The Global Impact of Brexit Uncertainty*

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Abstract

Using tools from computational linguistics, we propose a text-based method for isolating first and second moment exposures to shocks stemming from specific events at the firm level. Applying this method, we construct new measures of the impact of Brexit on listed firms in the United States and around the world: the proportion of discussions in quarterly earnings conference calls on the costs, benefits, and risks associated with the UK's decision to leave the EU. We identify which firms expect to gain or lose from Brexit and which are most affected by Brexit uncertainty. We then estimate effects of the different types of Brexit exposure on firm-level outcomes. We find that the impact of Brexit-related uncertainty extends far beyond British or even European firms; US and international firms most exposed to Brexit uncertainty lost a substantial fraction of their market value and have also reduced hiring and investment. In addition to Brexit uncertainty (the second moment), we find that international firms overwhelmingly expect negative direct effects from Brexit (the first moment) when it comes to pass. Most prominently, firms expect difficulties from regulatory divergence, reduced labor mobility, limited trade access, and the costs of post-Brexit operational adjustments. Consistent with the predictions of canonical theory, this negative sentiment is recognized and priced in stock markets but has not yet significantly affected firm actions.

Keywords: Brexit, uncertainty, sentiment, machine learning, cross-country effects

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Brexit, the UK's momentous decision to leave the European Union, exemplifies how political and economic shocks originating in one country can propagate to affect firms in other countries and across the globe. How exactly these shocks percolate through the economy and impact businesses around the world is, however, an open question, not the least to policy makers and politicians struggling to find an appropriate response.[1] Hampering a systematic examination of the impact of events such as Brexit is the challenge of measuring the extent to which individual firms are exposed to specific shocks. Our proposal is to glean such a measure from records of what executives and investors talk about when they talk about Brexit (or any other specific shock). We demonstrate how a text-based approach can simultaneously capture a given firm's exposure to the shock and provide a way to decompose this measured exposure into the expected costs, benefits, and risks as assessed by the firm's executives and its investors. We then illustrate our method with a comprehensive empirical analysis of how British, US, and international firms respond to the consequences of the 2016 Brexit referendum.

A growing body of work uses structural models and detailed micro data to estimate the direct and indirect effects of Brexit on UK-based firms (e.g., Sampson, 2017; Graziano et al., 2018; Bloom et al., 2019).[2] However, attempts to quantify the effect on and responses of firms outside the UK have proven more complicated. Indeed, the exposure of non-UK-based (international hereafter) firms to Brexit is hard to measure for at least three reasons. First, Brexit exposure can come from many potentially interdependent sources; these sources include barriers to product market access; frictions in managing relationships with customers, suppliers, and subsidiaries; and hurdles in expanding business. This means that any attempt to quantify Brexit exposure for an international firm may overlook economically meaningful but potentially indirect determinants. Second, exposure to Brexit is not a time-invariant

[1] Witness for example President Macron's comment that he would rather have a "no-deal" Brexit than continued uncertainty troubling the French economy (Waterfield et al., 2019).

[2] Other papers documenting a negative impact of Brexit on UK investments, employment, wages, trade, lending, and competition include Born et al. (2019); Berg et al. (2019); Van Reenen (2016); Breinlich et al. (2018); Davies and Studnicka (2018); Dhingra et al. (2017); Garetto et al. (2019); Costa et al. (2019); McGrattan and Waddle (2017); Steinberg (2019).

trait. Indeed, the prolonged political process stemming from the 2016 referendum has yielded a sequence of potential negotiation outcomes, which each come with their own implications for a given firm. A firm might be a Brexit "winner" one day, only to be in a disadvantaged position the next. Moreover, this uncertainty has not ended with the formal act of Britain withdrawing from the European Union on January 31, 2020. Thus, any proposed measure of exposure to a shock like Brexit (which varies substantially over Three years after the British electorate voted to leave the European Union, it is still uncertain how the economic relation between the EU and its former member country will evolve. While this persistent uncertainty clearly weighs on the minds of British voters (for example, witness Boris Johnson's pledge to "get Brexit done"), many commentators, business leaders, and politicians have also pointed to the high economic costs of time in both scope and potential outcome) needs to be able to track longitudinal impact while also accounting for cross-sectional variation. Third, in addition to the impact on uncertainty (the second moment), exposure to Brexit also stems from Brexit's effect on expectations about the mean of firms' fortunes (the first moment). Indeed, before the future relationship between the UK and the EU is finalized and legislatively and administratively enacted, one might expect that most of the impact occurs through uncertainty, where mean effects are perhaps limited to firms' costly preparations for implementation and to precautionary measures that reduce impact. Ultimately, however, quantifying the first and second-moment effects of Brexit must be achieved empirically.

Our study addresses each of these challenges. We propose a general text-based method for isolating first and second moment shocks stemming from specific events. Our approach identifies the exposure of firms to a given event (in this case, Brexit) by counting the number of times the event is mentioned in a given firm's (quarterly) earnings conference call with financial analysts. These calls usually happen in conjunction with an earnings release and are an opportunity for management to describe the current affairs of the company. Importantly, after the management's presentation, a Q&A session is held during which analysts probe management on challenges the firm is facing. In this "market place" of information, we intuit that managers and analysts devote more time to events that are of greater importance to the firm, which makes the time spent discussing an event a powerful measure of a firm's exposure to it. Since call participants are arguably among the foremost experts on the firm's business, any significant impact of Brexit—through financial, product, and labor markets or otherwise—will likely come up in conversations. Concerns about missing the difficult-to-observe effects of Brexit on international firms are therefore plausibly mitigated. Thus, using these calls to measure Brexit exposure allows us to identify its market-assessed, over-time variation from the moment that talks of a Brexit referendum began (before 2016) until the present. Indeed, our method allows us to track any changes in firm-level Brexit exposure (due to, for example, developments in the EU-UK negotiations) and without the need to conduct surveys of executives in multiple countries. Finally, we adapt the Hassan et al. (2019) (HHLT) method of measuring firm-level political risk and sentiment in order to bifurcate our overall measure of Brexit exposure into first (*BrexitSentiment*) and second-moment (*BrexitRisk*) scores. We determine whether call participants use "risk" or "uncertainty" synonyms near the term "Brexit" to measure *BrexitRisk* and use positive- and negative-tone words near "Brexit" to capture *BrexitSentiment*.

Using these newly constructed measures, we document a set of new empirical findings on the impact of Brexit on firms in 71 countries. While these findings validate our Brexit exposure measures, they are also significant in their own right. For example, not only do we show that concerns about Brexit explode for UK firms in the most recent quarters of our sample period (extending to the second quarter of 2019 where a "no deal" Brexit became a real possibility), we also show widespread worries about Brexit-related risks among *international* firms. For instance, Irish firms on average discuss Brexit significantly more than do UK firms. Remarkably, Brexit exposure is strongly felt as far afield as the United States, South Africa, and Singapore.

It is also noteworthy that both UK and non-UK firms overwhelmingly expect *negative* consequences from Brexit. When we aggregate *BrexitSentiment* to the country level, there is no single country with a significantly positive average. Only in extraterritorial tax havens such as the UK Channel Islands is the average Brexit sentiment of local firms positive, though this is not statistically distinguishable from zero. Next, we conduct a human audit of text snippets from conference calls that mention Brexit in order to determine the content of the associated discussions. We find that firms mostly expect Brexit headwinds from regulatory divergence, reduced labor mobility, limited trade access, and heightened uncertainty.

There are some instances where firms articulate positive outlooks—in the most optimistic text snippets, managers anticipate windfalls from the Brexit-induced depreciation of the British pound or express relief because their firm has little exposure to Brexit. Notably, we find little or no discussion about the major economic benefits touted by the Leave campaign (such as looser regulation or better trade deals), even for UK-based firms.[3]

We next examine how US and other international firms respond to Brexit exposure. Using our time-varying, firm-level measure, we show that, up to the end of our sample period, Brexit exposure mostly affects firm-level actions through risk (rather than through sentiment); we document large, negative effects of *BrexitRisk* on investment and employment decisions as well as on contemporaneous stock returns. As an example, we estimate that due to Brexit risk, the average Irish firm decreased its investment rate by 3.9% and reduced its employment growth rate by 4.2% relative to the mean in each of the first three years after the Brexit referendum. For US-based firms (which are, on average, about as exposed to Brexit as Italian firms), reductions in average investment and employment growth rates are 0.4% and 1.2%, respectively.

Though we lack a formal instrument for Brexit exposure, we systematically investigate the three most plausible challenges to a causal interpretation of these results: First, executives might use Brexit and Brexit risk as an excuse to justify poor performance; second, firms exposed to Brexit risk might also be more exposed to other types of risks, and it is the

[3]The Leave campaign focused on deregulation (from EU laws), new jobs in the UK, reduced UK contributions to the EU, and increased trade/exports from new trade agreements made on sovereign terms. See: http://www.voteleavetakecontrol.org/our_case.html

latter, not the former, that explains the investment and employment response; third, firms doing businesss with the UK may be systematically different from other firms. We investigate these alternative interpretations of our findings in a range of robustness checks and placebo experiments, but find little evidence in support. For example, our estimates remain unchanged when we control for a variety of measures of firms' current performance (and thus executives' incentives to engage in "cheap talk" about Brexit). Similarly, our results remain unchanged when we control for time spent discussing risks unrelated to Brexit and for the firm's exposure to trade policy risk.

We supplement these analyses with two key pieces of evidence. First, we investigate how stock markets reacted to information about the (surprising) outcome of the 2016 referendum. Pricing effects can stem from the effect of the Brexit vote on the expected discount rate or on the market's expectation of future cash flows (Gorbatikov et al., 2019). We disentangle these two sources and show that the mean of firm-level exposure to Brexit (i.e., *BrexitSentiment*) is positively associated with stock returns in a narrow event window around the date of the referendum, whereas the association with the variance of firm-level exposure (i.e., *BrexitRisk*) is significantly negative. In other words, both first- and second-moment exposure to Brexit is quickly incorporated into stock prices after the announcement of the referendum result.

Second, we examine whether the average Brexit exposure of firms in a given UK district is associated with the share of that district's electorate who voted to leave the EU in 2016. Our findings show that constituents who live closer to the firms most negatively affected by Brexit tended to vote to remain in the EU. For example, a one-standard-deviation increase in the district-level Brexit risk is associated with a 1.4 percentage-point decrease in the proportion of votes for leaving the EU.

Taking this evidence together, we conclude that during our sample period, the Brexit vote mostly acted as an uncertainty shock. While stock markets recognized and priced both Brexit sentiment and Brexit risk, the first moment effects of Brexit have not yet been realized. Firms' real decisions were a response to increased uncertainty, but not to the changes in the mean of their exposure to Brexit (i.e., whether the shock is good or bad news for the firm). In this sense, our analysis suggests that many of Brexit's effects have yet to materialize.

While investigating the economic consequences of Brexit is important in its own right, our aim is to showcase the versatility of our approach to measure firm-level exposures to a wide range of specific shocks, even those that did not become synonymous with a unique word-creation, such as 'Brexit.' To demonstrate this point, we provide a brief excursion to the nuclear disaster at Fukushima in March 2011. While "Fukushima" became a short-hand for the catastrophe at the Daiichi Nuclear Power Plant operated by the Tokyo Electric Power Company (Tepco), many other phrases were commonly used as well. We show how to use a training library method to identify these phrases and then count their use in the conference call transcripts. We then briefly characterize exposure to the Fukushima disaster across firms and countries. This illustration serves to show that our method can easily be modified to estimate the firm-level impact of natural disasters, pandemics (such as the coronavirus), technological breakthroughs or political events (revolutions, government shutdowns).

Related literature. Our paper builds on several strands of literature. A large set of recent studies argues that uncertainty about shocks emanating from the political system affect asset prices, international capital flows, investment, employment growth, and the business cycle (Belo et al., 2013; Gourio et al., 2015; Handley and Limao, 2015; Kelly et al., 2016; Koijen et al., 2016; Baker et al., 2016; Besley and Mueller, 2017; Mueller et al., 2017). This literature has relied on identifying variation in aggregate and sector-level risk using country-level indices, event studies, and textual analysis of newspapers. We add to this literature by proposing a general, text-based, method for estimating first-and second moment exposures to specific shocks at the firm level.

We show how this method can be applied to examine the corporate response to a major uncertainty shock by investigating the impact of the UK's vote to leave the EU on firms around the world. We thus complement contemporaneous studies that have also attempted to specifically quantify the impact of Brexit uncertainty. For example, Bloom et al. (2019)

conduct a large-scale survey of decision makers in UK firms to measure Brexit exposure and its associated (negative) impact on investment and productivity. While we also show economically meaningful negative consequences for UK firms, we in particular highlight the economic consequences of Brexit for non-UK firms, documenting the far-reaching global effects associated with this shock.[4] In addition, our method allows us to separate empirically the effects of Brexit risk from those of Brexit sentiment, and enables us to describe firms' concerns about Brexit in detail by identifying and analyzing the underlying text.

Beyond the specific application to Brexit, our work relates to a large literature on the spillover of shocks across borders and on "contagion." A long-standing idea in this literature is that an uncertainty shock from one region can affect valuations and investment across the world (Forbes and Warnock, 2012; Rey, 2015; Maggiori, 2017; Colacito et al., 2018). Our work shows a concrete and well-identified example of such a spillover, where an uncertainty shock originating in the UK affects valuations, investment, and other precautionary behavior in the United States and in other countries.

In this sense, our work also relates to a wider literature that documents the transmission of specific natural disasters or credit supply shocks across borders using data on subsidiaries or customer-supplier networks (e.g., Barrot and Sauvagnat, 2016; Schnabl, 2012; Boehm et al., 2019; Carvalho et al., 2016; Anderson et al., 2019).

Finally, we add to the growing literature using text-based measurement in macroeconomics and related fields (Gentzkow et al., 2019). Our work highlights the versatility of text-based measurement of firm-level variables, adding to recent work that uses earnings call transcripts and corporate filings to measure firm-level political and non-political risk (Hassan et al., 2019), overall risk (Handley and Li, 2018), and trade policy risk (Caldara et al., 2019; Kost, 2019). Others have used newspapers and FOMC minutes to measure economic policy uncertainty (Baker et al., 2016), the state of the economy (Bybee et al., 2019), and analyze news about monetary policy (Hansen et al., 2017; Cieslak and Vissing-Jorgensen, 2017).

[4] Campello et al. (2020) document the investment and hiring effects of Brexit on a sample of US firms exposed to the UK economy and Martin et al. (2019) consider the costs of Brexit to French exporters.

1. Data

Our primary data are transcripts of quarterly earnings conference calls from publicly listed firms. From Refinitiv EIKON, we collect the complete set of 145,902 English-language transcripts from 2011 to 2019, covering 7,733 firms headquartered in 71 countries. Firms host these calls in conjunction with their earnings announcements, allowing financial analysts and other market participants to ask questions about the firm's financial performance over the past quarter and to more broadly discuss current affairs with senior management (Hollander et al., 2010).[5] Our data coverage, as shown in Appendix Table 1 Panel A, consists of 7,733 unique firms: 1,367 are headquartered in EU countries (396 in the UK), 3,791 are in the United States, and 2,575 are in the rest of the world. Panel B shows the extensive global coverage of listed firms in our sample. This coverage is important because Brexit exposure is not likely to be limited to firms headquartered in the UK or in adjacent countries; firms may have subsidiaries, suppliers, customers, competitors, or shareholders in the UK, or they may use UK facilities as a hub for hiring or communication. Of the roughly 3,800 US-based firms, 1,633 have disclosed establishments in the UK.

Financial statement data, which includes information on employment, investments, revenue, and earnings, are taken from the Standard and Poor's Compustat North America (US) and Compustat Global (non-US) files. Stock return information is from the Center for Research in Security Prices and Refinitiv Datastream. UK district voting results on the Brexit referendum (as well as basic demographic data on these districts) are from the Office for National Statistics.

[5] As an alternative measure, we could have used firms' annual reports (10-K filing) as a text source (see, Campello et al., 2020). We decided against this approach and follow HHLT, who document better measurement properties of firm-level risk measures using conference call transcripts instead of financial statements. Anecdotally, according to a Wall Street Journal report, the SEC Chairman Mr. Jay Clayton lamented that firms fail to sufficiently disclose the potential risk posed by Brexit (Shumsky, 2018). If this is true, relying on 10-Ks would underestimate a firm's exposure to the shock. Most importantly, however, using 10-Ks would have limited our investigation to the impact of Brexit on US listed firms only, rather than on the global sample of international firms we examine currently.

2. Measuring Firm-Level Brexit Exposure, Risk, and Sentiment

To create a time-varying measure of a given firm's Brexit *exposure*, we parse the earnings call transcripts and count the number of times the word "Brexit" is used. We then divide this number by the total number of words in the transcript to account for differences in transcript length.[6]

$$BrexitExposure_{it} = \frac{1}{B_{it}} \sum_{b=1}^{B_{it}} 1[b = Brexit], \tag{1}$$

where $b = 0, 1, ...B_{it}$ are the words contained in the call of firm i in quarter t.[7]

To construct a measure of Brexit *risk*, we augment this procedure by conditioning on the proximity to synonyms for risk or uncertainty:

$$BrexitRisk_{it} = \frac{1}{B_{it}} \sum_{b=1}^{B_{it}} \{1[b = Brexit] \times 1[|b - r| < 10]\},$$

where r is the position of the nearest synonym of risk or uncertainty. Following the example of HHLT, we condition on a neighborhood of 10 words before and after the mention of Brexit and obtain a list of synonyms for "risk" and "uncertainty" from the Oxford English Dictionary.[8] To aid interpretation, we standardize $BrexitRisk$ by the average $BrexitRisk$ for UK headquartered firms as measured in the period after 2015; a value of 1 thus denotes the average Brexit risk of UK firms 2016-2019.

A major challenge for any text-based measure of risk is that innovations to the variance of shocks are likely correlated with innovations to the conditional mean. For example, a

[6]Google Trends shows the first use of the term "Brexit" in October 2012. Usage of the word increased in January 2016 and peaked in June 2016. "Br*i*xit" was proposed as an alternative term, but does not have a meaningful volume on Google Trends in the sample period.

[7]This procedure can easily be modified to obtain counts of variations on Brexit (e.g., "hard" or "soft" Brexit) and of other phrases that have become meaningful in the aftermath of the Brexit referendum (e.g., "no deal" or "WTO terms").

[8]See Appendix Table 2 for a list of these synonyms.

