Exporting Uncertainty: The Impact of Brexit on Corporate America*

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Abstract

Building on a real-options model of capital and labor responses to uncertainty, we show that the Brexit Referendum impacted American corporations, with measurable effects on decisions regarding investment, employment, R&D, and savings. The effects we identify are modulated by the degree of reversibility of production inputs like capital and labor. In particular, they are aggravated by the illiquidity of fixed assets and labor unionization rates. Among jobs lost in the US, most losses accrue to industries with less skilled workers. Our results describe how foreign-born uncertainty is transmitted across borders, shaping domestic capital formation and labor allocation. They warn against the consequences of rising uncertainty about the stability of political institutions in developed economies.

Keywords: Brexit, political uncertainty, international spillovers, investment, labor
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"Clearly, this is a very important decision for the UK. It could have consequences in turn for the US economic outlook that would be a factor in deciding on the appropriate path of policy. It is certainly one of the uncertainties that we discussed and that factored into today's decision."

— Janet Yellen, Federal Reserve Chair, on the last FOMC press conference before Brexit.

"Delta said economic uncertainty from Brexit prompted it to cut deeply into its capacity plans."

— *Wall Street Journal*, July 21, 2016.

1 Introduction

On June 23, 2016, voters in the United Kingdom elected to leave the European Union by a narrow margin of the ballots cast. The *Brexit* Referendum result was surprising since most opinion polls had the "remain" vote winning by safe margins. Perhaps most notable was the perception that voters went to polling stations with little knowledge about what casting a ballot for Brexit would entail.[1] Leaving the EU would change the status of the UK in the EU trade and customs agreements. It would also change the status of European workers in the UK and that of British workers in continental Europe. Brexit would trigger renegotiations of decades-old agreements running a gamut from financial regulation and legal jurisdiction authority, all the way to border restrictions and the fight against terrorism.

Rising political uncertainty appears to be a global phenomenon. This can be gleaned from the annotated time series of a global policy uncertainty index calculated by Davis (2017); see Figure 1. A salient feature of Figure 1 is that, even in light of events such as the Global Financial Crisis and the Iraq War, the largest spike in global uncertainty to that date had come with the Brexit Referendum. Notably, the referendum was not part of an institutional mandate or predetermined political cycle (such as the election of new administrations in the US). Instead, it was an *ad hoc* consultation of the public's sentiment about an international agreement that a politician (Prime Minister David Cameron) chose to gamble on. Formally, the Referendum had no immediately binding effect. It would simply initiate a process by which the UK would ask the EU to negotiate an exit (trigger EU's Article 50). Once this process was set off (at a date to be later determined), the parties would have years to design a new set of rules governing their relations. The Brexit vote did not represent a directly-measurable innovation to trade, capital, and labor markets within a well-defined range of anticipated outcomes. Instead, it brought about a fundamental change in ways agents form expectations about those markets going forward.

[1] It is said that many "leave" voters changed their minds immediately after the outcome was announced, prompting calls for another round of voting (see *The Economist*, October 15, 2016, *"After Brexit, Bregret"*). "Brexit" became Google's top article search in the UK on June 24, the day after the vote.

