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The real effects of Brexit on labor demand: Evidence from firm-level data

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[1]Hang Do, [2]Kiet Duong, [3]Toan Huynh, and [4]Nam Vu

[1] University of Southampton
[2] University of York
[3]Queen Mary University of London
[4] Miami University

Abstract

Using the most comprehensive longitudinal survey on small and medium-sized businesses (SMEs) in the United Kingdom to date, we study the extent to which the implementation of Brexit in 2020 impacts their labor demand in a difference-in-difference framework. Our identification strategy hinges on using firms' distance to the Irish border as a novel instrument to isolate the effects of Brexit at the firm level. Specifically, after Brexit in effect, while firms located in Great Britain are subjected to higher costs of doing business with the European Union, their Northern Irish counterparts are not, following the provisions arising from the Northern Ireland Protocol. Leveraging the distance to the border as a plausibly exogenous proxy for Brexit exposure among firms that did not change their location before and after the 2016 referendum, we find that the 2020 implementation of Brexit caused exposed firms to cut their workforce by up to 13.59% on average. The exposed firms are also more likely to have lower growth expectations and more likely to increase their research and development (R&D) expenditure in response. These results highlight the expectation channel and support the hypothesis that firms prioritize innovations in response to Brexit.

Keywords: Brexit; firm responses; technology; EU workers

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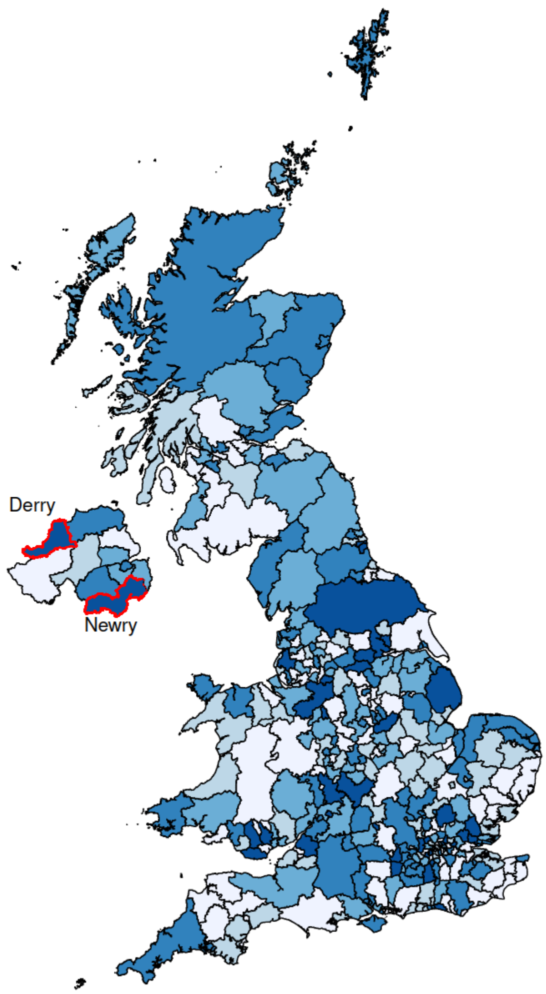
1 Introduction

After a much-debated referendum, the United Kingdom voted in favor of leaving the European Union in June 2016. Despite all the expectations built up to the time of its eventual implementation in January 2020, not all regions in the United Kingdom were set to be subjected to the same economic burden arising from Brexit. As a result of the provisions following the Northern Ireland Protocol, the United Kingdom does not maintain a hard border until 2021, effectively allowing free travel and, more importantly, free movements of goods across the Irish border into the European Union for firms located in Northern Ireland. In stark contrast, these provisions do not apply to firms located in Great Britain as they are separated from Northern Ireland via the Irish Sea. In other words, firms located in Great Britain are more likely to bear additional burdens to doing business than firms located in Northern Ireland as Brexit goes into effect.

Such a schism motivates us to consider how such variation in Brexit exposure impacts the labor demand of businesses. To single out the effects of Brexit on firms' labor decisions, our identification strategy takes advantage of the variation in Brexit exposure based on the de facto separation in terms of access to the E.U. market between firms located in Great Britain and firms located in Northern Ireland. Using a large-scale longitudinal survey of UK SME business owners and managers, we first compute the firms' shortest distance to the port of Newry - strategically located near the Republic of Ireland border with Northern Ireland on the main Belfast-Dublin route. We then use this distance as a plausibly exogenous proxy for Brexit among firms that did not change location after the Brexit referendum in 2016.

Intuitively, while all firms are aware of the implementation schedule for Brexit, some firms are not fully aware of the intensity of the extent to which leaving the EU may have on their business operations. As a result, by focusing on firms that do not change their locations throughout the sample period (2015-2022), we exclude the endogeneity arising from firms fully anticipating and therefore changing their locations in response to Brexit. Using the distance to the border for this subset of firms allows us to identify the causal effects of Brexit on small businesses. Specifically, by leveraging the distance to the port of Newry to proxy for Brexit exposure, our empirical strategy revolves around

Map of the United Kingdom



Notes: Colors are randomly assigned to each Local Authority District across the United Kingdom. The red line indicates two districts which share the border between Northern Ireland and the Republic of Ireland.

a difference-in-difference approach that examines what would happen to ex-ante otherwise similar firms if they are exposed to Brexit.

At the heart of any difference-in-difference analysis, we find that before the implementation of Brexit in 2020, firms with low exposure to Brexit were statistically similar to firms with high exposure to Brexit. Upon confirming this parallel trend assumption, we find that the 2020 implementation of Brexit causes exposed firms to cut their workforce by up to 13.59% on average. In addition, these exposed firms are also more likely to have lower growth expectations and more likely to increase their research and development (R&D) expenditure in response. On the one hand, these results highlight the role of the expectation channel in the sense that they reduce their labor demand following negative changes in their expectation of growth prospects. On the other hand, these results support the hypothesis that firms prioritize innovations in response to Brexit.

Our results are consistent across a battery of robustness checks. First, we use a dummy on whether a firm is located in Northern Ireland or Great Britain in lieu of the distance to the Irish border as a proxy for Brexit exposure. Second, we use the port of Derry - another major transportation hub near the Irish border for products entering the Republic of Ireland - instead of the port of Newry to compute the distance to the Irish border. Third, we conduct a placebo test, in which we randomly assign firms to different locations. Fourth, we exclude the period before the Brexit referendum in 2016 from our analysis. Fifth, we account for the expectation effects leading to Brexit implementation by interacting our benchmark proxy for Brexit exposure (i.e., distance to the border) with each individual year dummy. Overall, these robust analyses provide further support for the central hypothesis that firms located further from the Irish border experienced more significant impacts due to the implementation of Brexit in 2020.

Our paper contributes to two strands of literature. First, it extends research on Brexit and firm responses by examining the actual impacts. While existing studies predominantly focus on the 2016 Brexit referendum (Born et al., 2019; Breinlich et al., 2020; Fernandes and Winters, 2021; Bloom et al., 2019), our analysis highlights the initial year when Brexit's effects became tangible (i.e., January 2020), addressing both the European and U.K. markets. Second, our study examines the representative dataset of U.K. SMEs (Small & Medium-sized Enterprises) population. While current literature primarily focuses on listed UK firms (Hill et al., 2019; Davies and Studnicka, 2018) or utilizes structural estimation (McGrattan and Waddle, 2020), our study introduces a fresh perspective by examining small and medium-sized enterprises (SMEs). Although there is limited research on the impact of Brexit on SMEs due to its recent timing, our approach aligns with existing studies in several ways. The fact that SMEs typically do not have multiple manufacturing locations supports our method of measuring the distance to the Republic of Ireland–United Kingdom border as a valid identification strategy. While Zhao and Jones-Evans (2017) utilize the first-level Classification of Territorial Units for Statistics (NUTS) regions to define the geographical location of a business, our study identifies the location of SME firms using Local Enterprise Partnerships (LEPs) based on the

(BEIS, 2023) survey. Subsequently, we matched the firms' locations to their respective Local Authority Districts (LADs). Previous research indicates that SMEs, particularly those with significant levels of irreversible investment, are disproportionately affected by uncertainty due to their limited resources and reduced capacity to withstand sudden shocks (Brown et al., 2019; Chung, 2017). Third, our study offers empirical evidence on how firms navigate the trade-offs between labor-intensive and technology-intensive business models in response to the Brexit shocks that have taken effect.

The rest of this paper is organized in the following way. The next section (Section 2) discusses the evolution of Brexit literature to explain how our study contributes to the existing literature. Section 3 details our research methodology after explaining the nature and details of our data in Section 4. In Section 5, we discussed our main findings as well as the robustness of our findings. In addition, this paper also shows the potential mechanisms and other additional tests before concluding the paper in Section 7.

2 Literature review

Brexit refers to the United Kingdom's (UK) departure from the European Union (EU), representing a process rather than a singular event. Numerous studies have explored the impacts of Brexit on macroeconomic outcomes, including the economic cost of nationalism related to the referendum (Born et al., 2019), heterogeneous firm beliefs and expectations regarding Brexit outcomes (Faccini and Palombo, 2021; Hassan et al., 2024; Davies and Studnicka, 2018), a decline in productivity growth within the tradable sector (Broadbent et al., 2023), and an increase in CPI inflation (Geiger and Güntner, 2024).

Our paper is closely aligned with an emerging branch of literature that examines the regional economic consequences following trade policy shocks, specifically those associated with Brexit. First, Bell (2017) discussed how Great Britain experienced regional disparities, focusing on the public expenditure per capita on economic development and economic affairs in Scotland and Northern Ireland from 2014 to 2015. The impacts of Brexit vary significantly across sectors and regions. Utilizing detailed interregional trade data for goods and services within the EU, Thissen et al. (2020) argued that

Brexit's effects on regional production costs and the competitive position of firms are considerably greater for sectors and regions within the UK than for the EU as a whole. The disproportionate effects are more pronounced in European countries that are geographically peripheral and economically weaker, located in the far south, east, and north of Europe. These regions experienced minimal economic exposure to Brexit (Chen et al., 2018). These studies also found that certain UK regions, such as Cheshire, Greater Manchester, and West Yorkshire, experienced significant improvements in their competitive positions. However, these gains led to a deterioration in the competitive standings of other nearby UK regions (Thissen et al., 2020).

In addition to regional analysis, one important question is how UK and international firms have responded to Brexit shocks. Recently, Breinlich et al. (2020) observed an increase in the number of UK outward investment transactions in the remaining European countries following the 2016 Brexit referendum. In the same vein, private equity buyout targets are more likely to increase their export value and intensity compared to non-private equity-backed peers (Lavery et al., 2024). Not only have UK firms been affected, but US firms exposed to Brexit, by using identified through market- and textual-search-based measures, are also more likely to reduce jobs and investment (Campello et al., 2022). In another perspective, Fernandes and Winters (2021) employ the Brexit referendum 2016 as a quasi-natural experiment to evaluate the impact of exchange rate and uncertainty shocks on Portuguese exporters, using transaction-level data to examine changes in different aspects. This study reveals that exporters responded to the shock by reducing both export volumes and prices in the UK market, with variations in response based on firm productivity, import intensity, and financial constraints, and significant differences observed among goods types and export market entries. Complementing these empirical findings, McGrattan and Waddle (2020) use structural estimation to explain the optimal policy choices between EU countries and the UK. Accordingly, if UK and EU firms are subject to identical stricter regulations, UK firms, due to their relatively smaller size, are expected to cut back on R&D and other intangible investments and pull back from their EU subsidiaries. Additionally, by analyzing firms listed on the London Stock Exchange, Hill et al. (2019) found that Brexit has a disproportionately adverse impact on high-growth firms, with the financial sector and consumer goods/services industries experiencing the highest exposure to Brexit-related uncertainty.

