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## **The Global Impact of Brexit Uncertainty**

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Lent and Ahmed Tahoun

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## Abstract

We propose a text-based method for measuring and analyzing the international propagation of uncertainty shocks at the firm level. We apply this method to estimate the impact of Brexit-related uncertainty and find widespread reverberations on listed firms in 81 countries. International firms most exposed to Brexit uncertainty not only significantly lost market value but also reduced hiring and investments. In addition to Brexit uncertainty (the second moment), we find that international firms overwhelmingly expected negative direct effects from Brexit (the first moment). Most prominently, firms expected difficulties from regulatory divergence, reduced labor mobility, and limited trade access.

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Keywords: Brexit, uncertainty, sentiment, Machine Learning, cross-country effects

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# The Global Impact of Brexit Uncertainty\*

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March 2021

## Abstract

We propose a text-based method for measuring and analyzing the international propagation of uncertainty shocks at the firm level. We apply this method to estimate the impact of Brexit-related uncertainty and find widespread reverberations on listed firms in 81 countries. International firms most exposed to Brexit uncertainty not only significantly lost market value but also reduced hiring and investments. In addition to Brexit uncertainty (the second moment), we find that international firms overwhelmingly expected negative direct effects from Brexit (the first moment). Most prominently, firms expected difficulties from regulatory divergence, reduced labor mobility, and limited trade access.

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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 world economy is, however, an open question, not the least to policy makers and politicians struggling to find an appropriate response.<sup>1</sup> 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 transcripts of discussions during earnings conference calls between firms’ management and financial analysts when they talk about Brexit, or any other specific shock (e.g., the Fukushima nuclear disaster, studied later in the paper). We demonstrate how a text-based approach can simultaneously capture a given firm’s exposure to the shock and provide a way to decompose measured exposure into expected costs, benefits, and risks as assessed by the firm’s management and its analysts. We then illustrate our method with a comprehensive empirical analysis of how US and international firms respond to the Brexit referendum shock, and provide first evidence of the global repercussions of Brexit uncertainty.

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](#); [Broadbent et al., 2019](#)).<sup>2</sup> However, attempts to quantify the effect on and responses of firms *outside the UK* have proven more complicated. Indeed, the exposure of international firms (i.e., firms not located in the UK) to Brexit—and more generally the cross-border impact of any shock—is hard to measure for at least three reasons. First, international exposures can come from many potentially interdependent sources, including barriers to product market access, frictions in managing relationships with customers, suppliers, or subsidiaries, and hurdles in expanding business. This means that any attempt to

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<sup>1</sup>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](#)).

<sup>2</sup>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 \(2019\)](#).

quantify Brexit exposure for an international firm may overlook economically meaningful but potentially indirect determinants that are hard to glean from conventional financial disclosures. Second, exposure to Brexit is not a time-invariant 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.<sup>3</sup> (As yet, it still remains uncertain how the economic relation between the EU and its former member country will evolve.) Thus, any proposed measure of exposure to a shock like Brexit needs to be able to track its longitudinal impact (which, in the case of Brexit, has varied substantially over the years since the British electorate voted to leave the European Union), while also, at the same time, accounting for cross-sectional heterogeneity in the response to the shock. Third, in addition to the impact on uncertainty (the second moment), exposure to Brexit also stems from its 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. Using natural language processing, we propose a general text-based method for isolating first- and second-moment effects stemming from specific shocks. Our approach identifies the exposure of firms to a given shock (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 earnings calls usually happen in

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<sup>3</sup>While this persistent uncertainty clearly weighed 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.

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 participants on these earnings calls 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. Thus, using these earnings 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 method developed by [Hassan et al. \(2019\)](#), to bifurcate our overall measure of Brexit exposure into its first-moment (*BrexitSentiment*) and second-moment (*BrexitRisk*) effects. Specifically, 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*. By disentangling risk and sentiment, we take an important first step in providing evidence on the mechanisms at play in the firm’s response to a significant shock—detailing the extent to which *first* or *second* moment effects explain cardinal firm policy outcomes. Our text-based approach allows us to investigate further the nature of the Brexit-related impacts by identifying the exact topics call participants raise when discussing Brexit.

Using these new measures, we document a set of original empirical findings on the impact of Brexit on firms in 81 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 second quarter of 2019 when a “no deal” Brexit

became a real possibility, we also show widespread worries about Brexit-related risks among non-UK firms. For instance, Irish firms on average discuss Brexit significantly more than do UK firms. Remarkably, Brexit risk 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* up to the country level, there is no single country with a significantly positive average. Only in tax havens such as the Channel Islands is the average sentiment towards Brexit positive, though not statistically distinguishable from zero. Next, through a human reading of a large number of text snippets from earnings calls that mention Brexit, we 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 the costs of post-Brexit operational adjustments. There are some instances where firms articulate positive outlooks: in the most positively toned 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.<sup>4</sup>

We next examine how US and other international firms respond to their Brexit shock exposure. Using our time-varying firm-specific measure, we show that, up to the end of our sample period, Brexit exposure mostly affects firm-level actions through risk, as opposed to through sentiment. We document meaningful, negative effects of *BrexitRisk* on firms' investment and employment decisions as well as on contemporaneous stock returns. For example, we estimate that, due to Brexit risk, the average Irish firm decreased its investment rate by 2.53% and reduced its net hiring rate by 3.75%, relative to the mean in each of the first three years after the Brexit referendum. For US-based firms (which are, on average,

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<sup>4</sup>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](http://www.voteleavetakecontrol.org/our_case.html).



about as exposed to Brexit as Italian firms), reductions in average investment and net hiring rates are 0.33% and 0.86%, respectively.

Though we lack a formal instrument for Brexit exposure, we address the three most plausible challenges to a causal interpretation of these results. First, corporate 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 latter, not the former, that explains the investment and employment response. Third, firms doing business 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 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. Adding further controls for possibly unobserved heterogeneity that is correlated with Brexit and investments or hiring, also does not change inferences.

We supplement these analyses with two key pieces of evidence. First, we investigate how stock markets reacted to the—by most accounts, surprising—outcome of the 2016 referendum. We show that *BrexitSentiment* is positively associated with stock returns in an event window around the date of the referendum, whereas the association with the variance of firm-level exposure to Brexit (i.e., *BrexitRisk*) is significantly negative. In other words, both first- and second-moment exposure to Brexit is quickly impounded into stock prices after the announcement of the referendum result. The market thus prices international firms' Brexit-related costs, opportunities, and risks.

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 the 2016 referendum. Our findings show that constituents who live closer to the firms most negatively affected by Brexit tended to vote to remain in the EU.

Taking this evidence together, we conclude that during our sample period (through the end of December 2019), 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 predominantly a response to increased uncertainty, rather than to the changes in the mean of their exposure to the Brexit shock (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 consequences of the Brexit shock on firms’ employment and investment policies is important in its own right, our aim is to showcase the versatility of our text-based approach to measure firm-level exposure to a wide range of specific shocks, even those that do not become synonymous with a unique term, such as “Brexit.” To demonstrate this point, we apply our approach to the nuclear disaster in Fukushima, Japan, in March 2011. While “Fukushima” became a short-hand for the catastrophe at the Daiichi Nuclear Power Plant, many other phrases were commonly used as well. In this second application, we illustrate how to use training libraries to identify these phrases and count their use in international firms’ conference call transcripts. We then briefly characterize exposure to the Fukushima disaster across firms and countries. This case serves to show that our approach can easily be modified to measure the international propagation of various types of shocks, including natural disasters, epidemics (such as the coronavirus outbreak), technological breakthroughs, or political events (e.g., revolutions, government shutdowns).

**Related literature.** 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](#); [Maggiore, 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. We believe that, as such, it represents the first example of

such a transmitted uncertainty shock identified in firm-level data.

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., [Braggion et al., 2020](#); [Barrot and Sauvagnat, 2016](#); [Schnabl, 2012](#); [Boehm et al., 2019](#); [Carvalho et al., 2016](#); [Anderson et al., 2019](#)). We contribute to this literature by providing a broadly applicable, text-based, methodology for measuring the transmission of a wide range large shocks that flexibly captures a wide range of commercially important cross-firm dependencies that include, but are not limited to, customer-supplier or lender-borrower relationships.

A large and growing body of studies argues that variation in uncertainty affects 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](#); [Kojen 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 identifying variation in uncertainty stemming from specific events, policies, and other shocks at the firm level. In doing so, we take an important step towards causal identification of the effects of uncertainty shocks.

Our work complements contemporaneous studies that quantify the impact of Brexit on UK-based firms (e.g., [Sampson, 2017](#); [Graziano et al., 2018](#); [Broadbent et al., 2019](#)). [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 find economically meaningful negative consequences for UK firms, we in particular highlight the economic consequences of Brexit uncertainty for *non-UK* firms.<sup>5</sup>

Finally, we add to the growing literature in macroeconomics and related fields using text as data ([Gentzkow et al., 2019](#)). Our work highlights the versatility of text-based

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<sup>5</sup>[Campello et al. \(2020\)](#) document the investment and hiring effects of Brexit for a sample of US firms exposed to the UK economy. [Martin et al. \(2019\)](#) consider the costs related to Brexit to French exporters.

measurement of firm-time specific variables, adding to recent studies that use transcripts of earnings conference calls and corporate filings of US firms to measure firm-level political and non-political risk (Hassan et al., 2019), overall risk (Handley and Li, 2018), climate change exposure (Sautner et al., 2020), cyber risk (Jamilov et al., 2021), 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).

## 1. DATA

Our primary data are transcripts of quarterly earnings conference calls held by publicly listed firms. From Refinitiv EIKON, we collect the complete set of 176,149 English-language transcripts from 2011 through 2019, covering 10,059 firms headquartered in 81 countries. Firms host these conference 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).<sup>6</sup> As shown in Panel A of Appendix Table 1, our data covers 7,733 unique firms, of which 1,463 are headquartered in EU countries (428 in the UK), 3,948 in the United States, and 2,767 in the rest of the world. Panel B of Appendix Table 1 shows the extensive global coverage of listed firms in our sample. This coverage is important because Brexit exposure is not likely 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 3,900 US-based firms, 1,634 have disclosed establishments in the UK.

Financial statement data, which includes information on employment, investments, sales, and earnings, are taken from Standard & Poor’s Compustat North America (US) and Global

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<sup>6</sup>Alternatively, we could have used firms’ annual reports (SEC Form 10-K) as a text source (see, for example, Campello et al., 2020). We decided against this approach as using annual reports as a text source 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.

(non-US) files. Stock return data are from the Center for Research in Security Prices and Refinitiv Datastream. Data on UK subsidiaries are sourced from ORBIS; UK district voting results on the Brexit referendum (as well as basic demographic data on these districts) are from the Office for National Statistics. Details on these data sources and the construction of variables are in Appendix A.

## 2. MEASURING FIRM-LEVEL BREXIT EXPOSURE, RISK, AND SENTIMENT

To create a time-varying measure of a given firm’s Brexit *exposure*, we parse this firm’s 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:<sup>7</sup>

$$(1) \quad \text{BrexitExposure}_{it} = \frac{1}{B_{it}} \sum_{b=1}^{B_{it}} 1[b = \text{Brexit}],$$

where  $b = 0, 1, \dots, B_{it}$  are the words contained in firm  $i$ ’s earnings call held in quarter  $t$ .<sup>8</sup>

A key challenge to isolating the effect of Brexit-related uncertainty is that Brexit’s first- and second-moment impacts are likely correlated. For example, a French exporter may worry about the possibility of future tariffs on her UK-bound exports and could expect her business to be less profitable (a lower conditional mean) in addition to having 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.

To separate such first- and second-moment impacts we next construct measures of Brexit *risk* and *sentiment* by conditioning our word counts on proximity to synonyms for risk or

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<sup>7</sup>Google Trends shows the first use of the term “Brexit” in October 2012. Its usage increased in January 2016 and peaked in June 2016. “Brixit” was proposed as an alternative term, but does not have a meaningful volume on Google Trends in the sample period.

<sup>8</sup>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”).

uncertainty and positive and negative tone words, respectively. Following the procedure in Hassan et al. (2019), we define

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

where  $r$  is the position of the nearest synonym of risk or uncertainty. To measure risks associated with Brexit, we thus count only mentions of “Brexit” that occur within a neighborhood of 10 words of a synonym for “risk” or “uncertainty” from the Oxford English Dictionary.<sup>9</sup> 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 between 2016-2019.

To measure whether Brexit is good or bad news for the firm (its first-moment impact) we follow the same procedure, but now condition on proximity to positive and negative tone words, as obtained from the Loughran and McDonald (2011) sentiment dictionary:<sup>10</sup>

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

where  $S$  assigns sentiment, so that  $S(c)$  equals +1 if  $c \in \mathbb{S}^+$ , -1 if  $c \in \mathbb{S}^-$ , and zero otherwise. Positive-tone words include ‘good,’ ‘strong,’ ‘great,’ while negative-tone words include ‘loss,’ ‘decline,’ and ‘difficult.’<sup>11,12</sup> Appendix Tables 3 and 4 show the most frequently used tone

<sup>9</sup>See Appendix Table 2 for a list of these synonyms. We exclude ‘question’ and ‘questions’ from this list of synonyms as call moderators often ask for the ‘next question.’

<sup>10</sup>Thirteen of the synonyms for risk or uncertainty used in our sample of earnings conference calls also have a negative connotation 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*.

<sup>11</sup>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.

<sup>12</sup>One potential concern with this kind of sentiment analysis is the use of negation, such as ‘not good’ or ‘not terrible’ (Loughran and McDonald, 2016). However, in our human audit of snippets, we found only few instances in which inferences were affected by negation. Accordingly, we chose not to complicate the construction of our measures by explicitly allowing for it.

words in our corpus.<sup>13</sup> As for *BrexitRisk*, we standardize *BrexitSentiment* by the average *BrexitSentiment* for UK headquartered firms after 2015; a value of -1 thus denotes the average Brexit sentiment of UK firms between 2016-2019.

For use as control variables and in robustness checks, we also construct measures of each firm’s non-Brexit-related risk and sentiment following the above procedure, 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 newly created measures, *BrexitExposure*, *BrexitRisk*, and *BrexitSentiment*, to corroborate that they indeed 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. Then, we consider the constituent parts of *BrexitExposure* separately, describing (in detail) the patterns of both *BrexitRisk* and *BrexitSentiment* over time and across countries. Finally, to further validate our method, we present the results from extensive human reading of text fragments (“snippets”) in which Brexit is mentioned to determine the content of the associated discussions.

**Brexit exposure.** Table 1 presents estimates from cross-sectional regressions of the mean *BrexitExposure* of each firm across time onto firm-specific characteristics that are *ex*

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<sup>13</sup>The most common positive-tone word used near “Brexit” is ‘despite’; versions of *BrexitSentiment* constructed with and without ‘despite’ have a correlation of 98.73% and do not result in any differences in our results.

*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.<sup>14</sup> Because of the stickiness of firm location choice, we average each firm’s Brexit exposure across our sample period from 2016 through 2019, and report robust standard errors. Columns 1 and 2 in Table 1 only consider geographical location (having 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 sales earned in the UK. We consider 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 with international headquarters. Once more, this effect appears to be subsumed by 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.

**Brexit risk.** Having offered evidence that supports the validity of our Brexit exposure measure, *BrexitExposure*, we next explore the properties of *BrexitRisk* and *BrexitSentiment*. Panel A of Figure 1 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).

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<sup>14</sup>We determine headquarters location based on the field “Country of domicile” in EIKON. EIKON also offers the field “Country of legal registration,” which we do not use to determine physical presence.



*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 0.4; in other words, immediately after the referendum, Brexit risk for international firms reaches almost half the level of the average UK firm's Brexit risk in the 2016-2019 period. UK firms have a similar peak, with average *BrexitRisk* reaching about 1 immediately following the referendum.<sup>15</sup> While *BrexitRisk* subsides in 2017, it rises sharply in the second half of 2018, nearly reaching 2 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, the prospect of the UK leaving the EU without a deal (and resorting back to WTO trade terms) became more likely, and the uncertainty about Brexit remained high through the end of our sample.<sup>16</sup>

Figure 2 shows the average *BrexitRisk* by firm-headquarters country for all countries with non-zero *BrexitRisk* and a minimum of five headquartered firms. (Countries with zero country-level *BrexitRisk* include those far from the UK, such as Thailand, Nigeria, and Argentina and some nearby countries for which we have relatively low coverage—Portugal (9 firms) and the Czech Republic (6 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. By construction, the UK country-level *BrexitRisk* in this period equals unity. Perhaps the most immediate takeaway from this figure is the position of Ireland with a country-level Brexit risk of 1.74, far greater than the Brexit risk of the average UK firm.<sup>17</sup> (This difference is statistically

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<sup>15</sup>Fisman and Zitzewitz (2019) show a similar (aggregate) pattern for the period between July-December 2016 using their (stock returns-based) Brexit Long-Short Index.