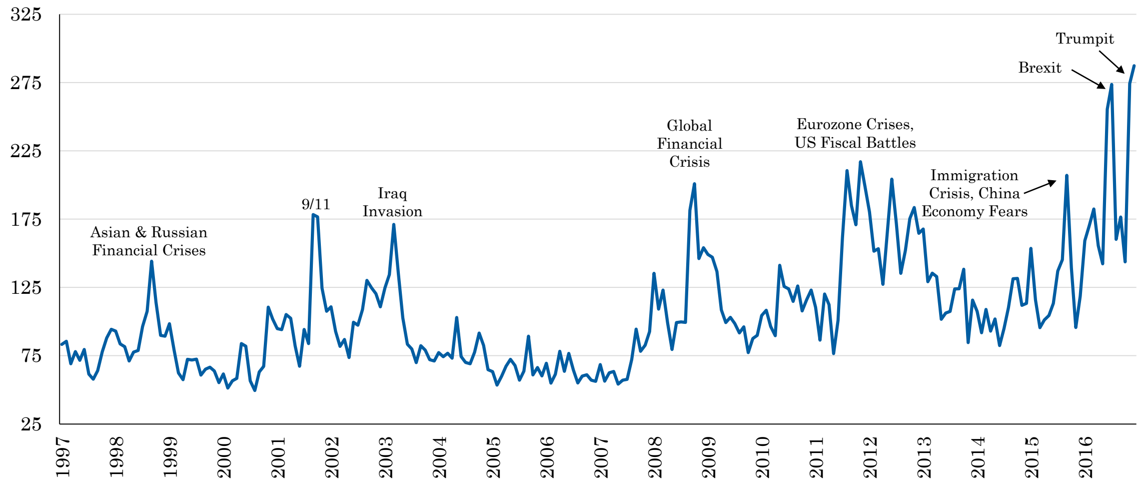

Figure 1. Global Economic Policy Uncertainty (1997:1–2017:12). This figure is a reproduction of Figure 1 in Davis (2017), who calculates a GDP-weighted average of Global Economic Policy Uncertainty using the methodology of Baker et al. (2016).

Uncertainty-filled events like Brexit may become more common in a world gone wary of the workings of the global financial markets, international trade, and immigration.[2] These are phenomena of much interest, yet of poorly-understood consequences. This paper sheds light into an array of cross-border connections between political uncertainty and economic activity. It does so gauging the impact of Brexit on firms located outside of the UK–EU geographical boundaries; in particular, firms located in the United States. The US economy is a candidate to study the international effects of Brexit for several reasons. Firstly, while EU-ties are at the root of Brexit, and effects observed across European countries would be endogenous to the Referendum itself, this is not true of the US. Secondly, there exist very strong trade and financial ties between the American and British economies.[3] Finally, it is particularly informative to look at a large player in the world economy to assess the global impact of Brexit.

We begin our analysis by estimating a series of Bayesian Vector Autoregressive (BVAR) models to gauge the impact of UK uncertainty on US aggregate outcomes. These models include both countries' key macroeconomic variables along with a political uncertainty proxy — the Baker et al. (2016) economic policy uncertainty (EPU) index. This exercise is conducted with data that purposedly excludes Brexit and allows us to gauge spillovers of UK uncertainty onto US macroeconomic variables through

[2]The surprising election of Donald Trump in the United States (dubbed *Trumpit*) is believed to be rooted in voter sentiment that find close parallels in Brexit (see Becker et al. (2017)).

[3]The UK is the 5$^{\text{th}}$ top destination of US exports and the 7$^{\text{th}}$ top US import partner (Census Bureau 2015). BIS data on counterparty exposures show that the US banking system has its strongest links with banks from the UK, and *vice-versa*. Foreign claims of the US banking system with UK banks average 4% of US GDP, while UK banks hold foreign claims with US banks averaging 37% of the British GDP.

various channels. Impulse-response functions systematically point to measurable, detrimental effects of large UK-born uncertainty shocks onto US aggregates. Negative effects are larger for investment than for employment. The patterns we report appear to be shaped by the fact that investment in the US is dominated by large corporations, which naturally are more exposed to the global economy.[4]

We then look for microeconomic support of our macro findings. We do so by first presenting a model of investment under uncertainty modified to incorporate firm-level exposure to macro-level uncertainty. Within a real-options framework, our analysis delivers a negative relationship between uncertainty and fixed capital investment, divestitures, and employment growth. The model we develop also predicts stronger effects of uncertainty for firms with higher capital (labor) adjustment costs on investment (employment). In other words, the model predicts that macro uncertainty effects are modulated by adjustment costs in each relevant production factor. Our analysis further implies that the negative relation between uncertainty and investment resulting from the deferral of investment activities is temporary, and that firms eventually return to normal levels of investment. Notably, we also model the impact of uncertainty on "growth options" activities such as R&D. We show how such activities may be positively affected by aggregate uncertainty. The model we present disciplines empirical testing and adds to the literature by embedding into a single framework a number of corporate decisions that have been previously separately examined.