The existing literature focuses on several pivotal insights. Firstly, Brexit has caused heterogeneous impacts across various regions and economic sectors, both within the UK and internationally. Additionally, the majority of these studies focus predominantly on the 2016 Brexit referendum rather than on the point when Brexit officially took effect in January 2020. Therefore, our paper seeks to assess the impacts of Brexit in its actual effective year (2020), using the proximity to Newry—a city bordering Ireland—as a proxy for exposure. To enhance the robustness of the results, the distance to Derry can be utilized as an alternative measure for calculating the proximity to the Republic of Ireland–United Kingdom border.

It is important to note that a hard border is avoided on the island of Ireland due to its sensitive nature[1]. Despite considerable efforts, a regulatory border has been implemented in the Irish Sea areas to conduct custom checks on specific products transported from Great Britain to Northern Ireland, especially those intended for the EU single market. This measure stems from the fact that while Northern Ireland is part of the UK customs territory, it must adhere to EU customs and single market regulations to enable the free movement of goods to the Republic of Ireland—and thereby into the EU (Murphy, 2022). However, this proposal has not been implemented due to concerns that it could hinder economic growth in Northern Ireland. Additionally, the idea has faced considerable controversy and debate regarding diplomatic and economic integration between the Republic of Ireland and Northern Ireland.

3 Empirical strategy

3.1 Identification of the Brexit effects

Since Northern Ireland does not maintain a physical border, known as a hard border, with the Republic of Ireland due to the *Northern Ireland Protocol* of the Brexit withdrawal agreement, firms that are located in Northern Ireland can transport products into the European Union via the Republic of Ireland without having to go through any checkpoints. Indeed, until its withdrawal in January of

[1] As stated by the European Commission, "a hard border on the island of Ireland is avoided" (EU, 2024).

2021, the *Northern Ireland Protocol* has protected free travel and, more importantly, free trade of goods across the border between Northern Ireland and the Republic of Ireland (i.e., "the border"). This stipulation puts Northern Ireland's firms in a unique position during the first year that Brexit takes effect (i.e., 31 January 2020) to be involved in *both* the European and the U.K. markets. In stark contrast, firms located in Great Britain must pass through the Irish Sea, which is the de facto border between Great Britain and Northern Ireland. This dichotomy in terms of E.U. access between firms in Northern Ireland and firms in Great Britain means that the latter fully bear the brunt of the economic burden arising from Brexit while the former does not. In other words, firms that are closer to the border (e.g., the firms located in Northern Ireland) are more exposed to the effects of Brexit than firms that are further away from the border (e.g., the firms located in Great Britain).

Conditional on firms knowing that Brexit was coming but not fully aware of *how large* its effects were going to be, such a schism between the two groups of firms allows us to use the distance to the border as a plausibly exogenous proxy for the extent to which firms are exposed to the Brexit effects. In our practical application, to identify the groups of firms not fully aware of the veracity of the Brexit effects, we focus on the group of firms that do not change their locations before and after the Brexit announcement. We then argue that using the distance to the border for this subset of firms allows us to identify the causal effects of Brexit on small businesses.

Turning to more details, we rely on the shortest distance from the firm's location to Northern Ireland's official border with the Republic of Ireland. Specifically, we use the location of the firms in our survey data, as identified by their Local Enterprise Partnerships (LEPs) and their Local Authority Districts (LADs), to compute their shortest distance to the port of Newry. We then take the natural log of such a distance and use it as a proxy for firms' exposure to Brexit.[2]

3.2 Regression Specification

Our empirical strategy revolves around a difference-in-difference approach that examines what would happen to *ex-ante* otherwise similar firms if they were exposed to Brexit. We leverage the variation

[2]To exclude the possibility that firms may preemptively relocate to avoid the negative effects of Brexit, we exclude the firms that change addresses during our sample period and find our results to remain consistent across all specifications.

in terms of whether a firm is subject to additional economic barriers due to Brexit taking effect in January 2020 by relying on their distance to Northern Ireland's border with the Republic of Ireland. In particular, we focus on the real effects of Brexit and ask whether Brexit can cause firms to reduce their labor force. To align our paper with the recent literature, we note that our identification strategy, which distinguishes us from Fernandes and Winters (2021), does not use exporting-importing activities to measure Brexit exposure.

Our baseline model writes

$$lnEmployment_{i,t} = \alpha + \beta(Brexit_t \times Distance_i) + \gamma Distance_i + \delta Brexit_t + \zeta Control_{i,t} + \lambda_k + \varphi_t + \epsilon_{i,t}, \tag{1}$$

where $lnEmployment_{i,t}$ denotes the natural logarithm of the number of employees at firm i in year t. α is the constant term, and $\epsilon_{i,t}$ is a mean-zero disturbance term. Standard errors are clustered by firm to manage the correlation of observations within a firm where Brexit exposure is measured. β is the key coefficient, capturing the differential impact of Brexit shocks on employment within UK firms, assessed using the proximity to Newry—a city situated on the Clanrye River in counties Down and Armagh, Northern Ireland. Newry is strategically located near the Republic of Ireland border, on the main Belfast-Dublin route. ζ represents coefficients for control variables such as $Firm\ Age_{i,t}$ and $Firm\ Networks_{i,t}$. λ_k and φ_t are the industry and year fixed-effects, respectively.

As a preamble to any difference-in-difference analysis, we investigate whether the firms with low exposure (i.e., close to the border) to Brexit are, on average, *ex-ante* similar to the firms with high exposure (i.e., far from the border). To that end, Figure 2 plots the average number of employees (in log) of firms with low exposure and high exposure to Brexit. Here we define *low-exposure* firms as firms with a distance to Northern Ireland's border smaller than or equal to the median distance to such a border. The remaining firms are considered *high-exposure* firms. In Figure 2, we include the confidence band (at the 95% level) for each year in the sample, along with the timing of three key events: the Brexit referendum in 2016, when Brexit took effect (January 2020), and the withdrawal of the Northern Ireland's Protocol (January 2021).

[Figure 2 Here]

One key insight from Figure 2 is that before Brexit took effect (on January 2020), low-exposure firms (blue line) and high-exposure firms (red line) largely had statistically similar numbers of employees, as evidenced by their overlapping confidence intervals, with the only exception is 2016, when the Brexit referendum results were announced.[3] In other words, before the treatment (i.e., Brexit implementation in 2020), low-exposure firms (i.e., the control group) are *statistically indistinguishable* from high-exposure firms (i.e., the treated group). In stark contrast, as soon as Brexit took effect in January 2020, the number of employees in low-exposure firms became statistically different (at the 95% level) from the number of employees in high-exposure firms.

It's crucial to emphasize that correctly using survey data involves applying sampling weights to achieve accurate point estimates. Weighting, clustering, and stratification within the survey design help in obtaining more precise standard errors. Our dataset comprises 342,320 observations, with 83,870 responses (approximately 24.5%) for our primary variable of interest, *employees (Log)*. Hastie et al. (2009) note that various means of subsetting the data, such as selecting respondents for specific purposes, may cause the original weights to not accurately reflect the representation of this subgroup relative to the overall population. Their concerns are shared by many in the related literature (Winship and Radbill, 1994; Hastie et al., 2009; Solon et al., 2015; Bollen et al., 2016). Consequently, we opted not to use a survey-weighted approach for our main analyses. However, to validate our findings, we conducted survey-weighted estimations as well, which are detailed in Appendix A. Despite the potential drawbacks arising from using survey weights for sub-samples as noted in the literature, our results are robust to survey-weighing.

4 Data

4.1 Longitudinal Small Business Survey

The study was drawn on a large-scale longitudinal small business survey (LSBS) of UK small business owners and managers, conducted between 2015-2022 (BEIS, 2023). This is one of the largest longitudinal data for UK SMEs, comprising eight waves. The data aims to investigate the economic

[3] We find that our results are robust to excluding the pre-2016 sample.

health of the SME population, perception of the barriers and enablers of the SMEs' growth and their behaviors and planning across numerous economic activities, considering their heterogeneity characteristics. Initiated by the Department for Business, Innovation and Skills (BEIS), the survey was first conducted by BMG Research Ltd. since 2003 and then continued annually with a similar research design targeting UK SMEs. LSBS past surveys have been widely used in the literature such as Brown et al. (2022, 2019); Harris and Moffat (2022) to explore UK SME economic and innovation behaviour as well as the business barriers.

The overall sample size accounts for 0.1% of all UK SME (Small & Medium-sized Enterprises) population (BEIS, 2023). The definition of SMEs in the UK is based on the number of employees lower than 250, which is consistent with that of the European Union. Accordingly, micro firms are those having fewer than 10 employees, small firms are those having from 11-49 employees, and those ranging 50-249 employees are classified as medium-sized firms (BEIS, 2023). With estimated 5.6 million businesses contributing to 61% of labor creation in the private sector workforce, SMEs have been considered the "backbone" and economic driver in the UK (GOV UK, 2023).

[Table 1 Here]

The sample is stratified by UK region, sector and size across England, Scotland, Wales, and Northern Ireland. According to (BEIS, 2023) The sample data for Scotland and Northern Ireland are boosted, and is disproportionate by business size. The sample was sorted by postcode within 1 digit SIC 2007. Overall, 14 'one digit' SIC 2007 categories (ABDE, C, F, G, H, I, J, KL, M, N, P, Q, R, S) were included, 6 firm size categories (unregistered zero employees, registered zero employee, 1-4 employees, 5-9 employees, 10-49 employees, 50-249 employees) were targeted. The focused sectors in the survey include manufacturing, construction, wholesale/retail/transport, accommodation, communication/information/financial/real estate, professional/scientific, administrative, education, health, arts/entertainment and other services. Table 1 reports the number of observations across these industries. With regard to region, all surveyed SMEs were pre-coded following their postcode districts and other 'geo-demographics', for example, the indices of multiple deprivations for each of the UK nations as well as urban or rural classification[4], and LEPS area. The sample size was 15,502

[4]Please refer to this link for the definition of rural areas using the rural urban classification in the UK

enterprises in 2015; 9,248 in 2016; 6,619 in 2017; 15,105 in 2018; 11,002 in 2019; 7,636 in 2020; 9,325 in 2021, and 9,524 in 2022, as described in Table 2.

[Table 2 Here]

The questionnaire comprises 70% of core questions that have been unchanged from 2015-2022. Only minor changes have been made in the questionnaire to reflect policy priority changes and priorities from the government. The questionnaire was published annually in the technical report from 2015 to 2022. Since 2018, BEIS introduced cohort questions which were used to ask a random third of the sample in addition to other questions. In structuring the questionnaire, 15 modules were designed, three of which were only asked within a single cohort, whereas the remaining modules were asked to all the participants.

The survey was collected by Computer Assisted Telephone Interviews (CATI) with a response rate of 59.6% for the panel, 4.4% for the Inter-Departmental Business Register (IDBR) top-up interviews and 3.2% for the market location top-up. Interviewers were not given named contacts and needed to screen to find an appropriate respondent. The data collection includes "panel interviews" and "top-up interviews" to boost the response rate and to ensure that the unregistered businesses can also be covered by BEIS (2022). The fieldwork was implemented during November 2022 - April 2023, where previous participants in the survey were re-contacted, similar to the period when they were involved in past surveys (BEIS, 2022).