<sup>16</sup>Bloom et al. (2019) report a measure of Brexit uncertainty based on a survey question included in the Decision Maker Panel, which asks whether Brexit is a top three driver of uncertainty. The correlation between *BrexitRisk* and this alternative Brexit uncertainty measure, which is available for UK firms only, is positive and significant.

<sup>17</sup>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

significant; standard errors are given in Appendix Table 7.) Further, distance to the UK matters: other high-scoring countries include nearby Denmark, the Netherlands, France, and Belgium (all EU member states). Non-EU countries showing high *BrexitRisk* scores include South Africa, Switzerland, Australia, and Singapore. Many non-EU countries with relatively high Brexit risk scores have longstanding Commonwealth ties to the UK. On the other hand, the Channel Islands are not part of the Commonwealth, the UK, or the EU, but are major offshore financial centers and tax havens. Their *BrexitRisk* falls between the scores reported for Sweden and France. 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 disproportionately high: *BrexitRisk* of the average US firm is 0.13, 13% 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 average *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 2016 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

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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).

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 April 2019 call, Arjo AB, also headquartered in Sweden recorded that “the entire decline in the quarter came from UK where Brexit uncertainty in the last quarter ...”

**Brexit sentiment.** We next repeat the same steps for *BrexitSentiment*. In Panel B of Figure 1, we start with a plot of the respective time series for UK and non-UK firms.<sup>18</sup> For both UK and non-UK firms, average *BrexitSentiment* is negative overall. We observe a sharp fall in sentiment immediately after the Brexit referendum (a phenomenon more pronounced for UK firms than for 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 for international firms. In the UK, the figure shows some recovery in the second quarter of 2019, after which average sentiment decreases again as the moment of Britain formally withdrawing from the EU nears.

Figure 4 plots the mean *BrexitSentiment* by country. Overwhelmingly, Brexit-related sentiment in the UK and elsewhere is 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 Channel Islands, where *BrexitSentiment* is strongly positive with a value of 0.65. Due to the limited number of sample firms headquartered in Channel Islands (8), however, we lack statistical power

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<sup>18</sup>In the firm-year panel beginning in 2016, the correlation between *BrexitRisk* and *BrexitSentiment* is -0.3.

to distinguish their *BrexitSentiment* score from zero. (Appendix Table 8 gives standard errors.)

**Human reading.** These findings raise the question of what specific concerns underlie this widespread aggregate negative sentiment towards Brexit. And, for those firms that expect 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 1,357 Brexit sentiment snippets (+/- 10 words around a tone word), of which 342 convey specific reasoning for the positive or 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 and with an eye to the concerns and benefits raised by politicians and other pundits active in the public debate about Brexit. <sup>19</sup>

Turning first to snippets that express positive sentiment about Brexit, Panel A of Table 3 shows that about 80 percent of positive excerpts in the UK and internationally 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 *weak 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 UK and non-UK firms, respectively). 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 earnings

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<sup>19</sup>The number of snippets is sufficiently small to allow human reading of each. For other events, the automated approach developed in Hassan et al. (2020) for assigning snippets to predefined categories might offer a viable alternative.

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.”

Interestingly, 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 Panel B of 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 for (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 seem 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.”

Taken together, the following picture emerges from these analyses. In the UK, Brexit sentiment is overwhelmingly negative and has precipitously declined in 2018, with only a partial restoration in 2019. In that same period, average Brexit risk has steeply increased, surpassing its initial level, which peaked right after the 2016 referendum. The negative sentiment towards Brexit among international firms stems predominantly from the weak British pound and the expectation of worse trade access after Brexit. The concerns of UK firms are more broad based, and also relate to labor market fictions, falling consumer

confidence, and adjustment or 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. More or less, countries outside of the UK mirror the UK’s time series pattern in Brexit-related risk and sentiment, albeit to a lesser extent. EU member states generally experience higher Brexit risk than do countries farther afield and, with few exceptions, their sentiment is negative.<sup>20</sup> Finally, negative sentiment towards Brexit among international firms centers mostly on the weak pound, concerns about trade access, and new and/or multiple regulatory regimes.

### *3.2. Event Study: Asset Pricing Effects of Brexit*

This section considers the implications of the June 23, 2016 referendum to leave the EU on the market valuation of UK, US, and international firms. The outcome of the referendum 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.<sup>21</sup> The lack of anticipation of the outcome creates favorable conditions for an event study assessing the asset pricing effects of the Brexit referendum. When investors learned about the referendum’s outcome, they formed new expectations about publicly listed firms’ future. Event-period stock price changes should thus reflect changes in investors’ expectations about the direct and indirect consequences of Brexit for international firms (Hill et al., 2019; Davies and Studnicka, 2018). 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

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<sup>20</sup>These findings are broadly consistent with evidence in Vandenbussche et al. (2019), who, using a country-sector analysis, document 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.

<sup>21</sup>ITV report on 24 June 2016.

variables used in our event study. Columns 4-8, provide the mean and standard deviation of each variable for the subsamples of UK, international, and US firms. As before, our key variables of interest are Brexit exposure, risk, and sentiment. For the purpose of this analysis, we consider both “average Brexit” and “pre-Brexit” *Exposure*, *Risk*, and *Sentiment*. The first group of variables are computed by averaging all available Brexit scores from 2016 to 2019, while pre-Brexit variables are calculated based on the sample of earnings conference calls held before June 23, 2016 (the date of the Brexit referendum). 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  $\overline{BrexitRisk}$  for the full sample is 0.195, but for the UK sample the corresponding value is equal to 1 (by construction). Brexit-related 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 the firm may be impacted. Event window stock returns are calculated using a 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 Ordinary Least Squares (OLS) estimates of the specification

$$(2) \quad r_i = \alpha_0 + \delta_j + \delta_c + \beta Brexit_i + X_i' \nu + \epsilon_i,$$

where  $r_i$  is the four-trading-day return following the Brexit vote,  $\delta_j$  and  $\delta_c$  are industry and headquarters-country fixed effects, respectively, and  $Brexit_i$  represents either firm  $i$ 's  $\overline{BrexitExposure}$ ,  $\overline{BrexitRisk}$ ,  $\overline{BrexitSentiment}$ ,  $Pre-BrexitRisk$ , or  $Pre-BrexitSentiment$ , and the vector  $X_i$  always includes the log of a firm's assets to control for firm size. In some specifications, we also include a stock's market beta, which we calculated by regressing daily returns in 2015 for firm  $i$  on the S&P500 or on the FTSE100 index, thus measuring a firm's exposure to the US and the UK capital markets separately. We exclude firms from the “Non

Classifiable” sector and firms with fewer than ten earnings call transcripts. Throughout, we use robust standard errors.

Panel A of Table 5 reports the estimates for the full sample. In Columns 1 and 2, we find a negative coefficient estimate between  $\overline{BrexitExposure}$  and event-window 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 a stock’s US- and UK-market beta, implying that the effect is not explained by differences in systematic 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 time window surrounding the announcement of the referendum result (Columns 3 and 4). As expected, we find that higher Brexit risk leads to lower stock returns (coef.= $-0.011$ , s.e.= $0.002$ ). In addition to this second-moment effect, we find that an increase in Brexit sentiment leads to higher stock returns (coef.= $0.002$ , s.e.= $0.001$ ), consistent with the view that firms expecting negative consequences of Brexit lose significant market valuation immediately after the referendum results became known. Again, our coefficient estimates remain unaffected when we control for a stock’s US- and UK-market beta (in Column 4). Finally, in an attempt to estimate the market’s response using only the information available at the time of the referendum, in the final column, we use the *Pre-BrexitRisk* and *Pre-BrexitSentiment* variables to explain the event-window stock price response. As reported in Column 5, we again find a negative effect of *Pre-BrexitRisk* ( $-0.005$ , s.e.= $0.001$ ) and a positive effect of *Pre-BrexitSentiment* ( $0.001$ , s.e.= $0.000$ ) on event-window stock returns.<sup>22</sup>

We repeat the same analysis in Panel B, but this time restrict the sample to firms

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<sup>22</sup>To corroborate our choice of standard errors, Appendix Figure 2 shows the results of a falsification exercise, where we repeatedly regress stock returns from four consecutive trading day windows at a time from January 1, 2012 and December 31, 2015 on  $Pre-BrexitRisk_i$  calculated. The figure shows a histogram of t-statistics on the estimated coefficient on  $Pre-BrexitRisk_i$ . The t-statistics are centered around zero, with no noticeable tendency for positive or negative estimates. Reassuringly, the rates of rejection at 5% significance level is about 3.06%.



headquartered in the United States, reducing the sample size from 4,572 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 to those in the corresponding columns in Panel A. 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 remain 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  $Pre-BrexitRisk$  (corresponding to Column 5 of Panel B in Table 5) onto a sequence of four-day return windows prior to the Brexit referendum vote on June 23, 2016. Each return window consists of four consecutive trading days, where the actual “treatment” window stretches from June 24 to 28, 2016, and the remaining four-day return windows are distributed in the periods before and after the treatment. As the referendum outcome was largely unexpected, we should not find a significant  $\hat{\beta}$  for return windows in periods before the vote took place. Similarly, if the effects of the leave vote are quickly impounded in stock prices, the effect should not linger after the vote. In line with these expectations, we find a significant negative coefficient estimate on  $Pre-BrexitRisk$  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 omitted factor or event. 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 return window between January 1, 2012 and December 31, 2015. Reassuringly, we find only a slight tendency to over-reject the null (3.06%).

Finally, in Figure 6, we estimate the event-study results separately for UK and international firms. Indeed, the figure shows two panels of binned scatter plots of four-day window returns over  $\overline{BrexitRisk}$ . The left (right) panel shows the relation for the sample of UK-headquartered (international) 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 find a negative relation in both panels (although the slope coefficient is more negative for the UK sample), implying that the asset price response to Brexit uncertainty is negative for both UK and non-UK firms.

To summarize, equity prices quickly impounded US and international firms’ exposures to Brexit-related, risks, costs, and opportunities, bolstering our confidence that our measures of  $\overline{BrexitSentiment}$  and  $\overline{BrexitRisk}$  indeed capture meaningful information about first and second-moment exposures to the event.

### 3.3. Regional Support for Brexit

The final validation test 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 “Remain” in the referendum. 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 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 UK firm’s location using the area code of its *operational* headquarters and then map these locations into electoral districts. Next, we compute the district-level Brexit risk and sentiment by averaging  $\overline{BrexitRisk}_i$  and  $\overline{BrexitSentiment}_i$ , respectively, 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,

$$(3) \quad \%leave_d = \alpha + \beta \overline{BrexitRisk}_d + \gamma \overline{BrexitSentiment}_d + X_d' \zeta + \epsilon_d.$$

These OLS regressions are estimated using data from 110 districts ( $d$ ), and inferences are based on robust standard errors.<sup>23</sup>

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.<sup>24</sup> Appendix Figure 1 shows this association graphically. For completeness, note that wealthier districts and districts with a larger immigrant population have lower support for Leave.<sup>25</sup>

#### 4. FIRM-LEVEL EFFECTS OF BREXIT

Two substantive facts emerge from the validation exercise in the previous section. First, firms are exposed to the shock caused by 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, equity markets quickly impound both the first- and second-moment implications in stock prices; in a four-day return window around the 2016 referendum, increases in Brexit risk lead to price drops, while increases in Brexit sentiment (implying that Brexit is viewed positively) lead to price gains. While these findings are consistent with the forward-looking nature of equity markets, they also leave

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<sup>23</sup>Note that the distribution of our 407 sample firms in the UK is geographically clustered. As reported in Appendix Table 5, many districts have only one sample firm and many sample firms are headquartered in a handful of districts (e.g., the City of London, Greater London).

<sup>24</sup>The partial  $R^2$  of these two variables in Column 3 is about 5%.

<sup>25</sup>These findings, on the one hand, validate our Brexit measures. On the other, they also speak to findings in 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.

open the question of the precise nature in which individual firms respond to the Brexit shock. Therefore, in this section, we estimate the effect of firm-level Brexit risk and sentiment on investments, hiring, and sales, using the following specification:

$$(4) \quad y_{i,t+1} = \delta_j + \delta_t + \delta_c + \beta \text{BrexitRisk}_{i,t} + \theta \text{BrexitSentiment}_{i,t} + X'_{i,t} \zeta + \epsilon_{i,t},$$

where  $y_{i,t+1}$  is one of the three firm-level outcomes of interest, and  $\delta_j$ ,  $\delta_t$ , and  $\delta_c$  are industry, year, and headquarters-country fixed effects, respectively. The vector  $X_{i,t}$  includes the log of the firm’s assets, to control for firm size, and *Non-BrexitRisk* and *Non-BrexitSentiment*, to control for other non-Brexit related sources of risk and overall (again, non-Brexit related) sentiment expressed in the earnings call, respectively. *BrexitRisk*, *BrexitSentiment*, *Non-BrexitRisk*, and *Non-BrexitSentiment* are computed annually by averaging across all available earnings call transcripts in a given year. Firm-level outcome variables are measured yearly from 2011 to 2019. 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).<sup>26</sup> 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., 2020). We examine these predictions in the context of Brexit, which, as 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).<sup>27</sup>

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<sup>26</sup>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 in the cross-section of firms. 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.

<sup>27</sup>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 uncertainty shock on non-UK firms generally or on US firms specifically.

Figure 7 shows a binned scatter 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: -0.583 (s.e.=0.249) for the UK and -0.614 (s.e.=0.150) for 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 0.614 percentage point decrease in its investment rate—corresponding to a 2.5% drop relative to the mean (24.5).

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 (-0.528, s.e.=0.134). Firms most affected by Brexit-related risks thus lower their investment rates, consistent with the effects of an uncertainty shock that raises the option value of delaying investments. Interestingly, we find no significant association between  $BrexitSentiment_{i,t}$  and  $I_{i,t+1}/K_{i,t}$ , so that firms for whom Brexit is purely good or bad news do not appear to be reacting systematically to this news prior to the UK’s exit from the single market.

In the next four columns, we work towards our preferred specification. Column 2 adds the interaction of country-of-headquarters and time fixed effects, thus controlling for any systematic movement in exchange rates between the UK and the firm’s headquarter country. (Such adjustments in the exchange rate appear to have been important for the initially resilient response of UK-based firms to the Brexit referendum (Broadbent et al., 2019).) Column 3 adds the interaction of sector and time fixed effects, thus absorbing any differential trends in the investment rates of firms in different sectors. The remaining two columns add

controls for the firm’s overall (i.e., non-Brexit related) risk and sentiment (Columns 4 and 5, respectively)—specifically, mentions of risk and positive and negative tone-words that do not appear in conjunction with the word “Brexit.” Reassuringly, we find that firms exposed to higher overall uncertainty (based on our text-based measure *Non-BrexitRisk*) have *lower* investment rates, where a one standard deviation increase in a firm’s non-Brexit related risk is associated with a 0.818 (s.e.=0.285) percentage point decrease in its investment rate. Similarly, firms for which overall sentiment is positive, using our text-based measure, 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<sub>i,t</sub>* and investments, with only a minor attenuation of the estimated coefficient. Indeed, the estimated effect of *BrexitRisk<sub>i,t</sub>* suggests that for firms exposed to Brexit risk equal to that of an average post-referendum UK firm (1), investments decrease by 0.434 percentage points (or 1.8 percent relative to the mean): a decrease comparable in magnitude to that associated with a persistent one-standard deviation increase in the firm’s non-Brexit related risk.<sup>28</sup>

Extrapolating from the country-specific mean Brexit risk in Figure 2, the estimate in Column 5 implies a  $0.43 \times 1.74 \times 100 = 0.74$  percentage point decrease in the investment rate for the average Irish firm (average investment rate 29.84%), and a  $0.43 \times 0.67 \times 100 = 0.28$  percentage point decrease for the average South African firm (average investment rate 17.98%) in our sample. Appendix Table 7 repeats this calculation to give the estimated impact of Brexit risk relative to the average investment rate in each country shown in Figure 2.

Results reported in Panel B of Table 7 for the subsample of US-headquartered firms point in the same direction as those obtained for the full sample. In Panel B, we repeat the same sequence of specifications as in Panel A but report only the coefficient es-

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<sup>28</sup>Appendix Table 6 shows robustness of these inferences to a range of alternative choices of standard errors.

timates on  $BrexitRisk_{i,t}$  to save space. (Consistent with our results above, the effect of  $BrexitSentiment_{i,t}$  remains statistically indistinguishable from zero in all specifications.) 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 subsample. Our preferred estimate in Column 5 (-0.794, s.e.=0.258) suggests that Brexit risk accounts for a 0.10 percentage point decrease in the investment rate of the average US-based firm in each year after 2016.