We derive testable implications from our model to examine how our macroeconomic findings may translate into observable firm-level outcomes. Within a well-specified setting, we study the behaviors of American firms following Brexit as a function of their exposure to uncertainty in the UK. Specifically, we trace how "UK-exposed" firms in the US (identified in several ways) conduct decisions regarding investment, employment, and R&D spending in the aftermath of Brexit. Difference-in-Differences (DID) estimates suggest that in the last two quarters of 2016, the investment-to-assets rates of UK-exposed firms fell 0.07 percentage points more (relative to the last two quarters of 2015) than the investment of non-UK-exposed firms. Given that the average quarterly investment rate in 2015 was 1.1% of assets, this decline represents a drop of 6% in baseline investment rates. Further, we find that UK-exposed firms reduced their divestitures by 0.04 percentage points in the last two quarters of 2016

[4] Capital expenditures by the top 100 US public corporations make up for more than 60% of aggregate investment of publicly-traded firms, accounting for most of the variation in aggregate net fixed private non-residential investment (Grullon et al. (2018)). The creation of employment, on the other hand, is reportedly driven by small, young firms (see, e.g., Haltiwanger et al. (2013)).

(relative to the same period in 2015), representing a drop of nearly 40% of the average 2015 divestiture rate. Our results suggest that the increase in uncertainty brought about by Brexit reduced *both* investment and disinvestment activities of UK-exposed firms — an expansion of firms' investment "inaction region." Notably, consistent with our real-options-based theory, we observe an increase in R&D spending by UK-exposed firms. Specifically, those firms increased their R&D expenditures by 0.15 percentage points more than non-UK-exposed firms in the last two quarters of 2016 when compared to the last two quarters of 2015 (the average R&D expenditure in 2015 was 3.2% of assets per quarter, implying an increase of 5% in R&D spending relative to the mean). Regarding employment, our estimates imply that employment growth declined from 3.4% (the average in 2015) to 0% for UK-exposed firms in 2016; that is, Brexit led to a slowdown in net job creation among UK-exposed firms in the United States — this, at a time when unemployment rates had declined significantly across the economy.

Consistent with our model, we find that the investment behavior of UK-exposed American firms was modulated by capital adjustment costs. Specifically, the investment contraction caused by Brexit was a function of the nature of the assets US firms operated — it was more acute for firms in industries where fixed capital is highly irreversible. Labor adjustment costs also seem to modulate the extent to which UK-exposed firms hired and fired workers. In particular, exposed firms in industries with higher unionization rates — where labor adjustments are costlier — registered a significantly lower job growth. Finally, we show that investment spending eventually begins to converge back to its long-run trend over time (approximately one year after Brexit).

We set out to characterize our findings on US companies' investment and employment decisions more prominently after Brexit by identifying whether those decisions affect their US-based or their foreign-based operations. We find that significant investment cuts and jobs losses take place within the United States. We further look into the workforce characteristics of the firms in our sample. Our tests show that workers with lower skills and in states with more stringent wrongful-discharge laws are those most likely to be terminated by firms subject to Brexit-induced uncertainty.

Looking beyond investment and employment, we consider auxiliary corporate policies and find that UK-exposed American firms also saved more cash and accumulated less inventory (non-cash working capital) in the aftermath of Brexit. Our estimates imply that in the last two quarters of 2016, UK-exposed firms increased their cash holdings by 8% relative to their 2015 baseline level. The results we report are in line with the theoretical literature on corporate liquidity management suggesting that in times of heightened aggregate volatility, firms with higher market exposure increase liquid assets for precautionary reasons (Acharya et al. (2013a)).