4.2 Firm-level variables

Our primary variable of interest is the number of employees. In the questionnaire, references BEIS (2022, 2023) asked, "Approximately how many employees are currently on your payroll in the UK, excluding owners and partners, across all sites?" (coded as A2 in the original dataset). This question aims to capture the official number of employees working at the business sites. Surveying firms about their number of employees is a common approach in existing literature (Altig et al., 2022). This variable reflects the operational efficiency of business activities within the economic context.

https://www.gov.uk/government/collections/rural-urban-classification

Additionally, the data provided categorizes the number of employees into eight groups (coded as *A2BND* in the original dataset), offering an alternative measure to validate the robustness of our previous model specification. It is worth mentioning that Boeri et al. (2020) differentiate between solo self-employed businesses and self-employed individuals with employees. Therefore, in our dataset, we can conduct additional robustness checks to ensure the impacts of Brexit implementation on the number of employees, which should be considered the actual labor forces engaged in business activities.

Regarding our independent variables, *Brexit* is defined as a dummy variable where surveyed SMEs from 2020, when Brexit was officially implemented, are coded as 1, and those surveyed before 2020 are coded as 0. This variable captures the period of Brexit implementation, while the existing literature primarily focuses on the 2016 Brexit referendum (Fernandes and Winters, 2021; Corsetti et al., 2022; Campello et al., 2022; Bloom et al., 2019). In summary, our dummy variable is analogous to those used in existing empirical studies to capture the post-Brexit period; however, the key difference is the timing of the significant event in 2020. One of our main important variables is *Distance to Northern Ireland*, which is considered a plausibly exogenous instrument for measuring Brexit's impact on these firms. To map the impacts of Brexit, we calculated the geographical distance between the locations where the surveyed SMEs are based and Newry, a city bordering Ireland, excluding those SMEs who have changed or moved their locations during 2015-2022. The distance between two places (x_1, y_1) and (x_2, y_2) was calculated using the following formula (Weber and Péclat, 2017).

$$\textbf{Distance} = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \tag{2}$$

One might argue that the distance could be sensitive to other locations along the border between the Republic of Ireland and Great Britain. Therefore, we select an alternative point known as Derry. The calculation *Distance (to Derry)* is applied using the previously referenced Formula 2. Since the survey only identifies firm locations within Local Enterprise Partnerships (LEPs), we correlate these with the Local Authority Districts (LAD) to ensure that there is no variation within firms across years, provided the firms do not change their locations.

In addition, we are focusing on two mechanism variables: *Firm R&D* and *Expected Growth*. The *Expected Growth* variable is derived from the responses to the survey question "Summary of expected growth in the next year," (coded as EXPGROW in the original dataset) which is divided into ten categories: (1) Substantial growth, (2) Significant growth, (3) Moderate growth, (4) Growth, don't know how much, (5) No change, (6) Minor shrinkage, (7) Significant shrinkage, (8) Substantial shrinkage, (9) Shrinkage, don't know how much, and (10) Don't know/Refused. We have developed a dummy variable for expected growth, coded as 1 if firms anticipate moving from a lower to a higher growth category, reflecting a more optimistic view of their future growth. Conversely, a value of 0 indicates that firms have lowered their growth expectations, signifying a more pessimistic outlook. It is important to note that we exclude responses from the tenth category where firms indicate uncertainty or refusal to answer. Thus, our expected growth dummy variable takes a value of 1 for positive future growth expectations and 0 otherwise.

Another variable of interest is *Firm R&D*, based on the survey question "How much have you invested in R&D in the last three years?" (coded as J5A in original dataset) This variable is continuous and captures the intensity of R&D activities. Although there are several databases that record firm activities related to innovation, such as the UK Community Innovation Survey (Audretsch and Belitski, 2020; Frenz and Ietto-Gillies, 2009) or bespoke surveys like Bloom et al. (2019), our study utilizes the question available in BEIS (2023). This approach allows us to match the data with firms' characteristics and locations effectively to estimate our specification models.

Our control variables include *Firm age* and *Firm networks*. *Firm age* categorizes firms into age groups from youngest to oldest: (1) 0-5 years, (2) 6-10 years, (3) 11-20 years, and (4) over 20 years, based on the survey question, "In what year did the firm start the business?" (coded as A6SUM in the original dataset). Previous research supports the influence of firm age on employment (Brown and Medoff, 2003). The study suggests that newly established firms may not set up pension or health insurance schemes initially, potentially making it challenging to recruit employees. Furthermore, Aubert et al. (2006) argue that the adoption of new technologies may hinder the recruitment of new employees; thus, including firm age as a control variable captures these dynamics. *Firm networks*, on the other hand, is quantified by the logarithm of the number of the firm's directors and partners based on the question "Total number of directors and partners" (coded as A17A2A in the original dataset). The connection between firm networks and labor outcomes has been extensively explored in economic research (Kramarz and Skans, 2014; Montgomery, 1991), indicating that larger networks can aid firms in increasing employee numbers and influencing technological decisions within the firms. We selected two control variables based on the completeness of the data available in the provided survey.

4.3 Geographical data

In recording SMEs, postcodes were used as a sorting criterion to avoid duplication and these businesses were also grouped based on Local Enterprises Partnerships (LEPs). LEPs were not-for-profit organizations formed in 2011 across the UK, initiated by BEIS, bringing together various stakeholders such as businesses, educators and local government offices, aiming to boost regional growth. In our data, 39 LEPS were coded. The geographical locations of the UK SMEs were measured by matching the postcode from the UK Local Authority District Partnerships map (Data GOV UK, 2023) and the Local Enterprise Partnerships postcode from the data.

Given the availability of Local Enterprise Partnerships (LEPs) data from the 2023 survey by the Department for Business, Energy & Industrial Strategy, we loaded geographic data from the boundaries of Local Authority Districts (LAD) as of December 2023 and merged it with the LEPs data. This merger facilitates analyses at a different administrative level. We also refined string data for clearer labeling and calculated distances from specific locations to each district, applying a natural logarithm transformation to these distances to prepare them for statistical analysis. We addressed mismatches between LEPs and LADs by managing cases where multiple districts fall within a single partnership. This meticulous preparation is crucial for enabling comprehensive spatial and statistical analyses.

4.4 Summary of descriptive statistics

As Table 1 illustrates, the distribution of observations across sectors shows both consistency and variability. Dominant sectors such as Wholesale/Retail, Professional/Scientific, Manufacturing, and

Construction exhibit a stable number of observations across Great Britain, Northern Ireland, and the UK. These sectors consistently show the highest number of observations in all regions. However, there is a noticeable difference in the Education sector between Northern Ireland and the rest of the UK; Northern Ireland has a significantly lower proportion of observations at 1.7%, compared to 3.2% in the rest of the UK. This discrepancy highlights regional variations within the data.

As indicated in Table 3, the dataset comprises 342,320 observations, of which 265,431 observations were found in variable *Distance* to either Newry or Derry. This is due to the missing values where the location of the firms can't be found or matched with the postcodes in the Local Authority District map. Regarding variable firm age, 76,320 observations can be seen. The average (mean) and median age of firms in the dataset is 3, suggesting that the majority of SMEs fall within the 11-20 year age range. The mean value for expected growth is approximately 0.3, indicating a generally positive trend in firm growth.

Regarding SMEs based in Great Britain, these observations represent an average of 94.4%, while 37.5% of the observations are derived from data collected from SMEs starting from 2020. There are 83,870 observations found in variable Employees and Firm Networks. Similarly, 79,511 observations can be seen in variable *expected growth*. Similarly, over 10,000 observations were found in the log of variable firm R&D variable. The average percentages of observations concerning the variables for barriers to recruiting skilled EU and unskilled EU workers are 49% and 42%, respectively.

According to Table 4, the correlation analysis among variables reveals significant relationships. Notably, there are negative correlations between the variable 'Distance' (to Newry or Derry) and other key variables such as firm employees, firm networks, and firm R&D. Conversely, the variable 'expected growth' shows a positive correlation with 'Distance'. These findings suggest that geographical proximity to Newry or Derry may influence certain business dynamics differently, impacting both operational aspects and the growth potential of firms.

5 Results

5.1 Baseline results

We begin by exploring the question: How does the implementation of the Brexit referendum affect the labor choices of SMEs in the United Kingdom? To address this, we first analyze the data presented in Table 5, employing both Ordinary Least Squares (OLS) and high-dimensional fixed effects (HDFE) regression models. The dependent variable in our analysis is the natural logarithm of the number of employees. Our sample includes all firms that reported their employee numbers in response to the question: "Approximately how many employees are currently on your payroll in the UK, excluding owners and partners, across all sites?". As outlined previously, our identification strategy distinguishes between two groups of firms: those with low exposure to Brexit (located close to the Northern Ireland and Republic of Ireland border) and those with high exposure (located farther from the border). This approach enables us to explore causal relationships, as the distance to the border serves as a plausibly exogenous instrument for measuring Brexit's impact on these firms.

[Table 5 Here]

All regression models incorporate fixed effects for industry and year to account for underlying differences across sectors and over time. We note an absence of within-firm variation for the interaction term *Brexit* $\times$ *Distance (to Newry)*, which is our primary variable of interest. The results, presented in Table 5, reveal a negative and statistically significant coefficient for this interaction term across all regressions. This initial analysis, depicted in Equation 1, offers a preliminary exploration of the core question. Our baseline estimates indicate that the implementation of Brexit in 2020 led exposed firms to decrease their workforce by between 10.65% and 13.59%. To understand the impact magnitude, our findings suggest that a 1% increase in distance from the Republic of Ireland–United Kingdom border correlates with an average workforce reduction of 10.65% to 13.59% post-Brexit. In comparison with existing literature, Bloom et al. (2019) demonstrated that approximately 10% of respondents from a sample of 42,000 active UK businesses with more than 10 employees identified labor availability as the largest current source of Brexit-related uncertainty, highlighting the significant impact of Brexit on workforce dynamics. This study employs the *Brexit exposure* treated for difference-in-difference, which quantifies the importance of Brexit as a source of uncertainty on a 1-4 scale, averaged per firm over the three years following the referendum. In contrast, our identification strategy utilizes the distance to the border as a plausibly exogenous instrument to measure Brexit's impact on these firms. Our findings align with the existing literature on labor reduction post-Brexit (Fuller, 2021; Sampson, 2017), which suggests that the British labor market may become less accessible to foreign workers (Born et al., 2019).

5.2 Robustness

This section presents a series of exercises to test the robustness of the main results of our paper. First, we use a dummy on whether a firm is located in Northern Ireland or Great Britain in lieu of the distance to the Irish border as a proxy for Brexit exposure. Second, we use the port of Derry - another major transportation hub near the Irish border for products entering the Republic of Ireland - instead of the port of Newry to compute the distance to the Irish border. Third, we conduct a placebo test, in which we randomly assign firms to different locations. Fourth, we exclude the period before the Brexit referendum in 2016 from our analysis. Fifth, we account for the expectation effects leading to Brexit implementation by interacting our benchmark proxy for Brexit exposure (i.e., distance to the border) with each individual year dummy. Overall, these robust analyses provide further support for the central hypothesis that firms located further from the Irish border experienced more significant impacts due to the implementation of Brexit in 2020.