The findings reported in Table 7 are based on regressions that constrain the association between  $BrexitRisk_{i,t}$  and the investment rate to be time-invariant. To analyze whether the effect of Brexit-related uncertainty is indeed constant or rather time-varying, we estimate a regression of  $I_{i,t+1}/K_{i,t}$  onto interactions of post-referendum year indicator variables and  $BrexitRisk$  and adding our usual set of controls along with country-time and industry-time fixed effects. Figure 9 presents the results. (Appendix Table 9 provides details and shows similar results for employment.) The figure shows the strongest marginal effect for a given level of  $BrexitRisk$  in the year immediately after the referendum vote (2017). The effect becomes somewhat weaker in the following year and then dissipates thereafter. This pattern again is consistent with reactions to uncertainty tied to a single future event: International (non-UK) firms likely have a limited number of investment projects that are vulnerable to Brexit. After the referendum, firms respond by postponing these investments, resulting in a level difference in the stock of investments that persists through the end of our sample.

Despite the comprehensive set of controls included in the specification of Column 5, there are three remaining concerns with a causal interpretation of these results. First, corporate executives might use 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 firm 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). Yet, our proxies for sentiment might not fully capture pertinent first-moment effects, preventing us from ruling out the possibility that *BrexitRisk* compounds both first and second moments.

For this reason, we add additional controls for the firm’s recent financial performance in Columns 2-4 of Table 8. These three columns, as well as all remaining specifications in this table include our standard controls, but for brevity, we report only the coefficients on Brexit risk and the newly added controls. Column 2 adds a measure for the firm’s earnings surprise (Ball and Bartov, 1996). Columns 3 and 4 add the firm’s contemporaneous stock return—measured either as the firm’s average return in the quarter of each earnings call or as the average return in the week before a call. Poor performance should be reflected in lower unexpected earnings and lower returns, but we find that none of these controls significantly attenuates 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 nor by inadequate controls for first-moment effects.

Importantly, to the extent that these additional controls capture first-moment effects that are not well reflected by *BrexitSentiment*, the findings can be interpreted as sensitivity checks on our inference that *BrexitRisk* captures second-moment rather than first-moment effects. That said, despite our efforts, we acknowledge that both *BrexitRisk* and *BrexitSentiment* likely suffer from measurement error, so that our firm-level estimates may well be attenuated (biased towards zero). At the same time, there is no reason to believe that measurement error differs systematically between the risk and sentiment variables. Yet, we consistently find a significant (negative) correlation between *BrexitRisk* and investments, whereas *BrexitSentiment* and investments are not significantly correlated.

The second concern is that firms affected by Brexit risk might also be disproportionately affected by other types of risk. Again, controlling for non-Brexit-related risk 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 Hassan et al. (2019)) 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.<sup>29</sup> 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 0.562 (s.e.=0.229) percentage point decrease in that firm’s investment rate). However, including this control has little effect on our coefficient of interest, which remains stable at -0.440 (s.e.=0.144).

The third and final potential concern 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-specific time-invariant measure of Brexit exposure,  $\overline{BrexitExposure}_i$ , that is calculated using all observations of a given firm in the sample. 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. That said, both of these control variables are plausibly correlated with unobserved differences across firms that are implicated in Brexit and that, in turn, may impact investments. Adding these variables to our specification is tantamount to controlling for this heterogeneity.<sup>30</sup> Mindful of the econometric concerns, we find little evidence that adding these additional controls changes the tenor of our main findings. Neither the pre-Brexit UK sales nor  $\overline{BrexitExposure}_i$  are significantly associated with firms’ investment rates. Furthermore, the significance of the estimated coefficient on  $BrexitRisk_{i,t}$  remains stable and highly statistically significant

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<sup>29</sup>As one might expect, this measure shows sharp increases coinciding with various trade disputes between the United States and other countries from 2016 to 2019. See [www.firmlevelrisk.com](http://www.firmlevelrisk.com) for details.

<sup>30</sup>Including firm fixed-effects offers an alternative approach to removing (time-invariant) unobserved heterogeneity. In most tests, we do not have sufficient power to implement this design. For the US sample, however, when adding firm fixed effects to the specification of Column 5 of Table 7 (Panel B), we find a coefficient estimate on  $BrexitRisk_{i,t}$  equal to -0.448 (s.e.=0.307), comparable to our corresponding estimate for the full sample in Panel A of the same table.

despite the inclusion of these controls.

Figure 8 shows the results of a placebo exercise where we re-estimate our preferred specification of Column 5 in 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 estimate from our preferred specification. Taken together, these results bolster our confidence that our estimates capture the causal effect of Brexit risk on firm-level investment.

Having established a consistent negative relation between Brexit risk (though not sentiment) and firms’ 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 changes in uncertainty since both activities exhibit adjustment costs. Supporting these predictions, Panel A in Table 9 shows (across both samples) a significantly negative relation between  $BrexitRisk_{i,t}$  and firms’ net hiring,  $\Delta emp_{i,t}/emp_{i,t-1}$ . Our preferred coefficient estimates are -0.315 (s.e.=0.115) and -0.762 (s.e.=0.242) for the full sample and for the US, respectively, where the point estimate for US-based firms is again considerably larger than the one for the full sample. The former estimate implies that an international firm with a Brexit risk equal to the average UK-based firm (1) experiences a decrease in its employment growth of 0.32 percentage points (relative to an average net hiring rate of 8.12%) (Appendix Table 7 breaks these numbers down by individual country); the latter implies a 0.10 percentage point reduction for the average US firm (the average net hiring

rate for US firms is 11.36%). As we did for the capital investment rate, we find no significant association between  $BrexitSentiment_{i,t}$  and employment growth, again likely reflecting the fact that, prior to the UK’s actual exit from the single market, Brexit affects firm decisions largely because it raises uncertainty. As before, the coefficients on  $Non-BrexitRisk$  and  $Non-BrexitSentiment$  are statistically significant and have the predicted sign. (Appendix Table 10 shows the same battery of robustness checks as in Table 8.)<sup>31</sup>

Finally, we consider sales growth, our third firm-level outcome variable, 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). We also find no significant evidence of a positive association between  $BrexitSentiment_{i,t}$  and sales growth. Instead, sales growth shows persistent positive correlations with  $Non-BrexitSentiment$ , consistent with the idea that sales respond more directly to positive and negative shocks only after they are realized. (See Appendix Table 11 for additional variations and robustness checks.)<sup>32</sup>

## 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, international transmission of any number of other small and large *shocks* is likely quite common in a globalized economy. Having a versatile method available to quantify and analyze the exposure of firms to such shocks is an important addition to the arsenal of (financial) economists and policy

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<sup>31</sup>Simulations reported in Broadbent et al. (2019), interpret the Brexit referendum as news about a future slowdown in productivity growth in the UK’s tradable sector and predict a reduction in investment growth, while employment remains relatively stable.

<sup>32</sup>In Appendix Table 12, 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.

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 term around which conversations in earnings conference calls coalesce. To generalize our method, we thus add a step to our procedure 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 [Hassan et al. \(2019\)](#)), 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 then filter out word combinations that also appear in 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 13 shows the results of this exercise for two-word combinations (bigrams).

Since we consider the occurrence of these n-grams in earnings 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 these n-grams over time and identify those that are widely used immediately after the incident, but not before. Therefore, in this instance, we exclude all n-grams from consideration that are used more than twice across all earnings calls prior to the date of the Fukushima 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  $i$ ’s quarter  $t$  earnings call divided by the total number of words in the transcript.

Having scored all transcripts in our sample this way, we can trace the exposure of international and Japanese firms to the event. Appendix Figure 3 shows the results. 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 in this fashion, 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 10 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 used for Table 2. The following observations seem pertinent: while Japanese firms struggle with power outages, the inaccessibility of plants and properties, and production disruptions, the international impacts of the Fukushima disaster are transmitted through more subtle links. For instance, 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, with this additional application, we demonstrate the versatility and, 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 marketwide 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 shocks. 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 having to conduct 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-moment effects of shocks. 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).

The 2016 Brexit referendum is an ideal test case of our method, to assess whether and the extent to which the vote’s outcome affected international firms. 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.” We document 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 Brexit-related risk, and Brexit risk also has a material (though weaker) impact in the United States and other non-EU countries.

Using transcripts of earnings conference calls as the source text provides a rich context, enabling us to identify firms’ concerns about Brexit in detail. From analyzing the underlying text, 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 “bad news,” 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 risk have significantly reduced investment and employment growth. We also find that equity markets quickly impounded both first- and second-moment exposures to Brexit: our Brexit sentiment and risk measures both partially explain the pricing response on equity markets in the days following the referendum.

Taking all of the evidence together, we conclude that up to the end of our sample in 2019, 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 depressing effect of sustained uncertainty, equity 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. As time goes by, after Britain has formally left the EU, the consequences for investments and employment may well turn out to 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 nuclear disaster). Useful future applications may estimate firm-level impacts of natural disasters, political events (e.g., revolutions, the US government shutdown), or specific regulatory reforms in response to the climate emergency.



## REFERENCES

- Alabrese, E., S. O. Becker, T. Fetzter, and D. Novy (2019). Who voted for Brexit? Individual and regional data combined. *European Journal of Political Economy* 56, 132 – 150.
- Anderson, A., W. Du, and B. Schlusche (2019). Money market fund reform and arbitrage capital. Technical report, Working Paper.
- Angrist, J. D. and J.-S. Pischke (2008). *Mostly harmless econometrics: An empiricist's companion*. Princeton university press.
- Baker, S. R., N. Bloom, and S. J. Davis (2016). Measuring economic policy uncertainty. *The Quarterly Journal of Economics* 131(4), 1593–1636.
- Ball, R. and E. Bartov (1996). How naive is the stock market's use of earnings information? *Journal of Accounting and Economics* 21(3), 319–337.
- Barrot, J.-N. and J. Sauvagnat (2016). Input specificity and the propagation of idiosyncratic shocks in production networks. *The Quarterly Journal of Economics* 131(3), 1543–1592.
- Belo, F., V. D. Gala, and J. Li (2013). Government spending, political cycles, and the cross section of stock returns. *Journal of Financial Economics* 107(2), 305–324.
- Berg, T., A. Saunders, L. Schäfer, and S. Steffen (2019). 'Brexit' and the contraction of syndicated lending. Available at SSRN 2874724.
- Berger, D., I. Dew-Becker, and S. Giglio (2020). Uncertainty shocks as second-moment news shocks. *Review of Economic Studies* 87, 40–76.
- Bernanke, B. S. (1983). Irreversibility, uncertainty, and cyclical investment. *Quarterly Journal of Economics* 98, 85–106.
- Besley, T. and H. Mueller (2017). Institutions, volatility, and investment. *Journal of the European Economic Association* 16, 604–649.
- Bloom, N., S. Bond, and J. Van Reenen (2007). Uncertainty and investment dynamics. *Review of Economic Studies* 74, 391–415.
- Bloom, N., P. Bunn, S. Chen, P. Mizen, P. Smietanka, and G. Thwaites (2019, September). The impact of Brexit on UK firms. Working Paper 26218, National Bureau of Economic Research.
- Bloom, N., M. Floetotto, N. Jaimovich, I. Saporta-Eksten, and S. Terry (2018). Really uncertain business cycles. *Econometrica* 86, 1031–1065.
- Boehm, C. E., A. Flaaen, and N. Pandalai-Nayar (2019). Input linkages and the transmission of shocks: Firm-level evidence from the 2011 Tōhoku earthquake. *Review of Economics and Statistics* 101(1), 60–75.
- Born, B., G. Mueller, M. Schularick, and P. Sedláček (2019). The costs of economic nationalism: Evidence from the Brexit experiment. *The Economic Journal* 129(10), 2722–2744.
- Braggion, F., A. Manconi, and H. Zhu (2020). Credit and social unrest: Evidence from 1930s china. *Journal of Financial Economics* 138(2), 295–315.

- Breinlich, H., E. Leromain, D. Novy, T. Sampson, and A. Usman (2018). The economic effects of Brexit: Evidence from the stock market. *Fiscal Studies* 39(4), 581–623.
- Broadbent, B., F. Di Pace, T. Drechsel, R. Harrison, and S. Tenreyro (2019). The Brexit vote, productivity growth and macroeconomic adjustments in the United Kingdom. *CEPR Discussion Paper No. DP13993*.
- Bybee, L., B. Kelly, A. Manela, and D. Xiu (2019). The structure of economic news. Working paper.
- Caldara, D., M. Iacoviello, P. Molligo, A. Prestipino, and A. Raffo (2019). The economic effects of trade policy uncertainty. *Journal of Monetary Economics*.
- Campello, M., G. Cortes, F. d’Almeida, and G. Kankanhalli (2020). Global effects of the Brexit referendum: Evidence from us corporations. *Available at SSRN 3078220*.
- Carvalho, V. M., M. Nirei, Y. Saito, and A. Tahbaz-Salehi (2016). Supply chain disruptions: Evidence from the great east japan earthquake. *Columbia Business School Research Paper* (17-5).
- Colacito, R., M. M. Croce, F. Gavazzoni, and R. Ready (2018). Currency risk factors in a recursive multicountry economy. *The Journal of Finance* 73(6), 2719–2756.
- Costa, R., S. Dhingra, and S. Machin (2019). Trade and worker deskilling. Working paper, National Bureau of Economic Research.
- Davies, R. B. and Z. Studnicka (2018). The heterogeneous impact of Brexit: Early indications from the FTSE. *European Economic Review* 110, 1–17.
- Dhingra, S., H. Huang, G. Ottaviano, J. Paulo Pessoa, T. Sampson, and J. Van Reenen (2017, 10). The costs and benefits of leaving the EU: trade effects. *Economic Policy* 32(92), 651–705.
- Dixit, A. K. and R. S. Pindyck (1994). *Investment Under Uncertainty*. Princeton University Press.
- Fernández-Villaverde, J., P. Guerrón-Quintana, K. Kuester, and J. Rubio-Ramírez (2015). Fiscal volatility shocks and economic activity. *The American Economic Review* 105(11), 3352–3384.
- Fetzer, T. (2019, November). Did austerity cause Brexit? *The American Economic Review* 109(11), 3849–86.
- Fisman, R. and E. Zitzewitz (2019). An event long-short index: Theory and applications. *American Economic Review: Insights* 1(3), 357–72.
- Forbes, K. J. and F. E. Warnock (2012). Capital flow waves: Surges, stops, flight, and retrenchment. *Journal of International Economics* 88(2), 235–251.
- Garetto, S., L. Oldenski, and N. Ramondo (2019). Multinational expansion in time and space. Technical report, National Bureau of Economic Research.
- Gentzkow, M., B. Kelly, and M. Taddy (2019). Text as data. *Journal of Economic Literature* 57(3), 535–74.
- Gilchrist, S., J. W. Sim, and E. Zakrajšek (2014). Uncertainty, financial frictions, and investment dynamics. Technical report, National Bureau of Economic Research.

- Gourio, F., M. Siemer, and A. Verdelhan (2015). Uncertainty and international capital flows. *Working paper, Federal Reserve Bank of Chicago, MIT.*
- Graziano, A., K. Handley, and N. Limão (2018). Brexit uncertainty and trade disintegration. Technical report, National Bureau of Economic Research.
- Handley, K. and J. F. Li (2018). Measuring the effects of firm uncertainty on economic activity: New evidence from one million documents. Technical report, Mimeo., University of Michigan.
- Handley, K. and N. Limao (2015). Trade and investment under policy uncertainty: theory and firm evidence. *American Economic Journal: Economic Policy* 7(4), 189–222.
- Hansen, S., M. McMahon, and A. Prat (2017). Transparency and deliberation within the FOMC: A computational linguistics approach. *The Quarterly Journal of Economics* 133(2), 801–870.
- Hassan, T. A., S. Hollander, L. Van Lent, M. Schwedeler, and A. Tahoun (2020). Firm-level exposure to epidemic diseases: Covid-19, SARS, and H1N1. *National Bureau of Economic Research.*
- Hassan, T. A., S. Hollander, L. van Lent, and A. Tahoun (2019). Firm-level political risk: Measurement and effects. *The Quarterly Journal of Economics* 134(4), 2135–2202.
- Hassan, T. A. and T. M. Mertens (2017). The social cost of near-rational investment. *The American Economic Review* 107(4), 1059–1103.
- Hill, P., A. Korczak, and P. Korczak (2019). Political uncertainty exposure of individual companies: The case of the Brexit referendum. *Journal of Banking & Finance* 100, 58–76.
- Hollander, S., M. Pronk, and E. Roelofsen (2010). Does silence speak? An empirical analysis of disclosure choices during conference calls. *Journal of Accounting Research* 48(3), 531–563.
- Jamilov, R., H. Rey, and A. Tahoun (2021). The anatomy of cyber risk. *Working paper, London Business School.*
- Kelly, B., L. Pástor, and P. Veronesi (2016). The price of political uncertainty: Theory and evidence from the option market. *The Journal of Finance* 71, 2417–2480.
- Koijen, R. S., T. J. Philipson, and H. Uhlig (2016). Financial health economics. *Econometrica* 84(1), 195–242.
- Kost, K. (2019). Trade policy uncertainty, investment, and lobbying. Working paper, University of Chicago.
- Loughran, T. and B. McDonald (2011). When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. *The Journal of Finance* 66(1), 35–65.
- Loughran, T. and B. McDonald (2016). Textual analysis in accounting and finance: A survey. *Journal of Accounting Research* 54(14), 1187–1230.
- Maggiore, M. (2017). Financial intermediation, international risk sharing, and reserve currencies. *American Economic Review* 107(10), 3038–71.