Our results are robust to several alternative specifications, including different firm-level measurements of exposure to UK uncertainty and sampling periods. Notably, similar DID analyses conducted in periods not characterized by high levels of uncertainty in the UK show no change in investment levels between our treated and control firm groups. Additional falsification tests, such as the exclusion of "Trumpit," suggest that the increase in uncertainty brought by Brexit is the reason behind the behavior of UK-exposed firms. We also find no change in investment among American firms exposed to other major economies that did not register increases in uncertainty at the same time as Brexit. Our combined macro- and micro-level analyses ultimately imply that uncertainty can be quickly transmitted across highly-integrated economies.

Our study builds upon a rapidly growing literature on the effects of political uncertainty. Macroeconomic studies on how uncertainty affects investment and output go back at least to Bernanke (1983), with recent contributions including Bloom (2009) and Bachmann et al. (2013). Corporate-level studies on the effect of uncertainty on investment include Julio and Yook (2012) and Gulen and Ion (2016). Our paper is different from the existing literature on several fronts, but particularly in that we focus on the international transmission of uncertainty, rather than its domestic effects. Indeed, the literature is silent on the international transmission of uncertainty at the firm-level.[5]

By looking at an externally-born uncertainty shock, we improve upon previously-used identification strategies. In particular, it is generally difficult to determine, within a one-country setting, whether deteriorating economic conditions create uncertainty or if uncertainty drives economic outcomes in the first place. Because Brexit is plausibly exogenous to the US, we are able to analyze the impact of a shock that is born outside the "uncertainty–business cycles conundrum" (see Ludvigson et al. (2017)). Our paper is also different from others in the literature in that we consider an unusual and unexpected policy uncertainty shock, whereas prior studies focus on cyclical political events (presidential and gubernatorial elections). Finally, we look at firm-level outcomes that go beyond fixed-capital expenditures, including employment, R&D, and savings policies.

Our work is also related to a literature concerned with the general transmission of shocks across

[5]Studies on the international spillovers of policy uncertainty are exclusively focused on aggregate, time-series evidence (see, e.g., Klössner and Sekkel (2014) and Bhattarai et al. (2017)).

countries. The Global Financial Crisis raised awareness to the fact that countries are interconnected through direct financial and trade links. Our paper points to a channel through which important aspects of the US economy are affected by political events that take place elsewhere. On this front, Kelly et al. (2016) analyze international political uncertainty transmission in the options market. Relatedly, global banks' liquidity spillovers are analyzed in Peek and Rosengren (1997), Cetorelli and Goldberg (2012), and Schnabl (2012). The main policy implications of our paper are tied to theoretical predictions from the literature on uncertainty (e.g., Dixit and Pindyck (1994)). On this dimension, we highlight an important aspect of policy-making: politicians and regulators may affect the economy not only through the *de facto* policies they adopt, but also by introducing uncertainty in the process of making decisions. Such uncertainty has real consequences not only for the originating country, but can also influence capital formation and labor allocation in other countries.

The remainder of the paper proceeds as follows. Section 2 provides a brief background of the Brexit Referendum. Section 3 motivates the analysis of international spillovers between the UK and the US through the lens of a Bayesian VAR model. Section 4 presents a model of corporate investment under uncertainty that generates testable predictions. Section 5 describes the data and the empirical strategy used to identify US firms' exposure to the UK economy. It also shows how we construct our event study window and set up our estimations. Section 6 presents our baseline results along with robustness checks. Section 7 concludes.

2 Background on the Brexit Referendum

What socio-economic forces led to Brexit? A plausible answer is that the call for the 2016 Referendum was driven by rapidly deteriorating conditions of the British economy. Figure 2 suggests that this may not be the case. Macroeconomic aggregates such as inflation and unemployment were not higher than their historical levels when the Brexit vote took place. The country's GDP, for example, had moderate, but positive growth in virtually every quarter since 2010, while unemployment had been declining since 2011. These indicators remained steady after two events of interest: the Brexit Referendum announcement and vote dates.[6] In sharp contrast, economic policy uncertainty in the

[6]Polls show that public awareness about Brexit spiked after the date of the Referendum was announced. See, e.g., *The Economist*, April 3, 2017, *"Brexit: A solution in search of a problem"*.