French exporter who learns that there may be future tariffs on her exports to the UK may conclude that she faces lower expected profits (a lower conditional mean) in addition to a higher variance (the tariffs may or may not materialize). Thus, teasing out the effects of Brexit-related uncertainty on a firm's actions also requires controlling for Brexit's effect on the conditional mean of the firm's future earnings. Thus, the construction of Brexit *sentiment* closely follows the procedure for *BrexitRisk* in that it counts the word "Brexit"; however, instead of conditioning on the proximity to words associated with risk, we condition on positive- or negative-tone words to capture the first moment. These positive and negative words are identified using the Loughran and McDonald (2011) sentiment dictionary:[9]

$$BrexitSentiment_{it} = \frac{1}{B_{it}} \sum_{b=1}^{B_{it}} \left\{ \{1[b = Brexit] \times \left(\sum_{c=b-10}^{b+10} S(c) \right) \right\},$$

where S assigns sentiment to each c:

$$S(c) = \begin{cases} +1 \text{ if } c \in \mathbb{S}^{+} \\ -1 \text{ if } c \in \mathbb{S}^{-} \\ 0 \text{ otherwise.} \end{cases}$$

Positive words include 'good,' 'strong,' 'great,' while negative include 'loss,' 'decline,' and 'difficult.'[10,11] Appendix Tables 3 and 4 show the most frequently used tone words in our corpus. As for *BrexitRisk*, we standardize *BrexitSentiment* by the average *BrexitSentiment*

[9] Thirteen of the synonyms of risk or uncertainty used in our conference calls also have negative tone according to this definition. Examples include 'exposed,' 'threat,' 'doubt,' and 'fear.' Our measures thus explicitly allow speakers to simultaneously convey risk and negative sentiment. Empirically, when we include both *BrexitRisk* and *BrexitSentiment* in a regression, any variation that is common to both of these variables (as a result of overlapping words) is not used to estimate parameters of interest. For this reason, overlap does not, in principle, interfere with our ability to disentangle *BrexitRisk* from *BrexitSentiment*.

[10] We choose to sum across positive and negative sentiment words rather than simply conditioning on their presence to allow multiple positive words to outweigh the use of one negative word, and vice versa.

[11] One potential concern that has been raised with this kind of sentiment analysis is the use of negation, such as 'not good' or 'not terrible' (Loughran and McDonald, 2016). However, we have found that the use of such negation is exceedingly rare in our sample, so we chose not to complicate the construction of our measures by explicitly allowing for it.

for UK headquartered firms after 2015; a value of -1 thus denotes the average Brexit sentiment of UK firms.

For use in robustness checks and as control variables, we also measure each firm's non-Brexit-related risk and sentiment using the above approach, defining $\mathbb{R}$ as the set of synonyms for risk and uncertainty taken from the Oxford English Dictionary:

$$NonBrexitRisk_{it} = \frac{1}{B_{it}} \sum_{b}^{B_{it}} \{1[b \in \mathbb{R}]\} - BrexitRisk_{it},$$

and

$$NonBrexitSentiment_{it} = \frac{1}{B_{it}} \sum_{b}^{B_{it}} S(b) - BrexitSentiment_{it}.$$

3. Validation

3.1. Global Exposure to Brexit

In this section, we explore the properties of our measures, *BrexitExposure*, *BrexitRisk*, and *BrexitSentiment*, to corroborate that they capture firm-level variation in the global corporate exposure to Brexit. First, we show that firms' *BrexitExposure* is significantly correlated with observable business links to the UK. We then consider the constituent parts of *BrexitExposure* separately, describing (in detail) the patterns of both *BrexitRisk* and *BrexitSentiment* over time and across countries. To further validate our method, we present the results of a human audit of the text fragments (or"snippets") where Brexit is mentioned.

Exposure. Table 1 presents cross-sectional regressions of the mean *BrexitExposure* of each firm across time onto firm-specific characteristics that are *ex ante* likely to affect a firm's exposure to Brexit. In particular, we consider the geographical location of the firm's operational headquarters and establishments as well as the proportion of total (worldwide) sales earned in the UK.[12] Because of the stickiness of firm location choice, we average the

[12] We determine headquarter location based on the Eikon field "Country of domicile." Eikon also offers the "Country of legal registration," which we do not use to determine physical presence.

Brexit exposure of each firm across our sample from 2016 until the first quarter of 2019 and report robust standard errors. Table 1 Columns 1 and 2 only consider geographical location (and have a larger number of observations), while Columns 3 and 4 also include the proportion of UK sales. Across specifications, we find a positive association between mean *BrexitExposure* and a firm having a UK subsidiary. The estimated coefficient is about 0.2, implying that foreign firms with UK subsidiaries mention Brexit about one fifth as often as do firms headquartered in the UK. (Recall that our measure of Brexit exposure is normalized so that the average exposure of a UK firm during the 2016-2019 period is 1.) We find a similar positive association between a firm being headquartered in the UK and mean *BrexitExposure*, but the estimated coefficient is sensitive to including the proportion of UK sales revenues. We include two different proxies for UK revenues: the first is based on UK sales reported *before* the Brexit vote, while the second is based on the period *after* the vote. We also find that firms headquartered in the EU but outside the UK are more exposed to Brexit than firms headquartered internationally. Once more, this effect appears to be subsumed by post-referendum UK sales. Taken together, these findings are consistent with the notion that *BrexitExposure* varies meaningfully with firm characteristics that increase the probability of a firm being commercially connected to the UK.

Risk and Sentiment. Having offered evidence that supports the validity of *BrexitExposure*, we next explore the properties of *BrexitRisk* and *BrexitSentiment*. Figure 1 Panel A plots the across-firm average of *BrexitRisk* at each point in time for firms headquartered in the UK and for firms headquartered in the rest of the world. Consistent with the outcome of the 2016 referendum being a surprise to most parties, we find very low levels of *BrexitRisk* before 2016 in the UK (right) and in the rest of the world (left). *BrexitRisk* increases somewhat in the run up to the referendum in the first half of 2016. Non-UK firms' *BrexitRisk* peaks in the immediate aftermath of the referendum at about 0.8; in other words, immediately after the referendum, Brexit risk for international firms reaches almost the height of the average UK-firm Brexit risk in the 2016-2019 period. UK firms have a similar peak, with average *BrexitRisk* reaching over 1.5 immediately following the referendum.[13] While *BrexitRisk* subsides in 2017, it rises sharply in the second half of 2018, nearly reaching 3 for UK firms (and about 0.5 for non-UK firms). This time-series pattern closely mimics the negotiation process between the EU and the UK, particularly at the end of 2018, where the specifics of the deal reached between Theresa May's government and the EU became increasingly clear, as did the difficulties of obtaining parliamentary approval for that deal. In 2019, at the end of our sample, the prospect of the UK leaving the EU without a deal (and resorting back to WTO trade terms) became more likely, consistent with the uncertainty about Brexit reaching unprecedented levels in the UK at that time.

Figure 2 shows the average *BrexitRisk* by firm-headquarters country for all countries with non-zero *BrexitRisk* and a minimum of five headquartered firms. Country level values are calculated by taking the mean *BrexitRisk* for all firms headquartered in a given country and computing each firm's average *BrexitRisk* using all available post-2015 observations. Countries with zero country-level *BrexitRisk* include those far from the UK, such as Thailand, Nigeria, and Argentina; we also do not register any Brexit risk in some nearby countries including Portugal and the Czech Republic. By construction, the UK country-level *BrexitRisk* in this period equals unity. Perhaps the most dramatic takeaway from this figure is the position of Ireland with a country-level Brexit risk of 1.68, far greater than the Brexit risk of the average UK firm.[14] (This difference is statistically significant. Standard errors are given in Appendix Table 6.) Distance to the UK matters, as other high-scoring countries include nearby France, the Netherlands, Belgium, and Denmark (all EU member states). The non-EU countries most affected by Brexit risk are South Africa, Switzerland, Singapore, and Australia. Many non-EU countries with relatively high Brexit risk scores

[13] Fisman and Zitzewitz (2019) show a similar (aggregate) pattern for the period between July-December 2016 using their Brexit Long-Short Index based on the stock returns of equities.

[14] Interestingly, this finding mirrors the result in Garetto et al. (2019), which uses a model to quantify the total welfare effect of Brexit on EU economies. They find that the Brexit shock most reduces purchasing power (i.e., real income) in Ireland. More generally, the literature on geography and trade argues that market and supplier access to neighboring countries is most important for small economies (Redding and Venables, 2004).

have longstanding Commonwealth ties to the UK. On the other hand, the Channel Islands are not part of the Commmonwealth, the UK, or the EU, but are major offshore financial centers and tax havens. Their *BrexitRisk* falls between the UK's and Ireland's. In all, EU-member states appear to have higher country-level Brexit risk than do affected countries in other parts of the world. US exposure also appears disproportionally high—the *BrexitRisk* of the average US firm is 0.11, around 10% of the average UK firm and similar to the average Italian firm.

In Figure 3, we plot the mean *BrexitRisk* by industry for both UK and non-UK headquartered firms. The mean industry *BrexitRisk* is computed by averaging all firms in a particular industry; we observe that in almost all industries (Health Services is an exception), the mean *BrexitRisk* is significantly larger in the UK than it is in non-UK countries. The difference between the UK and the rest of the world is particularly prominent in the Services and Finance, Insurance, and Real Estate industries.

Finally, we tabulate and review excerpts of conversations in earnings calls discussing Brexit and its associated risks. Table 2 reports excerpts of transcripts with the highest *BrexitRisk* among firms with the highest firm-level *BrexitRisk*. In Panel A, these excerpts are taken from UK companies such as Bellway, Millennium and Copthorne Hotels, and Endava, and are dated from 2016 to 2019. In all cases, a reading of the excerpts confirms that call participants are discussing risks associated with Brexit. For example, the July 2017 transcript of Berendsen Ltd. says that "Brexit raises any number of uncertainties for every single business." The transcript for the January 2019 call of SThree Plc. states that "there's also a lot of uncertainty around the UK and Brexit and that will affect most markets." Panel B shows excerpts discussing Brexit from companies headquartered outside of the UK. The top scoring transcripts are from a range of countries and come from across the post-Brexit-referendum sample period. In all cases, reading the text confirms that the discussion centers on Brexit-related uncertainty faced by the firm. For example, in October 2018 the Swedish firm Sweco claimed that "there is still an uncertainty when it comes to Brexit and some weakness in the real estate market." Similarly, during their January 2019 call, FBD Holdings in Ireland recorded that "our agri and agribusiness customers are very exposed to a hard Brexit."

We next repeat the same steps for *BrexitSentiment*; in Figure 1 Panel B, we start with a plot of the respective time series for UK and non-UK firms.[15] For both UK and non-UK firms, *BrexitSentiment* is negative overall. We observe a sharp fall in sentiment immediately after the Brexit referendum (a phenomenon more pronounced in UK firms than in international firms) with sentiment scores reverting to slightly below zero for most of 2017. In 2018, the average *BrexitSentiment* drops sharply both in the UK and internationally (though again, the effect is especially pronounced in the UK) with the drop continuing well into 2019.

Figure 4 plots the mean *BrexitSentiment* by country. Overwhelmingly, sentiment in the UK and elsewhere remains negative. Ireland continues to have the strongest negative sentiment scores, even compared to the UK. However, firms from EU member states like Germany, Austria, Italy, Denmark, Sweden, and France also hold strong negative views about the impact of Brexit. The one anomalous area is the UK Channel Islands, where *BrexitSentiment* is hugely positive with a value of +2 (truncated in the figure to save space). Due to the limited number of firms based in the Channel Island (8), however, we lack statistical power to distinguish their *BrexitSentiment* from zero. (Appendix Table 7 gives standard errors.)

These findings raise the question of what specific concerns underlie this widespread aggregate negative sentiment. And, for firms expecting to benefit from Brexit, what advantages do they perceive? We answer these questions by reading and classifying all snippets used in the construction of *BrexitSentiment* for the 100 most positively and most negatively exposed firms in the UK and internationally. In all, we read the text surrounding 1,357 snippets, of which 342 are specific enough to convey specific reasoning for the positive or

[15]In the firm-year panel beginning in 2016, the correlation between *BrexitRisk* and *BrexitSentiment* is -0.17.

negative tone words used. We classify the perceived benefits and concerns into six categories each. These categories are chosen based on an initial reading of the text excerpts, but with an eye to the concerns and benefits raised by politicians and other pundits active in the public debate about Brexit. Turning first to excerpts that express positive sentiment about Brexit (in Table 3), we find that about 80 percent of positive excerpts in the UK and elsewhere mention that the firm is *not* exposed to (and therefore does not expect much of an impact from) Brexit. The next most commonly perceived benefit of Brexit is a weaker British pound (14.03% and 16.67% of snippets from UK and non-UK firms, respectively). A telling example comes from the transcript of Millennium and Copthorne Hotels, who "saw a spike in leisure occupancy after the Brexit referendum in June as tourists took advantage of the cheaper pound." The final positive categories are the expectation of better trade access (5.26% and 1.52% for UK and non-UK firms, respectively) and relocation opportunities (just over 3.5% and 3.79%). For example, the Frankfurt-based Deutsche Boerse AG considers a scenario in which Brexit negatively affects London as a center of business; they have "seen a number of firms announcing that Frankfurt would ultimately be their European hub" and can see "potential opportunity coming from Brexit." An analyst on the call of the Dutch firm ForFarmers thinks "Brexit could be beneficial for ForFarmers" and that it "might have a positive impact on [their] position in the UK."

Importantly, we did not find a single excerpt from UK-based firms referring to two of the three major potential economic upsides of Brexit touted during the Brexit referendum campaign: decreased regulation and more flexibility in UK government spending.

As might be expected, some expected outcomes of Brexit are positive for certain firms but negative for others. Indeed, as tabulated in Table 3, worsening *trade access* and a *weaker pound* are reasons for the negative Brexit sentiment in 24.69 (22.84) and 24.69 (57.41) percent, respectively, of the snippets in (non-)UK firms. The former is illustrated by the excerpt from the Irish budget airline Ryan Air Holdings: "if the UK is unable to negotiate access to the single market or open skies it may have implications for our three UK domestic routes."

UK firms are more negative than non-UK firms about *labor market frictions*, with about 19 percent of UK but only 9 percent of non-UK firms mentioning reductions in labor mobility. Similarly, UK firms appear relatively more concerned about *falling consumer confidence* (18.52%) and *adjustment and transition costs* (8.64%), which both appear a minor concern for non-UK firms. However, both UK and non-UK firms fear *new and/or multiple regulatory regimes* (6.17% and 9.88% of snippets, respectively). For example, the Russian Yunipro expresses the hope that "for the implementation of the Brexit, reasonable solutions will be found that will preserve to a large extent the rules of the single market for energy."

Taking these findings together, the following picture emerges: In the UK, Brexit sentiment is negative and has precipitously declined since the last quarter of 2018. In that same period, average Brexit risk (which peaked after the 2016 referendum) has steeply increased, surpassing the risk measured immediately after the vote. Overwhelmingly, the firm-level negative sentiment in international firms stems from the weak pound and the expectation of worse trade access. The concerns of UK firms are more broad-based, and also include relatively more concern about labor market fictions, falling consumer confidence, and adjustment and transition costs. Even the vast majority of hopeful firms base their positive outlook on either their lack of exposure to Brexit or on the depreciation of the currency. On average, countries outside of the UK mirror the UK's time series pattern in risk and sentiment, albeit to a lesser extent. EU member states generally experience higher Brexit risk than do countries father afield and, with few exceptions, their sentiment is negative.[16] At the firm-level, negative international Brexit sentiment centers mostly on the weak pound, concerns about trade access, and new and/or multiple regulatory regimes.

[16] These findings are broadly consistent with Vandenbussche et al. (2019), who use a country-sector analysis to find substantial losses in value added and employment across the 27 EU member states, though there is significant heterogeneity in effect size that corresponds to the country's position in the global value chain.

3.2. Event Study: Asset Pricing Effects of Brexit

We turn next to the asset pricing implications of the June 23, 2016 referendum to leave the EU. The outcome of this vote was a surprise to most observers (Fisman and Zitzewitz, 2019); polling in the preceding months had persistently shown a "Remain" victory (Born et al., 2019). Famously, the British politician Boris Johnson, then one of the leading figures of the Leave campaign, went to bed resigned to losing the vote only to wake up to the sound of demonstrators protesting the vote's outcome at his private residence.[17] The lack of anticipation of the outcome creates favorable conditions for an event study assessing the asset pricing effects of Brexit. When investors learned the referendum's outcome, they formed new expectations about the future of publicly listed firms. Stock price changes capture changes in investors' expectations about the direct and indirect consequences of Brexit for the cash flows of the firm and for its discount rate (Fisman, 2001; Hill et al., 2019; Davies and Studnicka, 2018). For this reason, we investigate the response of firms' equity prices to the Brexit vote; this response captures the market's assessment of a given firm's exposure to Brexit. Correlating the market's assessment with our measures of Brexit exposure also serves to validate our method.

Summary statistics. Table 4 presents the mean, median, and standard deviation of the variables used in our event study. In Columns 4 and 6, we also provide the mean and standard deviation of each variable for the subsamples of UK and non-UK firms. As before, our key variables of interest are Brexit exposure, risk, and sentiment. For the purpose of this analysis, we consider both the "average Brexit" and "pre-Brexit" *Exposure*, *Risk*, and *Sentiment*. Brexit variables are computed by averaging all available Brexit scores from 2016 to 2019, while pre-Brexit variables are based on the sample of earnings conference calls before June 23, 2016. Brexit exposure, risk and sentiment are larger (in absolute value) in the UK than internationally regardless of whether they are calculated before or after the Brexit vote. For example, the mean $\overline{BrexitRisk}$ in the full sample is 0.195, but in the UK

[17] ITV report on 24 June 2016.

sample, the corresponding value is equal to 1 (by construction). Sentiment across our sample is on average negative. Median values of Brexit-related variables are zero, consistent with analysts and senior management discussing Brexit only when they expect that their firm may be impacted. Stock returns are calculated using a narrow window of four trading days starting on June 24 and ending on June 28, 2016 (since the referendum took place on a Thursday).

Regression results. In Table 5, we present estimates of Ordinary Least Squares (OLS) regressions of the following form:

$$r_i = \alpha_0 + \delta_j + \delta_c + \beta Brexit_i + X_i^{\prime}\nu + \epsilon_i, \tag{2}$$

where r_i is the four-trading-day return following the Brexit vote; δ_j and δ_c are industry and headquarters-country fixed effects, respectively, $Brexit_i$ represents either $\overline{BrexitExposure}$, $\overline{BrexitRisk}$, $\overline{BrexitSentiment}$, $PreBrexitRisk$, or $PreBrexitSentiment$ of firm i; the vector $X_{i,t}$ always includes the log of a firm's assets to control for firm size. In some specifications, we also include stock return betas, which are calculated by regressing daily returns in 2015 for firm i on the S&P500 or on the FTSE100 index (to measure a firm's exposure to the US and the UK capital markets, respectively). We exclude firms from the "Non Classifiable" sector and firms with fewer than ten earnings call transcripts. Throughout, we use robust standard errors.