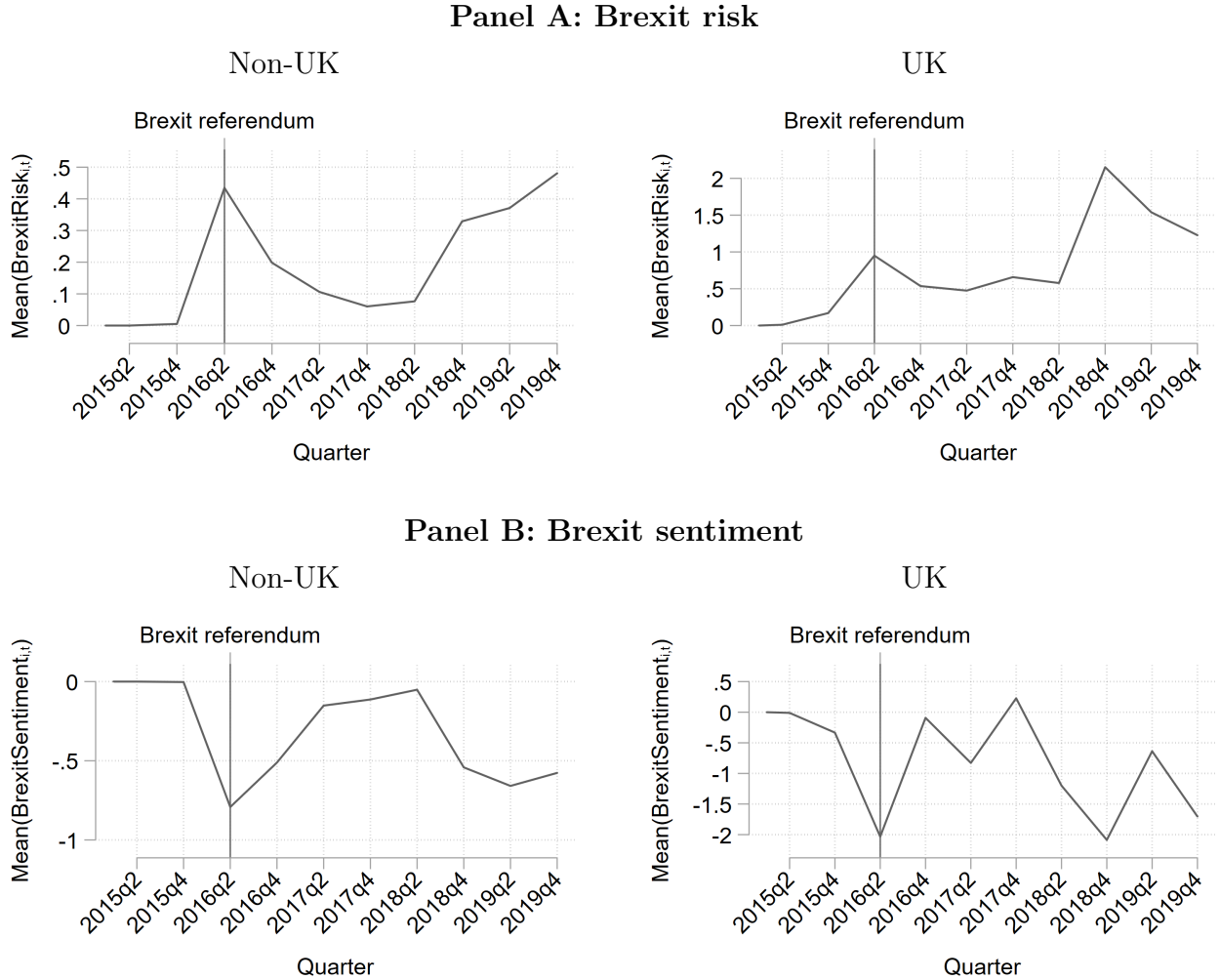
- Martin, J., A. Martinez, and I. Mejean (2019). The cost of brexit uncertainty: missing partners for french exporters. Technical report, IPP Policy Brief no. 48, Institut des Politiques Publiques.
- McGrattan, E. R. and A. Waddle (2017). The impact of Brexit on foreign investment and production. Working paper, National Bureau of Economic Research.
- Mueller, P., A. Tahbaz-Salehi, and A. Vedolin (2017). Exchange rates and monetary policy uncertainty. *The Journal of Finance* 72(3), 1213–1252.
- Pindyck, R. S. (1988). Irreversible investment, capacity choice, and the value of the firm. *American Economic Review* 78(5), 969.
- Redding, S. and A. J. Venables (2004). Economic geography and international inequality. *Journal of International Economics* 62(1), 53–82.
- Rey, H. (2015). Dilemma not trilemma: the global financial cycle and monetary policy independence. Technical report, National Bureau of Economic Research.
- Sampson, T. (2017). Brexit: the economics of international disintegration. *Journal of Economic Perspectives* 31(4), 163–84.
- Sautner, Z., L. van Lent, G. Vilkov, and R. Zhang (2020). Firm-level climate change exposure. Available at SSRN 3642508.
- Schnabl, P. (2012). The international transmission of bank liquidity shocks: Evidence from an emerging market. *The Journal of Finance* 67(3), 897–932.
- Steinberg, J. B. (2019). Brexit and the macroeconomic impact of trade policy uncertainty. *Journal of International Economics* 117, 175–195.
- Van Reenen, J. (2016). Brexit’s long-run effects on the UK economy. *Brookings papers on economic activity*, 367–383.
- Vandenbussche, H., W. Connell Garcia, and W. Simons (2019). Global value chains, trade shocks and jobs: An application to Brexit. *CESifo Working Paper* 7473.
- Waterfield, B., O. Wright, and H. Zeffman (2019, Oct). Growing risk of no-deal in six days after Macron blocks Brexit extension. *www.thetimes.co.uk*.

Table 1: Validation of BrexitExposure

	$\overline{\text{BrexitExposure}_i}$			
	(1)	(2)	(3)	(4)
$\mathbf{1}\{\text{UK HQ}\}$	0.860*** (0.074)	0.902*** (0.074)	0.110 (0.088)	0.145 (0.091)
$\mathbf{1}\{\text{UK subsidiary}\}$	0.194*** (0.018)	0.207*** (0.018)	0.244*** (0.022)	0.244*** (0.021)
$\mathbf{1}\{\text{EU non-UK HQ}\}$		0.295*** (0.034)	0.085 (0.086)	0.081 (0.082)
% of sales in UK (2010-2015)			1.838*** (0.398)	
% of sales in UK (2016-present)				1.751*** (0.394)
$R^2$	0.074	0.092	0.128	0.128
N	8,177	8,177	3,533	3,742

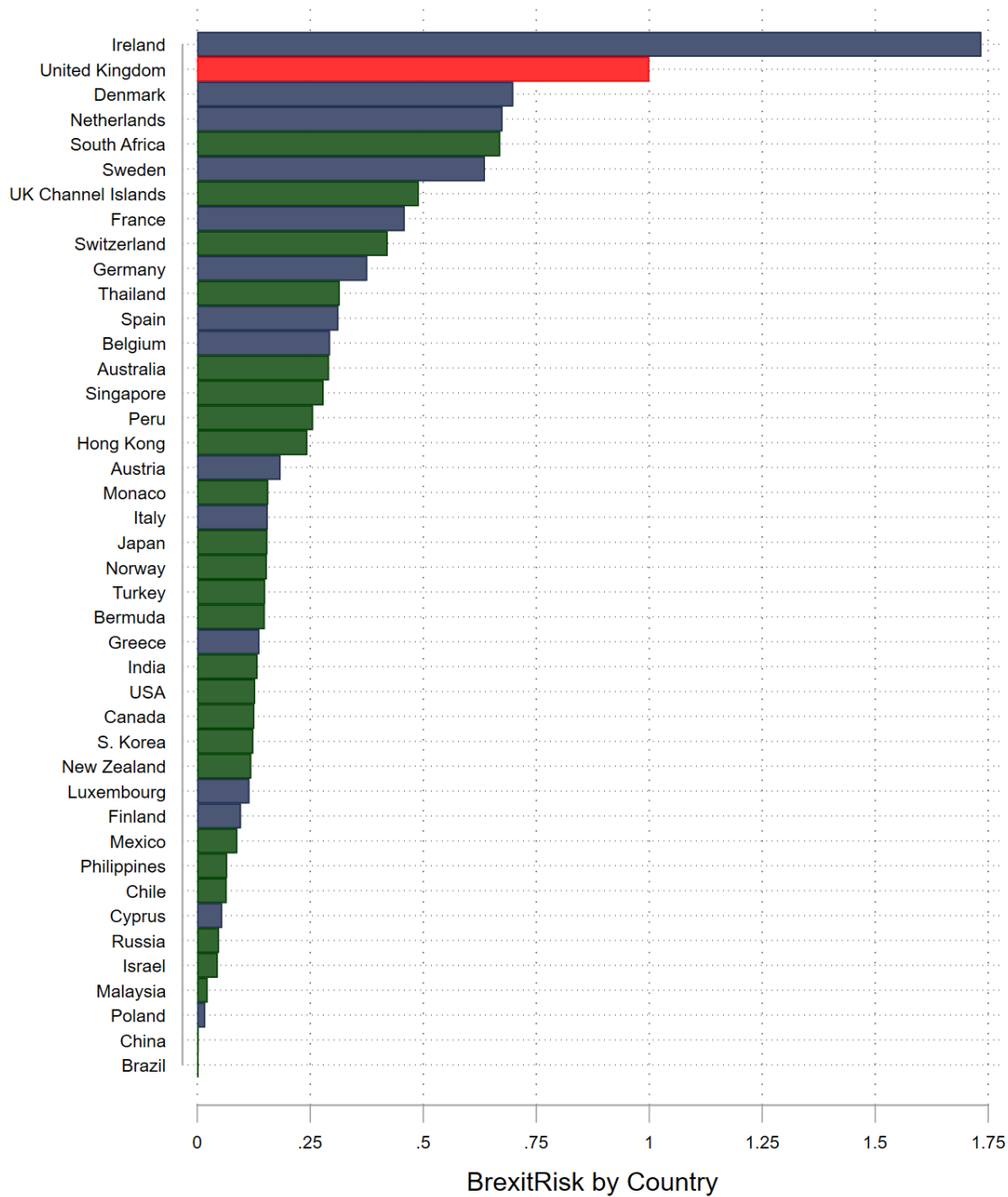
*Notes:* This table reports OLS estimates from cross-sectional regressions that use  $\overline{\text{BrexitExposure}_i}$  as the dependent variable. We use 84,297 earnings calls between 2016Q1 and 2019Q4 to calculate firm-level mean Brexit exposure. Robust standard errors are in parentheses. \*, \*\*, and \*\*\* indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

Figure 1: Time Series of BrexitRisk and BrexitSentiment



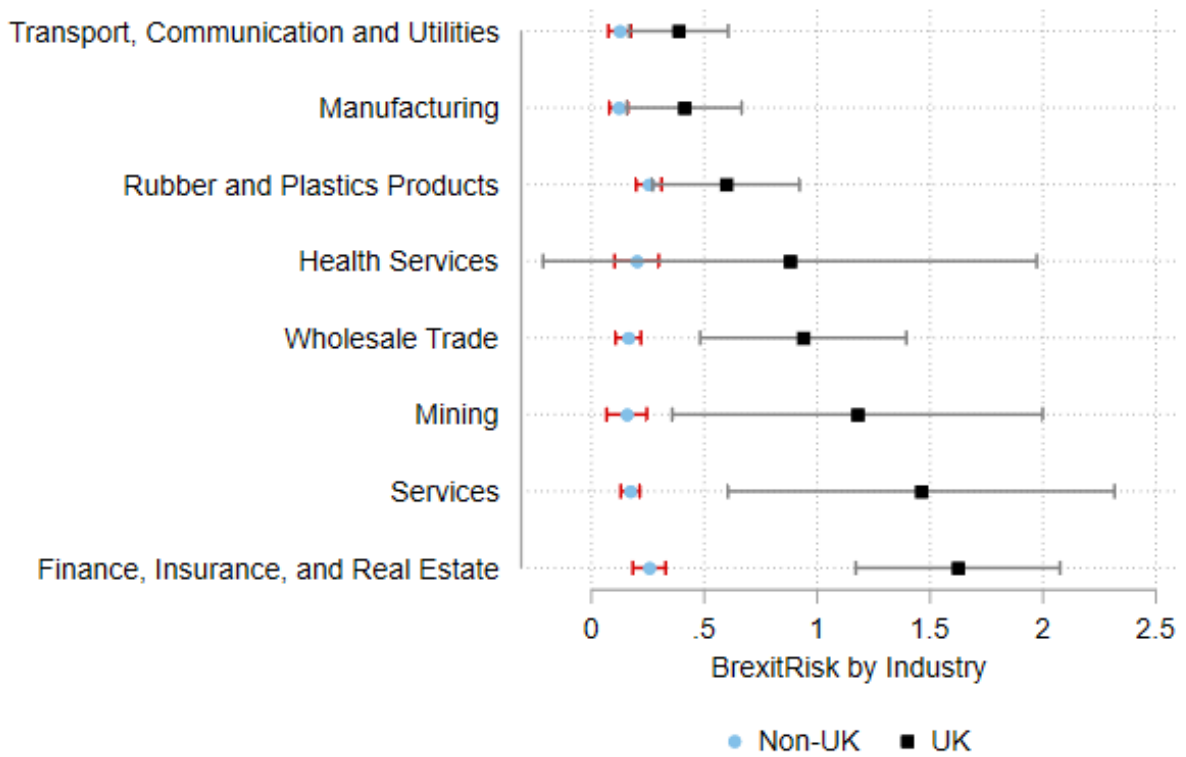
*Notes:* This figure plots the semi-annual mean of non-UK and UK headquartered firms' Brexit risk (Panel A) and Brexit sentiment (Panel B).  $\overline{\text{BrexitRisk}}_{i,t}$  is normalized using the average  $\overline{\text{BrexitRisk}}_{i,t}$  of UK-headquartered firms 2016-19;  $\overline{\text{BrexitSentiment}}_{i,t}$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

Figure 2: Mean BrexitRisk by Country



*Notes:* This figure shows the country-by-country mean of  $\overline{\text{BrexitRisk}}_{i,t}$  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 Colombia.