5.2.1 Alternative Measure for Brexit Exposure

In the baseline specification in Equation (1), we use the firms' distance to the port of Newry as a proxy for Brexit exposure. In this section, we use a dummy on whether a firm is located in Northern Ireland or Great Britain in lieu of the distance to the Irish border to capture such exposure. Specifically, we consider the following regression specification

$$\begin{aligned} lnEmployment_{i,t} = \alpha_i + \beta(Brexit_t \times \text{Great Britain}_i) \; &+ \; \gamma \text{Great Britain}_i + \delta Brexit_t \\ &+ \; \zeta Control_{i,t} + \lambda_k + \varphi_t + \epsilon_{i,t}, \qquad (3) \end{aligned}$$

where $lnEmployment_{i,t}$ denotes the natural logarithm of the number of employees at firm i in year t. α_i is the constant term, and $\epsilon_{i,t}$ is a mean-zero disturbance term. Great Britain$_i$ is a dummy variable that indicates whether the firm is located in Great Britain. β capturing the differential impact of Brexit shocks on employment within UK firms located in Great Britain relative to firms located in Northern Ireland. ζ represents coefficients for control variables such as $Firm\ Age_{i,t}$ and $Firm\ Networks_{i,t}$. λ_k and φ_t are the industry and year fixed-effects, respectively. The estimates for Equation (3) are presented in Table 6, in which the first two columns use the full sample of all firms whereas the last four columns only use firms that do not switch locations throughout the sample period (2015-2022).

[Table 6 Here]

One key insight from Table 6 is that firms located in Great Britain are more likely to be impacted by Brexit effects relative to firms located in Northern Ireland. The continued significance of these results across all specifications is consistent with our benchmark result that firms located near the Irish border (and therefore are less exposed to Brexit in effect) are less inclined to reduce their labor demand.

5.2.2 Alternative Location for Border Crossing

Our previous analysis primarily utilized the spatial variation arising from the proximity to the border between Northern Ireland and the Republic of Ireland, commonly referred to as the Irish or British–Irish border. Established in 1923 to facilitate the free movement of people (and in 1993 for goods), the precise timing of this border's creation should not raise concerns regarding its influence on the identification of UK firms' responses. We now evaluate the robustness of our results by considering different locations along the border between the United Kingdom and the Republic of Ireland, using the geographical area of "Derry City and Strabane" an alternative to the port of Newry.

[Table 7 Here]

Our results for an alternative measurement using the border point of Derry are presented in Table 7. The coefficients across six specifications are negative and significant, ranging between -

0.108 and -0.132. These results suggest that the signs and/or statistical significance of the baseline estimates remain robust despite these variations.

5.2.3 Placebo Test

To ensure a robust set of results, we also generate a random distance that is assigned to all firms, instead of using the precise distance from these surveyed firms to the previously defined locations (Newry Port or Derry City and Strabane). We generated two types of random datasets by assigning values from a uniform distribution and a normal distribution, having the same mean and standard deviation as our original variable *Distance (to Newry)'*. We conducted two placebo tests using the specifications from our baseline results, but with randomly assigned distances. In no instance in Tables 8 and 9 was the variable *Brexit* × *Distance (Placebo)'* precisely estimated. This indicates that the spatial distribution of UK firms significantly influences labor reductions following the Brexit shocks based on our previous identification strategy.

[Table 8 and 9 Here]

Additionally, the long-term legacy of this border remains intact when considering various distances to the Republic of Ireland. It is impractical to test every point along the border; therefore, we generated random distances for our main variables. All coefficients are imprecisely estimated across our specifications. In short, introducing distances to these alternative placebo points along the Irish or British-Irish border does not affect the sign or statistical precision of the benchmark estimates.

5.2.4 Accounting for Brexit referendum expectation

Building on the argument presented in Figure 2 that the 2016 Brexit referendum might influence the results, we observe significant differences in the number of employees between the two groups (low versus high exposure). Therefore, in our robustness check, we exclude the pre-2016 sample to determine whether the effects are robust. Our findings are reported in Table 10.

[Table 10 Here]

Overall, after excluding data from the 2016 Brexit referendum, the negative impacts of Brexit implementation on employee numbers range from 10.2% to 14.2%. These differences are not significant compared to the baseline results presented in Table 5. Therefore, we also exclude potential outliers, specifically the significant differences in the number of employees in 2016, from the regression and re-estimate the benchmark model. This adjustment suggests that the core findings are robust and unaffected by the inclusion of the 2016 Brexit referendum data.

5.2.5 Accounting for expectation of Brexit implementation

To understand how the expectation toward Brexit builds up over time, we consider a variation of the benchmark regression model in Equation (1) in which we interact the year dummy with the firm exposure to Brexit. The regression model, specified with robust standard errors, is

$$\begin{aligned} lnEmployment_{i,t} = \alpha \quad &+ \quad \beta(Year_t \times Distance(toNewry)_i) + \gamma Distance(toNewry)_i + \delta Year_t \\ &+ \quad \lambda_k + \varphi_t + \epsilon_{i,t}, \end{aligned}$$

where $lnEmployment_{i,t}$ represents the natural logarithm of the number of employees as the dependent variable. The fixed effects λ_k and φ_t correspond to industry and year, respectively. In Figure 3, we present the point estimate of β, along with the corresponding 90% (bold-shaded) and 95% (light-shaded) confidence bands. The figure also marks the timing of three key events: the Brexit referendum in 2016, the official implementation of Brexit in January 2020, and the withdrawal of the Northern Ireland Protocol in January 2021.

[Figure 3 Here]

Overall, Figure 3 shows that the effects of Brexit, as measured by the point estimate of β, are largely non-significant (except in 2017) before the Brexit implementation in 2020. In stark contrast, once Brexit is in effect, we document negative and statistically significant effects of this policy change: firms with higher exposure to Brexit as more likely to cut down their labor demand.

6 Mechanism

6.1 Main channels

The extant literature explains the channel for employment to technological substitution under wage shocks (Aaronson and Phelan, 2019; Van Reenen, 1997). The history of technology is not just about automation displacing human labor; it also includes the development of new technologies that respond to potential shocks. Therefore, Acemoglu and Restrepo (2019) argued that this effect can be called "reinstatement effect," which might counter the job reduction from technological development by expanding the roles and increasing the demand for human labor, thereby boosting productivity. Given the findings of well-established studies on substitution (Aaronson and Phelan, 2022, 2019; Acemoglu and Restrepo, 2019), we hypothesized that UK firms that reduce their number of employees, a process known as labor reduction, are more likely to increase their research and development (R&D) activities to acquire frontier technology. Table 11 presents the results of a study examining the impact of Brexit on firms' R&D activities, based on their varying levels of exposure to Brexit risk. This exposure is measured by the firms' proximity to the Irish or British-Irish border.

[Table 11 Here]

The coefficients in Table 11 are significantly positive across our six specification models. Specifically, a one-percent increase in the distance to Newry correlates with an approximate 0.562 percent increase in R&D expenditure for business activities. This finding suggests a substitution effect between employment reduction and technological development in UK SMEs, indicating that firms may compensate for reduced employment with increased investment in technology Autor et al. (2015). While Bloom et al. (2019) found that Brexit led to reduced spending on intangibles such as R&D in their surveyed firms, the effects might differ in SMEs. These smaller firms may choose to reduce the number of employees to increase their research and development activities.

In addition to exploring the relationship between labor reduction and technological development, the current literature also focuses on how UK firms have formed their own expectations regarding Brexit events. Therefore, Born et al. (2019) discovered a downward adjustment in growth expectations following the Brexit referendum in 2016. Similarly, Bloom et al. (2019) reported that firms anticipated reducing their investments, with pessimistic expectations observed among international firms as well (Hassan et al., 2024). In this study, we extend the existing literature by explaining why the UK firms choose to reduce their number of employees based on expectations. Using the survey question "Summary of expected growth in next year" from BEIS (2023), we created a dummy variable to determine whether firms expect to achieve economic growth in the coming year. Our findings are summarized in Table 12.

[Table 12 Here]

As shown in all columns of Table 12, the sample average marginal effect at the median indicates that a 1% increase in distance is estimated to reduce the probability of firms maintaining their optimistic outlook on future growth by up to 3.4%. We build upon and add to the existing literature by reflecting on this generally negative outlook and the economic benefits promised by the Vote Leave campaign Hassan et al. (2024). Our findings demonstrate the tangible impacts, showing that UK firms are likely to become more pessimistic about growth when Brexit takes effect. Concomitantly, our study extends the findings of Bloom et al. (2019) by suggesting that firms, perceiving Brexit as a source of uncertainty in 2016, would lower their expectations upon the activation of the referendum.

6.2 Additional analyses

Using the industry classification for listed firms, Hill et al. (2019) found that two sectors, specifically the financial sector and consumer goods/services industries, are more likely to be affected by Brexit. In a similar context, Douch and Edwards (2021) analyzed the impact of the Brexit referendum shock in 2016 on commercial services exports. The study revealed that 'other commercial services'[5] experienced the most severe negative shocks, whereas the tourism sector encountered a positive shock. Similarly, with the onset of COVID-19, one can expect heterogeneity across industries when Brexit takes effect (Chetty et al., 2024). The previous section demonstrated a decline in the number of employees following the implementation of Brexit, compared to the preceding period. Therefore,

[5]The term 'other commercial services' encompasses a range of sectors including construction, insurance and pension services, financial services, charges for the use of intellectual property, telecommunications, computer and information services, other business services, as well as personal, cultural, and recreational services (WTO, 2016).

we will now conduct a sub-sample analysis to explore the heterogeneity across 14 industries. These analyses are shown graphically in Figure 4.

[Figure 4 Here]

Across 14 industries, we found that 6 out of 14 industries showed no effects. Negative estimated coefficients were present in four industries—Primary, Construction, Health/Social Work, and Other Services—with coefficients ranging from -0.34 to -0.40. This implies that a 1% increase in distance from the Irish border leads firms in these industries to reduce their labor forces by up to 0.40%. Surprisingly, the estimated coefficients for the manufacturing industry were significantly positive.

The existing literature highlights the disproportionate effects on two groups, skilled and unskilled workers, indicating that neither would benefit from reduced trade with the EU (Burstein and Vogel, 2017). Additionally, Sampson (2017) hypothesized that the financial sector might face difficulties accessing highly skilled workers from across the EU (Sampson, 2017). We utilized responses from firms to two specific questions: *"Obstacles because of Brexit - difficulty in recruiting skilled labor"* and *"Obstacles because of Brexit - difficulty in recruiting unskilled labor"*. To analyze these issues, we created dummy variables *obstacles_skilled* and *obstacles_unskilled*, assigning a value of 1 if challenges were reported and 0 if not. These variables help us calculate the likelihood of encountering these obstacles post-Brexit. Figure 5 illustrates the impacts of Brexit on recruiting skilled and unskilled workers from the European Union based on our previous specifications.

[Figure 5 Here]

As depicted in Figure 5, the marginal effects of our main variable *Brexit* × *Distance (to Newry)* at the median on *Skilled EU labor obstacles"* remain positive, both with and without control variables, across the 90% and 95% confidence intervals. This implies that a 1% increase in distance is estimated to increase the probability that firms will face obstacles in recruiting skilled EU labor. However, for unskilled EU labor, the estimated marginal effects at the median are significant only at the 90% confidence interval, indicating a weak effect. Based on these findings, we can conclude that UK firms with greater exposure to Brexit—due to their proximity to the Irish border—are more likely to face obstacles in recruiting skilled EU labor, but not unskilled EU labor. Referring to Figure 5, we hypothesize that UK firms in the manufacturing industry, which have higher exposure to Brexit, may predominantly rely on unskilled labor and thus may not need to reduce their workforce following the implementation of Brexit.