In Columns 1 and 2 of Panel A (which reports the full sample estimates), we find a negative coefficient estimate between $\overline{BrexitExposure}$ and stock returns. For a firm with a post-Brexit-vote exposure equal to that of the average UK-headquartered firm (i.e., with a value of 1), we find that equity prices drop by 2.3 percent over the course of the four trading days. The magnitude of the coefficient remains unchanged after controlling for the (US- and UK-market) CAPM-betas of the stock, implying that the effect is not explained by differences in exposure to US or UK market risk. We then "decompose" Brexit exposure into a mean and variance component; i.e., we consider how markets priced differential exposure to $\overline{BrexitRisk}$ and $\overline{BrexitSentiment}$ in the short time window surrounding the announcement of the referendum result (Columns 3 and 4). We find that higher Brexit risk leads to lower stock returns (coef.=-0.011, s.e.=0.002), consistent with the event revising discount rates upward in the cross-section of firms. In addition to this effect of the second moment, we find that an increase in Brexit sentiment leads to higher stock prices (coef.=0.002, s.e.=0.001), consistent with the view that firms negatively exposed to Brexit lose significant market valuation immediately after the referendum results become known. Our coefficient estimates again remain unaffected when we control for CAPM-betas (in Column 4).

In an effort to estimate the market's response using only the information available during the referendum, in the final column, we use the $PreBrexitRisk$ and $PreBrexitSentiment$ variables to explain the short window price response. In Column 5, we again find a negative effect of $PreBrexitRisk$ (-0.005, s.e.=0.001) and a positive effect of $PreBrexitSentiment$ (0.001, std.err=0.000) on short-window stock returns.

We repeat the same analysis in Panel B, but restrict the sample to firms headquartered in the United States, reducing the sample size from 4,575 to 2,816 firms. Our estimates for the US-headquartered sample do not deviate meaningfully from the full sample. Indeed, the coefficient estimates on $\overline{BrexitExposure}$ for the US-headquartered sample are almost identical in Columns 1 and 2. When we tease out the two components of exposure to Brexit in Columns 3-5, we find a slightly stronger stock price response to $\overline{BrexitSentiment}$ and a somewhat weaker response to $\overline{BrexitRisk}$. Both are statistically significant at the one percent level.

We further examine the event study results in Figure 5, which graphically summarizes the OLS regression estimates of $PreBrexitRisk$ (corresponding to Column 5 of Panel B in Table 5) onto a sequence of four-day return windows prior to the June 23, 2016 Brexit vote. Each event window consists of four consecutive trading days, where the "treatment" window stretches from June 24 to 28 and the remaining event windows are distributed in the periods before and after the treatment. As the referendum outcome was largely unexpected, we should not find a significant $\hat{\beta}$ before the vote. Similarly, if the effects of the leave vote are quickly reflected in stock returns, the effect should not linger after the vote. In line with these expectations, we find a significant negative coefficient estimate on $PreBrexitRisk$ only during the treatment window, not before or after. These results bolster our confidence that the event-study estimates for Brexit risk are not inadvertently picking up some other factor/event. Importantly, the results also suggest that Brexit was not anticipated and that financial-market prices quickly reflected the news.[18]

Finally, in Figure 6, we estimate the asset pricing effect of the Brexit referendum separately for UK and non-UK firms. Indeed, the figure shows two panels of binned added-variable plots of four-trading-day returns over $\overline{BrexitRisk}$. The left panel shows the relation for the sample of UK-headquartered firms and the right panel shows the relation for non-UK-headquartered firms. The plots are again based on panel regressions that control for $\overline{BrexitSentiment}$, the log of assets, and sector and time fixed effects. We see a negative relation in both panels (although the slope coefficient is more negative in the UK sample), implying that the pricing response to Brexit uncertainty is negative for both UK and non-UK firms.

3.3. Regional Support for Brexit

The final empirical validation for our Brexit exposure measures builds on a simple intuition: Voters who live in a region where a firm with elevated Brexit exposure has its operational headquarters may be more likely to vote against Brexit. Previous studies have generally focused on voter characteristics (such as age, ethnicity, and educational achievements) to explain geographical variation in voting (Alabrese et al., 2019; Fetzer, 2019). We propose that a voter's referendum choice will also be guided by their assessment of how Brexit will

[18] Consistent with these results, Appendix Figure 2 shows the result of a placebo exercise where we re-run the same regression for each four-day window between Jan 1 2012 and Dec 31 2015. Reassuringly, we find only a slight tendency to over-reject the null (3.06%).

affect local economic and employment conditions. Thus, if local companies find Brexit risky, the regional share in support of "Leave" is likely to decrease. We test this intuition in Table 6.

We first determine each firm's location using the area code of its *operational* headquarters; we then map these locations into electoral districts. Next, we compute the district-level Brexit risk and sentiment by averaging $\overline{BrexitRisk_i}$ ($\overline{BrexitSentiment_i}$) across firms in the district. We then estimate cross-sectional regressions of the district-level vote in support of Leave ($\%leave_d$) onto $\overline{BrexitRisk_d}$, $\overline{BrexitSentiment_d}$, and two demographic controls: share UK born—i.e., the proportion of the district's population born in the UK—and income per capita. Specifically,

$$\%leave_d = \alpha + \beta\overline{BrexitRisk_d} + \gamma\overline{BrexitSentiment_d} + X_d^{'}\zeta + \epsilon_d. \tag{3}$$

These OLS regressions are estimated using data from 110 districts and their inferences are based on robust standard errors.[19]

In Column 1, where we only consider district-level $\overline{BrexitRisk_d}$, we find a negative association with the Leave vote share. Turning to $\overline{BrexitSentiment_d}$ in Column 2, we show that when firms in the district view Brexit negatively, the association with the Leave vote share is strongly negative. In Column 3, we include both Brexit variables and find results which are very similar to the separate estimates. The estimated coefficients imply that a one standard deviation increase in $\overline{BrexitRisk_d}$ (1.59) is associated with 1.48 percentage point decrease in share of the vote for leaving the EU. Similarly, a one standard deviation decrease in $\overline{BrexitSentiment_d}$ (4.44) is related to a 1.71 percentage point drop in support for Brexit.[20] Appendix Figure 1 shows this association graphically. For completeness, note that wealthier districts and districts with a larger immigrant population have lower support

[19] Note that the distribution of sample firms in the UK is geographically clustered. Appendix Table 5 provides additional details. Many districts have only a single sample firm, but there are few districts in which many sample firms are headquartered (e.g., the City of London and Greater London).

[20] The partial R^2 of these two variables in Column 3 is about 5%.

for Leave.

These findings, on the one hand, validate our Brexit measures. On the other, they also speak to Alabrese et al. (2019) and Fetzer (2019), who find substantial *geographical* heterogeneity in the extent to which demographic variables can explain the Brexit vote. Our findings suggest that "spillovers" from local companies might be a partial source of this geographical heterogeneity.

4. The Firm-level Effects of Brexit

Two substantive facts emerge from the validation exercise in the previous section. First, firms are exposed to the shock of the Brexit referendum, not just in the UK, but globally; though the shock is perhaps strongest in the (nearby) EU countries, it extends as far as the United States, Singapore, and South Africa. Second, stock markets quickly impound both the first and second moment implications in stock prices; increases in Brexit risk lead to price drops while increases in Brexit sentiment (implying that Brexit is viewed positively) lead to price gains in a tight window around the 2016 referendum. While these findings are consistent with the forward-looking properties of equity markets, they also leave open the question of the degree to which individual firms respond to the Brexit referendum shock. We therefore estimate the effect of firm-level Brexit risk and sentiment on investments, hiring, and sales using the following specification:

$$y_{i,t+1} = \delta_j + \delta_t + \delta_c + \beta BrexitRisk_{i,t} + \theta BrexitSentiment_{i,t} + X'_{i,t}\zeta + \epsilon_{i,t} \tag{4}$$

where $y_{i,t+1}$ is the firm-level outcome of interest; δ_j, δ_t, and δ_c are industry, year, and headquarters-country fixed effects, respectively; with the vector $X_{i,t}$ including the log of the firm's assets to control for firm size, and *NonBrexitRisk* and *NonBrexitSentiment* to control for other (non-Brexit related) sources of risk and overall (again, non-Brexit related) sentiment of the call, respectively. $BrexitRisk$, $BrexitSentiment$, $NonBrexitRisk$, and

$NonBrexitSentiment$ are computed annually by averaging across all available earnings call transcripts in a given year. Firm outcomes are measured yearly from 2011 to 2018. Descriptive statistics of all firm-level variables are presented in Table 4. Inferences are based on standard errors clustered at the firm-level.

It is well-recognized in both theoretical and empirical work that uncertainty can directly influence firm-level investments and employment (Pindyck, 1988; Bernanke, 1983; Dixit and Pindyck, 1994; Bloom et al., 2007; Gilchrist et al., 2014).[21] Furthermore, recent developments in the literature have highlighted that first and second moment shocks can appear together, either amplifying or confounding each other (Bloom et al., 2018; Berger et al., 2017; Hassan et al., 2019). We examine these predictions in the context of Brexit, which (it has been argued) represents an "almost ideal" uncertainty shock inasmuch as it was large, unanticipated, and delayed in implementation (Fisman and Zitzewitz, 2019; Born et al., 2019).[22]

Figure 7 shows a binned added-variable plot of firm-level capital investment ($I_{i,t+1}/K_{i,t}$) over $BrexitRisk_{i,t}$ while controlling for $BrexitSentiment_{i,t}$, the log of assets, and sector and time fixed effects. The red (blue) line represents the slope estimate for the sample of UK (international) firms. In both panels, $BrexitRisk_{i,t}$ is negatively and significantly associated with the capital investment rate. In fact, the estimated coefficients are very similar in magnitude: -0.609 (s.e.=0.011) in the UK and -0.670 (s.e.=0.001) in the non-UK sample. The latter coefficient implies that for each year after 2016, an international firm with a $BrexitRisk$ equal to that of the average UK firm experienced a 2.6% decrease in its investment rate relative to the mean (24.5).

[21] In macroeconomic models, an increase in aggregate risk may increase or decrease aggregate investment due to general equilibrium effects on the interest rate (see, e.g., Fernández-Villaverde et al., 2015; Hassan and Mertens, 2017). However, this ambiguity does not usually exist at the firm level (i.e., it is conditional on a time fixed effect). In models with adjustment costs, a firm facing a relative increase in firm-level risk should always decrease its investment as compared to other firms.

[22] Bloom et al. (2019) points out that Brexit presents a persistent uncertainty shock that should have a heterogeneous impact on UK firms; the impact depends on firms' prior exposure to the EU. Moving beyond the impact on UK firms, however, we are also able to estimate the effects of this shock on non-UK firms generally or on US firms specifically.

In Table 7, we conduct a more systematic analysis of the relation between a firm's capital investment rate and Brexit risk and sentiment. In Panel A, we consider the full sample of UK and international firms. Column 1 presents estimates of a base specification with our two variables of interest, $BrexitRisk_{i,t}$ and $BrexitSentiment_{i,t}$, and, as controls, the log of assets and time and sector fixed effects. As expected, we find a significant negative association between $BrexitRisk_{i,t}$ and the capital investment rate (-0.843, s.e.=0.175). However, we find no significant association between $BrexitSentiment_{i,t}$ and $I_{i,t+1}/K_{i,t}$. Next, we add an interaction term between $BrexitRisk_{i,t}$ and an indicator variable that takes the value of unity when the firm is headquartered in the UK (zero otherwise) in order to explore whether the relation between uncertainty and investment is different for UK and non-UK firms.[23] Consistent with the evidence in Figure 7, however, we find no statistically reliable evidence for such a difference. Specifically, with a comparable exposure to Brexit risk, the elasticity of investment with respect to Brexit risk is not significantly different for UK and international firms.

In the next three columns, we work towards our preferred specification by adding sector-time and country fixed effects (Column 3) and controls for the firm's overall (i.e., non-Brexit related) risk and sentiment (Columns 4 and 5, respectively). Reassuringly, we find that firms exposed to more overall uncertainty (measured by textual analysis of their earnings call transcripts, as outlined in section 2) have *lower* investment rates. A one standard deviation increase in a firm's non-Brexit related risk is associated with a 0.770 (std. err=0.253) percentage point decrease in its investment rate. Similarly, firms for which overall sentiment is positive (using our text-based measure of sentiment) have *higher* investment rates. Turning to our variables of interest, we find that our earlier conclusions regarding Brexit-related risk and sentiment are unchanged when we include these additional controls. We continue to find a negative association between $BrexitRisk_{i,t}$ and investments, with only a minor attenuation of the estimated coefficient. Indeed, the estimated effect of $BrexitRisk_{i,t}$ suggests

[23] As expected, the main effect of a given firm being headquartered in the UK is negative (-3.63, s.e.=0.808). For brevity, we suppress details in the table.

that for firms exposed to Brexit risk equal to that of an average post-referendum UK firm (1), investments decrease by 0.640 percentage points (or 2.6 percent relative to the mean) – a decrease comparable in size to that associated with a persistent one-standard deviation increase in the firm's non-Brexit related risk.

Extrapolating from the country-specific mean Brexit risk in Figure 2, the estimate in Column 5 implies a $0.64 \times 1.86/27.52 \times 100 = 3.91$ percent decrease in the investment rate for the average Irish firm, and a $0.64 \times 0.60/18.63 \times 100 = 1.99$ percent decrease for the average South African firm in our sample. Appendix Table 6 repeats this calculation to give the estimated impact of Brexit risk for each country shown in Figure 2.

As for the full sample, so for the sub-sample of firms headquartered in the US. In Panel B, we repeat the same sequence of specifications as in Panel A but report only the coefficient estimates on $BrexitRisk_{i,t}$ to save space. Our estimates for US firms are somewhat larger than for the full sample, potentially because firm-level variables are measured with less error in this more homogeneous sub-sample. Our preferred estimate in Column 5 (-1.026, s.e.=0.346) suggests that Brexit risk accounts for a 0.37% decrease in the investment rate of the average US-based firm in each year after 2016.

Despite the rich set of controls included in the standard specification in Column 5, there are three remaining concerns with a causal interpretation of these results. First, executives might use Brexit and Brexit risk as an excuse to justify bad performance, even if their firm is not really exposed to the shock. The correlation between our measure $BrexitRisk$ and the decline in investment might then be spurious, picking up "cheap talk" about Brexit. However, we have already seen that introducing controls for the firm's Brexit and overall (non-Brexit related) sentiment has no perceptible effects on our coefficient of interest (compare Columns 4 and 5 of Table 7). In Columns 2 and 3 of Table 8, we add additional controls for the firm's recent performance. All specifications in this table include our standard controls, but for brevity report only the coefficients on Brexit risk and the newly added controls. Column 2 adds a measure for the firm's earnings surprise and Column 3 adds the firm's contemporaneous stock return, since bad performance should correlate with lower earnings and lower contemporaneous stock returns. Although the latter is arguably endogenous to Brexit's effect, neither of the two controls significantly attenuate the coefficient of interest (if anything, the estimated coefficient on Brexit risk *increases* in Column 2), bolstering our confidence that our estimates are not driven by cheap talk.

The second concern with our results is that firms affected by Brexit risk might also be disproportionately affected by other types of risk. Again, controlling for non-Brexit-related discussions of risk and uncertainty had no perceptible effect on our estimates (compare Columns 3 and 4 of Table 7), demonstrating that the reduction in investment we document is specific to Brexit-related risk. Furthermore, Column 4 of Table 8 also controls for the firm's exposure to trade policy risk ($PRiskTrade_{it}$). This variable (developed in HHLT) is constructed in the same way as $BrexitRisk$, but counts synonyms of risk or uncertainty near words that indicate a discussion of political interference in trade policy.[24] As expected, we find that exposure to trade-policy risk lowers the firm's investment rate (a one standard deviation increase in $PRiskTrade_{it}$ is associated with a 0.402 (s.e.=0.209) percentage point decrease in that firm's investment rate). However, including this control has essentially no effect on our coefficient of interest, which remains stable at -0.692 (s.e.=0.186).

The third and final concern with our results is that UK-exposed international firms may be systematically different and may generally invest less than do other firms. To address this concern, Column 5 adds a firm's average sales in the UK *before* the Brexit referendum as a control variable. Column 6 further adds a firm-level, time-invariant measure of Brexit exposure that is calculated using all observations of a given firm in the sample ($\overline{BrexitExposure_i}$). Note that both of these variables are "bad controls" (Angrist and Pischke, 2008) inasmuch as they are potential proxies for Brexit-related risk and/or sentiment and might therefore inappropriately reduce the explanatory power of our variables of interest. Despite these econometric concerns, we find little evidence that adding these additional controls changes

[24] As one might expect, this measure shows sharp increases coinciding with various trade disputes between the United States and other countries 2016-19. See www.firmlevelrisk.com for details.

the tenor of our main findings. Neither the pre-Brexit UK sales nor $\overline{BrexitExposure_i}$ are significantly associated with the investment rate. Furthermore, the significance of the estimated coefficient on $BrexitRisk_{i,t}$ is not affected by their inclusion.

Figure 8 shows the results of a placebo exercise where we re-estimate our standard specification in Column 5 of Table 7, but erroneously assign each firm's $BrexitRisk$ to a three-year period prior to 2016. The first coefficient shows the results when we assign each firm's $BrexitRisk$ to the years from 2011 to 2013. The second repeats the exercise for the years 2013 to 2015. Comfortingly, point estimates are close to zero, and we find no statistically significant effect of Brexit risk prior to 2016. For comparison, the third coefficient shows the actual Brexit risk from our standard specification. Taken together, these results bolster our confidence that our estimates do indeed capture the causal effect of Brexit risk on firm-level investment.

Having established a consistent negative association between Brexit risk (though not sentiment) and the capital investment rate, we now turn to firms' employment and sales growth. In Table 9, we report panel regressions that correspond to our preferred specification in Column 5 of Table 7, both with and without the full set of fixed effects. In all of these regressions, we provide estimates based on the full sample, and, separately, our sample of US firms.

Prior work on the economic consequences of uncertainty suggests that hiring and investment should respond similarly to rises in uncertainty since both activities exhibit adjustment costs. Supporting these predictions, Panel A in Table 9 shows (across both samples) a significant negative association between $BrexitRisk_{i,t}$ and employment growth $\Delta emp_{i,t}/emp_{i,t-1}$. Our preferred coefficient estimates are -0.391 (s.e.=0.179) and -1.272 (s.e.=0.460) for the full sample and for the US, respectively, where the point estimate for US-based firms is now considerably larger than the one for the full sample.[25] The former estimate implies

[25] One possibility, in addition to the possible presence of differential measurement error mentioned above, is that American firms are generally more flexible in adjusting their labor force in response to shocks than European firms. Consistent with this conjecture, the table also shows a significantly larger elasticity of employment growth with respect to non-Brexit related risk for US firms (-1.388, s.e.=0.344 vs. -0.758,

that a firm with an average Brexit risk of a UK-based firm experiences a decrease in its employment growth of 4.5% relative to the sample mean (Appendix Table 6 breaks these numbers down by individual country.); the latter implies a 1.21% reduction for the average US firm. As we did for the capital investment rate, we find no significant association between $BrexitSentiment_{i,t}$ and employment growth. As before, the coefficients on $NonBrexitRisk$ and $NonBrexitSentiment$ are statistically significant and have the predicted sign. (Appendix Table 8 shows the same battery of robustness checks is in Table 8.)