Figure 3: BrexitRisk by Industry



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

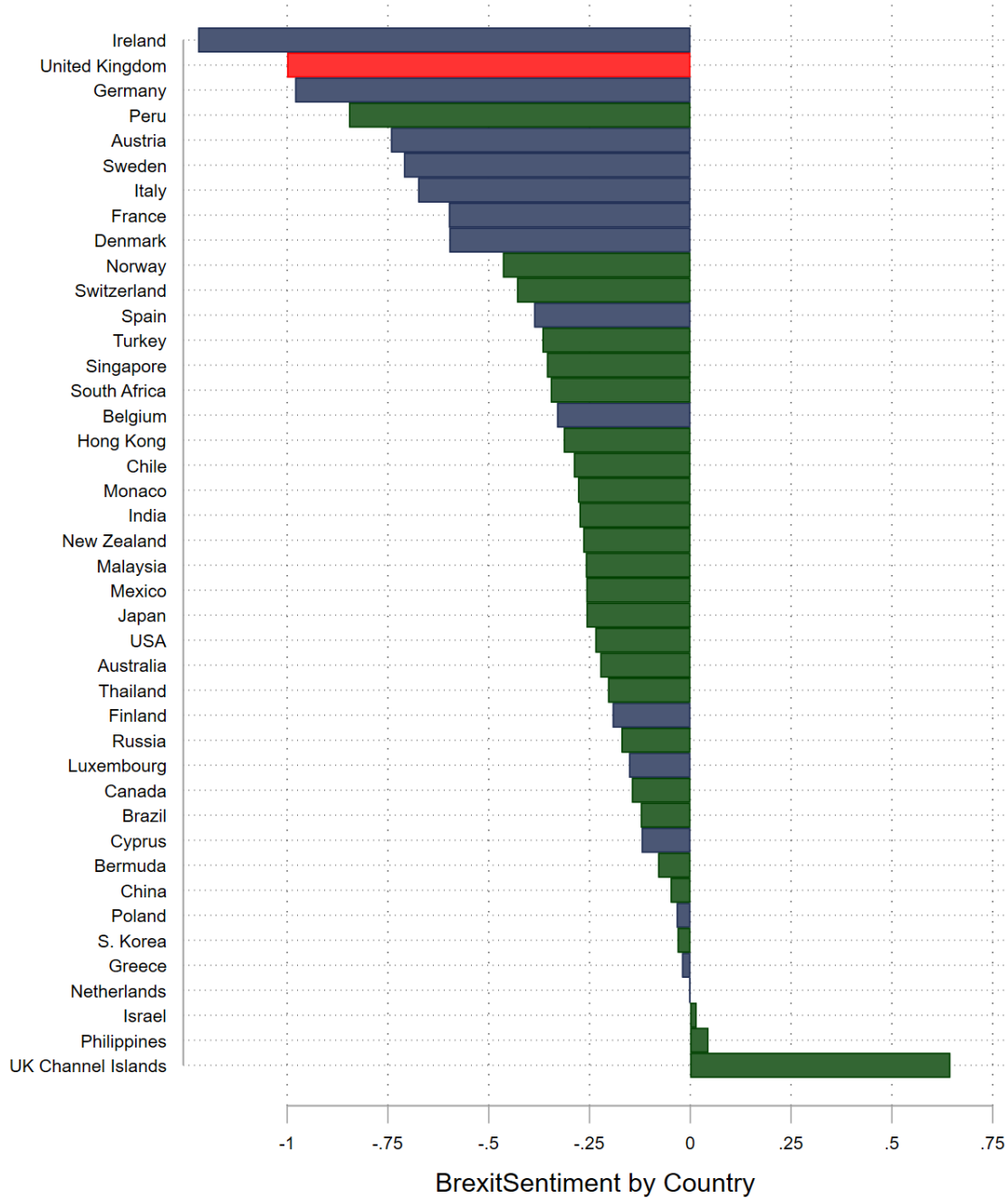


Table 2: Top BrexitRisk Firms' Transcript Excerpts

Panel A: UK firms				
Company	$\overline{\text{BrexitRisk}}_i$	Country	Quarter	Transcript excerpts
Bellway PLC	15.34	GB	2018-10	deliver completions in fy we are mindful of the <b>uncertainty</b> surrounding <b>brexit</b> and we will wait to see whether customer sentiment is affected
Berendsen Ltd	13.06	GB	2016-07	and we have i think a pretty proven resilient business however <b>brexit</b> raises any number of <b>uncertainties</b> for every single business so were
Endava PLC	11.73	GB	2019-01	plans with us as a result of the <b>uncertainties</b> caused by <b>brexit</b> mark will talk about how weve mitigated fx <b>risk</b> in his
Millennium & Cophorne Hotels PLC	10.9	GB	2018-01	as you know there is still <b>uncertainty</b> about british economy and <b>brexit</b> for example we are seeing a rise in costs here because
SThree PLC	10.18	GB	2019-01	year theres also a lot of <b>uncertainty</b> around the uk and <b>brexit</b> and that will affect most markets but i think again the
Panel B: Non-UK firms				
Company	$\overline{\text{BrexitRisk}}_i$	Country	Quarter	Transcript excerpts
Cherokee Inc	43.45	US	2019-04	licensees in europe were hampered by the economic <b>uncertainty</b> surrounding <b>brexit</b> we think this trend may continue in the future quarters people
Atlantic Leaf Properties Ltd	40.77	MU	2019-10	much has been said about <b>brexit</b> and the delays of <b>brexit</b> thats on page brexit delays really prolong the <b>uncertainty</b> in our
Northstar Realty Europe Corp	21.15	US	2016-07	rise to greater <b>uncertainty</b> this <b>uncertainty</b> has been exasperated by <b>brexit</b> the <b>prospect</b> of <b>brexit</b> has resulted in a high degree of
Arjo AB (publ)	20.47	SE	2019-04	the entire decline in the quarter came from uk where <b>brexit</b> uncertainty in the last quarter of the nhs financial year has
Apollo Tourism & Leisure Ltd	18.26	AU	2019-07	to what we experienced in north america the <b>uncertainty</b> surrounding <b>brexit</b> greatly reduced consumer sentiment and suppressed discretionary spending the result of
Sweco AB (publ)	16.6	SE	2018-10	still there is still an <b>uncertainty</b> when it comes to <b>brexit</b> and some weakness in the real estate market so once again
Ryanair Holdings PLC	14.55	IE	2017-01	the pricing environment has also been affected by the post <b>brexit</b> uncertainty which has seen weaker sterling and a switch of charter
Nobia AB	14.03	SE	2019-01	delays in the product deliveries somewhat impacted by increased <b>uncertainty</b> for <b>brexit</b> but also due to general delays in the construction sites however
Stonegate Mortgage Corp	12.01	US	2016-07	primarily driven by economic concerns abroad in particular <b>uncertainty</b> around <b>brexit</b> played a major role related to the <b>instability</b> of interest rates
Asetek A/S	11.2	DK	2019-10	unresolved china trade issues still an issue for us the <b>brexit</b> uncertainty is definitely not helping and its influencing this segment both
Bank of Ireland Group PLC	10.89	IE	2018-07	mortgages weve got the impacts of some <b>uncertainty</b> because of <b>brexit</b> sentiment in ireland and that has resulted in some of the

*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 'MU' stands for Mauritius.

Figure 4: Mean BrexitSentiment by Country



Notes: This figure shows the country-by-country mean of  $\text{BrexitSentiment}_{i,t}$  across all firms headquartered in a specific country for the same set of countries as in Figure 2.

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 oppportunity 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 of 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 convey specific reasoning for the positive or negative tone words used or did not intersect with the predefined categories.

Table 4: Summary Statistics

	All firms			UK firms		Non-UK firms		US firms		Total
	Mean	Median	SD	Mean	SD	Mean	SD	Mean	SD	N
<b>Panel A: Firm-level risk and sentiment</b>										
$\overline{\text{BrexitExposure}}_i$	0.223	0.000	0.728	1.000	1.517	0.180	0.631	0.129	0.407	8,177
$\overline{\text{BrexitRisk}}_i$	0.232	0.000	1.107	1.000	2.058	0.189	1.013	0.128	0.651	8,177
$\overline{\text{BrexitSentiment}}_i$	-0.317	0.000	2.541	-1.000	4.057	-0.279	2.425	-0.237	1.480	8,177
<b>Panel B: Event study variables</b>										
Pre-BrexitExposure <sub><i>i</i></sub>	0.042	0.000	0.366	0.251	0.716	0.034	0.343	0.022	0.250	4,399
Pre-BrexitRisk <sub><i>i</i></sub>	0.038	0.000	0.478	0.230	1.209	0.030	0.422	0.025	0.377	4,399
Pre-BrexitSentiment <sub><i>i</i></sub>	-0.084	0.000	2.130	-0.335	3.067	-0.074	2.084	-0.033	0.983	4,399
Stock Returns <sub><i>s</i></sub> : June 24-28, 2016	-0.033	-0.027	0.065	-0.085	0.100	-0.030	0.062	-0.031	0.061	6,077
<b>Panel C: District level variables</b>										
Pct Vote for Leave <sub><i>c</i></sub>	48.816	50.769	11.334	NA	NA	NA	NA	NA	NA	116
Brexit Risk <sub><i>c</i></sub>	1.000	0.375	1.585	NA	NA	NA	NA	NA	NA	116
Brexit Sentiment <sub><i>c</i></sub>	-1.000	-0.065	4.442	NA	NA	NA	NA	NA	NA	116
<b>Panel D: Firm-year outcomes</b>										
$\overline{\text{BrexitExposure}}_{i,t}$	0.117	0.000	0.655	0.558	1.484	0.095	0.574	0.067	0.424	52,363
$\overline{\text{BrexitRisk}}_{i,t}$	0.111	0.000	0.953	0.495	2.042	0.092	0.858	0.063	0.663	52,363
$\overline{\text{BrexitSentiment}}_{i,t}$	-0.162	0.000	2.446	-0.544	5.379	-0.142	2.194	-0.122	1.687	52,363
$\overline{\text{Non-BrexitRisk}}_{i,t}$	1.389	1.186	1.000	1.240	1.017	1.396	0.999	1.467	0.945	52,363
$\overline{\text{Non-BrexitSentiment}}_{i,t}$	1.609	1.597	1.000	1.951	1.002	1.592	0.997	1.745	0.927	52,363
$I_{i,t+1}/K_{i,t} \cdot 100$	24.467	14.236	41.103	19.800	31.194	24.713	41.544	26.280	43.946	51,387
$\Delta emp_{i,t}/emp_{i,t-1} \cdot 100$	8.123	2.863	29.567	7.227	28.191	8.173	29.642	8.714	30.607	54,860
$\Delta sales_{i,t}/sales_{i,t-1} \cdot 100$	17.666	6.489	70.807	12.204	52.278	17.941	71.602	18.769	73.930	64,024

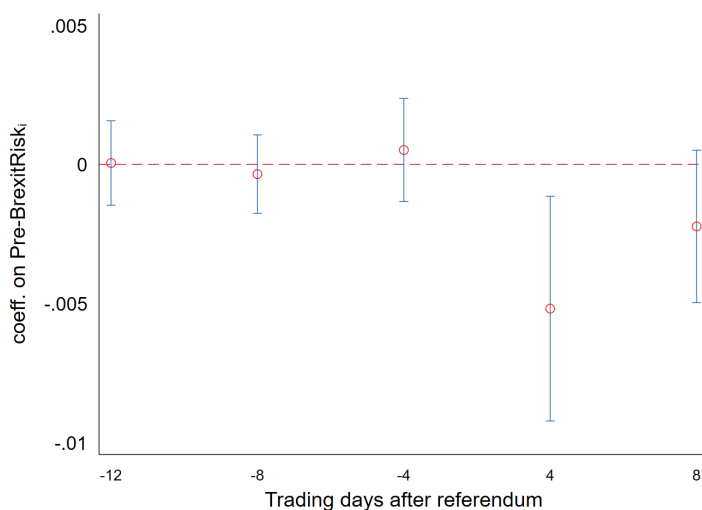
*Notes:* This table shows the mean, median, standard deviation, and the number of firms for the variables used in the subsequent analysis. Columns 1 to 3 refer to the sample of all firms, Columns 4 and 5 to the sample of UK firms, Columns 6 and 7 to the sample of non-UK firms and Columns 8 and 9 to US firms.  $\overline{\text{BrexitExposure}}_i$ ,  $\overline{\text{BrexitRisk}}_i$ ,  $\overline{\text{BrexitSentiment}}_i$ ,  $\overline{\text{Non-BrexitRisk}}_i$  and  $\overline{\text{Non-BrexitSentiment}}_i$  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 headquartered in the UK 2016-19, respectively. In Panel B,  $\overline{\text{Pre-BrexitExposure}}_i$ ,  $\overline{\text{Pre-BrexitRisk}}_i$ , and  $\overline{\text{Pre-BrexitSentiment}}_i$  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<sub>*s*</sub> 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<sub>*c*</sub> 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 2011-2019;  $\overline{\text{BrexitExposure}}_{i,t}$ ,  $\overline{\text{BrexitRisk}}_{i,t}$ ,  $\overline{\text{BrexitSentiment}}_{i,t}$ ,  $\overline{\text{Non-BrexitRisk}}_{i,t}$  and  $\overline{\text{Non-BrexitSentiment}}_{i,t}$  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*** (0.002)	-0.023*** (0.002)			
$\overline{\text{BrexitRisk}}_i$			-0.011*** (0.002)	-0.011*** (0.002)	
$\overline{\text{BrexitSentiment}}_i$			0.002** (0.001)	0.002** (0.001)	
Pre-BrexitRisk <sub>i</sub>					-0.005** (0.002)
Pre-BrexitSentiment <sub>i</sub>					0.001** (0.000)
Constant	-0.007 (0.004)	0.006 (0.004)	-0.006 (0.004)	0.006 (0.004)	0.009* (0.005)
$R^2$	0.169	0.205	0.155	0.190	0.171
N	4,572	4,528	4,572	4,528	3,811
PANEL B			US firms		
$\overline{\text{BrexitExposure}}_i$	-0.024*** (0.003)	-0.024*** (0.002)			
$\overline{\text{BrexitRisk}}_i$			-0.009*** (0.002)	-0.008*** (0.002)	
$\overline{\text{BrexitSentiment}}_i$			0.003*** (0.001)	0.003*** (0.001)	
Pre-BrexitRisk <sub>i</sub>					-0.005** (0.002)
Pre-BrexitSentiment <sub>i</sub>					0.002** (0.001)
Constant	-0.011** (0.005)	0.008 (0.005)	-0.009* (0.005)	0.009* (0.005)	0.007 (0.005)
$R^2$	0.077	0.132	0.067	0.123	0.115
N	2,816	2,785	2,816	2,785	2,534
Beta controls	N	Y	N	Y	Y

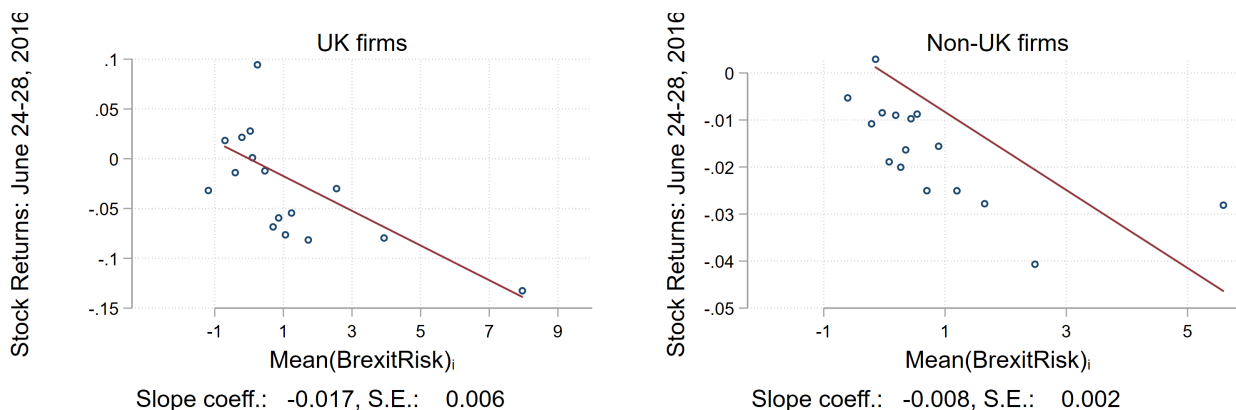
*Notes:* This table reports OLS estimation results from cross-sectional regressions of stock returns from June 24 to June 28, 2016 on  $\overline{\text{BrexitRisk}}_i$  and  $\overline{\text{BrexitSentiment}}_i$ , separately for all firms (Panel A) and for US headquartered firms (Panel B). Stock returns 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  $\text{Pre-BrexitRisk}_i$  for consecutive return windows before and after the June 23, 2016 Brexit referendum using the specification of Column 5 in Table 5. Each return window consists of 4 consecutive trading days.