7 Conclusion

To sum up, drawing on the LSBS 2015-2022, our findings confirm that Brexit imposed significant effects on labor demand within UK SMEs. Our evidence suggests that the impacts of Brexit vary significantly across sectors and regions. Additionally, our investigation shows that while SMEs experience a declining trend in their employment, there is still a consistent increase in their R&D investment. Our further analysis indicates that high-exposure SMEs experience a much stronger declining effect on employment compared to low-exposure SMEs. This indicates that SMEs located closer to the Northern Irish border are less adversely affected. Furthermore, these firms are also less likely to encounter obstacles in recruiting skilled EU labor, possibly benefiting from their unique geographic and economic position relative to Brexit changes.

Our paper contributes to clarifying existing literature on regional economic consequences following trade policy shocks particularly related to UK SMEs' perception and reaction to Brexit as in Bell (2017) and Thissen et al. (2020). Our findings provide a deeper insight into the SMEs research with regard to their responses and adaption to uncertain environments and provide implications to research policy concerning immigration and innovation issues. This enhances further understanding of SME owner-managers' perception of Brexit in previous studies and policy research regarding their reduced market access and declining capital investment in innovation (Brown et al., 2019; Chung, 2017). Finally, our paper contributes to the existing literature on regional economic consequences following trade policy shocks, particularly ones related to UK SMEs responses (Bell, 2017; Douch and Edwards, 2021). Overall, our research highlights the complex but discernible impact of Brexit on different sectors and regions within the UK, underscoring the importance of geographic location in mitigating economic disruptions.

Table 1: Summary of the number of observations of *"Employee (log)"* By Industry Classification

	Full sample		Northern Ireland		Great Britain	
	Obs.	%	Obs.	%	Obs.	%
ABDE - Primary (Agriculture & Mining)	3,369	4.017	313	7.161	3,056	3.844
C - Manufacturing	8,026	9.570	493	11.279	7,533	9.476
F - Construction	8,024	9.567	482	11.027	7,542	9.487
G - Wholesale/Retail	12,990	15.488	869	19.881	12,121	15.247
H - Transport/Storage	3,098	3.694	156	3.569	2,942	3.701
I - Accommodation/Food	6,567	7.830	357	8.167	6,210	7.811
J - Information/Communication	4,708	5.613	174	3.981	4,534	5.703
KL - Financial/Real Estate	3,649	4.351	195	4.461	3,454	4.345
M - Professional/Scientific	12,076	14.398	424	9.700	11,652	14.657
N - Administrative/Support	6,512	7.764	224	5.125	6,288	7.910
P - Education	2,674	3.188	76	1.739	2,598	3.268
Q - Health/Social Work	6,267	7.472	298	6.818	5,969	7.508
R - Arts/Entertainment	2,479	2.956	113	2.585	2,366	2.976
S - Other service	3,431	4.091	197	4.507	3,234	4.068
Total	83,870	100.000	4,371	100.000	79,499	100.000

Notes: This paper presents the number of observations (of *"Employee (log)"*) across 14 industries, based on our data focused on the main variable of interest, *employees (Log)*. Additionally, the table provides a summary of two subsamples from Northern Ireland and Great Britain, detailing the number of observations across various sectors within these regions.

Table 2: Summary of Dataset By Year

	Full sample		Northern Ireland		Great Britain	
	Obs.	%	Observations	%	Observations	%
2015	15,501	18.482	494	11.302	15,007	18.877
2016	9,248	11.027	505	11.553	8,743	10.998
2017	6,619	7.892	497	11.370	6,122	7.701
2018	15,015	17.903	588	13.452	14,427	18.147
2019	11,002	13.118	483	11.050	10,519	13.232
2020	7,636	9.105	493	11.279	7,143	8.985
2021	9,325	11.118	732	16.747	8,593	10.809
2022	9,524	11.356	579	13.246	8,945	11.252
Total	83,870	100.000	4,371	100.000	79,499	100.000

Notes: This paper presents the number of observations (of *"Employee (log)"*) across 8 years from 2015 to 2022, based on our data focused on the main variable of interest, *employees (Log)*. Additionally, the table provides a summary of two subsamples from Northern Ireland and Great Britain, detailing the number of observations over the period from 2015 to 2022.

Table 3: Summary of Descriptive Statistics

	Obs.	Mean	Std.	Q1	Median	Q3	Min	Max
Distance (to Newry)	265,431	12.824	0.309	12.491	12.904	13.116	0.000	13.518
Distance (to Derry)	265,431	13.029	0.323	12.807	13.134	13.309	0.000	13.484
Not NI (Great Britain)	342,320	0.944	0.230	1.000	1.000	1.000	0.000	1.000
Brexit	342,320	0.375	0.484	0.000	0.000	1.000	0.000	1.000
Employees (Log)	83,870	1.963	1.550	0.693	1.946	3.091	0.000	5.283
Employees (Ordinal)	83,870	4.098	2.012	3.000	4.000	6.000	1.000	9.000
Firm Age	76,320	3.122	1.044	2.000	3.000	4.000	1.000	4.000
Firm Networks (Log)	83,597	1.039	0.505	0.693	1.099	1.386	0.000	2.565
Expected Growth	79,511	0.124	0.329	0.000	0.000	0.000	0.000	1.000
Firm R&D (Log)	10,059	2.528	4.451	0.000	0.000	0.693	0.000	14.221
Skilled-EU Recruit Obstacles	3,364	0.491	0.500	0.000	0.000	1.000	0.000	1.000
Unskilled-EU Recruit Obstacles	2,825	0.412	0.492	0.000	0.000	1.000	0.000	1.000

Notes: This table presents the descriptive statistics for all variables used in our analysis. The survey data covers a total of 342,320 observations from the years 2015 to 2022 with 42,790 unique firms without having any missing data. Differences between the total observations and the *Distance (to Newry/Derry)"* data occur due to some firms not disclosing their location, whether categorized by Local Enterprise Partnership (LEP) or Local Authority District (LAD). Distances to these locations are calculated using a formula referenced from Weber and Péclat (2017). The variable *Brexit"* is a dummy variable, assigned a value of '1' for the period post-2020 and 0 for prior years. The *Employees (Log/Ordinal)* variable quantifies the number of employees, expressed as the natural logarithm for continuous analysis or in original values for ordinal analysis. *Firm Age* is divided into four categories. *Firm Networks (Log)* represents the natural logarithm of the number of directors and partners, based on survey data. *Expected Growth* is another dummy variable, marked '1' for firms with a more optimistic outlook on their future growth and '0' otherwise. *Firm R&D (Log)* is the natural logarithm of the expenditure on research and development activities over the last three years. Lastly, *Skilled-EU Recruit Obstacles* and *Unskilled-EU Recruit Obstacles* are dummy variables assigned a value of '1' if firms face recruitment challenges for skilled and unskilled EU employees, respectively.

Table 4: Correlations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Distance (to Newry)	1									
(2) Distance (to Derry)	0.977***	1								
(3) Not NI (Great Britain)	0.265***	0.363***	1							
(4) Brexit	-0.159***	-0.220***	-0.220***	1						
(5) Employees (Log)	-0.0435***	-0.0453***	-0.0230*	0.0434***	1					
(6) Employees (Ordinal)	-0.0380***	-0.0395***	-0.0251**	0.0414***	0.985***	1				
(7) Firm Age	-0.0137	-0.00796	0.0266**	0.0113	0.236***	0.230***	1			
(8) Firm Networks	-0.0274**	-0.0340***	-0.0136	0.0799***	0.320***	0.323***	0.0767***	1		
(9) Expected Growth	-0.0483***	-0.0599***	-0.00483	0.258***	0.0199*	0.0169	0.0469***	0.0357***	1	
(10) Firm R&D (Log)	-0.168***	-0.230***	-0.205***	0.667***	0.118***	0.111***	0.00397	0.155***	0.317***	1

Notes: Significance levels are indicated by: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Table 5: Baseline Results: Brexit and Firm Employment

	Full sample		No Switching			
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	HDFE	OLS	HDFE	OLS	HDFE
Brexit × Distance (to Newry)	-0.136***	-0.136***	-0.128***	-0.128***	-0.107***	-0.107***
	(0.044)	(0.044)	(0.044)	(0.044)	(0.041)	(0.041)
Distance (to Newry)	0.050	0.050	0.050	0.050	0.024	0.024
	(0.038)	(0.038)	(0.039)	(0.039)	(0.035)	(0.035)
Brexit	1.773***	1.773***	1.674***	1.674***	1.313**	1.313**
	(0.561)	(0.561)	(0.569)	(0.569)	(0.528)	(0.528)
Constant	0.792	1.342***	0.799	1.351***	0.114	0.763*
	(0.494)	(0.495)	(0.500)	(0.502)	(0.455)	(0.456)
Control variables	No	No	No	No	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adj R-squared	0.090	0.090	0.088	0.088	0.198	0.198
Observations	63,558	63,558	61,318	61,318	55,990	55,990

Notes: This table presents all baseline results for the effects of Brexit on Firm employment as outlined in the specification model (1). Columns (1), (3), and (5) utilize the Ordinary Least Squares (OLS) method for estimation, whereas the other columns employ regression with high-dimensional sets of fixed effects (HDFE). The *Brexit* variable is a dummy indicator (1 - post-2020; 0 - otherwise), and *Distance (to Newry)* measures the firm's proximity to the Irish border. Columns (1)-(4) do not include control variables (i.e., Firm age and Firm Networks), while Columns (5)-(6) include them. Standard errors are clustered at firm level and presented in parentheses. Significance levels are indicated by: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Table 6: The impact of Brexit on firm employment - Robustness tests (N.I. vs. Great Britain)

	Full sample		No Switching			
	(1) OLS	(2) HDFE	(3) OLS	(4) HDFE	(5) OLS	(6) HDFE
Brexit × Not NI (Great Britain)	-0.136***	-0.136***	-0.130**	-0.130**	-0.093*	-0.093*
	(0.050)	(0.050)	(0.051)	(0.051)	(0.048)	(0.048)
Not NI (Great Britain)	0.112***	0.112***	0.110**	0.110**	0.024	0.024
	(0.043)	(0.043)	(0.043)	(0.043)	(0.040)	(0.040)
Brexit	0.156***	0.156***	0.151***	0.151***	0.023	0.023
	(0.051)	(0.051)	(0.051)	(0.051)	(0.049)	(0.049)
Constant	1.271***	1.878***	1.271***	1.882***	0.354***	1.041***
	(0.058)	(0.043)	(0.059)	(0.043)	(0.058)	(0.044)
Control variables	No	No	No	No	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adj R-squared	0.092	0.092	0.091	0.091	0.203	0.203
Observations	83,870	83,870	81,630	81,630	74,000	74,000

Notes: This table displays the baseline results for the real effects of Brexit on firm employment, using a conventional difference-in-differences approach. The variable *"Not NI (Great Britain)"* is a dummy variable assigned a value of 1 if the firm is located in Great Britain. The *"Brexit"* variable is a dummy indicator (1 - post-2020; 0 - otherwise). Columns (1), (3), and (5) utilize the Ordinary Least Squares (OLS) method for estimation, whereas the other columns employ regression with high-dimensional sets of fixed effects (HDFE). Columns (1)-(4) do not include control variables (i.e., Firm Age and Firm Networks), while Columns (5)-(6) include them. Standard errors are clustered at firm level and presented in parentheses. Significance levels are indicated by: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Table 7: Robustness tests (An alternative variable - "Distance (to Derry)")