Finally, we consider sales growth in Panel B. While we still find a negative relation between $BrexitRisk_{i,t}$ and sales growth in all sample partitions, the association is no longer statistically significant. This finding is consistent with predictions from the real options literature, which postulates a larger short-run effect of risk on hard-to-reverse investments in physical and human capital than on short-run sales growth (e.g. Baker et al., 2016). In sharp contrast, however, and consistent with sales responding more directly to both good and bad news events, we find a positive and significant association between $BrexitSentiment_{i,t}$ and sales growth. These first moment effects are again larger for the US sample, where our estimated coefficient of 0.410 (s.e.=0.167) implies that firms with Brexit sentiment equal to that of the average UK firm after the referendum vote (-1) have 0.41 percentage point lower sales growth in each year after 2016. See Appendix Table 9 for additional variations and robustness checks.)[26]

5. Additional application: the Fukushima incident

While Brexit is a momentous economic and historical event, the consequences of which for firms around the globe are worthwhile to examine in their own right, *shocks* to the firm's market and non-market environment are part and parcel of the corporate world. Having a

s.e.=0.214 in columns 2 and 4, respectively).

[26]In Appendix Table 10, we examine the timing of the effect of Brexit risk on investment and employment outcome variables. Specifically, we regress both the capital investment rate and the employment growth rate onto contemporaneous $BrexitRisk_{i,t}$ and onto one-period-lagged $BrexitRisk_{i,t-1}$. We find that employment responds more quickly than investment to changes in Brexit risk. Indeed, firm hiring responds more to concurrent than to lagged Brexit risk, while the opposite is true for the investment rate.

versatile method available to quantify and analyze the exposure of firms to these shocks is an important addition to the arsenal of economists and policy makers. We therefore briefly consider how to generalize our measure of firm-level exposure to a variety of other specific shocks, using the Fukushima incident as an illustration.

On Friday, March 11, 2011, an earthquake and tsunami hit the Fukushima Daiichi Nuclear Power Plant in Okuma, Japan. The tsunami produced waves that swept over the power plant's protective seawalls, disabling the emergency generators that were designed to continue circulating coolants to the reactors' cores, which were automatically shut down upon detection of the earthquake. The loss of coolant led to a nuclear meltdown and a release of radioactive contamination. Ultimately, the fallout made Fukushima the most severe nuclear accident since the 1986 Chernobyl catastrophe.

To quantify the impact of this disaster on Japanese and international firms, we build a measure in an analogous fashion to our procedure for Brexit exposure. Unlike Brexit, however, for the Fukushima incident, there is no obvious single word around which conversations in earnings conference calls coalesce. To generalize our method, we thus add a step to our analysis that uses training data to generate a list of appropriate search terms. While this use of training data can be fully automated and used without any human intervention (as demonstrated in HHLT), we choose a hybrid approach where we first use training libraries to generate a list of possible search terms, and then manually select the most appropriate of these terms.

Accordingly, we generate lists of the top 100 one, two, and three word combinations (n-grams), that were commonly used to discuss the disaster in newspaper articles at the time. Specifically, we use Factiva to search for "fukushima AND nuclear AND (disaster OR accident)" in the source "Newspapers: All,", with language "English." We download the first 300 newspaper articles by date of publication and count all n-grams. We filter out word combinations that also appear in a set of word combinations formed from a random selection of 300 newspaper articles on generic economic news published before 2011, and sort the remaining word combinations by their frequency of usage. Appendix Table 11 shows the results of this exercise for two-word combinations (bigrams).

We then consider the occurrence of these n-grams in conference calls. Ideally, we need n-grams to be uniquely used to describe the Fukushima disaster and nothing else. One way to verify this requirement is to examine the use of bigrams over time and identify those that are widely used immediately after the incident, but not before. In this instance, we exclude all n-grams from consideration that are used more than twice across all conference calls prior to the date of the incident.

From the remaining list of n-grams, we then choose the following set $\mathbb{F}$ to construct our count-based measure $FukushimaExposure$: "japan earthquake," "japanese earthquake," "japanese nuclear," "earthquake in japan," "fukushima," "earthquake and tsunami," "tsunami in japan," "japanese tsunami," "japan disaster," "nuclear crisis," "damaged nuclear," "japan tsunami," "worst nuclear," "nuclear accidents," "earthquake and tsunami," and finally, "dai-ichi power." Following equation (1), our firm-quarter level measure of Fukushima *exposure* is then simply the number of mentions of n-grams in $\mathbb{F}$ in the transcript of firm i in quarter t divided by the total number of words in the transcript.

Having scored all transcripts in our sample in this fashion, we can trace the exposure of international and Japanese firms to the event. We do so in Appendix Figure 3. For both Japanese and international firms, we observe no exposure prior to the second quarter of 2011 and a large spike just after the event. Reassuringly, Japanese firms have higher exposure throughout the post-event sample period and their exposure appears to be more subject to change over time.

After validating the measure this way, we can use it to consider regional patterns; for example, by, as before, averaging the firm-level exposure of all firms headquartered in a given country and comparing these country-level averages. We can also leverage our micro data to offer further insights to better understand these patterns, namely by reading the relevant snippets taken from the conference call transcripts. Figure 9 displays these country averages. As one would expect, Japan's exposure to the event is high (and in fact, we normalize scores by setting Japan equal to unity), as is the exposure of nearby Taiwan and Hong Kong. Aside from this straightforward geographic pattern, several interesting narratives emerge. For example, insurance companies, heavily represented in the sectoral mix of faraway Cayman Islands, Bermuda, and Luxembourg, appear highly exposed. Our analysis of snippets confirms that these firms faced probing questions from financial analysts about their exposure to the event. Other global impacts are transmitted through a fear for the future acceptance of nuclear technology (particularly in France and other European countries), the future of Uranium mining (particularly in Canada and Australia), and the disruption of supply chains.

Table 10, shows some examples of snippets taken from Japanese and international firms, using the same sampling rules as for Table 2. We observe that while Japanese firms struggle with power outages, the inaccessibility of plants and properties, and production disruptions, the international impacts of the Fukushima disaster are transmited through more subtle links. Insurance companies (such as Global Indemnity with headquarters in the Cayman Islands), discuss losses due to clients' policies taken out to protect against natural disasters. Others are (uranium) suppliers to the nuclear industry, fearing increased regulatory scrutiny to their own operations as an energy company, or think to benefit from a crackdown on nuclear energy as suppliers of different power sources.

Though brief, we hope that this additional application shows more generally the potential of our approach to trace out and understand at the microeconomic level the impacts of a wide range of specific shocks on the fortunes and actions of publicly listed firms around the world.

6. Conclusion

Assessing the economic impact of specific policy measures, reforms, and other shocks requires measuring how these events affect the calculations and expectations of decision makers. In this paper, we develop a simple and adaptable text-based method to measure the costs, benefits, and risks that thousands of international decision makers associate with specific events. Our method offers several helpful features that address some of the challenges identified in recent research. First, it measures perceptions directly and in real time without conducting expensive large-scale surveys. Second, it meaningfully distinguishes between the perceived risks, costs, and opportunities associated with a given event, thus separating variation in first and second moments stemming from the event. This is particularly interesting in the context of Brexit, where policymakers have long pointed to the potentially detrimental effects of Brexit-related uncertainty, which we quantify directly. Third, many shocks do not (fully) play out in a short period of time, but present persistent challenges to economic actors. A method allowing researchers to measure over-time variation in a firm's exposure to a persistent shock is particularly valuable in light of recent evidence that the response to a persistent shock might be very different from the response to a shock that quickly fades away (Bloom et al., 2019).

We use our method to assess the extent to which international firms are affected by the outcome of the 2016 Brexit referendum. Our measures of Brexit exposure, risk, and sentiment behave in economically meaningful ways, strengthening our validity claims. In the process, we also document that firms inside and outside of the UK overwhelmingly view Brexit as "bad news." There are significant cross-country differences in Brexit risk: Ireland's Brexit risk is larger even than the UK's; nearby EU countries experience the strongest increase in risk; and Brexit risk also has a material (though weaker) impact in the United States and other non-EU countries.

When examining the earnings call discussions of individual firms, we find that even "Brexit winners" most often simply point out that they are presently not much affected by the prospect of Brexit. Those who see Brexit as negative, however, expect concrete difficulties for their businesses as a result of regulatory divergence, reduced labor mobility, decreased trade access, and post-Brexit operational adjustments. Indeed, we find that US and international firms most exposed to Brexit-related risks have significantly reduced investment and employment growth. We also find that equity markets quickly impounded both the future cash flow consequences of the Brexit vote and its impact on the discount rate; Brexit sentiment and Brexit risk both partially explain the pricing response on equity markets in the days following the referendum.

Taking this evidence together, we conclude that during our sample period, the Brexit vote mostly acted as an uncertainty shock, leading to significant precautionary reductions in investment and employment growth in the firms and countries most exposed. In addition to this detrimental effect of sustained uncertainty, stock markets also anticipate large negative (first-moment) effects from the implementation of Brexit on firms around the world, which have not yet been realized in firm actions. Our reading of the evidence suggests that the greater the rupture between the UK and the EU, the larger these direct effects (including post-Brexit adjustment costs) will be. When Brexit is finally implemented, the consequences for investments and employment may well be larger than those associated with Brexit uncertainty alone.

Beyond this application to Brexit, we show that our method is sufficiently versatile to be more generally useful for characterizing and quantifying firm-level exposures to the costs, benefits, and risks associated with specific policy measures, reforms, and other shocks (such as the Fukushima disaster). Useful future applications may estimate firm-level impacts of natural disasters, the spread of diseases like SARS or the coronavirus, political events such as revolutions or the US government shutdown, or specific regulatory reforms in response to the climate emergency.

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Table 1: Validation of BrexitExposure

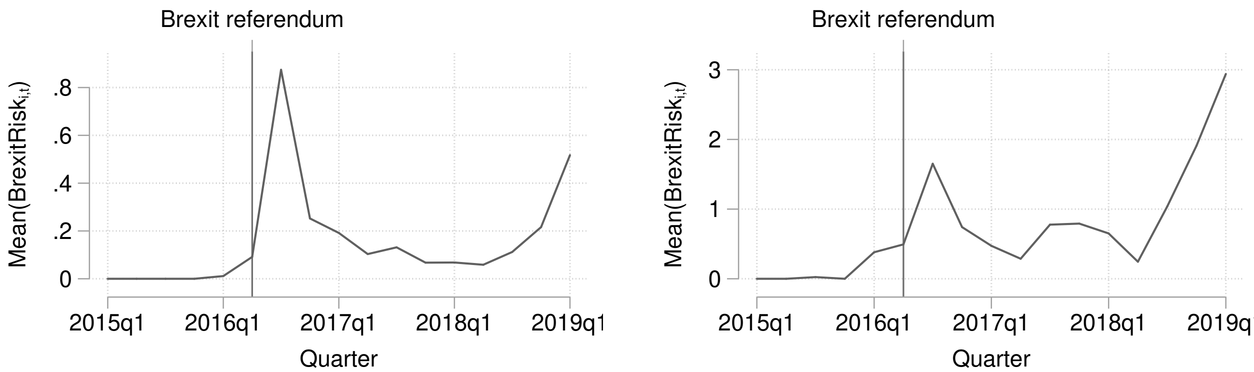
	$\overline{\text{BrexitExposure}}_i$			
	(1)	(2)	(3)	(4)
$\mathbb{1}\{\text{UK HQ}\}_i$	0.872***	0.909***	0.064	0.116
	(0.075)	(0.075)	(0.088)	(0.092)
$\mathbb{1}\{\text{UK subsidiary}\}_i$	0.188***	0.200***	0.227***	0.227***
	(0.017)	(0.017)	(0.022)	(0.021)
$\mathbb{1}\{\text{EU non-UK HQ}\}_i$		0.263***	0.073	0.072
		(0.032)	(0.087)	(0.084)
% of sales in UK (2010-2015)			1.842***	
			(0.405)	
% of sales in UK (2016-present)				1.766***
				(0.403)
R^2	0.086	0.103	0.120	0.121
N	7,733	7,733	3,497	3,678

Notes: This table reports OLS estimates from cross-sectional regressions that use $\overline{\text{BrexitExposure}}_i$ as the dependent variable. We use 66,750 earnings calls between 2016Q1 and 2019Q1 to calculate firm-level mean Brexit exposure. Robust standard errors are in parenthesis. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

Figure 1: Time Series of BrexitRisk and BrexitSentiment

Panel A: Brexit risk

Non-UK UK

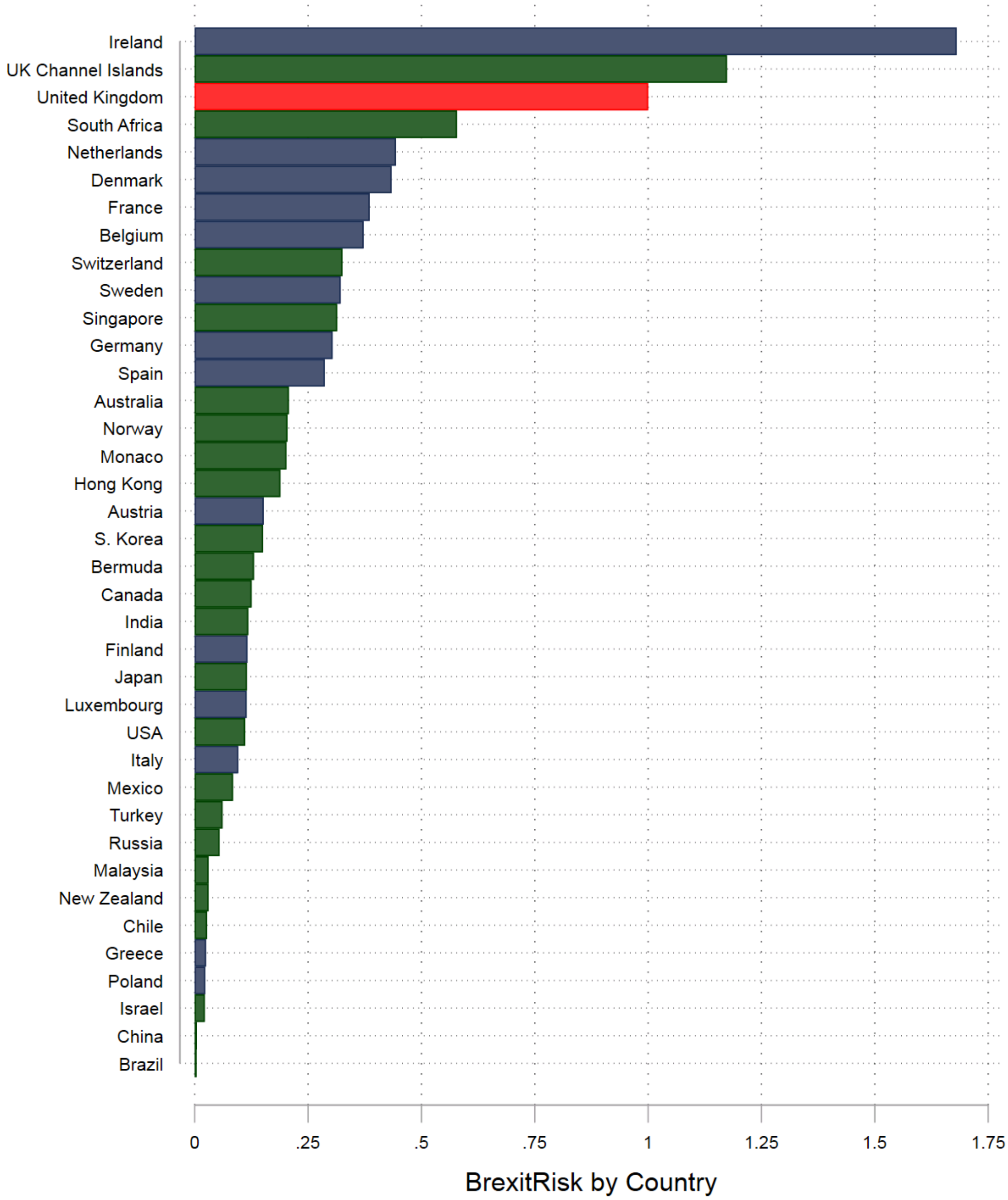


Panel B: Brexit sentiment

Non-UK UK

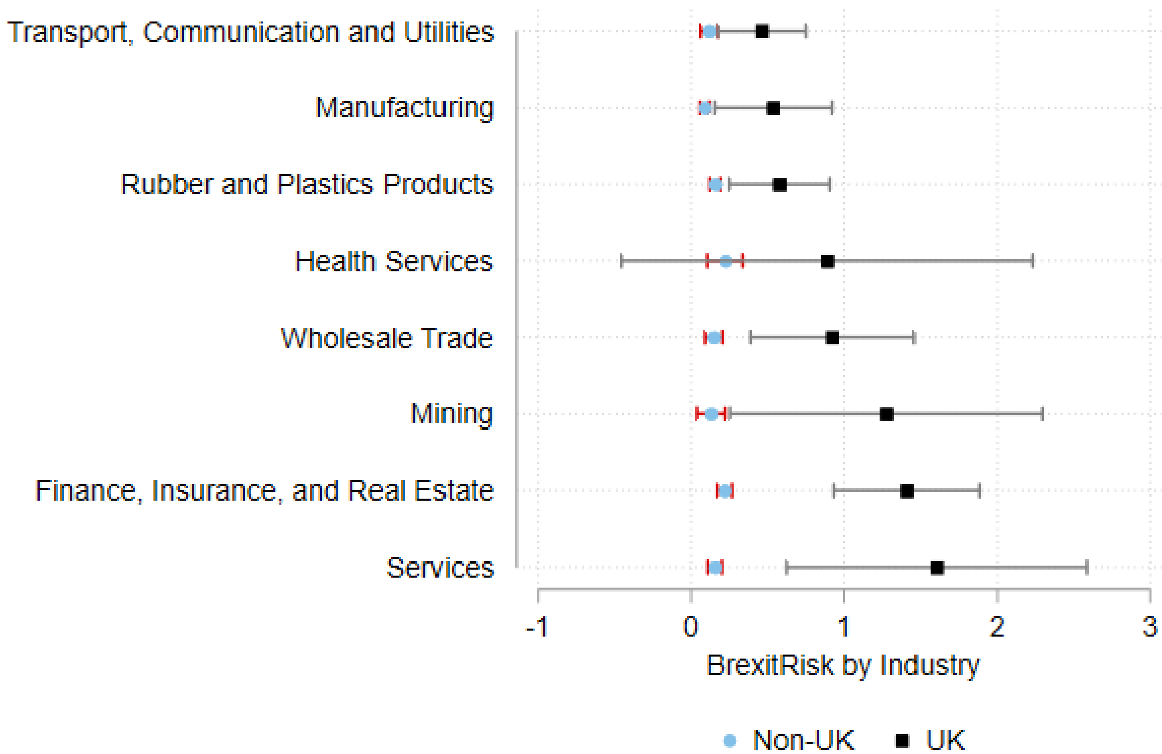
Notes: This figure plots the quarterly mean of non-UK and UK headquartered firms' Brexit risk (Panel A) and Brexit sentiment (Panel B). $\overline{\text{BrexitRisk}}_{i,t}$ is normalized using the average $\overline{\text{BrexitRisk}}_{i,t}$ of UK-headquartered firms 2016-19; $\overline{\text{BrexitSentiment}}_{i,t}$ is normalized using the average $|\overline{\text{BrexitSentiment}}_{i,t}|$ of UK-headquartered firms 2016-19. The Brexit referendum line indicates the quarter when the referendum took place (2016q2).