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



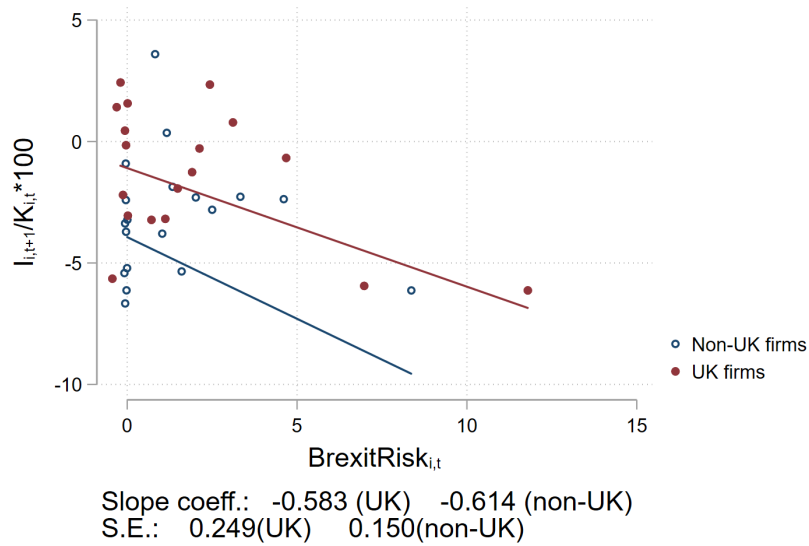
*Notes:* These figures show binned scatter plots and a linear regression line for the relationship between stock returns from June 24 to June 28, 2016 and  $\overline{\text{BrexitRisk}}_i$  for firms headquartered in the UK (left panel) and outside of the UK (right panel). The relationship is plotted after controlling for  $\overline{\text{BrexitSentiment}}_i$ ,  $\log(\text{assets})$ , 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 by firm-year observations with non-zero  $\overline{\text{BrexitRisk}}_i$ .

Table 6: Voting in Brexit Referendum

	Pct Vote for Leave <sub>d</sub>		
	(1)	(2)	(3)
BrexitRisk <sub>d</sub>	-0.838* (0.456)		-0.929** (0.378)
BrexitSentiment <sub>d</sub>		0.358*** (0.133)	0.386*** (0.114)
Share UK born <sub>d</sub>	50.481*** (7.296)	51.592*** (7.484)	52.395*** (7.380)
Income per capita <sub>d</sub>	-0.024*** (0.004)	-0.022*** (0.003)	-0.023*** (0.004)
<i>R</i> <sup>2</sup>	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<sub>d</sub> on BrexitRisk<sub>d</sub> and BrexitSentiment<sub>d</sub>, as defined in Table 4. Share UK born<sub>d</sub> (the share UK-born individuals residing in a district *d*), and Income per capita<sub>d</sub> 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: BrexitRisk<sub>*i,t*</sub> 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) 2011-2018. The scatter controls for  $\log(\text{assets})$ , 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: BrexitRisk<sub>*i,t*</sub>, BrexitSentiment<sub>*i,t*</sub> and Firm Investment

	$I_{i,t+1}/K_{i,t} \cdot 100$				
	(1)	(2)	(3)	(4)	(5)
<hr/>					
PANEL A	All firms				
BrexitRisk <sub><i>i,t</i></sub>	-0.528*** (0.134)	-0.396*** (0.136)	-0.464*** (0.138)	-0.430*** (0.135)	-0.434*** (0.138)
BrexitSentiment <sub><i>i,t</i></sub>	-0.083 (0.069)	-0.086 (0.070)	-0.084 (0.073)	-0.080 (0.072)	-0.089 (0.073)
Non-BrexitRisk <sub><i>i,t</i></sub>				-0.818*** (0.285)	-0.694** (0.286)
Non-BrexitSentiment <sub><i>i,t</i></sub>					0.833*** (0.232)
$R^2$	0.033	0.058	0.079	0.080	0.080
N	25,837	25,760	25,745	25,745	25,745
<hr/>					
Year FE	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y
Country x year FE	N	Y	Y	Y	Y
Industry x year FE	N	N	Y	Y	Y
<hr/>					
PANEL B	US firms				
BrexitRisk <sub><i>i,t</i></sub>	-0.871*** (0.263)	-0.871*** (0.263)	-0.822*** (0.255)	-0.765*** (0.256)	-0.794*** (0.258)
$R^2$	0.040	0.040	0.068	0.068	0.069
N	16,386	16,386	16,368	16,368	16,368
<hr/>					
Year FE	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y
Industry x year FE	N	N	Y	Y	Y
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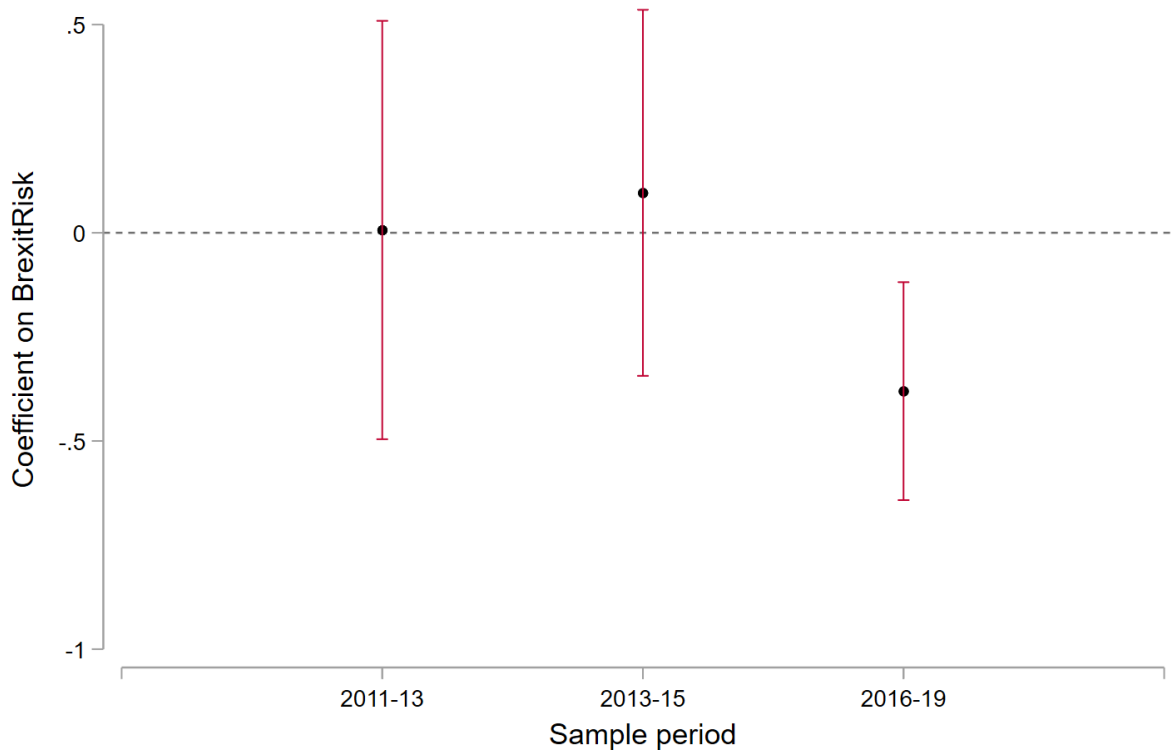
*Notes:* This table reports results from regressions of  $I_{i,t+1}/K_{i,t} \cdot 100$  on BrexitRisk<sub>*i,t*</sub> and BrexitSentiment<sub>*i,t*</sub> using yearly data, separately for the full sample (Panel A) and for sample firms headquartered in the US (Panel B). BrexitRisk<sub>*i,t*</sub> and BrexitSentiment<sub>*i,t*</sub> 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. All specifications include controls for log(assets) and industry fixed effects are at two-digit-SIC levels. 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:  $\text{BrexRisk}_{i,t}$ ,  $\text{BrexSentiment}_{i,t}$ , and Firm Investment

	$I_{i,t+1}/K_{i,t} \cdot 100$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PANEL A		All firms					
BrexRisk $_{i,t}$	-0.434*** (0.138)	-0.545** (0.231)	-0.369*** (0.137)	-0.430*** (0.139)	-0.440*** (0.144)	-0.455** (0.224)	-0.530*** (0.172)
Earnings surprise $_{i,t}$		-0.017 (0.051)					
Stock returns $_{i,t}$ : Quarterly			0.254*** (0.026)				
Stock returns $_{i,t}$ : Week before EC				0.128** (0.057)			
PRiskTrade $_{i,t}$ (std.)					-0.562** (0.229)		
Average UK sales $_i$ (pre-Brexit)						1.273 (4.118)	
$\overline{\text{BrexitExposure}}_i$							0.614 (0.661)
$R^2$	0.080	0.095	0.095	0.081	0.085	0.110	0.080
N	25,743	18,303	24,595	24,829	24,651	17,500	25,743
PANEL B		US firms					
BrexRisk $_{i,t}$	-0.794*** (0.258)	-0.732*** (0.256)	-0.621** (0.260)	-0.761*** (0.261)	-0.584*** (0.205)	-1.058*** (0.339)	-0.759*** (0.258)
$R^2$	0.069	0.071	0.084	0.071	0.085	0.069	0.070
N	16,368	14,159	15,884	16,091	14,099	16,368	15,836
Controls	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Industry x Year FE	Y	Y	Y	Y	Y	Y	Y
Country x Year FE	Y	Y	Y	Y	Y	Y	Y

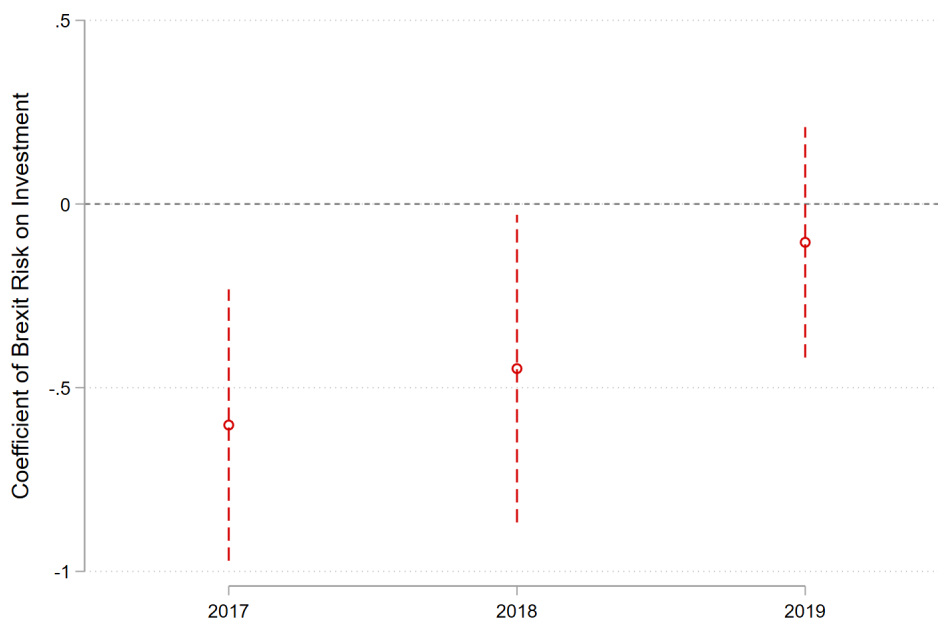
*Notes:* This table reports estimation results from regressions of  $I_{i,t+1}/K_{i,t} \cdot 100$  on  $\text{BrexRisk}_{i,t}$  and  $\text{BrexSentiment}_{i,t}$  using yearly data for the full sample.  $\text{BrexRisk}_{i,t}$  is defined as in Table 7. Earnings surprise $_{i,t}$  is defined as  $(\text{EPS}_{i,t} - \text{EPS}_{i,t-1})/\text{end-of-year stock price}_{i,t}$ , where  $\text{EPS}_{i,t}$  are earnings per share of firm  $i$  during year  $t$  (Compustat item `epspx`). Stock returns $_{i,t}$ : Quarterly is the average of the firm's stock returns during the quarters in which earnings calls are held; and Stock returns $_{i,t}$ : Week before EC is the average stock return during the week before earning calls held in year  $t$ .  $\text{PRiskTrade}_{i,t}$  (std.) is the Political Risk: Trade Policy Index variable from [Hassan et al. \(2019\)](#), standardized by its own standard deviation. All specifications control for  $\log(\text{assets})$ , and industry fixed effects are two-digit-SIC levels. 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 2016-2019  $\text{BrexitRisk}_{i,t}$  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.

Figure 9: Investment and  $\text{BrexRisk}_{i,t}$ : Timing of the Effect of  $\text{BrexRisk}_{i,t}$



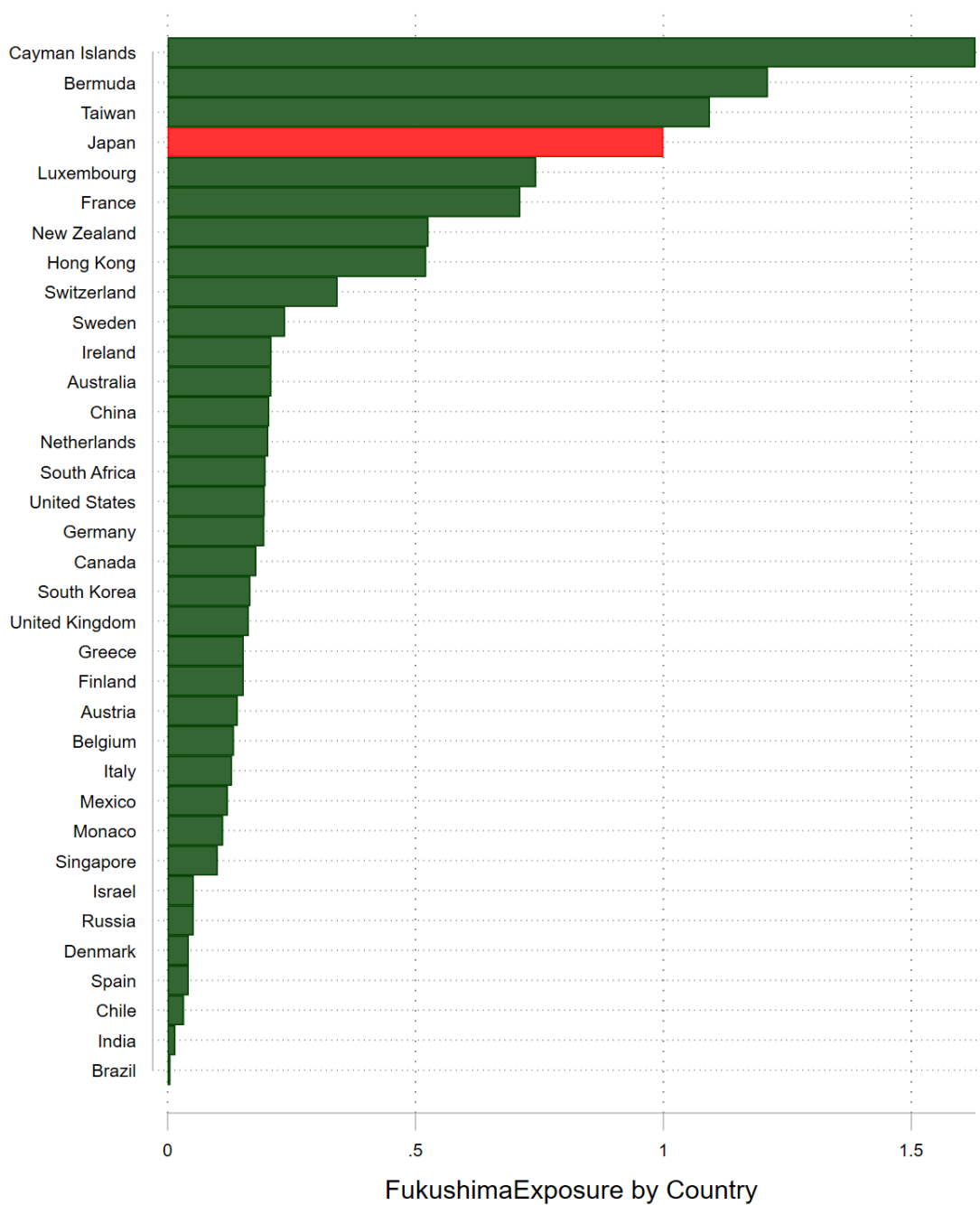
*Notes:* This figure plots the coefficients estimates along with 95% confidence intervals from a regression of  $I_{i,t+1}/K_{i,t} \cdot 100$  on interactions of post-referendum year (2016, 2017, 2018) indicator variables and  $\text{BrexRisk}$ . Note that the dependent variable is the one-year ahead investment rate; accordingly, the coefficient on the interaction between the 2016 indicator variable and  $\text{BrexRisk}$  is reported as ‘2017’ on the horizontal axis, and so on. The regression controls for  $\text{BrexRiskSentiment}$ ,  $\log(\text{assets})$ ,  $\text{Non-BrexRisk}$ ,  $\text{Non-BrexRiskSentiment}$  along with country-year and industry-year interacted fixed effects. The dependent variables are winsorized at the 1 and 99 percentile. Standard errors are clustered at the firm level.