	Full sample		No Switching			
	(1) OLS	(2) HDFE	(3) OLS	(4) HDFE	(5) OLS	(6) HDFE
Brexit × Distance (to Derry)	-0.132***	-0.132***	-0.129***	-0.129***	-0.108***	-0.108***
	(0.041)	(0.041)	(0.042)	(0.042)	(0.039)	(0.039)
Distance (to Derry)	0.056	0.056	0.061	0.061	0.033	0.033
	(0.036)	(0.036)	(0.038)	(0.038)	(0.035)	(0.035)
Brexit	1.748***	1.748***	1.717***	1.717***	1.357***	1.357***
	(0.531)	(0.531)	(0.549)	(0.549)	(0.512)	(0.512)
Constant	0.702	1.251***	0.641	1.192**	-0.001	0.648
	(0.474)	(0.476)	(0.501)	(0.503)	(0.459)	(0.460)
Control variables	No	No	No	No	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adj R-squared	0.090	0.090	0.088	0.088	0.198	0.198
Observations	63,558	63,558	61,318	61,318	55,990	55,990

Notes: This table displays the robust results for Brexit in effect on firm employment, using an alternative measurement *Distance (to Derry)* instead of *Distance (to Newry)*. The *"Brexit"* variable is a dummy indicator (1 - post-2020; 0 - otherwise). Columns (1), (3), and (5) utilize the Ordinary Least Squares (OLS) method for estimation, whereas the other columns employ regression with high-dimensional sets of fixed effects (HDFE). Columns (1)-(4) do not include control variables (i.e., Firm Age and Firm Networks), while Columns (5)-(6) include them. Standard errors are clustered at firm level and presented in parentheses. Significance levels are indicated by: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Table 8: Robustness tests (Placebo Distance - Uniform Distribution)

	Full sample		No Switching			
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	HDFE	OLS	HDFE	OLS	HDFE
Brexit × Distance (Placebo)	0.002	0.002	0.001	0.001	0.002	0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Distance (Placebo)	0.000	0.000	0.001	0.001	-0.000	-0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Brexit	0.017	0.017	0.021	0.021	-0.064**	-0.064**
	(0.029)	(0.029)	(0.030)	(0.030)	(0.029)	(0.029)
Constant	1.439***	1.988***	1.435***	1.987***	0.430***	1.077***
	(0.055)	(0.020)	(0.055)	(0.020)	(0.057)	(0.029)
Control variables	No	No	No	No	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adj R-squared	0.089	0.089	0.088	0.088	0.197	0.197
Observations	63,558	63,558	61,318	61,318	55,990	55,990

Notes: This table displays the robust results for Brexit in effect on firm employment, using a placebo measurement *Distance (Placebo)* instead of *Distance (to Newry)*, which is a random variable from a uniform distribution. The *"Brexit"* variable is a dummy indicator (1 - post-2020; 0 - otherwise). Columns (1), (3), and (5) utilize the Ordinary Least Squares (OLS) method for estimation, whereas the other columns employ regression with high-dimensional sets of fixed effects (HDFE). Columns (1)-(4) do not include control variables (i.e., Firm Age and Firm Networks), while Columns (5)-(6) include them. Standard errors are clustered at firm level and presented in parentheses. Significance levels are indicated by: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Table 9: Robustness tests (Placebo Distance - Randomness with same mean and standard deviation)

	Full sample		No Switching			
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	HDFE	OLS	HDFE	OLS	HDFE
Brexit × Distance (Placebo)	0.032	0.032	0.027	0.027	-0.003	-0.003
	(0.040)	(0.040)	(0.041)	(0.041)	(0.039)	(0.039)
Distance (Placebo)	0.001	0.001	0.013	0.013	0.021	0.021
	(0.024)	(0.024)	(0.024)	(0.024)	(0.025)	(0.025)
Brexit	-0.385	-0.385	-0.308	-0.308	-0.016	-0.016
	(0.510)	(0.510)	(0.520)	(0.520)	(0.501)	(0.501)
Constant	1.427***	1.975***	1.277***	1.828***	0.162	0.809**
	(0.311)	(0.308)	(0.318)	(0.314)	(0.318)	(0.315)
Control variables	No	No	No	No	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adj R-squared	0.089	0.089	0.088	0.088	0.197	0.197
Observations	63,558	63,558	61,318	61,318	55,990	55,990

Notes: This table displays the placebo test for Brexit in effect on firm employment, using using a placebo measurement *Distance (Placebo)* instead of *Distance (to Newry)*, which is a random variable from the same mean and standard deviation distribution. The *"Brexit"* variable is a dummy indicator (1 - post-2020; 0 - otherwise). Columns (1), (3), and (5) utilize the Ordinary Least Squares (OLS) method for estimation, whereas the other columns employ regression with high-dimensional sets of fixed effects (HDFE). Columns (1)-(4) do not include control variables (i.e., Firm Age and Firm Networks), while Columns (5)-(6) include them. Standard errors are clustered at firm level and presented in parentheses. Significance levels are indicated by: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Table 10: Robustness check: Excluding Pre-referendum

	Full sample		No Switching			
	(1) OLS	(2) HDFE	(3) OLS	(4) HDFE	(5) OLS	(6) HDFE
Brexit × Distance (to Newry)	-0.142***	-0.142***	-0.136***	-0.136***	-0.104**	-0.104**
	(0.043)	(0.043)	(0.044)	(0.044)	(0.042)	(0.042)
Distance (to Newry)	0.063	0.063	0.063	0.063	0.027	0.027
	(0.041)	(0.041)	(0.041)	(0.041)	(0.039)	(0.039)
Brexit	1.970***	1.970***	1.883***	1.883***	1.380**	1.380**
	(0.554)	(0.554)	(0.562)	(0.562)	(0.537)	(0.537)
Constant	0.534	1.066**	0.532	1.061**	-0.020	0.613
	(0.519)	(0.520)	(0.527)	(0.529)	(0.495)	(0.497)
Control variables	No	No	No	No	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adj R-squared	0.084	0.084	0.082	0.082	0.197	0.197
Observations	46,637	46,637	44,840	44,840	44,671	44,671

Notes: This table displays the robustness for Brexit in effect on firm employment, excluding the pre-referendum (2016). It means that all regressions cover the period from 2017-2022. The *"Brexit"* variable is a dummy indicator (1 - post-2020; 0 - otherwise) while *Distance (to Newry)* measures the firm's proximity to the Irish border. Columns (1), (3), and (5) utilize the Ordinary Least Squares (OLS) method for estimation, whereas the other columns employ regression with high-dimensional sets of fixed effects (HDFE). Columns (1)-(4) do not include control variables (i.e., Firm Age and Firm Networks), while Columns (5)-(6) include them. Standard errors are clustered at firm level and presented in parentheses. Significance levels are indicated by: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Table 11: Mechanism tests - Brexit and Firm R&D (Log)

	Full sample		No Switching			
	(1) OLS	(2) HDFE	(3) OLS	(4) HDFE	(5) OLS	(6) HDFE
Brexit × Distance (to Newrry)	0.562**	0.562**	0.577**	0.577**	0.609***	0.609***
	(0.232)	(0.232)	(0.234)	(0.234)	(0.232)	(0.232)
Distance (to Newrry)	0.002	0.002	-0.000	-0.000	-0.007	-0.007
	(0.060)	(0.060)	(0.061)	(0.061)	(0.061)	(0.061)
Brexit	3.131	3.131	2.934	2.934	2.483	2.483
	(2.993)	(2.993)	(3.017)	(3.017)	(2.989)	(2.989)
Constant	0.160	0.177	0.209	0.209	-0.018	0.029
	(0.783)	(0.778)	(0.788)	(0.783)	(0.793)	(0.789)
Control variables	No	No	No	No	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R-squared	0.926	0.926	0.927	0.927	0.928	0.928
Observations	7,367	7,367	7,137	7,137	7,022	7,022

Notes: This table presents our mechanism tests, which examine the real effects of Brexit on SMEs' R&D spending. It specifically analyzes the continuous variable *Firm R&D (Log)*, which represents the natural logarithm of R&D expenditure from 2018 to 2022. The *"Brexit"* variable is a dummy indicator (1 - post-2020; 0 - otherwise) while *Distance (to Newry)* measures the firm's proximity to the Irish border. Columns (1), (3), and (5) utilize the Ordinary Least Squares (OLS) method for estimation, whereas the other columns employ regression with high-dimensional sets of fixed effects (HDFE). Columns (1)-(4) do not include control variables (i.e., Firm Age and Firm Networks), while Columns (5)-(6) include them. Standard errors are clustered at firm level and presented in parentheses. Significance levels are indicated by: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

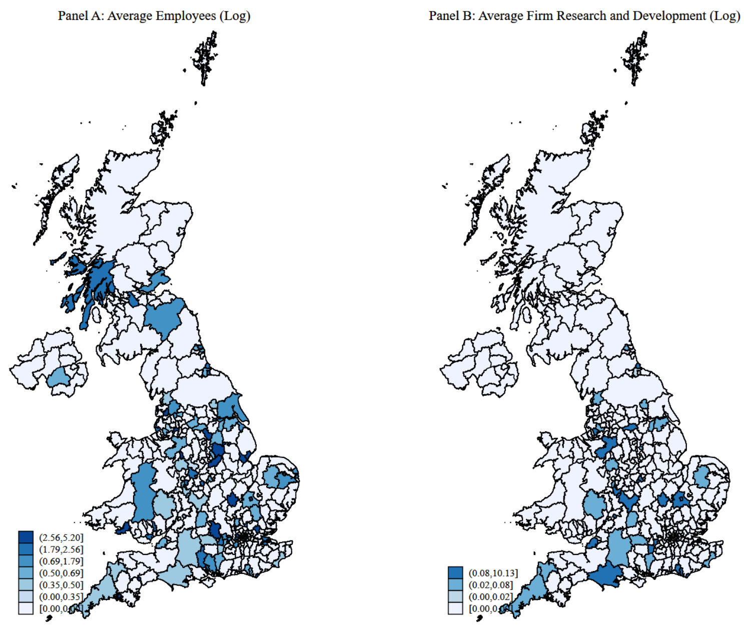
Table 12: Mechanism tests - Brexit and Firm Expected growth

	Full sample	No Switching	Full sample	No Switching
	(1)	(2)	(3)	(4)
	PROBIT	PROBIT	PROBIT	PROBIT
Brexit × Distance (to Newry)	-0.020**	-0.024**	-0.031***	-0.034***
	(0.010)	(0.010)	(0.010)	(0.010)
Distance (to Newry)	0.053***	0.054***	0.058***	0.059***
	(0.007)	(0.007)	(0.007)	(0.007)
Brexit	0.192	0.238*	0.331***	0.372***
	(0.125)	(0.127)	(0.127)	(0.128)
Control variables	No	No	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Pseudo R-squared	0.036	0.036	0.039	0.039
Observations	49,741	47,826	43,841	42,132

Notes: This table displays our second mechanims based on firms expectations by using the Probit estimations. The number presented as the marginal effects at median for the dependent variable The *"Expected Growth"* (1 - firms with a more optimistic outlook on their future growth and '0' otherwise). The *"Brexit"* variable is a dummy indicator (1 - post-2020; 0 - otherwise) while *Distance (to Newry)* measures the firm's proximity to the Irish border. Columns (1), (3), and (5) utilize the Ordinary Least Squares (OLS) method for estimation, whereas the other columns employ regression with high-dimensional sets of fixed effects (HDFE). Columns (1)-(4) do not include control variables (i.e., Firm Age and Firm Networks), while Columns (5)-(6) include them. Standard errors are clustered at firm level and presented in parentheses. Significance levels are indicated by: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