Figure 2: Mean BrexitRisk by Country



Notes: This figure shows the country-by-country mean of $\text{BrexitRisk}_{i,t}$ across all firms headquartered in a specific country. Countries with zero $\overline{\text{BrexitRisk}}_c$ or countries for which we have fewer than five headquartered firms are excluded. Zero $\overline{\text{BrexitRisk}}_c$ countries are Puerto Rico, Thailand, Cayman Islands, Portugal, Indonesia, Cyprus, Nigeria, Czech Republic, United Arab Emirates, Argentina, Peru, Phillipines, and Columbia.

Figure 3: BrexitRisk by Industry



Notes: This figure shows the mean $\text{BrexitRisk}_{i,t}$ by one-digit SIC industry for UK and non-UK firms. Whiskers around industry means indicate 95% confidence intervals.

Table 2: Top BrexitRisk Firms' Transcript Excerpts

Panel A: UK firms

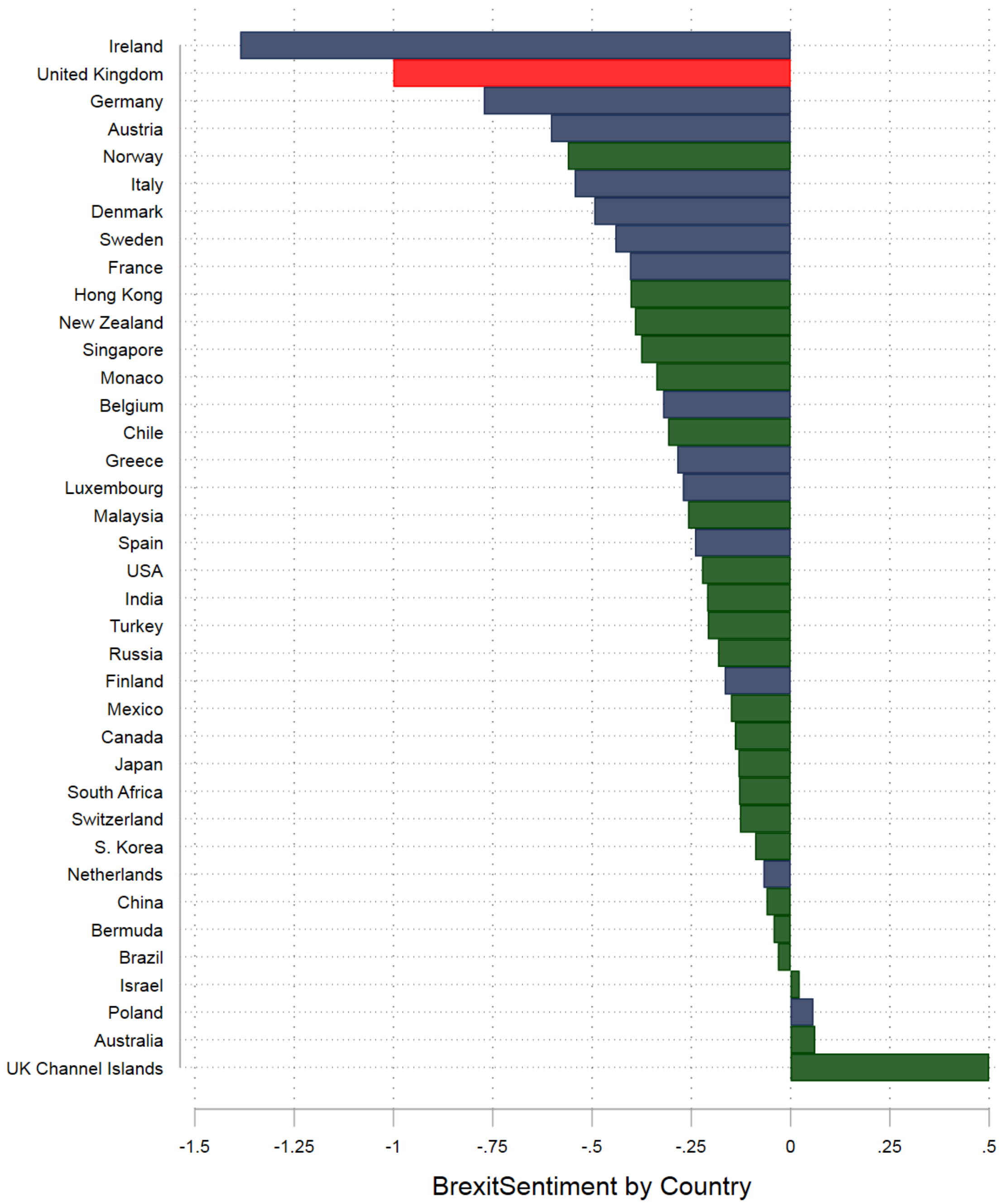
Company	$\overline{\text{BrexitRisk}}_i$	Country	Quarter	Transcript excerpts
Bellway PLC	18.89	GB	2018 Q4	deliver completions in fy we are mindful of the **uncertainty** surrounding **brexit** and we will wait to see whether customer sentiment is affected
Berendsen Ltd	14.14	GB	2016 Q3	and we have i think a pretty proven resilient business however **brexit** raises any number of **uncertainties** for every single business so were
SThree PLC	13.64	GB	2019 Q1	year theres also a lot of **uncertainty** around the uk and **brexit** and that will affect most markets but i think again the
Endava PLC	12.9	GB	2019 Q1	plans with us as a result of the **uncertainties** caused by **brexit** mark will talk about how weve mitigated fx **risk** in his
Millennium & Copthorne Hotels PLC	10.48	GB	2018 Q1	as you know there is still **uncertainty** about british economy and **brexit** for example we are seeing a rise in costs here because

Panel B: Non-UK firms

Company	$\overline{\text{BrexitRisk}}_i$	Country	Quarter	Transcript excerpts
Northstar Realty Europe Corp	18.35	US	2016 Q3	give rise to greater **uncertainty** this **uncertainty** has been exasperated by **brexit** the **prospect** of **brexit** has resulted in a high degree of
Ryanair Holdings PLC	18.29	IE	2017 Q1	airlines the pricing environment has also been affected by the post **brexit uncertainty** which has seen weaker sterling and a switch of charter
Breedon Group PLC	17.58	JE	2019 Q1	quarter and the increased input costs but also an element of **brexit uncertainty** in ireland our performance was strong and benefited from the
Sweco AB	12.58	SE	2018 Q4	but still there is still an **uncertainty** when it comes to **brexit** and some weakness in the real estate market so once again
Stonegate Mortgage Corp	11.65	US	2016 Q3	markets primarily driven by economic concerns abroad in particular **uncertainty** around **brexit** played a major role related to the **instability** of interest rates
FBD Holdings PLC	10.76	IE	2019 Q1	our agri and agribusiness customers are very **exposed** to a hard **brexit** and any contingency planning that we can do and we have
Nanosonics Ltd	9.9	AU	2019 Q1	this in the uk but there is some underlying **uncertainty** around **brexit** with the likes of confirmation of product supply chain questionnaires that
Bank of Ireland Group PLC	9.18	IE	2019 Q1	of the sme market continues to be impacted by the ongoing **brexit uncertainties** our corporate banking business which includes property lending had a
Cairn Homes PLC	8.75	IE	2019 Q1	enjoys we are all faced with **uncertainty** with the **uncertainty** which **brexit** brings from a cairn perspective our operations are currently all focused
EQT Holdings Ltd	8.58	AU	2019 Q1	about **brexit** and whether the **uncertainty** being driven by the ultimate **brexit** solution and the timing of that is causing an issue for

Notes: This table shows transcript excerpts for the top five UK (Panel A) and the top ten non-UK (Panel B) firms ranked by $\overline{\text{BrexitRisk}}_i$. $\overline{\text{BrexitRisk}}_i$ is calculated as the mean across all of a firm's available transcripts of earnings calls held 2016-19. Synonyms of risk and mentions of "Brexit" are in boldface. Country code 'JE' stands for Jersey, which is a part of UK Channel Islands.

Figure 4: Mean BrexitSentiment by Country



Notes: This figure shows the country-by-country mean of BrexitSentiment$_{i,t}$ across all firms headquartered in a specific country for the same set of countries as in Figure 2. $\overline{\text{BrexitSentiment}}_c$ for the UK Channel Islands has a value of +2 but is truncated at 0.5 for visual clarity.

Table 3: Brexit-Related Concerns and Opportunities Expressed by Management

Panel A: Positive Brexit sentiment

Category	UK (in %)	Non-UK (in %)	Transcript excerpts
Not exposed	78.95	79.55	despite whats going on with the brexit noise so thus far we havent seen a whole lot of softening and just to remind you our uk office portfolio we have no financial institution exposure (Kennedy-Wilson Holdings Inc, US, 2019 Q1)
Weak pound	14.03	16.67	saw a spike in leisure occupancy after the brexit referendum in june as tourists took advantage of the cheaper pound (Millennium & Copthorne Hotels PLC, UK, 2017 Q1)
Better trade access	5.26	1.52	brexit could be beneficial for forfarmers i can understand that it might have a positive impact on your position in the uk (ForFarmers, NL, 2019 Q1)
Relocation opportunities	3.51	3.79	potential opportunity coming from brexit and weve seen a number of firms announcing that frankfurt would ultimately be their european hub (Deutsche Boerse AG, DE, 2017 Q3)
Higher government expenditure	0	1.52	probably greater amount of private capital going into those assets simply because of the other pressures on government spending so i think brexit is neutral to who knows maybe mildly positive for us (International Public Partnerships Ltd, GG, 2016 Q3)
Less regulation	0	0.76	I also heard in response to a brexit question that over time you think that the regulatory arena with brexit could create opportunity for you. Did we hear that correctly? Julie Howard Navigant Consulting Inc. you did and I think its just an assumption on our part that there will certainly be and theres going to be all sorts of opportunity (Navigant Consulting, US, 2016 Q3)

Panel B: Negative Brexit sentiment

Category	UK (in %)	Non-UK (in %)	Transcript excerpts
Weak pound	24.69	57.41	on the cost side weve had some cost headwinds fx particularly as sterling has still been weaker this year than last after brexit has impacted us (Flybe Group PLC, UK, 2018 Q2)
Worse trade access	24.69	22.84	if the uk is unable to negotiate access to the single market or open skies it may have implications for our three uk domestic routes (Ryan Air Holdings, IE, 2016 Q3)
Labor market frictions	18.52	9.26	labor market is getting tighter brexit will bring additional challenges with regard to particularly experienced people within all over banking organizations in ireland (Permanent TSB Group Holdings PLC, IE, 2018 Q3)
Falling consumer confidence	18.52	2.47	brexit has been and will continue to be a significant focus for the industry over the coming months we will be affected by the outcomes to the extent that there is significant changes in consumer confidence (Auto Trader Group PLC, UK, 2018 Q4)
Adjustment and transition costs	8.64	1.23	gbp million related to our investment in our operating platform regulatory developments and brexit preparations (Jupiter Fund Management PLC, UK, 2019 Q1)
New, multiple regulatory regimes	6.17	9.88	i sincerely hope that for the implementation of the brexit reasonable solutions will be found that will preserve to a large extent the rules of the single market for energy (Yunipro PAO, RU, 2016 Q3)

Notes: We manually classify positive (Panel A) and negative (Panel B) Brexit sentiment excerpts (+/- 10 words around a sentiment word) from earnings call transcripts into predefined categories. The numbers in the 'UK' and 'Non-UK' columns denote percentages from classified excerpts. They need not equal 100 because a transcript excerpt can be assigned to multiple categories. We classified excerpts from the top 100 UK and non-UK positive and negative BrexitSentiment firms. We classified 189 out of 473 total positive sentiment excerpts, and 243 out of 884 total negative sentiment excerpts. Any remaining excerpts did not intersect with the predefined categories.

Table 4: Summary Statistics

	All firms			UK firms		Non-UK firms		Total
	Mean	Median	SD	Mean	SD	Mean	SD	N
Panel A: Firm-level risk and sentiment								
$\overline{\text{BrexitExposure}_i}$	0.211	0.000	0.674	1.000	1.496	0.169	0.568	7,733
$\overline{\text{BrexitRisk}_i}$	0.195	0.000	0.931	1.000	2.287	0.152	0.771	7,733
$\overline{\text{BrexitSentiment}_i}$	-0.255	0.000	2.104	-1.000	4.196	-0.215	1.920	7,733
Panel B: Event study variables								
$\text{PreBrexitExposure}_i$	0.043	0.000	0.366	0.261	0.744	0.034	0.340	4,399
PreBrexitRisk_i	0.040	0.000	0.511	0.250	1.312	0.032	0.449	4,399
$\text{PreBrexitSentiment}_i$	-0.083	0.000	2.014	-0.344	3.148	-0.073	1.955	4,399
Stock Returns_i: June 24-28, 2016	-0.033	-0.027	0.065	-0.085	0.100	-0.030	0.062	6,077
Panel C: District level variables								
Pct Vote for Leave_c	48.816	50.769	11.334	NA	NA	NA	NA	116
Brexit Risk_c	1.000	0.375	1.585	NA	NA	NA	NA	116
Brexit Sentiment_c	-1.000	-0.065	4.442	NA	NA	NA	NA	116
Panel D: Firm-year outcomes								
$\text{BrexitExposure}_{i,t}$	0.083	0.000	0.502	0.414	1.216	0.067	0.433	44,665
$\text{BrexitRisk}_{i,t}$	0.060	0.000	0.619	0.300	1.620	0.049	0.522	44,665
$\text{BrexitSentiment}_{i,t}$	-0.088	0.000	1.822	-0.351	4.215	-0.075	1.618	44,665
$\text{NonBrexitRisk}_{i,t}$(std.)	1.596	1.364	1.000	1.317	0.778	1.610	1.008	44,665
$\text{NonBrexitSentiment}_{i,t}$(std.)	1.267	1.287	1.000	1.650	0.925	1.249	1.000	44,665
$I_{i,t+1}/K_{i,t} \cdot 100$	24.208	14.250	40.367	19.568	31.431	24.449	40.763	43,868
$\Delta emp_{i,t}/emp_{i,t-1} \cdot 100$	8.168	2.941	29.492	6.853	27.155	8.240	29.613	47,713
$\Delta sales_{i,t}/sales_{i,t-1} \cdot 100$	17.452	6.538	70.393	11.069	47.544	17.766	71.314	55,402

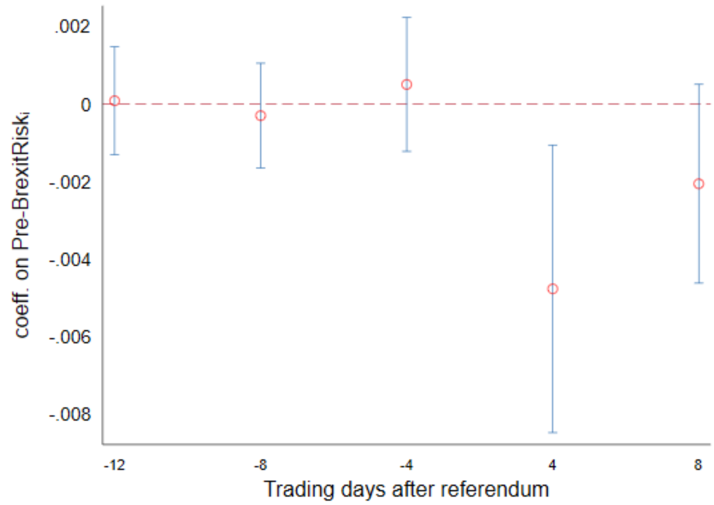
Notes: This table shows the mean, median, standard deviation, and the number of firms for the variables used in the subsequent analysis. Columns 1 to 3 refer to the sample of all firms, Columns 4 and 5 to the sample of UK firms, and Columns 6 and 7 to the sample of non-UK firms. BrexitExposure, BrexitRisk, BrexitSentiment, NonBrexitRisk and NonBrexitSentiment are calculated, as defined in section 2, for every call transcript by each firm in the sample. In Panel A, $\overline{\text{BrexitExposure}_i}$, $\overline{\text{BrexitRisk}_i}$, and $\overline{\text{BrexitSentiment}_i}$ are averages for each firm in the sample from 2016-2019, normalized by the mean $\overline{\text{BrexitExposure}_i}$, the mean $\overline{\text{BrexitRisk}_i}$ and absolute value of mean $\overline{\text{BrexitSentiment}_i}$ of firms in the UK 2016-19, respectively. In Panel B, $\overline{\text{PreBrexitExposure}_i}$, $\overline{\text{PreBrexitRisk}_i}$, and $\overline{\text{PreBrexitSentiment}_i}$ are calculated as in Panel A except using only transcripts of calls held before June 23, 2016 (the day of the Brexit referendum). Stock returns_i are calculated as $\sum_{t=0}^{t=N} log(P_{i,t}/P_{i,t-1})$, where t is at a daily frequency, and [0,N] represents the period of four trading days following the Brexit referendum starting on June 24 and ending on June 29, 2016. In Panel C, Pct Votes for Leave_c is percentage votes for leave cast by a district in the UK, and $\overline{\text{BrexitRisk}_c}$ and $\overline{\text{BrexitSentiment}_c}$ are calculated by taking an average across firms headquartered in a district. $\overline{\text{BrexitRisk}_c}$ and $\overline{\text{BrexitSentiment}_c}$ are normalized such that the mean of $\overline{\text{BrexitRisk}_c}$ is 1 and $\overline{\text{BrexitSentiment}_c}$ is -1 across the cross-section of districts. In Panel D, the sample period for yearly outcomes is 2011-2018; $\text{BrexitExposure}_{i,t}$, $\text{BrexitRisk}_{i,t}$, $\text{BrexitSentiment}_{i,t}$, $\text{NonBrexitRisk}_{i,t}$ and $\text{NonBrexitSentiment}_{i,t}$ are calculated as firm-year averages across all transcripts by a firm in a year.