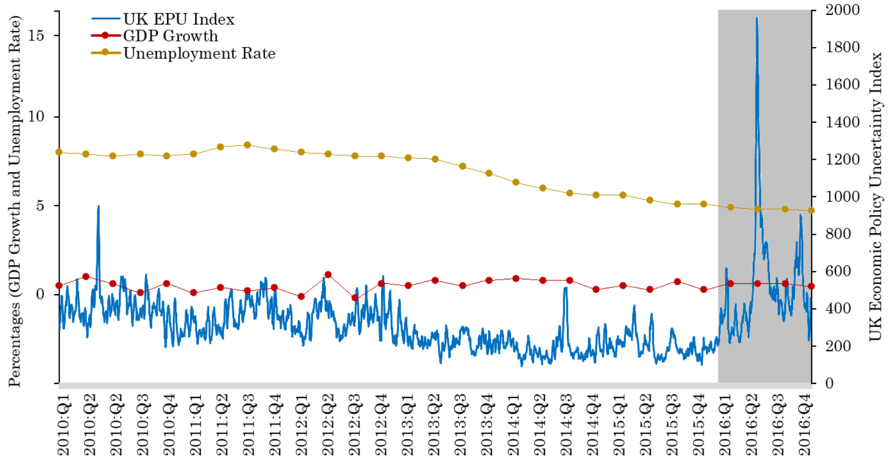

Figure 2. UK Macroeconomic Fundamentals and Economic Policy Uncertainty (2010–2017). The series on the left-hand-side vertical axis (in %) are quarterly macroeconomic activity indicators of the UK: GDP Growth and Unemployment Rate. The right-hand-side vertical axis shows a 7-day moving average of the Economic Policy Uncertainty Index of Baker et al. (2016) for the UK. Shaded area marks the beginning of Brexit-related events, starting with the Announcement of the date of the UK–EU Referendum by PM David Cameron.

UK, as measured by the Baker et al. (2016) index, increased to strikingly high levels with those two events, starting in the first quarter of 2016 (see highlighted area in Figure 2). Comparing the average UK EPU before (133) and after (542) Brexit, its increase amounted to an impressive jump of 409 points — four times the baseline average and 3.4 standard deviations of the historical series.

Brexit is arguably rooted in long-standing political and social tensions within Europe (see Becker et al. (2017)). In 1957, the UK declined the invitation to join the European Economic Community (EEC). Four years later, as the British economy declined, the UK government applied for membership in the EEC, but its application was vetoed by France. It was only in 1973 that the UK became part of the EEC. In the 2000s, attempts of the EU to deepen integration among its members fueled British opposition forces against the oversight of a supranational entity. The rise of the UK Independence Party (UKIP) in the European elections captured this voter sentiment. The UKIP achieved the third place in 2004, second in 2009, and first in 2014. This was the first time in modern history that a party other than the Labour or Conservative parties had taken the largest share of the vote in the UK.

Facing the rise of the UKIP in 2013, Prime Minister David Cameron announced a contingent (non-binding) policy plan: If the Conservative Party were to win the general elections of May 2015, he would commit to a referendum on Britain's membership in the EU before 2017. Granted another term on a narrow victory, Cameron fulfilled his electoral promise, and on June 2015 the House of

Commons approved the European Union Referendum Act.

David Cameron was against UK's exit from the EU and vowed to resign from the Prime Minister post if Brexit was approved. The Conservatives' plan was to use the Referendum as leverage to renegotiate better terms within the trade bloc. On February 20, 2016, Cameron announced that voting would take place on June 23, 2016. In the months leading up to the Referendum, the polls indicated that the chances of the UK leaving the EU were very low. A few weeks before the Referendum, the "leave" vote led for the first time, only to trail again one week before the vote, following the assassination of a "remain" supporter (Labour MP Jo Cox) by a "leave" extremist. On the day of the Referendum, bookmakers' odds showed chances of around 90% that the UK would remain part of the EU. The upsetting Referendum result led to Cameron's immediate resignation.