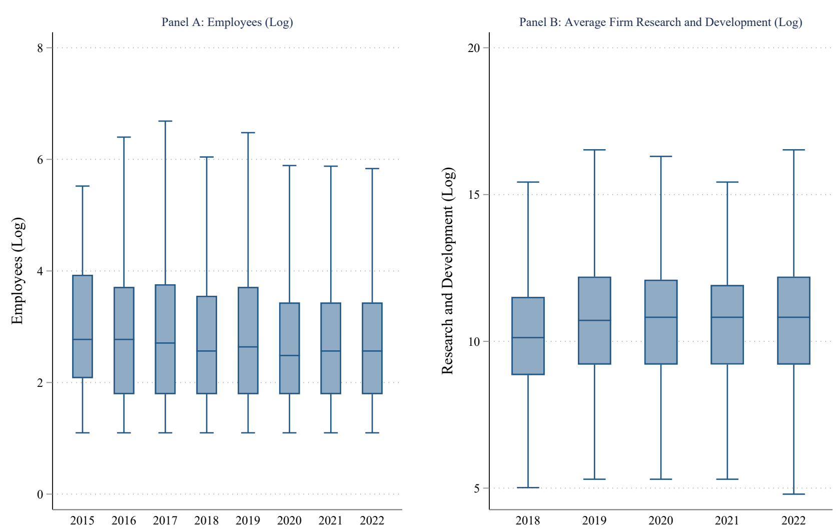
Figure 1: Data Distribution

(a) Across Locations



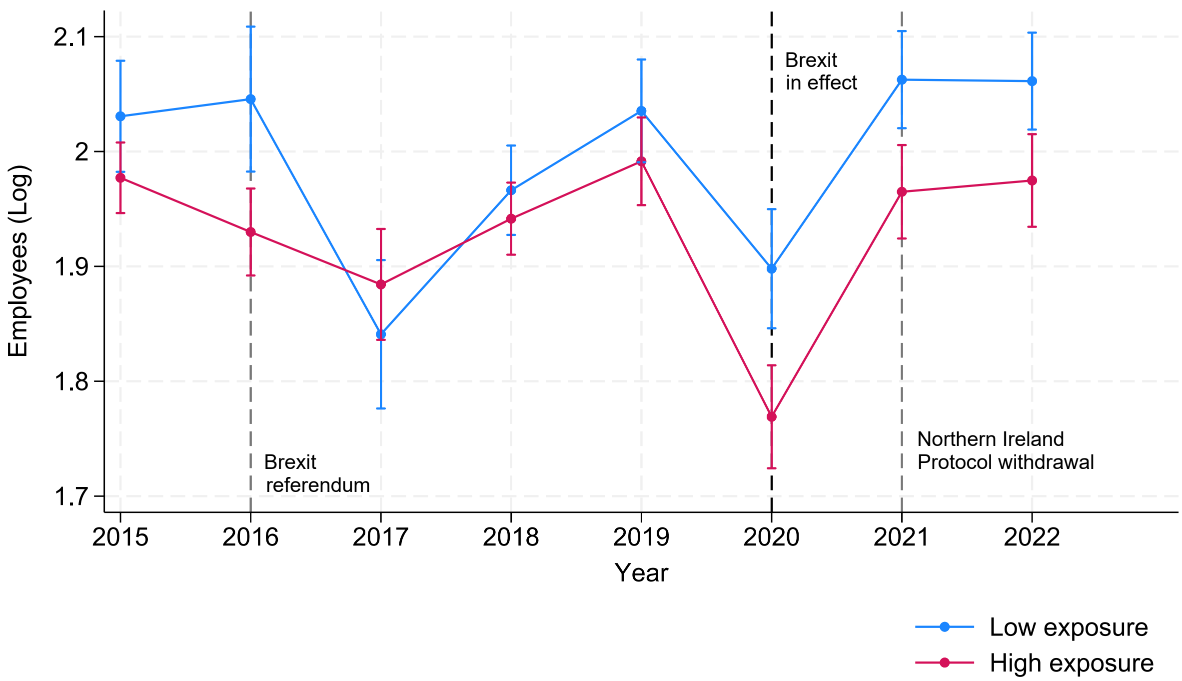
Notes: Figure 1a illustrates the geographical distribution using Local Authority Districts (LAD) (December 2023) boundaries in the United Kingdom for our two main variables of interest. We aggregate firm-level employee data to the LAD level. Areas with a darker color represent a higher number of employees.

(b) Over Time



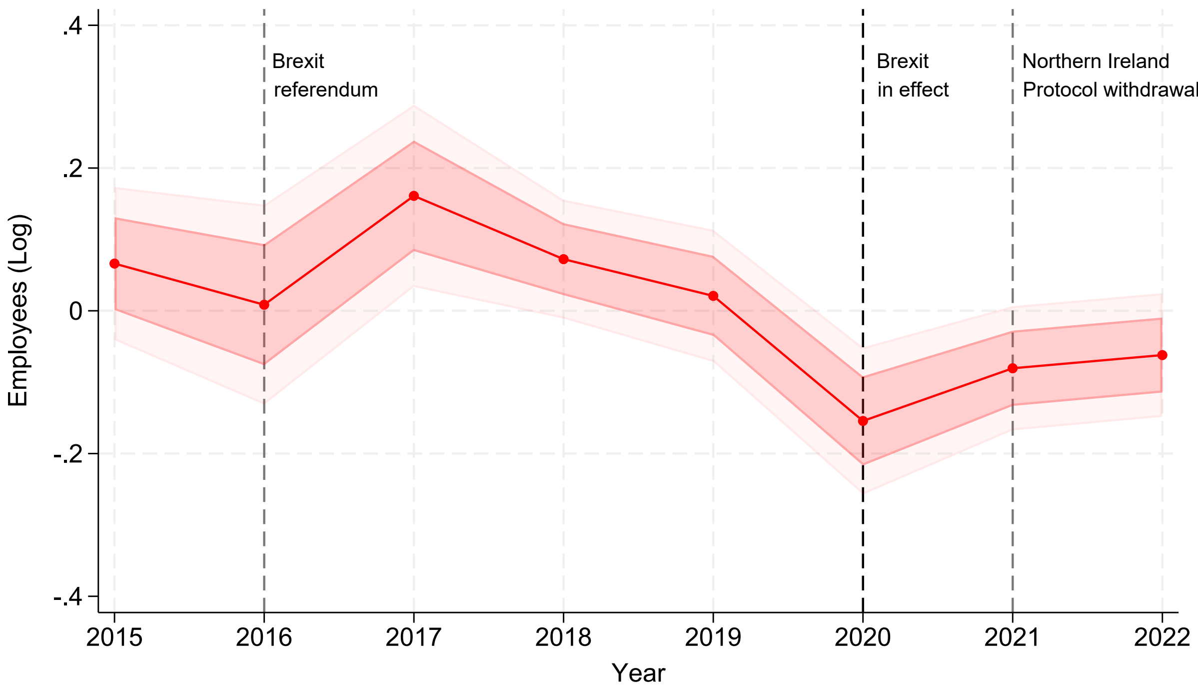
Notes: Figure 1b illustrates the box plot for two main variables of interest: the average number of employees and the average R&D expenditure, presented in natural logarithm form, across different years. It should be noted that data for R&D expenditure are only available from 2018 onwards. Both figures exclude outliers.

Figure 2: Employment of High vs. Low-exposure Firms



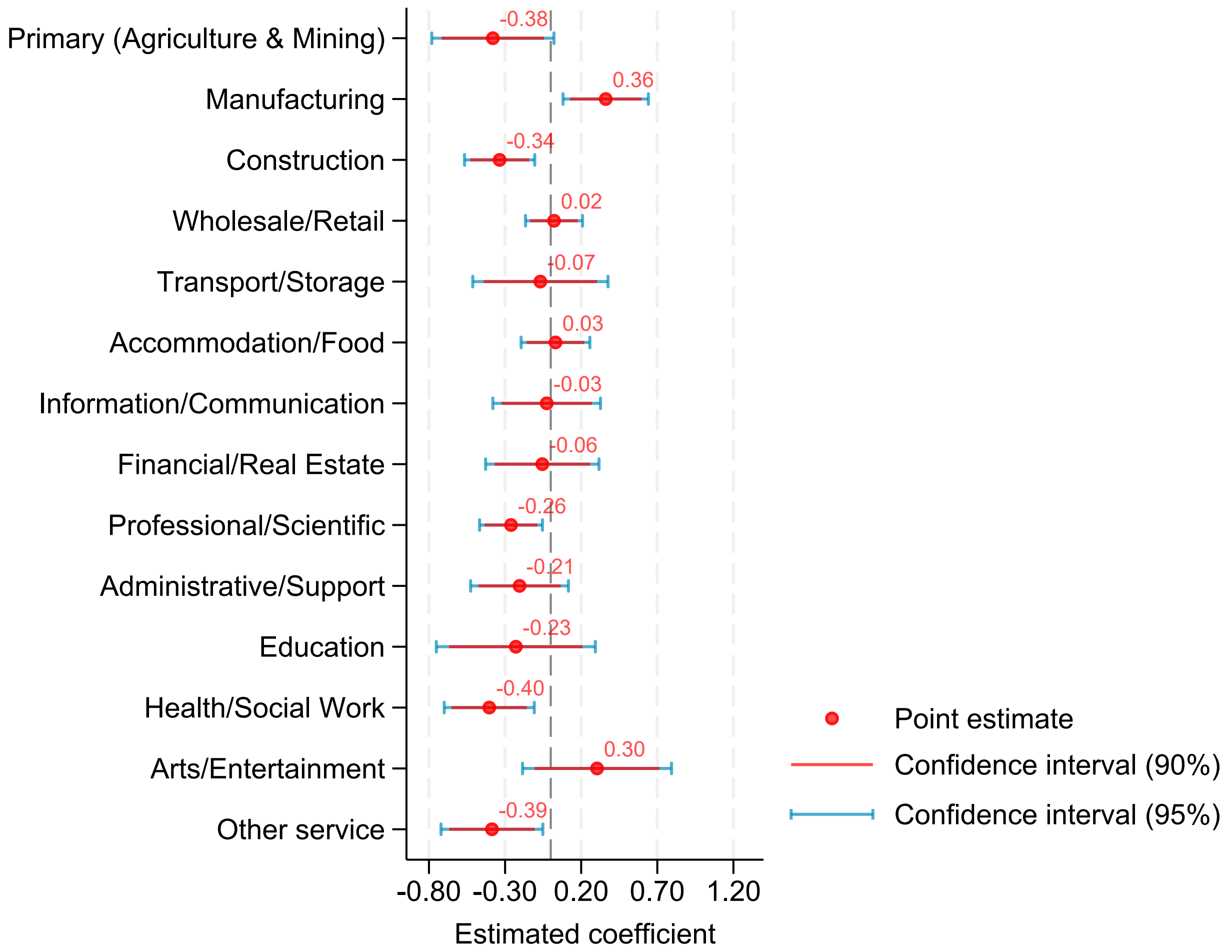
Notes Figure 2 displays the average number of employees (in logarithmic form) for firms categorized by their exposure to Brexit. *Low-exposure* firms are defined as those located at or below the median distance to Northern Ireland's border, while firms beyond this threshold are categorized as *high-exposure* firms. The figure also includes a 95% confidence band for each year represented in the data. It marks the timing of three significant events: the Brexit referendum in 2016, the official implementation of Brexit in January 2020, and the withdrawal of the Northern Ireland Protocol in January 2021.

