import-shock exposure:					
Within-region × $d2009$	0.244	0.640	−0.914[b]	−1.214[a]	0.830
	(0.773)	(0.829)	(0.396)	(0.258)	(0.547)
Social neighbours × $d2009$	−0.919	−0.067	−0.148	−0.950[b]	−0.589
	(0.750)	(1.107)	(0.402)	(0.461)	(0.425)
Within-region × $d2014$	0.340	0.005	−0.925[a]	−1.094[a]	−0.562
	(0.767)	(1.402)	(0.322)	(0.254)	(0.419)
Social neighbours × $d2014$	−1.211	0.753	−0.125	−0.736[c]	−0.562
	(0.795)	(1.320)	(0.360)	(0.369)	(0.373)
Estimation method	2SLS	2SLS	2SLS	2SLS	2SLS
Commuting zone FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Observations	286	286	286	286	286
Within-R^2	0.008	0.008	0.050	0.140	0.039
Kleibergen–Paap F	252.2	252.2	252.2	252.2	252.2

Notes: Robust standard errors in parentheses are two-way clustered at the level of 31 lower commuting zones and years. All independent variables are standardised to have zero mean and unit variance. The dummies $d2009$ and $d2014$ are equal to one when the observation is in the corresponding year and zero otherwise. Social neighbours are the five most socially connected regions as measured by the $SCI_{(-c)}$, which is equal to the SCI (Bailey et al., 2020) after discarding region-pairs in the same commuting zone or with substantial pairwise commuting flows. Import-shock exposure in a set of social neighbours is the $SCI_{(-c)}$ weighted sum of exposure over the sum of $SCI_{(-c)}$ in the set. $^{a}p < 0.01$, $^{b}p < 0.05$, $^{c}p < 0.1$.

Table F.12
Regional-level results, geographic neighbours.

	Leave vote share					
	(1)	(2)	(3)	(4)	(5)	(6)
Import-shock exposure:						
Within-region	3.511[a]	3.456[a]	3.426[a]	4.395[a]	4.451[a]	4.405[a]
	(1.003)	(0.971)	(1.106)	(1.215)	(1.214)	(1.393)
Geographic neighbours		0.335			−0.301	
		(1.131)			(1.098)	
Spatial lag			0.706			−0.064
			(2.478)			(2.279)
Estimation method	OLS	OLS	OLS	2SLS	2SLS	2SLS
Commuting zone FE	✓	✓	✓	✓	✓	✓
Observations	143	143	143	143	143	143
Within-R^2	0.128	0.129	0.129	0.120	0.119	0.120
Kleibergen–Paap F				880.7	391.4	451.8

Notes: Robust standard errors in parentheses are clustered at the level of 31 lower commuting zones. All independent variables are standardised to have zero mean and unit variance. Geographic neighbours are the five most geographically proximate regions as measured by $1/GEO_{(-c)}$, which is the pairwise inverse least-cost land distance after discarding region-pairs in the same commuting zone or with substantial pairwise commuting flows. Import-shock exposure in a set of geographic neighbours is the $1/GEO_{(-c)}$ weighted sum of exposure over the sum of $1/GEO_{(-c)}$ in the set. The spatial lag of import-shock exposure is the $1/GEO_{(-c)}$ weighted sum of exposure across all regions over the respective $1/GEO_{(-c)}$ value sum. $^{a}p < 0.01$.

Table F.13
Individual-level results, average marginal effects.

	Voted Leave					
	(1)	(2)	(3)	(4)	(5)	(6)
Import-shock exposure:						
Within-region	0.0215[a]	0.0185[a]	0.0173[b]	0.0218[a]	0.0171[a]	0.0154[c]
	(0.0066)	(0.0063)	(0.0076)	(0.0071)	(0.0065)	(0.0082)
Social neighbours		0.0153[b]			0.0198[a]	
		(0.0063)			(0.0066)	
Social lag			0.0205[c]			0.0258[b]
			(0.0113)			(0.0112)
Estimation method	Probit	Probit	Probit	IV Pr.	IV Pr.	IV Pr.
Commuting zone FE	✓	✓	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓	✓	✓

(*continued on next page*)

Table F.13 (*continued*).

	Voted Leave					
	(1)	(2)	(3)	(4)	(5)	(6)
Observations	22,231	22,231	22,231	22,231	22,231	22,231
Regions	143	143	143	143	143	143

Notes: Robust delta-method standard errors in parentheses. Coefficients represent average marginal effects retrieved from the respective non-linear specifications. All independent variables are standardised to have zero mean and unit variance. Demographic controls include age, gender, and five education dummies. Social neighbours are the five most socially connected regions as measured by the $SCI_{(-c)}$, which is equal to the SCI (Bailey et al., 2020) after discarding region-pairs in the same commuting zone or with substantial pairwise commuting flows. Import-shock exposure in a set of social neighbours is the $SCI_{(-c)}$ weighted sum of exposure over the sum of $SCI_{(-c)}$ in the set. The social lag of import-shock exposure is the $SCI_{(-c)}$ weighted sum of exposure across all regions over the respective $SCI_{(-c)}$ value sum. $^a p < 0.01$, $^b p < 0.05$, $^c p < 0.1$.

Table F.14
Individual-level robustness, social lag of import-shock exposure.