Although the June vote resolved the uncertainty about the Referendum *per se*, Brexit's non-binding mandate and unspecified procedures were still very problematic. Under Prime Minister Theresa May, it became clear that conditions under which the UK would leave the EU were unsettled, creating uncertainty about final agreements dictating international trade, immigration, and financial relations, among others, between the UK and the EU. Voicing her intention to proceed with the Article 50 of the Lisbon Treaty, Prime Minister May triggered the exit process on March 29, 2017.

3 Uncertainty Spillover: Macroeconomic Evidence

We first estimate a VAR model to assess whether UK-born uncertainty may affect US macroeconomic variables. We follow the US-based VAR specification of Baker et al. (2016) in setting up our model. A few modifications are needed to address our objectives, nonetheless. First, our model includes variables for both the US and the UK economies, so that cross-country dynamics can be analyzed. Second, because we include seven variables for each country, we end up with a large-scale VAR. Given the high dimensionality of the model, we opt for a Bayesian approach.[7] Our data coverage is set up so as to exclude Brexit itself, ranging from 1957:Q1 through 2016:Q1.

We estimate the model using the Minnesota prior distribution, which combines a prior belief that

[7]When the VAR's system of equations is large or the lag structure is long, the number of free parameters in the model becomes impractically large. In such cases, reducing the dimensionality of the model through Bayesian shrinkage improves estimation (see, e.g., Canova (2007)).

a random-walk may partially describe the dynamics of the variables in a VAR.[8] This is the standard prior for VARs with persistent variables such as ours. We choose values for the hyperparameters of the prior distribution as suggested in Canova (2007). Variables are included in the same fashion as in Baker et al. (2016): (1) EPU index; (2) US dollar/British pound exchange rate; (3) log of stock market index; (4) short-term interest rate;[9] (5) log of gross fixed investment; (6) log of unemployment; and (7) log of real GDP. We include four lags of each variable in the system to allow for an entire year of persistence in the quarterly-based series. A Gibbs sampler algorithm is used to obtain draws from the posterior distribution.

Figure 3 depicts the estimated impact of a "Brexit-size" orthogonalized shock — a 3.4-standard deviation innovation — to UK uncertainty on several US macroeconomic variables. The two plots on top show that while the impact of UK uncertainty on US GDP (Panel A) is not as strong as its impact on UK GDP (Panel B), it plausibly poses a threat to US output. Likewise, the two middle plots suggest that the impact of UK uncertainty is highly detrimental for UK investment (Panel D), and still negative and significant for US investment (Panel C). Finally, the two bottom plots (Panels E and F) show that UK uncertainty also poses concerns to employment in the US.[10]

The takeaway from our macro evidence is that UK uncertainty has the potential to harm the US economy, with a special impact on investment. One of the reasons to consider investment as the main international transmission channel of Brexit is that firms are essentially forward-looking when investing, thus more sensitive to uncertainty (Bloom (2017)). Given that the American economy is relatively open and that US private investment is dominated by large firms (see Grullon et al. (2018)), our evidence suggests that Corporate America should be particularly sensitive to Brexit's uncertainty shock. We will dig deeper into the issue of corporate investment in fixed capital and employment in our micro-level analyses. Before doing so, we derive testable implications from a model of investment under uncertainty to discipline our empirical analysis.

[8] This method is laid out in Doan et al. (1984) and is arguably the most popular prior structure used in the literature (see, e.g., Koop and Korobilis (2010)).

[9] As is common in recent macroeconomic studies, we replace the effective short-term rate in the 2009:Q1–2015:Q4 period ("zero lower bound") with the US and UK "shadow rates" from Wu and Xia (2016).