Table 5: Event Study

	Stock Returns: June 24-28, 2016				
	(1)	(2)	(3)	(4)	(5)
Panel A:	All firms				
$\overline{\text{BrexitExposure}_i}$	–0.023***	–0.023***			
	(0.002)	(0.002)			
$\overline{\text{BrexitRisk}_i}$			–0.011***	–0.011***	
			(0.002)	(0.002)	
$\overline{\text{BrexitSentiment}_i}$			0.002***	0.002***	
			(0.001)	(0.001)	
PreBrexitRisk_i					–0.005**
					(0.002)
$\text{PreBrexitSentiment}_i$					0.001**
					(0.000)
Constant	–0.007*	0.006	–0.006	0.007	0.010**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
R^2	0.168	0.207	0.153	0.191	0.175
N	4,575	4,531	4,575	4,531	3,814
Panel B:	US firms				
$\overline{\text{BrexitExposure}_i}$	–0.024***	–0.023***			
	(0.003)	(0.002)			
$\overline{\text{BrexitRisk}_i}$			–0.008***	–0.008***	
			(0.001)	(0.002)	
$\overline{\text{BrexitSentiment}_i}$			0.003***	0.004***	
			(0.001)	(0.001)	
Pre-BrexitRisk_i					–0.004**
					(0.002)
$\text{Pre-BrexitSentiment}_i$					0.002**
					(0.001)
Constant	–0.011**	0.008	–0.010*	0.010*	0.008
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
R^2	0.073	0.135	0.063	0.126	0.124
N	2,816	2,785	2,816	2,785	2,534
Beta controls	N	Y	N	Y	Y

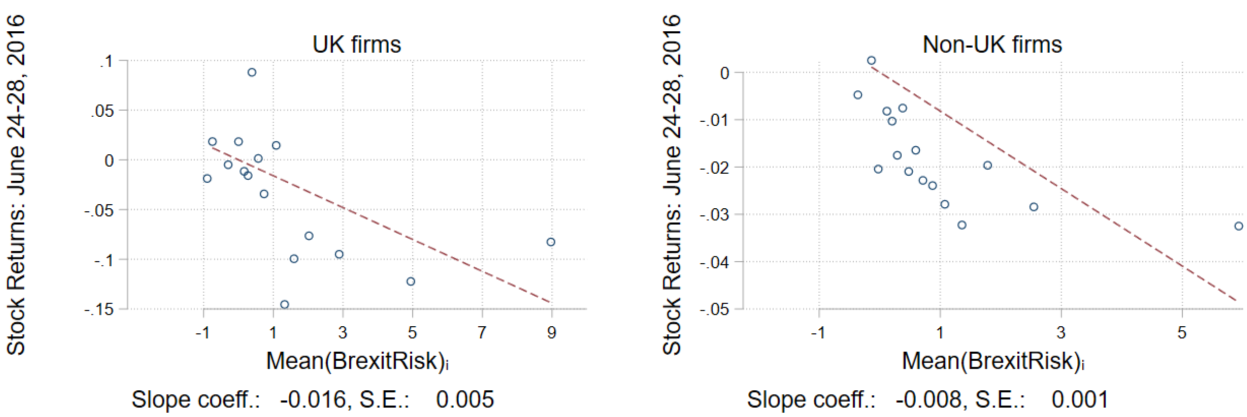
Notes: This table reports OLS estimation results from cross-sectional regressions of stock returns from June 24 to June 28, 2016 on $\overline{\text{BrexitRisk}_i}$ and $\overline{\text{BrexitSentiment}_i}$, separately for all firms (Panel A) and for US headquartered firms (Panel B). Stock returns are calculated as $\sum_{t=0}^{t=N} log(P_{i,t}/P_{i,t-1})$, where t is at a daily frequency, and [0,N] represents the period of four trading days (including weekend days) following the Brexit referendum starting on June 24 and ending on June 29, 2016. All other variables are as defined in Table 4. All specifications include one-digit-SIC and headquarters-country fixed effects (with the exception of Panel B). Standard errors are robust. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively. These regressions exclude non-UK firms with less than seven transcripts in the sample, and firms in the 'Non Classifiable' sector.

Figure 5: Alternative Event Windows around the Referendum



Notes: This figure shows coefficients and 95% confidence intervals of PreBrexitRisk$_i$ for consecutive event windows before and after the June 23, 2016 Brexit referendum using the specification in Column 5 of Table 5. Each event window consists of 4 consecutive trading days.

Figure 6: Effect of Brexit Risk on Stock Returns: June 24-28, 2016



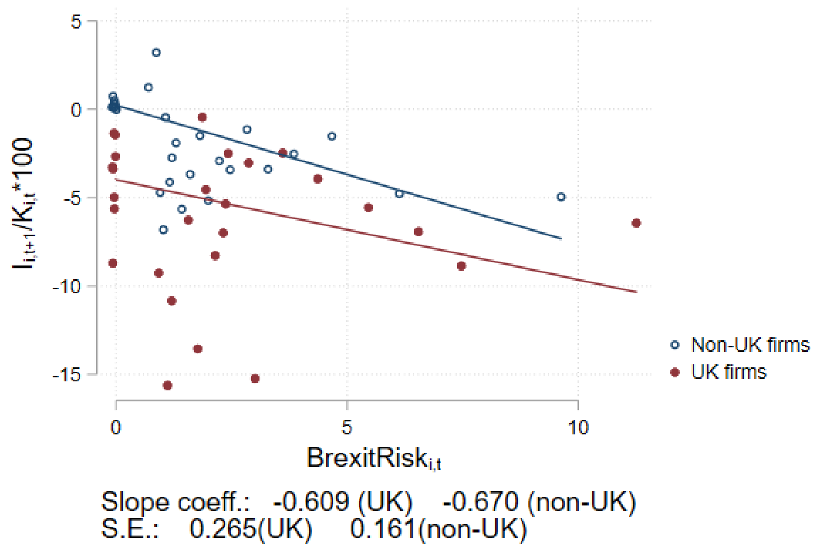
Notes: These figures show binned scatter plots and a linear regression line for the relationship between stock returns from June 24 to June 28, 2016 and $\overline{\text{BrexitRisk}}_i$ for firms headquartered in the UK (left panel) and outside of the UK (right panel). The relationship is plotted after controlling for $\overline{\text{BrexitSentiment}}_i$, log(assets), and one-digit-SIC and country fixed effects. Standard errors are clustered by firm. Each scatter plot has 16 bins: the first bin has all firm-year observations with zero $\overline{\text{BrexitRisk}}_i$; the other 15 bins are equally populated with non-zero firm-year observations $\overline{\text{BrexitRisk}}_i$.

Table 6: Voting in Brexit Referendum

	Pct Vote for Leave$_d$		
	(1)	(2)	(3)
BrexitRisk$_d$	–0.838*		–0.929**
	(0.456)		(0.378)
BrexitSentiment$_d$		0.358***	0.386***
		(0.133)	(0.114)
Share UK born$_d$	50.481***	51.592***	52.395***
	(7.296)	(7.484)	(7.380)
Income per capita$_d$	–0.024***	–0.022***	–0.023***
	(0.004)	(0.003)	(0.004)
R^2	0.580	0.586	0.604
N	110	110	110

Notes: This table reports OLS estimates from cross-sectional regressions of Pct Vote for Leave$_d$ on BrexitRisk$_d$ and BrexitSentiment$_d$, as defined in Table 4. Share UK born$_d$ (the share UK-born individuals residing in a district d), and Income per cepita$_d$ are controls in the regression measured for district d as reported in the 2011 census. We use 2,945 transcripts of the earnings calls of 407 unique sample firms held between 2015-Q1 and 2019-Q1 to calculate firm-level means. Standard errors are robust. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

Figure 7: $\text{BrexitRisk}_{i,t}$ and Firm Investment



Notes: This figure shows the binned scatter plot and the linear regression line for the regression of $I_{i,t+1}/K_{i,t} \cdot 100$ on $\text{BrexitRisk}_{i,t}$, separately for UK firms (red) and non-UK firms (blue) and controlling for log(assets), one-digit-SIC and year fixed effects. Standard errors are clustered by firm. The scatter plot has 29 bins for UK and non-UK firms: The first nine bins are for all firm-year observations with zero $\text{BrexitRisk}_{i,t}$ grouped by nine one-digit SIC codes; the other 20 bins are equally populated by firm-year observations with non-zero $\text{BrexitRisk}_{i,t}$.

Table 7: $\text{BrexitRisk}_{i,t}$, $\text{BrexitSentiment}_{i,t}$ and Firm Investment

	$I_{i,t+1}/K_{i,t} \cdot 100$				
	(1)	(2)	(3)	(4)	(5)
PANEL A	All firms				
$\text{BrexitRisk}_{i,t}$	–0.843***	–0.788***	–0.663***	–0.628***	–0.640***
	(0.175)	(0.190)	(0.185)	(0.182)	(0.184)
$\text{BrexitSentiment}_{i,t}$	–0.115	–0.117	–0.108	–0.107	–0.115
	(0.094)	(0.093)	(0.097)	(0.096)	(0.097)
$\text{BrexitRisk}_{i,t} \times \mathbb{1}\{\text{UK HQ}\}$		0.093			
		(0.331)			
$\text{NonBrexitRisk}_{i,t}$(std.)				–1.033***	–0.770***
				(0.244)	(0.253)
$\text{NonBrexitSentiment}_{i,t}$(std.)					0.799***
					(0.262)
R^2	0.034	0.035	0.068	0.069	0.070
N	22,225	22,225	22,204	22,204	22,204
Year FE	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y
Industry x year FE	N	N	Y	Y	Y
Country FE	N	N	Y	Y	Y
PANEL B	US firms				
$\text{BrexitRisk}_{i,t}$	–1.089***	–1.089***	–1.079***	–0.994***	–1.026***
	(0.344)	(0.344)	(0.343)	(0.342)	(0.344)
R^2	0.042	0.042	0.070	0.071	0.072
N	14,219	14,219	14,198	14,198	14,198
Year FE	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y
Industry x year FE	N	N	Y	Y	Y

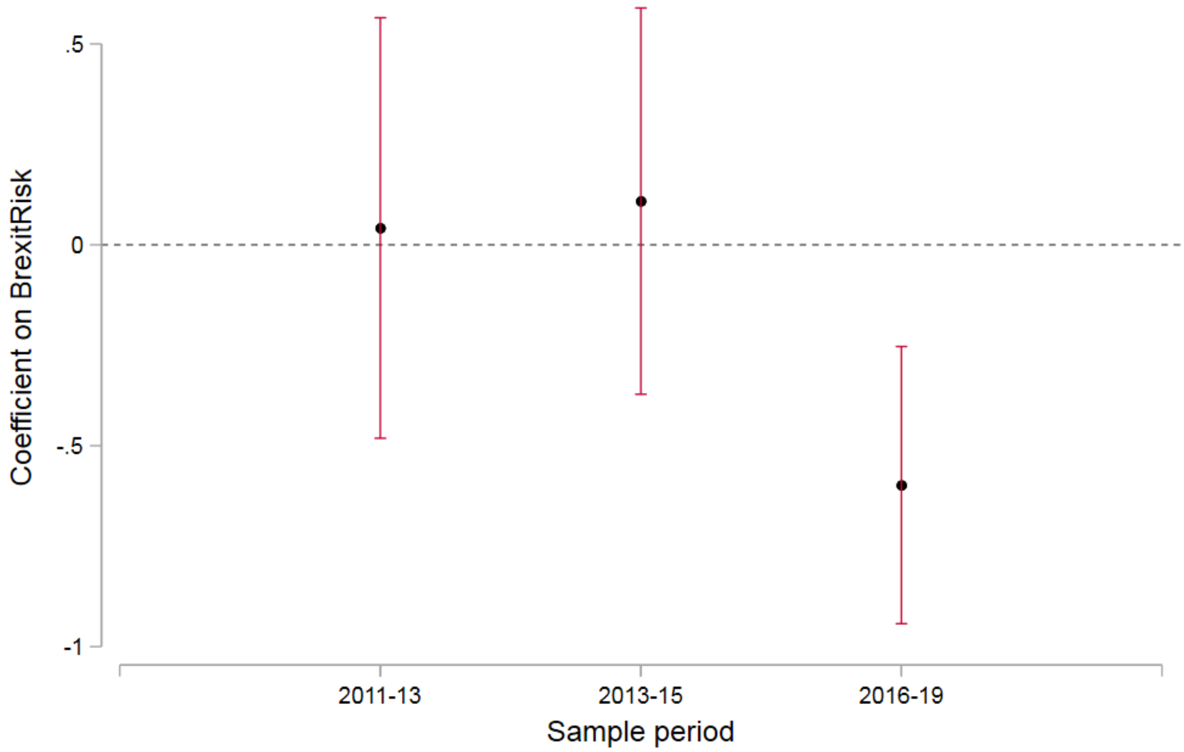
Notes: This table reports results from regressions of $I_{i,t+1}/K_{i,t} \cdot 100$ on $\text{BrexitRisk}_{i,t}$ and $\text{BrexitSentiment}_{i,t}$ using yearly data, separately for the full sample (Panel A) and for sample firms headquartered in the US (Panel B). $\text{BrexitRisk}_{i,t}$ and $\text{BrexitSentiment}_{i,t}$ are calculated by taking the yearly average across a firm's quarterly earnings call transcripts. The dependent variable is winsorized at the 1st and 99th percentile. The regressions include controls for log(assets) and for year, two-digit-SIC, and country (with the exception of the Panel B specifications) fixed effects. The regressions exclude non-UK firms with fewer than 10 transcripts in 2015-2018, and firms in the 'Non Classifiable' sector. Standard errors are clustered by firm. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

Table 8: Robustness: BrexitRisk$_{i,t}$, BrexitSentiment$_{i,t}$, and Firm Investment

	$I_{i,t+1}/K_{i,t} \cdot 100$					
	(1)	(2)	(3)	(4)	(5)	(6)
BrexitRisk$_{i,t}$	–0.640***	–0.836***	–0.513***	–0.692***	–0.686***	–0.699***
	(0.184)	(0.283)	(0.180)	(0.186)	(0.206)	(0.218)
Earnings surprise$_{i,t}$		–0.037				
		(0.044)				
Stock return$_{i,t}$			0.254***			
			(0.028)			
PRiskTrade$_{i,t}$ (std.)				–0.402*		
				(0.209)		
Average UK sales$_i$ (pre-Brexit)					1.476	
					(4.301)	
$\overline{\text{BrexitExposure}}_i$						0.463
						(1.007)
R^2	0.070	0.081	0.084	0.075	0.097	0.070
N	22,204	15,728	21,176	21,156	15,301	22,204
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y
Industry x Year FE	Y	Y	Y	Y	Y	Y
Country FE	Y	Y	Y	Y	Y	Y

Notes: This table reports estimation results from regressions of $I_{i,t+1}/K_{i,t} \cdot 100$ on BrexitRisk$_{i,t}$ and BrexitSentiment$_{i,t}$ using yearly data for the full sample. BrexitRisk$_{i,t}$ is defined as in Table 7. Earnings surprise$_{i,t}$ is defined as (EPS$_{i,t}$-EPS$_{i,t-1}$)/end-of-year stock price$_{i,t}$, where EPS$_{i,t}$ are earnings per share of firm i during year t (Compustat item `epspx`). Stock return$_{i,t}$ is the annual average of quarter-on-quarter stock return. PRiskTrade$_{i,t}$ (std.) is the Political Risk: Trade Policy Index variable from Hassan et al. (2019), standardized by its own standard deviation. All specifications control for log(assets) and for year, two-digit-SIC, and country fixed effects. The dependent variable is winsorized at the 1st and 99th percentile. The regressions exclude non-UK firms with fewer than 10 transcripts in 2015-2018, and firms in the 'Non Classifiable' sector. Standard errors are clustered by firm. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

Figure 8: Placebo Test: Counterfactual Brexit



Notes: This figure plots coefficient estimates and 95% confidence intervals for $\text{BrexitRisk}_{i,t}$ from three separate panel regressions of $I_{i,t+1}/K_{i,t} \cdot 100$ on $\text{BrexitRisk}_{i,t}$ and the same control variables as in Column 5 of Table 7. For the 2011-13 and 2013-15 sample periods, we have reassigned each firm's time series of 2016-2018 $\text{BrexitRisk}_{i,t}$ to the sample period indicated; for the 2016-19 sample period, $\text{BrexitRisk}_{i,t}$ is the firm's actual $\text{BrexitRisk}_{i,t}$ in that sample period.