	Voted Leave				
	(1)	(2)	(3)	(4)	(5)
Import-shock exposure:					
Within-region	0.0466^b	0.0472^b	0.0470^b	0.0413^b	0.0383^b
	(0.0209)	(0.0215)	(0.0208)	(0.0211)	(0.0183)
Social lag	0.0473	0.0518^c	0.0562^c	0.0492	−0.0122
	(0.0296)	(0.0311)	(0.0300)	(0.0344)	(0.0482)
(× At risk of poverty)	0.0041				
	(0.0349)				
(× Unemployed)		0.0971			
		(0.0602)			
(× Student)			−0.0636		
			(0.0858)		
(× Follows news online)				−0.0011	
				(0.0214)	
(× UK-born parents)					0.0800^c
					(0.0420)
At risk of poverty	−0.0213				
	(0.0266)				
Unemployed		0.2510^a			
		(0.0574)			
Student			−0.6330^a		
			(0.0841)		
Follows news online				−0.0077	
				(0.0236)	
UK-born parents					0.1800^a
					(0.0568)
Estimation method	Probit	Probit	Probit	Probit	Probit
Commuting zone FE	✓	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓	✓
Observations	20,852	22,231	22,231	21,605	16,658
Regions	143	143	143	143	143

Notes: Robust standard errors in parentheses are clustered at the level of 31 lower commuting zones. All independent variables are standardised to have zero mean and unit variance. Demographic controls include age, gender, and five education dummies. The social lag of import-shock exposure is the $SCI_{(-c)}$ weighted sum of exposure across all regions over the respective $SCI_{(-c)}$ value sum. The $SCI_{(-c)}$ is equal to the SCI (Bailey et al., 2020) after discarding region-pairs in the same commuting zone or with substantial pairwise commuting flows. $^a p < 0.01$, $^b p < 0.05$, $^c p < 0.1$.

Table F.15
Individual-level robustness, social neighbours' exposure (2SLS).

	Voted Leave				
	(1)	(2)	(3)	(4)	(5)
Import-shock exposure:					
Within-region	0.0161^b	0.0171^a	0.0162^a	0.0148^b	0.0128^c
	(0.0066)	(0.0066)	(0.0063)	(0.0068)	(0.0072)
Social neighbours	0.0205^a	0.0196^a	0.0222^a	0.0188^a	0.0100
	(0.0076)	(0.0067)	(0.0069)	(0.0072)	(0.0162)
(× At risk of poverty)	−0.0021				
	(0.0098)				
(× Unemployed)		0.0023			
		(0.0241)			
(× Student)			−0.0327		
			(0.0312)		
(× Follows news online)				−0.0028	
				(0.0071)	
(× UK-born parents)					0.0066
					(0.0133)
At risk of poverty	−0.0072				
	(0.0096)				
Unemployed		0.0917^a			
		(0.0218)			
Student			−0.2190^a		
			(0.0270)		
Follows news online				−0.0032	
				(0.0083)	
UK-born parents					0.0664^a
					(0.0215)
Estimation method	2SLS	2SLS	2SLS	2SLS	2SLS
Commuting zone FE	✓	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓	✓
Observations	20,852	22,231	22,231	21,605	16,658
Regions	143	143	143	143	143
Kleibergen–Paap F	206.5	210.6	210.4	210.4	224.9

Notes: Robust standard errors in parentheses are clustered at the level of 31 lower commuting zones. All independent variables are standardised to have zero mean and unit variance. Demographic controls include age, gender, and five education dummies. Social neighbours are the five most socially connected regions as measured by the $SCI_{(-c)}$, which is equal to the SCI (Bailey et al., 2020) after discarding region-pairs in the same commuting zone or with substantial pairwise commuting flows. Import-shock exposure in a set of social neighbours is the $SCI_{(-c)}$ weighted sum of exposure over the sum of $SCI_{(-c)}$ in the set. $^a p < 0.01$, $^b p < 0.05$, $^c p < 0.1$.

Table F.16
Individual-level robustness, social lag of exposure (2SLS).

	Voted Leave				
	(1)	(2)	(3)	(4)	(5)
Import-shock exposure:					
Within-region	0.0149[c]	0.0154[c]	0.0148[c]	0.0133	0.0090
	(0.0082)	(0.0083)	(0.0079)	(0.0083)	(0.0070)
Social lag	0.0233[b]	0.0246[b]	0.0265[b]	0.0231[c]	0.0032
	(0.0103)	(0.0112)	(0.0105)	(0.0124)	(0.0171)
(× At risk of poverty)	0.0006				
	(0.0129)				
(× Unemployed)		0.0325			
		(0.0229)			
(× Student)			−0.0236		
			(0.0237)		
(× Follows news online)				0.0000	
				(0.0081)	
(× UK-born parents)					0.0276[c]
					(0.0154)
At risk of poverty	−0.0071				
	(0.0097)				
Unemployed		0.0924[a]			
		(0.0207)			
Student			−0.216[a]		
			(0.0258)		
Follows news online				−0.0031	
				(0.0086)	
UK-born parents					0.0655[a]
					(0.0202)
Estimation method	2SLS	2SLS	2SLS	2SLS	2SLS
Commuting zone FE	✓	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓	✓
Observations	20,852	22,231	22,231	21,605	16,658
Regions	143	143	143	143	143
Kleibergen–Paap F	191.0	193.0	193.0	194.2	203.2

Notes: Robust standard errors in parentheses are clustered at the level of 31 lower commuting zones. All independent variables are standardised to have zero mean and unit variance. Demographic controls include age, gender, and five education dummies. The social lag of import-shock exposure is the $SCI_{(-c)}$ weighted sum of exposure across all regions over the respective $SCI_{(-c)}$ value sum. The $SCI_{(-c)}$ is equal to the SCI (Bailey et al., 2020) after discarding region-pairs in the same commuting zone or with substantial pairwise commuting flows. $^{a}p < 0.01$, $^{b}p < 0.05$, $^{c}p < 0.1$.

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