[10] Our VAR results are robust to alternative modeling choices. Appendix B contains several US GDP response functions to UK EPU. It shows that the tenor of our IRFs remains unchanged when we consider lags as chosen by the Bayesian information criterion (Panel A). It also unaffected by using the data-driven hyperparameter grid-search method from Giannone et al. (2015) (Panel B). Finally, results are also robust to changing the methodology to Uhlig's (2005) sign-restrictions identification (Panel C).

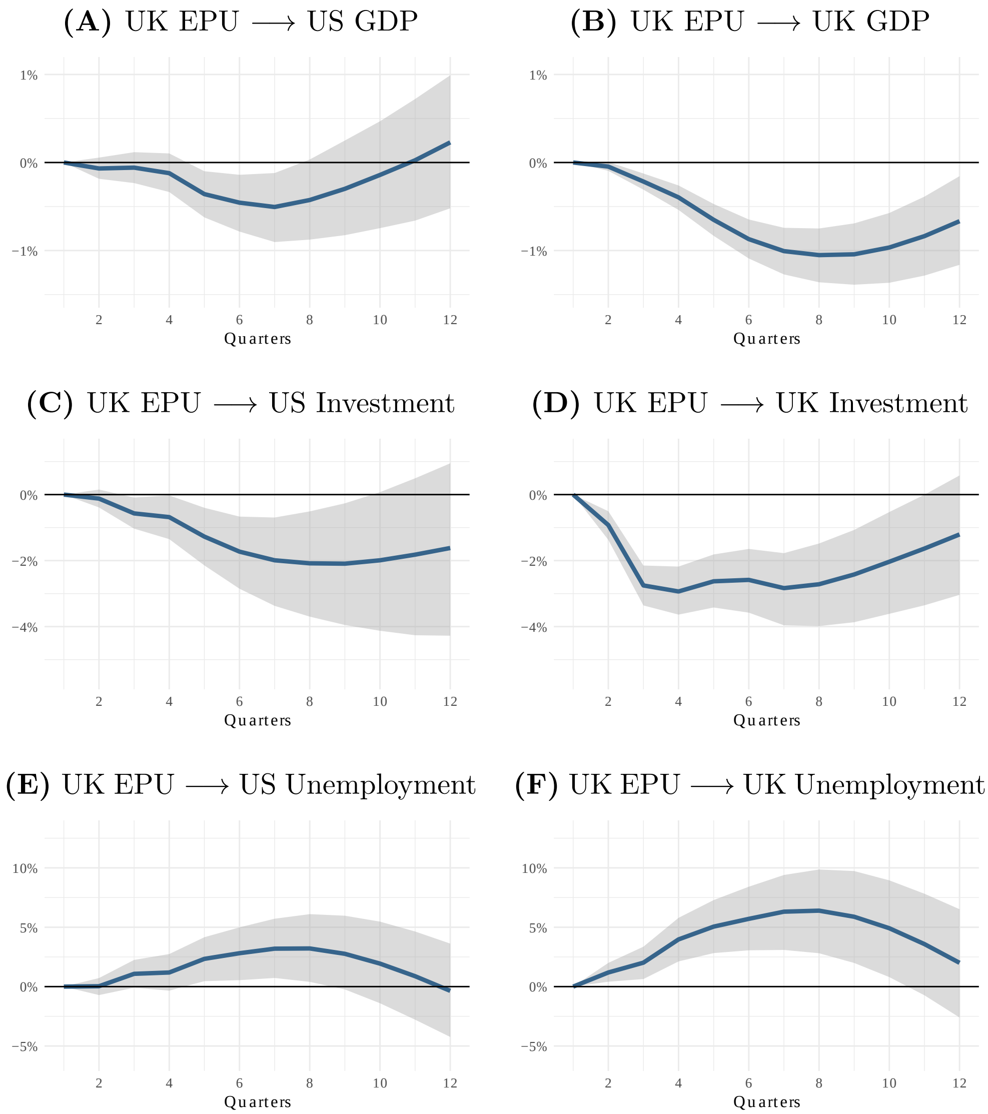

Figure 3. Impulse-Response Functions from Bayesian VAR. Each figure shows the impulse-response function of a 3.4-standard deviations shock to UK Economic Policy Uncertainty and its response on key macroeconomic variables for both the US and the UK along with 68% confidence intervals.