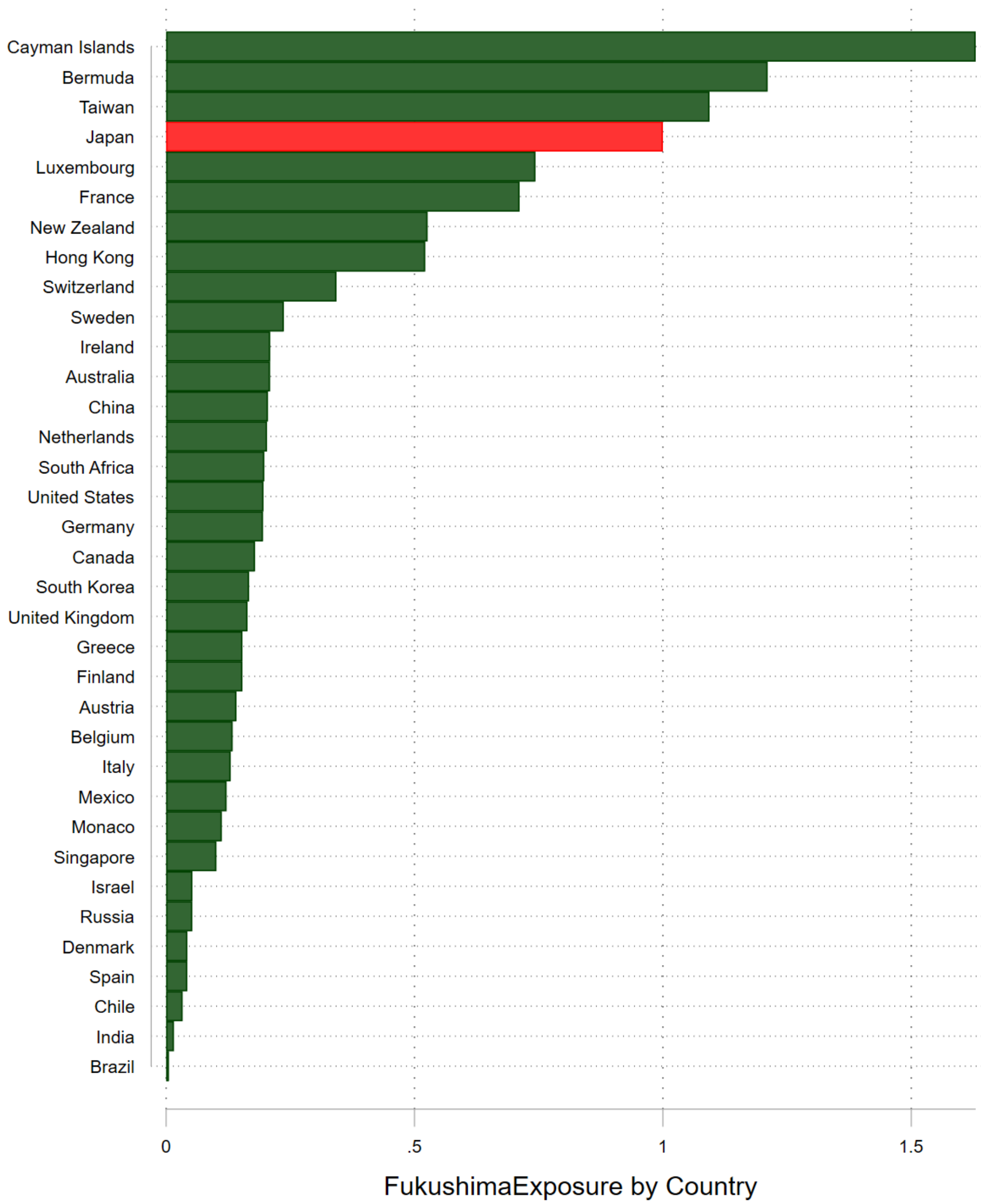
Table 9: $\text{BrexitRisk}_{i,t}$, $\text{BrexitSentiment}_{i,t}$, and Other Firm Outcomes

Panel A	$\Delta emp_{i,t}/emp_{i,t-1} \cdot 100$			
	All firms		US firms	
$\text{BrexitRisk}_{i,t}$	–0.495***	–0.391**	–1.211***	–1.272***
	(0.179)	(0.179)	(0.430)	(0.460)
$\text{BrexitSentiment}_{i,t}$	–0.016	–0.011	–0.219	–0.197
	(0.084)	(0.082)	(0.201)	(0.207)
$\text{NonBrexitRisk}_{i,t}$ (std.)	–0.155	–0.758***	–1.441***	–1.388***
	(0.195)	(0.214)	(0.340)	(0.344)
$\text{NonBrexitSentiment}_{i,t}$ (std.)	1.464***	1.498***	1.637***	1.543***
	(0.192)	(0.210)	(0.275)	(0.281)
R^2	0.024	0.052	0.027	0.057
N	27,156	27,141	18,117	18,099

Panel B	$\Delta sales_{i,t}/sales_{i,t-1} \cdot 100$			
	All firms		US firms	
$\text{BrexitRisk}_{i,t}$	–0.396	–0.135	–0.091	–0.096
	(0.253)	(0.251)	(0.613)	(0.591)
$\text{BrexitSentiment}_{i,t}$	0.118	0.135*	0.305**	0.410**
	(0.075)	(0.081)	(0.142)	(0.167)
$\text{NonBrexitRisk}_{i,t}$ (std.)	0.597	–0.009	–0.813	–0.864
	(0.368)	(0.435)	(0.752)	(0.761)
$\text{NonBrexitSentiment}_{i,t}$ (std.)	1.947***	1.939***	2.386***	1.937***
	(0.345)	(0.379)	(0.512)	(0.521)
R^2	0.025	0.052	0.035	0.058
N	29,059	29,042	18,846	18,828
Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Industry × Year FE	N	Y	N	Y
Country FE	N	Y	n/a	n/a

Notes: This table reports results from panel regressions of $\Delta emp_{i,t}/emp_{i,t-1} \cdot 100$ (Panel A) and $\Delta sales_{i,t}/sales_{i,t-1} \cdot 100$ (Panel B) on $\text{BrexitRisk}_{i,t}$ and $\text{BrexitSentiment}_{i,t}$. $\text{BrexitRisk}_{i,t}$ and $\text{BrexitSentiment}_{i,t}$ are calculated as in Table 7. All specifications control for $\text{NonBrexitRisk}_{i,t}$, $\text{NonBrexitSentiment}_{i,t}$, and log(assets) and for year, two-digit-SIC and country fixed effects. The regressions exclude non-UK firms with fewer than 10 transcripts in 2015-2018, and firms in the 'Non Classifiable' sectors. Standard errors are clustered by firm. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

Figure 9: Mean FukushimaExposure by Country



Notes: This figure shows the country-by-country mean of $\text{FukushimaExposure}_{i,t}$ across all firms headquartered in a specific country. Countries with zero $\overline{\text{FukushimaExposure}}_c$ or countries for which we have fewer than five headquartered firms are excluded. Zero $\overline{\text{FukushimaExposure}}_c$ countries are Argentina, Egypt, Indonesia, United Arab Emirates, Portugal, Colombia, Turkey, Norway, Poland, Cyprus, Malaysia.

Table 10: Top FukushimaExposure Firms' Transcript Excerpts

Company	$\overline{\text{Fukushima Exposure}_i}$	Country	Month	Transcript excerpts	Exposure description
				Panel A: JP firms	
East Japan Railway Co	20.97	JP	2013-04	in the materials at hand last year the great east **japan earthquake** occurred and i feel that was the biggest crisis in	Disruption of operations
Toyota Motor Corp	14.64	JP	2012-07	from the lack of supply caused by the great eastern **japan earthquake** last year especially in japan a market stimulated by ecocar	Supply chain disruption
Aeon Mall Co Ltd	8.38	JP	2012-04	of a loss on disaster related to the great east **japan earthquake** as well as provisions for asset retirement obligations for previouss	Exposed properties (shopping malls)
Osaka Gas Co Ltd	7.44	JP	2013-04	far this plan was created before the great east of **japan earthquake** despite the earthquake we believe the planned activities have progressed	Power shortages
Showa Denko KK	7.07	JP	2011-10	year but profit of heat exchangers affected by great east **japan earthquake** declined overall profit decreased jpy billion year on year to	Production disruption
MCubs MidCity Investment Corp	6.78	JP	2012-07	recovery in the market deteriorated due to the great east **japan earthquake** in the first quarter of but the downward trend had	Exposed properties
				Panel B: Non-JP firms	
Company	$\overline{\text{Fukushima Exposure}_i}$	Country	Month	Transcript excerpts	Exposure description
Lightbridge Corp	30.83	US	2013-10	be while they are still slowly reopening their reactors after **fukushima** our relationship with areva has been primarily based on thorium fuel	Nuclear fuel provider
Areva SA	30.05	FR	2011-07	japan with the earthquake and tsunami and the accident in **fukushima** nuclear power plant as of today reactors out of have been	Nuclear power supplier
Uranium One Inc.	20.47	CA	2012-10	options and pressure from business interests we believe that the **japanese nuclear** industry is probably on more of a longterm recovery plan	Uranium mining
Momentive Performance Materials Inc	19.73	US	2011-07	specialty products offset by raw material headwinds the effects of **japanese earthquake** foreign exchange and the onetime yearoveryear inventory change continued pricing	Nearby production plant disrupted
GSE Systems Inc	16.34	US	2012-04	safety control has been submitted to the state council previous **nuclear accidents** have resulted in new regulations requiring additional operator training higher	Supplier to nuclear industry
EnergySolutions, Inc.	15.85	US	2012-07	low cost of natural gas and the continuing reverberations from **fukushima** will increasingly drive the decommissioning of more nuclear power plants around	Nuclear waste disposal
Lite-On Technology Corporation	15.53	TW	2011-01	and i have another question given the supply disruption after **japanese earthquake** and the nokia transition whats your outlook in the second	Supplier to nuclear industry
Paladin Energy Ltd	14.46	AU	2011-04	kick in the teeth in its early days the damage **fukushima** sustained appeared very negative for nuclear but as cool heads start	Nuclear production
Cameco Corp	14.2	CA	2011-04	discuss the financial results and our latest assessments following the **fukushima** accident thanks for joining us with us are of camecos senior	Uranium producer
Global Indemnity plc	13.4	KY	2011-07	significantly impacted by million of catastropherelated losses resulting from the **earthquake and tsunami** in japan the earthquake in new zealand the floods	Insurance claims

Notes: This table shows transcript excerpts for the top five JP (Panel A) and the top ten non-JP (Panel B) firms ranked by $\overline{\text{FukushimaExopsure}_i}$. $\overline{\text{FukushimaExposure}_i}$ is calculated as the mean across all of a firm's available transcripts of earnings calls held between 2011 to 2013. Mentions of "Fukushima words" are in boldface.

Appendix

to

"The Global Impact of Brexit Uncertainty"

by

Tarek A. Hassan, Stephan Hollander, Laurence van Lent, and Ahmed Tahoun

A. Data Appendix

A.1. Earnings conference call transcripts

We start with all conference call transcripts held between 2011 and 2019 from Thomson Reuters' StreetEvents: N = 145, 902. In the process, we lose 1,509 transcripts because we could not reliably match them to a company name in Compustat.
We excluded (modified) the following bigrams from (in) transcripts:

- We modify "Bill" to "bbill" to avoid inflating bill as in "proposed law" with bill as in a person's name;
- We modify "Constitution" to "cconstitution" to avoid inflating "constitution" as in "the United States constitution" with "constitution" as in "a pipeline project";
- We remove "risk officer", "risk credit officer" to avoid the synonym "risk" catching these persons/positions;
- We remove "unknown speaker", "unknown participant", "unknown speaker", "unknown participant", "unknown caller", "unknown operator", and "unknown firm analyst" to avoid the synonym "unknown" catching these persons;
- We remove "in the states".

In addition, we removed 17,750 "safe harbor" snippets from transcripts. Specifically, if in a snippet from the first half of the transcript, either more than 2 words are safe harbor key words (see next) or less than 2 words are safe harbor key words and the word "forwardlooking" is in the snippet, then the snippet is removed. Safe harbor key words used: ['safe', 'harbor', 'forwardlooking', 'forward', 'looking', 'actual', 'statements', 'statement', 'risk', 'risks', 'uncertainty', 'uncertainties', 'future', 'events', 'sec', 'results']. Safe harbor statements use formulaic legal language to remind participants at the beginning of the call that forward looking information disclosed in the call will not be considered fraudulent unless it is made in bad faith or without reasonable basis.

A.2. Other data sources

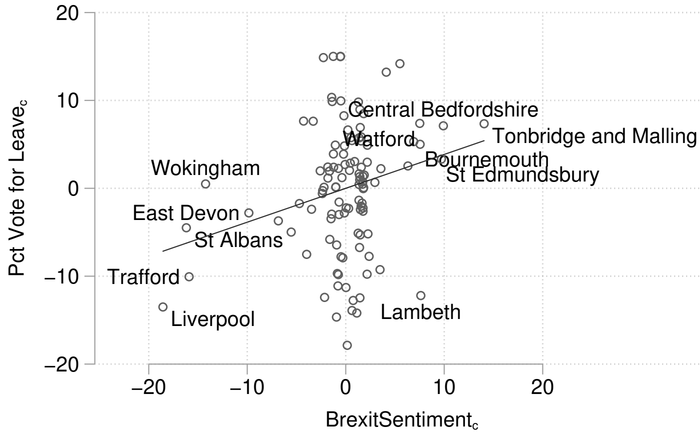
Investment rate, capital expenditure, sales, employment, and earnings announcement surprise. We obtain data on earnings per share, capital expenditure, property, plant, and equipment, investment, sales, and employment from Compustat. Our measure for capital expenditure, $\mathrm{I}_{i,t}/\mathrm{K}_{i,t-1}$, is calculated recursively using a perpetual-inventory method. Specifically, we calculate the investment rate as follows: for $t = 2$, $\frac{\mathrm{Capxy}_2}{\mathrm{Ppent}_1}$, for $t > 2$, $\frac{\mathrm{capxy}_t}{\mathrm{Recursive\ K}_{t-1}}$, where the denominator for $t > 2$ is calculated recursively as $\mathrm{Recursive\ K}_{t-1} = \Delta p_K \times \delta \times \mathrm{Recursive\ K}_{t-2} + \mathrm{Capxy}_{t-1}$, where Capxy is Compustat's out-of-the-box capital expenditure, Ppent is Compustat's out-of-the box property, plant, and equipment, and Δp_K is the ratio of this period's to last period's Producer Price Index (obtained from FRED), and δ is depreciation and set at 10%. We winzorize the variable at the first and last percentile. Change in sales, $\Delta\mathrm{sales}_{i,t}/\mathrm{sales}_{i,t-1}$, is the change in quarter-to-quarter sales over last quarter's value, winsorized at the first and last percentile. Employment change, $\Delta\mathrm{emp}_{i,t}/\mathrm{emp}_{i,t-1}$, is the change in year-to-year employment over last year's value, winsorized at the first and last percentile. Earnings announcement $\mathrm{surprise}_{i,t}$ is defined as $(\mathrm{EPS}_{i,t} - \mathrm{EPS}_{i,t-4})/\mathrm{price}_{i,t}$, where $\mathrm{EPS}_{i,t}$ is earnings per share (basic) of firm i at time t, and $\mathrm{price}_{i,t}$ is the closing price of quarter t.

Appendix Table 1: Data Coverage

	Number of Sample Firms	
	Headquarter country	With UK subsidiaries
Panel A: By country group		
UK	396	NA
EU non-UK	971	432
US	3,791	1,633
Rest of the world	2,575	776
Panel B: By country		
USA	3,791	1,633
Canada	546	155
UK	396	NA
Australia	321	105
India	270	65
China	181	24
Japan	153	95
Germany	150	79
Sweden	147	40
Brazil	139	17
France	130	77
Switzerland	98	51
Hong Kong	77	28
Netherlands	76	40
Italy	75	35
South Africa	74	36
Norway	68	23
Mexico	68	7
Bermuda	63	40
Israel	61	28
Spain	61	29
Ireland	53	32
Denmark	50	24
Finland	45	19
Singapore	41	11
Russia	41	2
New Zealand	39	5
S. Korea	34	14
Luxembourg	34	12
Taiwan	33	11
Belgium	31	9
Austria	31	15
Poland	28	6
Chile	25	3
Turkey	23	7
Thailand	21	5
Greece	20	1
Malaysia	18	5
Argentina	17	0
Philippines	15	4
Colombia	15	2
Indonesia	15	1
UK Channel Islands	15	6
Cyprus	14	4
United Arab Emirates	14	5
Nigeria	12	5
Cayman Islands	11	3
Peru	10	0
Monaco	10	1
Portugal	9	4
Czech Republic	6	2
Puerto Rico	5	0

Notes: This table reports the number of firms in our sample that are headquartered in each country (left column) and the number of these with one or more subsidiaries in the UK (right column). Panel A splits the sample by country group; Panel B splits by country. Countries with fewer than five headquartered firms are excluded.

Appendix Figure 1: Voting in Brexit Referendum: Column 3 of Table 6



Slope coeff.: 0.39, S.E.: 0.15

Notes: This figure presents an added variable plot for the specification in Column 3 of Table 6. We label the observations with a residual value larger than 1.6 standard deviations from the sample mean.

Appendix Table 2: Most Frequent Synonyms for Risk or Uncertainty

Word	Frequency	Word	Frequency
uncertainty	1,157	prospect	4
uncertainties	260	unsure	3
risk	205	bet	3
uncertain	96	insecurity	3
risks	77	risky	3
unknown	33	danger	3
possibility	26	faltering	2
exposed	23	dilemma	2
instability	20	probability	2
threat	17	indecision	2
pending	17	suspicion	2
doubt	16	hesitant	2
fear	16	unpredictability	2
unclear	14	unstable	2
unresolved	13	sticky	1
chance	12	venture	1
likelihood	7	fluctuating	1
unsettled	6	hesitating	1
unpredictable	6	reservation	1
variable	5	speculative	1

Notes: This table shows the frequency across all 85,468 earnings call transcripts between 2015q1 and 2019q1 of all single-word synonyms of "risk," "risky," "uncertain," and "uncertainty" as given in the Oxford Dictionary (excluding "question" and "questions") that appear within 10 words of "Brexit".

Appendix Table 3: Most Frequent Positive Tone Words

Word	Frequency	Word	Frequency
despite	250	improvement	23
good	231	greater	23
strong	170	profitability	23
positive	162	benefited	23
opportunities	99	improving	23
great	98	stability	20
opportunity	70	improve	19
better	67	optimistic	19
stable	65	advantage	16
able	55	favorable	14
benefit	49	stabilize	13
leading	48	rebound	13
confident	37	strengthening	12
progress	35	gain	11
pleased	33	successful	11
improved	31	tremendous	11
gains	29	excellent	11
stronger	28	successfully	9
strength	26	achieve	9
best	24	stabilized	9

Notes: This table shows the frequency across all 85,468 earnings call transcripts between 2015q1 and 2019q1 of all positive tone words from Loughran and McDonald (2011) (their list contains 354 positive tone words) appearing within 10 words of "Brexit."

Appendix Table 4: Most Frequent Negative Tone Words

Word	Frequency	Word	Frequency
volatility	297	negatively	40
concerns	220	slowing	39
negative	182	adverse	38
difficult	102	aftermath	37
challenges	99	unexpected	37
slowdown	99	turmoil	35
decline	85	slower	35
concerned	85	slowed	32
concern	84	shutdown	31
against	74	challenge	31
weakness	74	crisis	30
disruption	72	fears	29
weak	63	delays	26
weaker	63	weakened	25
slow	50	problems	25
late	49	delay	24
weakening	47	caution	23
challenging	43	delayed	23
volatile	43	exposed	23
fallout	42	recall	22

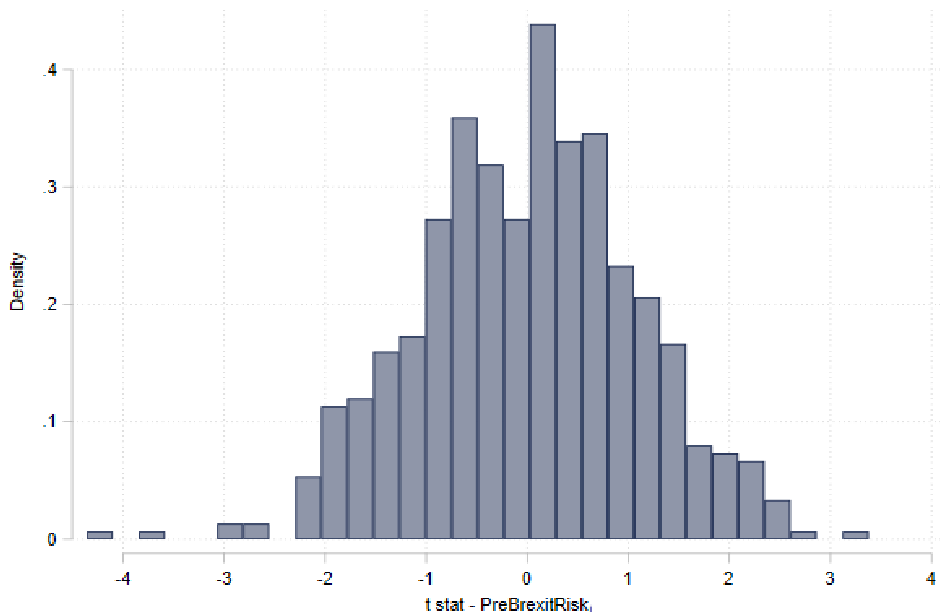
Notes: This table shows the frequency across all 85,468 earnings call transcripts between 2015q1 and 2019q1 of all negative tone words (with the exception of "question," "questions," and "ill") from Loughran and McDonald (2011) (their list contains 2,352 negative tone words) appearing within 10 words of "Brexit".