Table 9: BrexitRisk<sub>*i,t*</sub>, BrexitSentiment<sub>*i,t*</sub>, and Other Firm Outcomes

PANEL A	$\Delta emp_{i,t}/emp_{i,t-1} \cdot 100$			
	All firms		US firms	
BrexitRisk <sub><i>i,t</i></sub>	-0.339*** (0.106)	-0.315*** (0.115)	-0.721*** (0.228)	-0.762*** (0.242)
BrexitSentiment <sub><i>i,t</i></sub>	-0.009 (0.053)	-0.019 (0.053)	-0.116 (0.118)	-0.094 (0.122)
Non-BrexitRisk <sub><i>i,t</i></sub>	-0.787*** (0.203)	-0.799*** (0.210)	-0.744*** (0.260)	-0.678*** (0.263)
Non-BrexitSentiment <sub><i>i,t</i></sub>	1.475*** (0.168)	1.461*** (0.186)	1.642*** (0.241)	1.590*** (0.245)
$R^2$	0.026	0.061	0.027	0.057
N	31,031	30,940	20,513	20,493
PANEL B	$\Delta sales_{i,t}/sales_{i,t-1} \cdot 100$			
	All firms		US firms	
BrexitRisk <sub><i>i,t</i></sub>	-0.334* (0.175)	-0.161 (0.187)	-0.317 (0.309)	-0.297 (0.308)
BrexitSentiment <sub><i>i,t</i></sub>	0.095 (0.075)	0.098 (0.084)	0.153 (0.198)	0.229 (0.217)
Non-BrexitRisk <sub><i>i,t</i></sub>	-0.007 (0.479)	-0.081 (0.499)	0.085 (0.653)	0.121 (0.659)
Non-BrexitSentiment <sub><i>i,t</i></sub>	1.999*** (0.312)	2.108*** (0.344)	2.197*** (0.455)	1.865*** (0.462)
$R^2$	0.026	0.064	0.037	0.059
N	33,274	33,169	21,333	21,313
Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Industry $\times$ Year FE	N	Y	N	Y
Country $\times$ Year 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 BrexitRisk<sub>*i,t*</sub> and BrexitSentiment<sub>*i,t*</sub>. BrexitRisk<sub>*i,t*</sub> and BrexitSentiment<sub>*i,t*</sub> are calculated as in Table 7. All specifications control for Non-BrexitRisk<sub>*i,t*</sub>, Non-BrexitSentiment<sub>*i,t*</sub>, and log(assets), and industry fixed effects are at two-digit-SIC levels. 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 10: Mean FukushimaExposure by Country



*Notes:* This figure shows the country-by-country mean of  $\overline{\text{FukushimaExposure}_{i,t}}$  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, and Malaysia.

Table 10: Top Fukushima Exposure Firms' Transcript Excerpts

Panel A: Japanese firms					
Company	$\overline{\text{Fukushima Exposure}_i}$	Country	Month	Transcript excerpts	Exposure description
East Japan Railway Co	20.97	JP	2013-04	in the materials at hand last year the great east <b>japan earthquake</b> 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 <b>japan earthquake</b> 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 <b>japan earthquake</b> as well as provisions for asset retirement obligations for previous	Exposed properties (shopping malls)
Osaka Gas Co Ltd	7.44	JP	2013-04	far this plan was created before the great east of <b>japan earthquake</b> 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 <b>japan earthquake</b> 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 <b>japan earthquake</b> in the first quarter of but the downward trend had	Exposed properties
Panel B: Non-Japanese 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 <b>fukushima</b> 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 <b>fukushima</b> 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 <b>japanese nuclear</b> 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 <b>japanese earthquake</b> 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 <b>nuclear accidents</b> 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 <b>fukushima</b> 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 <b>japanese earthquake</b> 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 <b>fukushima</b> 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 <b>fukushima</b> 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 <b>earthquake and tsunami</b> in japan the earthquake in new zealand the floods	Insurance claims

Notes: This table shows transcript excerpts for the top 5 Japanese (Panel A) and the top 10 non-Japanese (Panel B) firms ranked by  $\overline{\text{Fukushima Exposure}_i}$ .  $\overline{\text{Fukushima Exposure}_i}$  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

#### *A.1. Earnings conference call transcripts*

From Refinitiv EIKON, we collect the complete set of 176,149 English-language transcripts of earnings conference calls held from 2011 through 2019. 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 remove ‘risk officer’ and ‘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.

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 we remove this snippet. 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*

We obtain headquarters locations for firms from Refinitiv EIKON and subsidiary location information from Orbis. We measure firm level pre-Brexit and post-Brexit share of sales in



UK from Compustat Historical Segments Data (summing all mentions of United Kingdom, UK, Great Britain, Northern Ireland, England, Wales, Scotland, and variations thereof). Compustat Historical Segments provides yearly sales data for a firm split by country, and using this we calculate the share of sales in UK before and after 2016 (year of Brexit). To measure a firm’s investment rate, capital expenditure, change in sales, employment change, quarterly stock return and earnings surprise, we use financial statement data from Standard & Poor’s Compustat North America (US) and Global (non-US) files. Specifically, we obtain the following data from Compustat: earnings per share, capital expenditure, property, plant, and equipment, investment, sales, employment and quarterly stock return. We also download daily stock returns from Center for Research in Security Prices, LLC (CRSP). Our measure for capital expenditure,  $I_{i,t}/K_{i,t-1}$ , is calculated recursively using a perpetual-inventory method. Specifically, we calculate the investment rate as follows: for  $t = 2$ ,  $\frac{\text{Capxy}_2}{\text{Ppent}_1}$ , for  $t > 2$ ,  $\frac{\text{capxy}_t}{\text{Recursive K}_{t-1}}$ , where the denominator for  $t > 2$  is calculated recursively as  $\text{Recursive K}_{t-1} := \Delta p_K \times \delta \times \text{Recursive K}_{t-2} + \text{Capxy}_{t-1}$ , where Capxy is Compustat’s out-of-the-box capital expenditure, Ppent is Compustat’s out-of-the-box property, plant, and equipment, and  $\Delta p_K$  is the ratio of this period’s to last period’s Producer Price Index (obtained from FRED), and  $\delta$  is depreciation (set at 10%). We winsorize the variable at the first and last percentile. Change in sales,  $\Delta \text{sales}_{i,t}/\text{sales}_{i,t-1}$ , is the change in quarter-to-quarter sales over last quarter’s value, winsorized at the first and last percentile. Employment change,  $\Delta \text{emp}_{i,t}/\text{emp}_{i,t-1}$ , is the change in year-to-year employment over last year’s value, winsorized at the first and last percentile. Earnings surprise $_{i,t}$  is defined as  $(\text{EPS}_{i,t} - \text{EPS}_{i,t-4})/\text{price}_{i,t}$ , where  $\text{EPS}_{i,t}$  is earnings per share (basic) of firm  $i$  at time  $t$ , and  $\text{price}_{i,t}$  is the closing price of quarter  $t$ . We calculate the Average UK sales $_i$ (pre-Brexit) as the average sales for a firm in compustat before 2016 (year of Brexit referendum). Finally, for a firm  $i$  and year  $t$ , we calculate Stock returns $_{i,t}$  : Quarterly as the firm’s return in the quarter in which the conference call was held (as given in Compustat), averaged across all quarters in which calls are held. Similarly, we calculate Stock returns $_{i,t}$  : Week before EC as the firm’s return seven days before the earnings call, averaged across all weeks prior to earnings calls in year  $t$ .

We use firm’s exposure to other types of risk from [Hassan et al. \(2019\)](#).  $\text{PRiskTrade}_{i,t}(\text{std.})$  is the Political Risk: Trade Policy Index variable standardized by its own standard deviation.

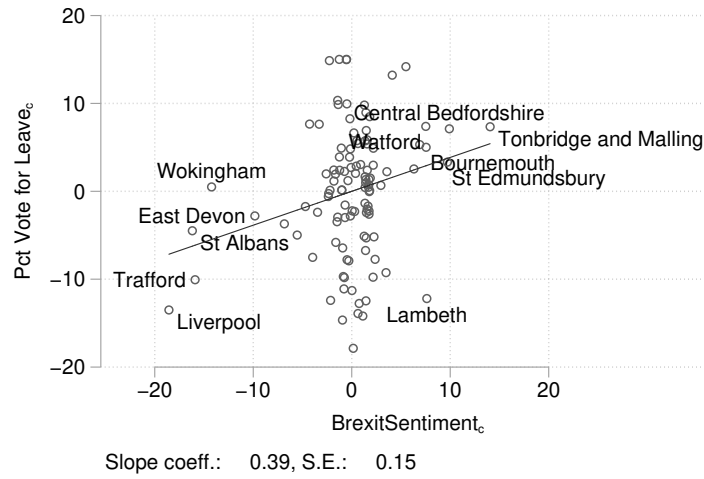
To measure income and share of people born in the UK, we obtain the following data from Office of National Statistics ([www.ons.gov.uk](http://www.ons.gov.uk)): total annual income by output area, and population by output area and country of origin. We then calculate income per capita as  $\frac{\text{total annual income}_d}{\text{total population}_d}$  and share UK born $_d$  as  $\frac{\text{UK born}_d}{\text{total population}_d}$ , where  $d$  is output area.

Appendix Table 1: Data Coverage

	Number of sample firms	
	Headquarters country	With UK subsidiaries
Panel A: Split by country group		
UK	428	NA
EU non-UK	1,035	435
US	3,948	1,634
Rest of the world	2,767	781
Panel B: Split by country		
Canada	583	155
Australia	356	105
India	279	66
China	208	24
Japan	159	95
Germany	164	79
Sweden	162	40
Brazil	144	17
France	133	77
Switzerland	101	52
Hong Kong	83	28
Netherlands	76	40
Italy	81	35
South Africa	81	36
Norway	77	23
Mexico	71	7
Bermuda	64	40
Israel	72	30
Spain	63	30
Ireland	57	33
Denmark	53	24
Finland	52	20
Singapore	42	12
Russia	42	2
New Zealand	48	5
S. Korea	37	14
Luxembourg	37	12
Taiwan	34	11
Belgium	32	9
Austria	32	15
Poland	28	6
Chile	26	3
Turkey	25	7
Thailand	22	5
Greece	23	1
Malaysia	18	5
Argentina	17	0
Philippines	15	4
Colombia	16	2
Indonesia	15	1
UK Channel Islands	22	6
Cyprus	16	4
United Arab Emirates	15	5
Nigeria	13	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



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

Appendix Table 2: Synonyms for Risk or Uncertainty

Word	Frequency	Word	Frequency
uncertainty	1,562	variable	6
uncertainties	367	prospect	6
risk	279	unpredictability	5
uncertain	119	insecurity	5
risks	99	danger	4
unknown	38	faltering	3
possibility	34	unstable	3
pending	29	unsure	3
exposed	23	risky	3
threat	22	bet	3
instability	21	suspicion	2
fear	21	indecision	2
doubt	20	hesitant	2
unclear	17	hesitating	2
unresolved	17	dilemma	2
chance	16	indecisive	2
likelihood	14	apprehension	2
probability	8	fluctuating	1
unpredictable	8	speculative	1
unsettled	6	sticky	1

*Notes:* This table shows the frequency across all 102,567 earnings call transcripts between 2015Q1 and 2019Q4 of all single-word synonyms of “risk,” “risky,” “uncertain,” and “uncertainty” as given in the Oxford English 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	298	greater	29
good	277	strength	29
strong	210	profitability	27
positive	188	improving	24
great	116	benefited	24
opportunities	107	stability	23
opportunity	86	optimistic	23
better	84	improve	22
stable	77	advantage	20
able	72	favorable	18
benefit	58	tremendous	18
leading	52	rebound	15
pleased	41	stabilize	15
confident	40	strengthening	14
progress	38	excellent	13
improved	37	gain	13
improvement	35	leadership	12
stronger	32	smooth	11
gains	30	successfully	11
best	30	successful	11

*Notes:* This table shows the frequency across all 102,567 earnings call transcripts between 2015Q1 and 2019Q4 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	317	volatile	47
concerns	269	fallout	45
negative	210	adverse	45
slowdown	133	slower	44
challenges	133	slowed	44
difficult	124	crisis	40
concern	105	turmoil	40
decline	102	aftermath	38
concerned	97	challenge	38
against	96	unexpected	37
disruption	86	delays	35
weakness	81	fears	33
weak	77	delay	33
weaker	70	shutdown	32
challenging	63	delayed	32
slowing	61	weakened	28
slow	59	problems	28
weakening	56	caution	27
late	52	bad	27
negatively	50	disruptions	25

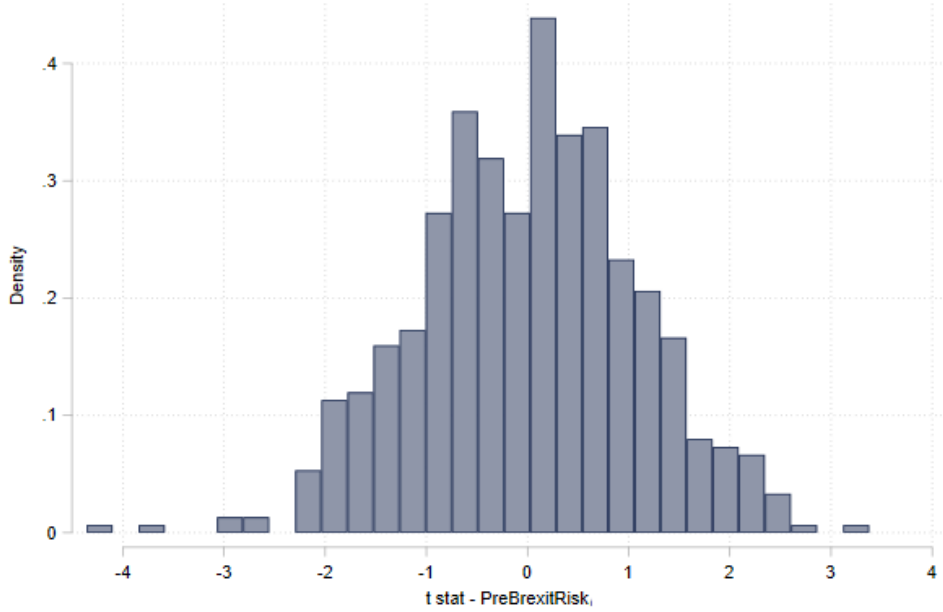
*Notes:* This table shows the frequency across all 102,567 earnings call transcripts between 2015Q1 and 2019Q4 of all negative tone words (with the exception of ‘question,’ ‘questions,’ and ‘ill’) from [Loughran and McDonald \(2011\)](#) (their list contains 2,352 negative tone words) appearing within +/- 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 specification of Column 5 in 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  $\text{Pre-BrexitRisk}_i$  from each of those regressions.

Appendix Table 6: Alternative Ways of Clustering Standard Errors

Clustering scheme	s.e.	$t$ -stat
Clustered by firm (standard)	.14	-3.14
Clustered by country	.18	-2.35
Clustered by industry	.18	-2.42
Two-way clustered by country and industry	.2	-2.13
Robust	.12	-3.48

*Notes:* This table reports alternative standard errors (s.e.) and  $t$ -stats for the coefficient estimate on *BrexitRisk* in the regression specification of Column 5 in Panel A of Table 7.