Figure 3: Regression Coefficient of Employees (Log) on each Dummy Year × Distance to Border



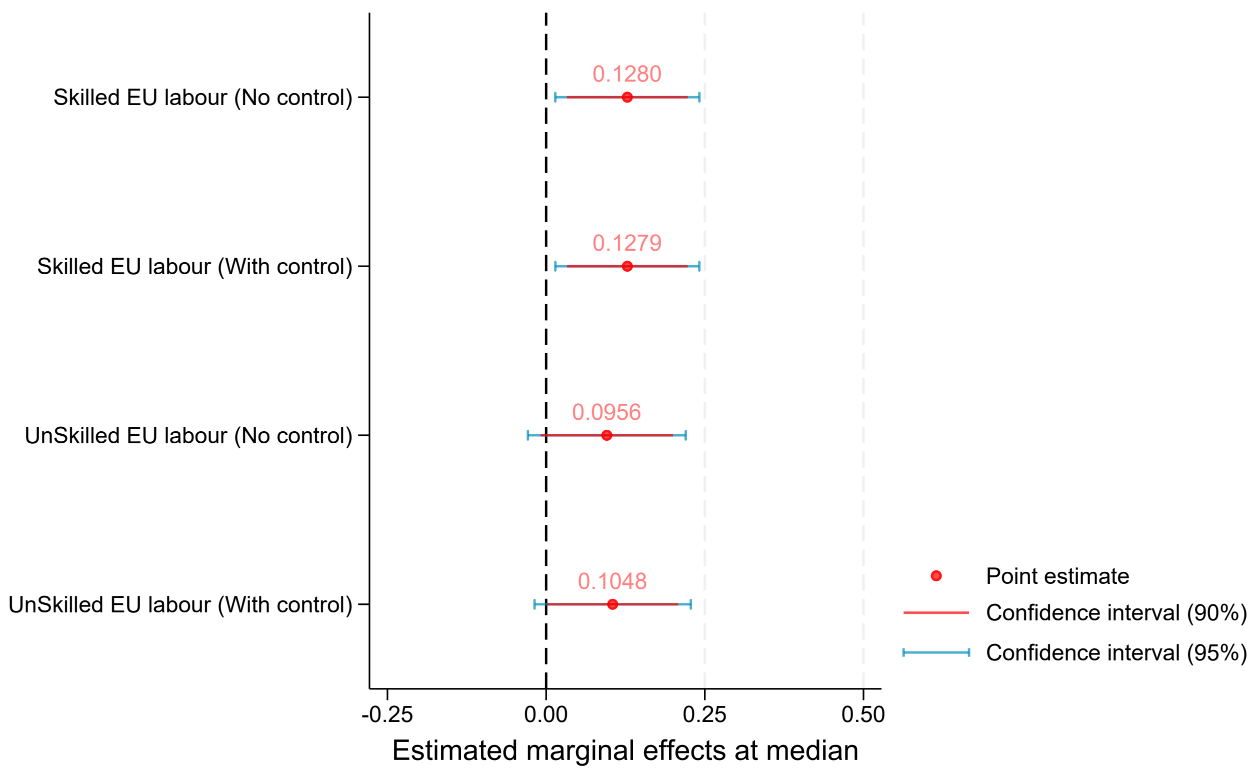
Notes: Figure 3 illustrates the coefficients of $Distance(toNewry) \times Year_t$ from each regression analysis. The regression model, specified with robust standard errors, is defined as $lnEmployment_{i,t} = \alpha + \beta(Year_t \times Distance(toNewry)i) + \gamma Distance(toNewry)_i + \delta Year_t + \lambda_k + \varphi_t + \epsilon_{i,t}$, where $lnEmployment_{i,t}$ represents the natural logarithm of the number of employees as the dependent variable. The fixed effects λ_k and φ_t correspond to industry and year, respectively. The bold shaded area denotes the 95% confidence interval for the estimated coefficients, while the lighter shaded area corresponds to the 90% interval. The figure also marks the timing of three key events: the Brexit referendum in 2016, the official implementation of Brexit in January 2020, and the withdrawal of the Northern Ireland Protocol in January 2021.

Figure 4: Coefficient plots for heterogeneity across industries



Notes: Figure 4 presents the estimated coefficients from regression model, specified with robust standard errors, across 14 industries, along with their respective 90% and 95% confidence intervals. The model can be formulated as $lnEmployment_{i,t} = \alpha + \beta(Year_t \times Distance(toNewry)i) + \gamma Distance(toNewry)i + \delta Year_t + \lambda_k + \varphi_t + \epsilon_{i,t}$, where $lnEmployment_{i,t}$ represents the natural logarithm of the number of employees as the dependent variable. The fixed effects λ_k and φ_t correspond to industry and year, respectively. Each estimated point is a representative for each industry.

Figure 5: Coefficient plots for difficulty in recruiting/retaining (un)skilled EU labor



Notes: Figure 5 demonstrates the marginal effects (at median) from a regression model, specified with robust standard errors for two variables *Skilled EU labor* and *UnSkilled EU labor*. The specification for the Probit regression can be written as: $P\left[(Un)SkilledEUlabor_{i,t} = 1|0\right] = \alpha + \beta(Year_t \times Distance(toNewry)i) + \gamma Distance(toNewry)i + \delta Year_t + \lambda_k + \epsilon_{i,t}$, where $P\left[(Un)SkilledEUlabor_{i,t} = 1|0\right]$ is the dummy variable with '1' if firms have obstacles on recruiting EU (un)skilled workers; otherwise. The fixed effects λ_k correspond to industry fixed effects. The estimated points with or without control can be described in the bracket information. The fixed effects λ_k in the regression model represent industry-specific fixed effects. The estimated effects, both with and without additional controls (including *Firm Age* and *Firm Network* and excluding firms choosing to switch their business sites), are detailed within the bracket information in the analysis. This approach helps to isolate the influence of industry characteristics on the recruitment challenges faced by firms in sourcing EU skilled and unskilled labor.

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A Appendix

A.1 Survey-weighted explanations

In our analysis, we adjust for varying sampling probabilities across firms by employing sampling weights in the baseline results. Initially, we adhered to the guidelines provided in the data codebook concerning sample weights and stratification. As instructed, in order to adjust the aggregate figures to the national business population and correspond to the survey response rates, weights are calculated annually. The provided weights are similar to post-stratified weights, with strata defined as cross-classifications by country, size band and 1-digit SIC (BEIS, 2023). In case of missing values due to some blank cells in Scotland, Wales or Northern Ireland, post-strata were merged with adjacent post-strata to allow weights to be calculated. The post-strata used a broader industrial breakdown with just 4 categories instead of 14 for cohort and longitudinal weights in these nations. All the weights in a post-stratum had the same value, even though most cells contain a mixture of past panelists and top-ups (BEIS, 2023). In 2022, to address the issue of high weighting factors (10 or higher), the data collector mitigated extreme values by merging cells with equivalent samples or population figures with adjacent cells, aiming for a more even distribution. This approach was specifically applied to cells containing zero unregistered and zero registered businesses. Unlike previous surveys, this method allowed us to avoid capping the weights, thereby maintaining the integrity and representatives of the data. As indicated by BEIS (2023), 15 weights were provided as below: The dataset includes various types of weights: there are eight cross-sectional weights (*WEIGHT_2015*, *WEIGHT_2016*, etc.), each corresponding to the SME population distribution for the respective year. Additionally, there are four longitudinal weights (*LWEIGHT_2019* to *LWEIGHT_2022*) that facilitate the analysis of SMEs consistently participating in the survey from 2019 to 2022, adjusted to match the 2019 SME population distribution. Lastly, the dataset contains fifteen cohort weights (*COAWEIGHT_2018*, *COBWEIGHT_2018*, *COCWEIGHT_2018* for 2018, and similar sets for 2019, 2020, and 2021) which are used for cross-sectional analysis of the survey questions from 2018 through 2022, with each cohort weight reflecting the SME population distribution of the year it represents. Owing to the weight, the numbers of respondents were adjusted to the overall totals across 336 strata. The panel attrition rate was 35.9%. To address the uneven distribution of the attrition rate between firm size and sector, longitudinal calibration weights are provided.

Although the original dataset supports the construction of three-way stratum divisions, we opted to organize our groups along two dimensions: nation (comprising England, Wales, Northern Ireland, and Scotland) and industry to obtain more observational data. This approach allows us to maintain a focused and relevant analysis based on geographic and sectoral characteristics. Our baseline results with survey-weighted probabilities are reported in Table A1.

Table A1: Baseline Results: Brexit and Firm Employment with surveyed-weighted estimates

	Full sample		No Switching			
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	HDFE	OLS	HDFE	OLS	HDFE
Brexit X Distance (to Newry)	-0.068**	-0.068**	-0.066**	-0.066**	-0.051*	-0.051*
	(0.027)	(0.027)	(0.028)	(0.028)	(0.028)	(0.028)
Distance (to Newry)	-0.021	-0.021	-0.020	-0.020	-0.023	-0.023
	(0.015)	(0.015)	(0.015)	(0.015)	(0.016)	(0.016)
Brexit	0.933***	0.933***	0.906**	0.906**	0.659*	0.659*
	(0.350)	(0.350)	(0.354)	(0.355)	(0.358)	(0.359)
Constant	0.660***	0.660***	0.652***	0.652***	0.164	0.164
	(0.197)	(0.198)	(0.200)	(0.200)	(0.203)	(0.204)
Control variables	No	No	No	No	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adj R-squared	0.001	0.001	0.000	0.001	0.000	0.084
Observations	63,488	63,432	61,249	61,195	55,939	55,885

Notes: This table reports estimates from survey-weighted OLS and HDFE regressions. Baseline results with survey-weighted based on two-dimension (industry and nation) include control variables as outlined in the specification model (1). Columns (1), (3), and (5) use the Ordinary Least Squares (OLS) method for estimation, whereas the other columns employ regression with high-dimensional sets of fixed effects (HDFE). The *Brexit* variable is a dummy indicator (1 - post-2020; 0 - otherwise), and *Distance (to Newry)* measures the firm's proximity to the Irish border. Significance levels are indicated by: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

A.2 Alternative measurement for employment (with ordinal values)

One might question the validity of the dependent variable Employment (log), which represents the number of employees expressed in natural logarithm form. To address this, we conducted an analysis using a new dependent variable, categorized into nine distinct groups based on the number of employees. We present our findings in Table A2. Our results are in line with the core findings.

Table A2: Alternative measurement for dependent variable as ordinal values

	Full sample		No Switching	
	(1) OLS	(2) ORDINAL LOGIT	(3) OLS	(4) ORDINAL LOGIT
Brexit × Distance (to Newry)	-0.169***	-0.147***	-0.158***	-0.138***
	(0.053)	(0.050)	(0.053)	(0.051)
Distance (to Newry)	0.063	0.045	0.063	0.048
	(0.045)	(0.044)	(0.046)	(0.045)
Brexit	2.080***	1.842***	1.946***	1.739***
	(0.674)	(0.644)	(0.684)	(0.651)
Control variables	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Adj R-squared	0.191		0.189	
Pseudo R-squared		0.054		0.053
Observations	58,043	58,043	55,990	55,990

Notes: This table presents OLS and Ordinal Logit estimates for the dependent variable, the number of employees, categorized into nine groups ranging from solo-employed businesses to firms with more than 250 employees. The regression model, defined with robust standard errors, is given by: $Employment\_Category_{i,t} = \alpha + \beta(Brexit_t \times Distance(toNewry)i) + \gamma Distance(toNewry)_i + \delta Brexit_t + \lambda_k + \varphi_t + \epsilon_{i,t}$, where $Employment_Category_{i,t}$ denotes the nine ordinal categories of employee numbers in our sample. The fixed effects λ_k and φ_t represent industry and year, respectively. The Brexit variable is a binary indicator (1 for post-2020; 0 otherwise), and Distance (to Newry) measures the firm's proximity to the Irish border. Standard errors, clustered at the firm level, are shown in parentheses. Significance levels are denoted by: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.