Appendix Table 5: Distribution of Sample Firms across Districts in UK

Number of counties	Number of firms
54	1
26	2
14	3
7	4
5	5
3	6
3	7
1	8
1	10
1	54
1	90

Notes: This table shows the number of UK districts (left column) with the number of UK firms in our sample headquartered in that district (right column).

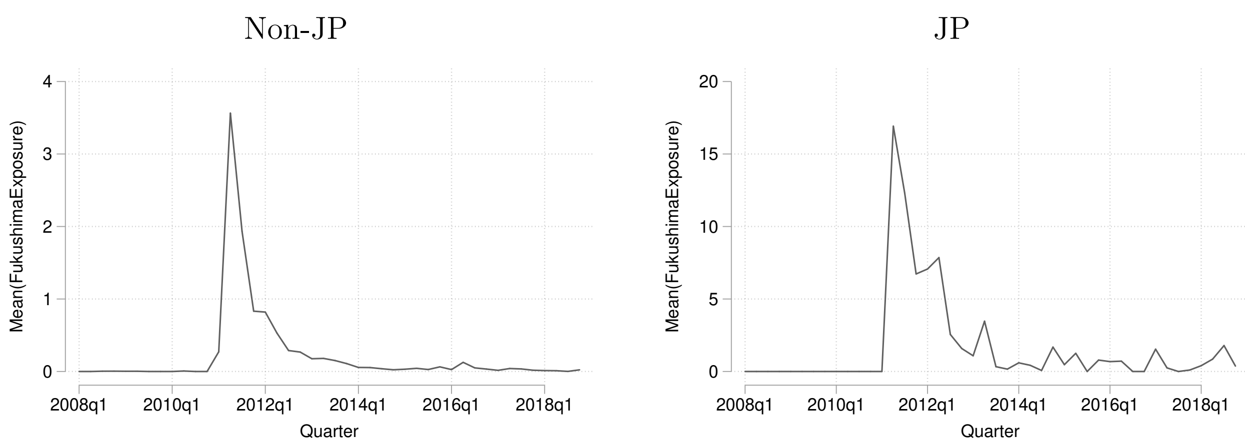
Appendix Figure 2: Placebo Tests



Rejection rate (< -1.96): 3.06%

Notes: As a placebo exercise, we repeat the regression specifications in Column 5 of Table 5 taking four consecutive trading days at a time from January 1, 2012 and December 31, 2015. This figure plots the distribution of the t-statistic for the coefficient on PreBrexitRisk$_i$ from each of those regression specifications.

Appendix Figure 3: Time Series of FukushimaExposure



Notes: This figure plots the quarterly mean of non-Japan and Japan headquartered firms' FukushimaExposure. $\overline{\text{FukushimaExposure}}_i$ is normalized using the average $\overline{\text{FukushimaExposure}}_i$ of JP-headquartered firms.

Appendix Table 6: Brexit Risk and Estimated Average Effects by Country

Country	Mean Brexit risk (s.e.)	Max Brexit risk	N	Estimated effect (%) on $I_{i,t+1}/K_{i,t}$	$\Delta emp_{i,t}/emp_{i,t-1}$
All firms	0.196 (0.011)	12.387	7,674	-0.43	-0.71
USA	0.111 (0.010)	18.371	3,791	-0.37	-1.21
Ireland	1.681 (0.489)	18.312	53	-3.91	-4.21
UK Channel Islands	1.174 (1.628)	10.564	8	-2.10	-3.30
United Kingdom	1.000 (0.115)	18.911	396	-2.82	-4.25
South Africa	0.579 (0.164)	7.926	74	-1.99	-8.10
Netherlands	0.444 (0.118)	5.560	76	-1.18	-2.04
Denmark	0.434 (0.158)	5.299	50	-1.57	-1.84
France	0.386 (0.078)	4.617	130	-1.38	-2.59
Belgium	0.372 (0.188)	5.054	31	-1.49	-2.24
Switzerland	0.326 (0.099)	7.673	98	-1.19	-2.79
Sweden	0.322 (0.109)	12.592	147	-0.75	-1.18
Singapore	0.314 (0.145)	5.565	41	-0.87	-1.82
Germany	0.304 (0.056)	3.658	150	-0.88	-1.71
Spain	0.287 (0.098)	3.696	61	-1.21	-2.48
Australia	0.208 (0.058)	9.910	321	-0.43	-0.72
Norway	0.205 (0.124)	7.506	68	-0.44	-0.65
Monaco	0.202 (0.202)	2.021	10	-0.45	-0.30
Hong Kong	0.189 (0.091)	4.437	77	-0.55	-0.98
Austria	0.152 (0.089)	2.523	31	-0.62	-1.10
S. Korea	0.151 (0.069)	1.658	34	-0.28	-2.56
Bermuda	0.131 (0.051)	2.291	63	-0.42	-0.44
Canada	0.125 (0.029)	6.469	546	-0.25	-0.33
India	0.118 (0.032)	5.104	270	-0.25	-0.61
Finland	0.116 (0.095)	4.245	45	-0.48	-2.06
Japan	0.115 (0.040)	4.382	153	-0.44	-0.77
Luxembourg	0.114 (0.059)	1.713	34	-0.28	-0.62
Italy	0.096 (0.052)	3.494	75	-0.37	-0.74
Mexico	0.084 (0.063)	4.151	68	-0.28	-0.50
Turkey	0.061 (0.043)	0.808	23	-0.49	-0.48
Russia	0.055 (0.055)	2.238	41	-0.09	-0.20
Malaysia	0.030 (0.030)	0.548	18	-0.09	-0.40
New Zealand	0.030 (0.030)	1.183	39	-0.07	-0.06
Chile	0.027 (0.027)	0.681	25	-0.12	-0.57
Greece	0.025 (0.025)	0.498	20	-0.11	-0.55*
Poland	0.023 (0.023)	0.644	28	-0.07	-0.08
Israel	0.022 (0.022)	1.353	61	-0.05	-0.07
China	0.005 (0.005)	0.870	181	-0.00	-0.01
Brazil	0.004 (0.004)	0.561	139	-0.01	-0.03

Notes: For the country indicated in the first column, this table shows the mean (standard error), and max of Brexit risk; the number of firms, and the estimated effect relative to the country-specific sample mean on $I_{i,t+1}/K_{i,t}$ and $\Delta emp_{i,t}/emp_{i,t-1}$. The mean and max of Brexit risk are calculated over all firms headquartered in that country. N is the total number of our sample firms within a specific country. The estimated effect (%) is calculated as $\hat{\beta}_y \times \overline{\text{BrexitRisk}_{i,t}}^c / \overline{y_{i,t}}^c$, where $y \in \{I_{i,t+1}/K_{i,t}.100, \Delta emp_{i,t}/emp_{i,t-1}.100\}$, and $\hat{\beta}_y$ is the estimated coefficient from Column 5 of Table 7 (Panel A for all countries and Panel B for the US) and Table 9 (Panel A column 2 for all countries and Panel A Column 4 for the US), respectively. For Greece, the estimated effect on employment (marked by an *) is normalized by average employment growth in the entire panel instead of average employment growth rate in Greece (which is just below zero). As before, the Table excludes countries for which we have fewer than five headquartered firms.

Appendix Table 7: Brexit Sentiment by Country

	Brexit sentiment			
Country	Mean (s.e.)	Min	Max	N
Ireland	-1.386 (1.056)	-44.593	8.898	53
United Kingdom	-1.000 (0.211)	-37.778	10.806	396
Germany	-0.773 (0.224)	-17.177	8.064	150
Austria	-0.604 (0.509)	-12.918	2.507	31
Norway	-0.561 (0.291)	-14.526	1.670	68
Italy	-0.544 (0.309)	-18.209	3.872	75
Denmark	-0.494 (0.299)	-9.236	5.241	50
Sweden	-0.441 (0.364)	-33.137	12.056	147
France	-0.404 (0.243)	-22.672	9.341	130
Hong Kong	-0.403 (0.243)	-14.837	5.014	77
New Zealand	-0.392 (0.264)	-9.267	0.000	39
Singapore	-0.376 (0.181)	-6.424	0.887	41
Monaco	-0.338 (0.338)	-3.379	0.000	10
Belgium	-0.321 (0.151)	-3.250	1.352	31
Chile	-0.308 (0.265)	-6.565	0.000	25
Greece	-0.285 (0.193)	-3.712	0.000	20
Luxembourg	-0.271 (0.129)	-3.461	0.000	34
Malaysia	-0.258 (0.258)	-4.649	0.000	18
Spain	-0.241 (0.148)	-6.095	2.173	61
India	-0.210 (0.108)	-12.173	15.205	270
Turkey	-0.208 (0.124)	-2.433	0.000	23
Russia	-0.182 (0.182)	-7.481	0.000	41
Finland	-0.166 (0.150)	-4.368	3.816	45
Mexico	-0.150 (0.101)	-5.373	1.084	68
Canada	-0.140 (0.049)	-13.691	9.301	546
Japan	-0.131 (0.197)	-25.473	10.767	153
South Africa	-0.130 (0.232)	-4.569	11.808	74
Switzerland	-0.128 (0.217)	-6.600	6.718	98
S. Korea	-0.089 (0.124)	-3.369	1.386	34
Netherlands	-0.068 (0.231)	-6.199	10.260	76
China	-0.060 (0.045)	-7.817	0.000	181
Bermuda	-0.043 (0.151)	-4.750	4.579	63
Brazil	-0.032 (0.025)	-2.449	1.013	139
Israel	0.023 (0.023)	0.000	1.388	61
Poland	0.057 (0.057)	0.000	1.607	28
Australia	0.062 (0.169)	-16.335	38.573	321
UK Channel Islands	1.713 (2.233)	-2.341	15.728	8

Notes: For the country indicated in the first column, this table shows the mean (standard error), min, and max of Brexit sentiment, and the number of firms. The mean, min, and max of Brexit sentiment are calculated over all firms headquartered in a specific country. N is the total number of our sample firms in a specific country. We exclude countries for which we have fewer than five firms.

Appendix Table 8: Robustness: BrexitRisk, BrexitSentiment, and Employment Growth

	$\Delta emp_{i,t}/emp_{i,t-1} \cdot 100$					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A	All firms					
$\text{BrexitRisk}_{i,t}$	−0.487***	−0.495***	−0.391**	−0.403**	−0.589**	−0.531***
	(0.176)	(0.179)	(0.179)	(0.187)	(0.289)	(0.190)
$\text{BrexitSentiment}_{i,t}$	0.000	−0.016	−0.011	−0.024	−0.038	0.015
	(0.083)	(0.084)	(0.082)	(0.084)	(0.108)	(0.082)
$\text{NonBrexitRisk}_{i,t}$ (std.)		−0.155	−0.758***	−1.114***	−1.511***	−0.754***
		(0.195)	(0.214)	(0.255)	(0.327)	(0.214)
$\text{NonBrexitSentiment}_{i,t}$ (std.)		1.464***	1.498***	1.526***	1.596***	1.501***
		(0.192)	(0.210)	(0.214)	(0.261)	(0.210)
$\text{PRiskTrade}_{i,t}$ (std.)				−0.134		
				(0.214)		
Average UK sales_i (pre-Brexit)					−2.756	
					(3.198)	
$\overline{\text{BrexitExposure}_i}$						1.158**
						(0.493)
R^2	0.020	0.024	0.052	0.055	0.064	0.052
N	27,156	27,156	27,141	26,160	18,326	27,141
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y
Industry x Year FE	N	N	Y	Y	Y	Y
Country FE	N	N	Y	Y	Y	Y
Panel B	US firms					
$\text{BrexitRisk}_{i,t}$	−1.277***	−1.211***	−1.272***	−1.238***	−0.952***	−1.423***
	(0.442)	(0.430)	(0.460)	(0.463)	(0.335)	(0.488)
R^2	0.022	0.027	0.057	0.059	0.060	0.057
N	18,117	18,117	18,099	17,817	14,856	18,099
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y
Industry x Year FE	N	N	Y	Y	Y	Y

Notes: This table reports results from regressions of $\Delta emp_{i,t}/emp_{i,t-1} \cdot 100$ on $\text{BrexitRisk}_{i,t}$ and $\text{BrexitSentiment}_{i,t}$ using yearly data. Panel A uses the sample of all firms, while Panel B restricts the analysis to firms headquartered in the US. The dependent variable is winsorized at the 1st and 99th percentile. All right-hand side variables are defined as in Table 8. All regressions control for log(assets) and for year, two-digit-SIC, and country fixed effects. The regressions exclude non-UK firms with fewer than 10 transcripts in 2015-2018, and firms in the 'Non Classifiable' sector. Standard errors are clustered by firm. *, **, *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

Appendix Table 9: Robustness: BrexitRisk, BrexitSentiment, and Sales Growth

	$\Delta sales_{i,t}/sales_{i,t-1} \cdot 100$					
	(1)	(2)	(3)	(4)	(5)	(6)
PANEL A	All firms					
BrexitRisk$_{i,t}$	–0.377	–0.396	–0.135	–0.049	–0.574	–0.243
	(0.251)	(0.253)	(0.251)	(0.262)	(0.394)	(0.272)
BrexitSentiment$_{i,t}$	0.136*	0.118	0.135*	0.130	0.135	0.153*
	(0.074)	(0.075)	(0.081)	(0.082)	(0.129)	(0.079)
NonBrexitRisk$_{i,t}$ (std.)		0.597	–0.009	–0.261	–0.993	–0.009
		(0.368)	(0.435)	(0.552)	(0.732)	(0.436)
NonBrexitSentiment$_{i,t}$ (std.)		1.947***	1.939***	2.002***	2.329***	1.941***
		(0.345)	(0.379)	(0.381)	(0.455)	(0.379)
PRiskTrade$_{i,t}$ (std.)				–0.698**		
				(0.324)		
Average UK sales$_i$ (pre-Brexit)					–3.111	
					(8.740)	
$\overline{\text{BrexitExposure}}_i$						0.841
						(0.824)
R^2	0.024	0.025	0.052	0.054	0.061	0.052
N	29,059	29,059	29,042	27,890	18,967	29,042
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y
Industry x Year FE	N	N	Y	Y	Y	Y
Country FE	N	N	Y	Y	Y	Y
PANEL B	US firms					
BrexitSentiment$_{i,t}$	0.346**	0.305**	0.410**	0.383**	0.295*	0.422**
	(0.140)	(0.142)	(0.167)	(0.164)	(0.158)	(0.166)
R^2	0.034	0.035	0.058	0.060	0.061	0.058
N	18,846	18,846	18,828	18,532	15,371	18,828
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y
Industry x Year FE	N	N	Y	Y	Y	Y

Notes: This table reports results from regressions of $\Delta sales_{i,t}/sales_{i,t-1} \cdot 100$ on BrexitRisk$_{i,t}$ and BrexitSentiment$_{i,t}$ using yearly data. The dependent variable is winsorized at the 1st and 99th percentile. All right-hand side variables are defined as in Table 8. All regressions control for log(assets) and for year, two-digit-SIC, and country fixed effects. The regressions exclude non-UK firms with fewer than 10 transcripts in 2015-2018, and firms in the 'Non Classifiable' sector. Standard errors are clustered by firm. *, **, *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

Appendix Table 10: Timing of the Effect of Brexit Risk

	$I_{i,t}/K_{i,t-1} \cdot 100$	$\Delta emp_{i,t}/emp_{i,t-1} \cdot 100$
	(1)	(2)
$\text{BrexitRisk}_{i,t}$	–0.251	–0.509**
	(0.156)	(0.210)
$\text{BrexitRisk}_{i,t-1}$	–0.471***	–0.172
	(0.150)	(0.238)
R^2	0.072	0.047
N	21,449	22,698

Notes: This table reports estimates from panel regressions using yearly data. In all specifications, we control for log(assets) and for two-digit-SIC×year and country fixed effects. The regressions exclude non-UK firms with fewer than 10 transcripts in 2015-2018, and firms in the 'Non Classifiable' sectors. Standard errors are clustered by firm. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

Appendix Table 11: Top 100 Ngrams from Newspaper Articles

Ngram	Count
nuclear power	544
the nuclear	382
the fukushima	371
the plant	320
fukushima daiichi	285
the reactor	282
nuclear plant	218
the reactors	215
power plant	199
a nuclear	182
of radiation	179
fuel rods	167
earthquake and	158
of nuclear	157
the earthquake	154
and tsunami	140
nuclear plants	136
tokyo electric	134
power plants	131
three mile	125
mile island	123
the plants	123
radiation levels	115
the disaster	114
nuclear energy	112
at fukushima	112
daiichi nuclear	111
nuclear reactors	101
the quake	98
disaster in	97
atomic energy	95
the tsunami	93
reactors at	93

Ngram	Count
japans nuclear	89
per cent	87
no reactor	87
nuclear disaster	86
of radioactive	86
the chernobyl	85
nuclear safety	85
nuclear crisis	82
cooling systems	82
a meltdown	81
nuclear industry	80
daiichi plant	79
explosion at	79
the cooling	77
the accident	76
fukushima nuclear	76
nuclear accident	71
japanese government	71
fukushima plant	70
international atomic	70
edano said	69
prime minister	68
cooling system	67
plant and	66
energy agency	65
spent fuel	65
reactor no	64
yukio edano	63
nuclear regulatory	62
the radiation	61
in fukushima	60
an earthquake	60
radioactive material	58

Ngram	Count
the containment	57
power co	57
from japan	57
cool the	56
us nuclear	55
nuclear fuel	55
safety agency	53
the stricken	52
magnitude earthquake	51
reactors in	51
reactors and	50
sea water	49
cabinet secretary	49
reactor core	49
japanese authorities	49
accident in	49
to japan	49
plants are	49
the site	49
japanese nuclear	48
plant the	48
nuclear reactor	47
at japans	46
of water	46
the pacific	46
fukushima no	44
containment vessel	44
a tsunami	44
the radioactive	44
reactors are	43
knocked out	42
natural disaster	42
reactor and	41
chief cabinet	41

Notes: This table shows the top 100 Bigrams from newspaper articles published after the Fukushima accident in March 2011. To get to this list, we proceed as follows: We use Factiva to search for "fukushima AND nuclear AND (disaster OR accident)" in the source "Newspapers: All," with language "English," and date within 3 months after the accident. We download the first 300 newspaper articles by date of publication, remove non-letters, force words to be lower case, and count all adjacent two-word combinations (bigrams). Finally, we remove bigrams that are also in the set of bigrams formed from 300 randomly selected newspaper articles about economic news before 2011.