Appendix Table 7: BrexitRisk and Estimated Average Effects by Country

Country	Mean	Max	N	Average effect (pct. point)	
	Brexit risk (s.e.)	Brexit risk		$I_{i,t+1}/K_{i,t}$	$\Delta emp_{i,t}/emp_{i,t-1}$
All firms	0.228 (0.011)	21.106	8,110	-0.18	-0.17
USA	0.128 (0.010)	21.106	3,948	-0.10	-0.10
Ireland	1.739 (0.443)	14.517	57	-0.75	-0.55
United Kingdom	1.000 (0.099)	15.301	428	-0.43	-0.32
Denmark	0.701 (0.279)	11.176	53	-0.30	-0.22
Netherlands	0.677 (0.202)	9.127	76	-0.29	-0.21
South Africa	0.672 (0.176)	7.883	81	-0.29	-0.21
Sweden	0.638 (0.198)	20.423	162	-0.28	-0.20
UK Channel Islands	0.491 (0.692)	5.893	11	-0.21	-0.15
France	0.460 (0.099)	6.377	132	-0.20	-0.14
Switzerland	0.422 (0.109)	7.102	101	-0.18	-0.13
Germany	0.377 (0.065)	3.917	164	-0.16	-0.12
Thailand	0.316 (0.316)	6.952	22	-0.14	-0.10
Spain	0.313 (0.099)	3.263	63	-0.14	-0.10
Belgium	0.294 (0.143)	4.071	32	-0.13	-0.09
Australia	0.292 (0.076)	18.217	356	-0.13	-0.09
Singapore	0.280 (0.118)	4.617	42	-0.12	-0.09
Peru	0.257 (0.257)	2.566	10	-0.11	-0.08
Hong Kong	0.244 (0.108)	6.599	83	-0.11	-0.08
Austria	0.185 (0.125)	3.879	32	-0.08	-0.06
Monaco	0.157 (0.157)	1.572	10	-0.07	-0.05
Italy	0.156 (0.061)	3.181	81	-0.07	-0.05
Japan	0.155 (0.045)	3.717	159	-0.07	-0.05
Norway	0.154 (0.078)	4.159	77	-0.07	-0.05
Turkey	0.150 (0.091)	1.686	25	-0.07	-0.05
Bermuda	0.150 (0.060)	3.068	64	-0.06	-0.05
Greece	0.138 (0.122)	2.799	23	-0.06	-0.04
India	0.133 (0.034)	4.591	279	-0.06	-0.04
Canada	0.127 (0.028)	7.479	583	-0.05	-0.04
S. Korea	0.124 (0.051)	1.270	37	-0.05	-0.04
New Zealand	0.120 (0.101)	4.784	48	-0.05	-0.04
Luxembourg	0.116 (0.065)	1.928	37	-0.05	-0.04
Finland	0.097 (0.061)	3.115	52	-0.04	-0.03
Mexico	0.089 (0.059)	4.074	71	-0.04	-0.03
Philippines	0.066 (0.066)	0.991	15	-0.03	-0.02
Chile	0.065 (0.049)	1.181	26	-0.03	-0.02
Cyprus	0.055 (0.055)	0.884	16	-0.02	-0.02
Russia	0.048 (0.048)	2.026	42	-0.02	-0.02
Israel	0.045 (0.035)	2.332	72	-0.02	-0.01
Malaysia	0.023 (0.023)	0.410	18	-0.01	-0.01
Poland	0.017 (0.017)	0.485	28	-0.01	-0.01
China	0.003 (0.003)	0.668	208	-0.00	-0.00
Brazil	0.003 (0.003)	0.420	144	-0.00	-0.00

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 average effect on  $I_{i,t+1}/K_{i,t}$  (sample average: 29.66%) and  $\Delta emp_{i,t}/emp_{i,t-1}$  (sample average: 10.67%). 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 from a specific country. The average effect (in pct point.) is calculated as  $\hat{\beta}_y \times \text{BrexitRisk}_{i,t}^c$ , where  $y \in \{I_{i,t+1}/K_{i,t} \cdot 100, \Delta emp_{i,t}/emp_{i,t-1} \cdot 100\}$ , 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. As before, the Table excludes countries for which we have fewer than five sample firms headquartered in that country.

Appendix Table 8: BrexitSentiment by Country

Country	Mean (s.e.)	Min	Max	<i>N</i>
Ireland	-1.227 (0.948)	-40.497	13.741	57
United Kingdom	-1.000 (0.196)	-39.628	10.332	428
Germany	-0.985 (0.213)	-15.061	5.924	164
Peru	-0.851 (0.569)	-4.567	0.000	10
Austria	-0.746 (0.544)	-12.712	2.503	32
Sweden	-0.714 (0.448)	-43.267	25.500	162
Italy	-0.679 (0.295)	-18.289	3.250	81
France	-0.602 (0.269)	-22.928	9.399	132
Denmark	-0.601 (0.397)	-15.355	7.627	53
Norway	-0.467 (0.245)	-15.701	2.046	77
Switzerland	-0.432 (0.228)	-8.000	6.815	101
Spain	-0.389 (0.165)	-5.718	1.862	63
Turkey	-0.369 (0.232)	-4.531	0.689	25
Singapore	-0.357 (0.175)	-6.101	0.705	42
South Africa	-0.348 (0.325)	-12.915	14.030	81
Belgium	-0.332 (0.158)	-3.433	1.100	32
Hong Kong	-0.315 (0.263)	-15.700	8.333	83
Chile	-0.290 (0.256)	-6.633	0.000	26
Monaco	-0.280 (0.280)	-2.798	0.000	10
India	-0.276 (0.098)	-9.435	15.095	279
New Zealand	-0.267 (0.170)	-6.213	0.000	48
Malaysia	-0.260 (0.260)	-4.688	0.000	18
Mexico	-0.259 (0.146)	-8.170	0.871	71
Japan	-0.259 (0.188)	-23.712	8.194	159
Australia	-0.224 (0.256)	-70.955	38.326	356
Thailand	-0.205 (0.300)	-3.210	4.203	22
Finland	-0.194 (0.110)	-3.712	2.165	52
Russia	-0.172 (0.172)	-7.212	0.000	42
Luxembourg	-0.153 (0.117)	-2.377	2.606	37
Canada	-0.146 (0.054)	-13.408	9.189	583
Brazil	-0.124 (0.089)	-12.330	0.993	144
Cyprus	-0.122 (0.122)	-1.946	0.000	16
Bermuda	-0.080 (0.152)	-4.679	3.761	64
China	-0.049 (0.038)	-7.665	0.000	208
Poland	-0.034 (0.093)	-2.218	1.265	28
S. Korea	-0.032 (0.092)	-2.716	1.130	37
Greece	-0.021 (0.285)	-3.861	4.982	23
Netherlands	-0.003 (0.267)	-6.045	14.768	76
Israel	0.016 (0.016)	0.000	1.154	72
Philippines	0.045 (0.111)	-0.753	1.434	15
UK Channel Islands	0.649 (0.789)	-1.932	7.736	11

*Notes:* For the country indicated in the first column, this table shows the mean (standard error), min, and max of BrexitSentiment, and the number of firms. The mean, min, and max of BrexitSentiment 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 9: Timing of the Effect of  $BrexitRisk_{i,t}$ : Investment and Employment

	$I_{i,t+1}/K_{i,t} \cdot 100$			$\Delta emp_{i,t}/emp_{i,t-1} \cdot 100$		
	(1)	(2)	(3)	(4)	(5)	(6)
2016* $BrexitRisk_{i,t}$	-0.667*** (0.174)	-0.603*** (0.174)	-0.602*** (0.188)	-0.633** (0.298)	-0.580** (0.288)	-0.654** (0.304)
2017* $BrexitRisk_{i,t}$	-0.532** (0.216)	-0.483** (0.212)	-0.448** (0.214)	-0.455 (0.295)	-0.413 (0.300)	-0.318 (0.304)
2018* $BrexitRisk_{i,t}$	-0.169 (0.156)	-0.125 (0.155)	-0.104 (0.160)	-0.165 (0.124)	-0.107 (0.122)	-0.114 (0.141)
2019* $BrexitRisk_{i,t}$				-0.212 (0.135)	-0.191 (0.142)	-0.191 (0.147)
$BrexitSentiment_{i,t}$	-0.093 (0.072)	-0.094 (0.071)	-0.085 (0.072)	-0.015 (0.052)	-0.027 (0.053)	-0.020 (0.053)
Non- $BrexitRisk_{i,t}$		-1.173*** (0.364)	-1.179*** (0.370)		-0.970*** (0.303)	-1.007*** (0.303)
Non- $BrexitSentiment_{i,t}$		0.724** (0.282)	0.712** (0.285)		1.535*** (0.247)	1.452*** (0.250)
$R^2$	0.072	0.075	0.081	0.034	0.039	0.051
N	10,149	10,149	10,145	14,763	14,763	14,756
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y
Industry $\times$ Year FE	N	N	Y	N	N	Y
Country $\times$ Year FE	N	N	Y	N	N	Y

*Notes:* This table reports estimation results from regressions of  $I_{i,t+1}/K_{i,t} \cdot 100$  (columns 1-3) and  $\Delta emp_{i,t}/emp_{i,t-1} \cdot 100$  (columns 4-6) on  $BrexitRisk_{i,t}$  and  $BrexitSentiment_{i,t}$  using yearly data for the full sample.  $BrexitRisk_{i,t}$  is defined as in Table 4. All specifications control for  $\log(\text{assets})$  and for year and two-digit-SIC 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.

Appendix Table 10: Robustness: BrexitRisk, BrexitSentiment, and Employment Growth

	$\Delta emp_{i,t}/emp_{i,t-1} \cdot 100$					
	(1)	(2)	(3)	(4)	(5)	(6)
<hr/>						
PANEL A	All firms					
BrexitRisk <sub><i>i,t</i></sub>	-0.353*** (0.105)	-0.339*** (0.106)	-0.315*** (0.115)	-0.308*** (0.119)	-0.507*** (0.184)	-0.423*** (0.124)
BrexitSentiment <sub><i>i,t</i></sub>	0.002 (0.052)	-0.009 (0.053)	-0.019 (0.053)	-0.029 (0.055)	-0.021 (0.081)	0.007 (0.055)
Non-BrexitRisk <sub><i>i,t</i></sub>		-0.787*** (0.203)	-0.799*** (0.210)	-0.803*** (0.215)	-0.868*** (0.274)	-0.798*** (0.210)
Non-BrexitSentiment <sub><i>i,t</i></sub>		1.475*** (0.168)	1.461*** (0.186)	1.467*** (0.188)	1.549*** (0.228)	1.463*** (0.186)
PRiskTrade <sub><i>i,t</i></sub> (std.)				-0.070 (0.105)		
Average UK sales <sub><i>i</i></sub> (pre-Brexit)					-3.870 (3.235)	
BrexitExposure <sub><i>i</i></sub>						0.919*** (0.354)
<hr/>						
$R^2$	0.022	0.026	0.061	0.064	0.074	0.062
N	31,031	31,031	30,940	29,833	20,571	30,940
<hr/>						
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 x Year FE	N	N	Y	Y	Y	Y
<hr/>						
PANEL B	US firms					
BrexitRisk <sub><i>i,t</i></sub>	-0.718*** (0.229)	-0.721*** (0.228)	-0.762*** (0.242)	-0.742*** (0.245)	-0.626*** (0.180)	-0.933*** (0.268)
<hr/>						
$R^2$	0.023	0.027	0.057	0.059	0.060	0.057
N	20,513	20,513	20,493	20,192	16,764	20,493
<hr/>						
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
<hr/>						

Notes: This table reports results from regressions of  $\Delta emp_{i,t}/emp_{i,t-1} \cdot 100$  on BrexitRisk<sub>*i,t*</sub> and BrexitSentiment<sub>*i,t*</sub> 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 11: Robustness: BrexitRisk, BrexitSentiment, and Sales Growth

	$\Delta sales_{i,t}/sales_{i,t-1} \cdot 100$					
	(1)	(2)	(3)	(4)	(5)	(6)
<hr/>						
PANEL A	All firms					
BrexitSentiment <sub><i>i,t</i></sub>	0.184 (0.193)	0.153 (0.198)	0.229 (0.217)	0.216 (0.217)	0.242** (0.099)	0.255 (0.218)
<i>R</i> <sup>2</sup>	0.035	0.037	0.059	0.060	0.061	0.059
N	21,333	21,333	21,313	20,996	17,340	21,313
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 x Year FE	N	N	Y	Y	Y	Y
<hr/>						
PANEL B	US firms					
BrexitSentiment <sub><i>i,t</i></sub>	0.184 (0.193)	0.153 (0.198)	0.229 (0.217)	0.216 (0.217)	0.242** (0.099)	0.255 (0.218)
<i>R</i> <sup>2</sup>	0.035	0.037	0.059	0.060	0.061	0.059
N	21,333	21,333	21,313	20,996	17,340	21,313
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

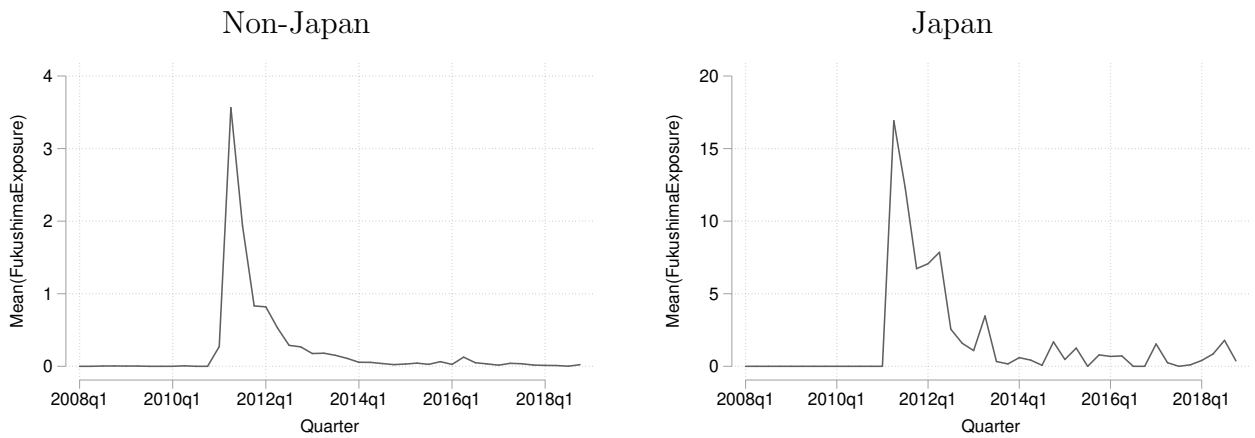
*Notes:* This table reports results from regressions of  $\Delta sales_{i,t}/sales_{i,t-1} \cdot 100$  on BrexitRisk<sub>*i,t*</sub> and BrexitSentiment<sub>*i,t*</sub> using yearly data. The dependent variable is winsorized at the 1st and 99th percentile. All right-hand side variables are defined as 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 12: Timing of the Effect of BrexitRisk

	$I_{i,t}/K_{i,t-1} \cdot 100$	$\Delta emp_{i,t}/emp_{i,t-1} \cdot 100$
	(1)	(2)
BrexitRisk $_{i,t}$	-0.119 (0.081)	-0.310*** (0.117)
BrexitRisk $_{i,t-1}$	-0.283** (0.111)	-0.006 (0.155)
$R^2$	0.070	0.045
N	24,992	26,403

*Notes:* This table reports estimates from panel regressions using yearly data. In all specifications, we control for log(assets) and for two-digit-SIC  $\times$  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’ sector. Standard errors are clustered by firm. \*, \*\*, and \*\*\* indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

Appendix Figure 3: Time Series of FukushimaExposure



*Notes:* This figure plots the quarterly mean of non-Japan (left) and Japan-headquartered (right) firms’ FukushimaExposure. We normalized  $\overline{\text{FukushimaExposure}}_i$  using the average  $\overline{\text{FukushimaExposure}}_i$  of Japan-headquartered firms.

Appendix Table 13: Top 100 Fukushima-Disaster Bigrams from Newspaper Articles

Ngram	Count	Ngram	Count	Ngram	Count
nuclear power	544	japans nuclear	89	the containment	57
the nuclear	382	per cent	87	power co	57
the fukushima	371	no reactor	87	from japan	57
the plant	320	nuclear disaster	86	cool the	56
fukushima daiichi	285	of radioactive	86	us nuclear	55
the reactor	282	the chernobyl	85	nuclear fuel	55
nuclear plant	218	nuclear safety	85	safety agency	53
the reactors	215	nuclear crisis	82	the stricken	52
power plant	199	cooling systems	82	magnitude earthquake	51
a nuclear	182	a meltdown	81	reactors in	51
of radiation	179	nuclear industry	80	reactors and	50
fuel rods	167	daiichi plant	79	sea water	49
earthquake and	158	explosion at	79	cabinet secretary	49
of nuclear	157	the cooling	77	reactor core	49
the earthquake	154	the accident	76	japanese authorities	49
and tsunami	140	fukushima nuclear	76	accident in	49
nuclear plants	136	nuclear accident	71	to japan	49
tokyo electric	134	japanese government	71	plants are	49
power plants	131	fukushima plant	70	the site	49
three mile	125	international atomic	70	japanese nuclear	48
mile island	123	edano said	69	plant the	48
the plants	123	prime minister	68	nuclear reactor	47
radiation levels	115	cooling system	67	at japans	46
the disaster	114	plant and	66	of water	46
nuclear energy	112	energy agency	65	the pacific	46
at fukushima	112	spent fuel	65	fukushima no	44
daiichi nuclear	111	reactor no	64	containment vessel	44
nuclear reactors	101	yukio edano	63	a tsunami	44
the quake	98	nuclear regulatory	62	the radioactive	44
disaster in	97	the radiation	61	reactors are	43
atomic energy	95	in fukushima	60	knocked out	42
the tsunami	93	an earthquake	60	natural disaster	42
reactors at	93	radioactive material	58	reactor and	41
				chief cabinet	41

*Notes:* This table shows the top 100 Fukushima-disaster bigrams by frequency in newspaper articles published after the Fukushima accident in March 2011. To get to this list, we proceed as follows: in Factiva, we 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 downloaded 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.