4 Theoretical Framework

We develop a simple theoretical framework to guide our tests of the impact of aggregate uncertainty on various types of corporate activity. To this end, we characterize increases in uncertainty using the concept of mean-preserving spread (MPS). An uncertainty-increasing MPS only requires that a zero-mean, non-degenerate source of randomness has been added to the distribution of the uncertain outcome. This approach allows us to derive a set of results that hold with generality, while remaining agnostic about the functional forms governing the distribution and moments of the outcomes of interest (see also Lee and Shin (2000)). Our model helps one differentiate between a theory of the impact of uncertainty on corporate decisions and an alternative story of how firms react to the expectation of "bad news" (lower mean).[11] A key innovation in our approach is that we model a number of different corporate decisions under a single framework.

4.1 Set Up

We model the investment decision of a firm, i, that operates for three periods, $t = 0,\ 1$, and 2. The firm chooses whether and when to invest in two types of projects: standard-type investments ("capital" and "labor") and "growth option-type" investments ("R&D"). The menu of potential capital investment projects is indexed by n, which lies on the interval $[0, N]$. The menu of potential R&D projects is indexed by m, on the interval $[0, M]$. The firm has an endowment of existing capital investment projects that it had already invested in prior to $t = 0$. The menu of existing capital projects is indexed by w, on the interval $[0, W]$. There is no time discounting.

4.1.1 Investment Income

If the firm decides to invest in a capital project n, its income at $t = 1,\ 2$, denoted by $v_{it}^{(n)} > 0$, is an IID random variable:

$$v_{it}^{(n)} = v_{it} = \beta_i V_t + \epsilon_{it}. \tag{1}$$

Likewise, if the firm decides to invest in a R&D project m, its income at $t = 1,\ 2$, denoted by $u_{it}^{(m)} > 0$, is:

$$u_{it}^{(m)} = u_{it} = \beta_i V_t + \xi_{it}. \tag{2}$$

Finally, the firm's income from disinvesting (selling) an existing project from its capital endowment, w, at $t = 1,\ 2$, is denoted by $s_{it}^{(w)} > 0$, such that:

$$s_{it}^{(w)} = s_{it} = \beta_i V_t + \zeta_{it}. \tag{3}$$

In this setting, $V_t > 0$ represents the demand curve facing the firm and $\beta_i \in (0, 1]$ is the firm's (exogenous) sensitivity to demand. ϵ_{it}, ξ_{it}, and ζ_{it} are independent, idiosyncratic, mean-zero shocks,

[11] See Bloom (2009) for a detailed discussion of first-moment *versus* second-moment shocks.

with variances σ_ϵ^2, σ_ξ^2, and σ_ζ^2, respectively. V_t is distributed as:

$$V_t \sim G(\overline{V_t}, r), \tag{4}$$

where the mean of V_t is equal to $\overline{V_t}$, the variance is equal to $\sigma^2(r)$, and r is an index of the mean-preserving spread. Specifically, $r' > r \implies G(\cdot, r')$ is a MPS of $G(\cdot, r)$, and:

$$\int V_t dG(\cdot, r) = \overline{V_t} \ \forall \ r. \tag{5}$$

The firm's revenue from each capital investment project it decides to invest in can be characterized as a MPS with distribution $v_{it} \sim P(\overline{v_{it}}, r)$ and mean $\overline{v_{it}} = \beta_i \times \overline{V_t}$, with variance $\sigma_i^2(r) = \beta_i^2 \times \sigma^2(r) + \sigma_\epsilon^2$. Likewise, each R&D project's revenue can be characterized as a MPS with distribution $u_{it} \sim Q(\overline{u_{it}}, r)$ and mean $\overline{u_{it}} = \beta_i \times \overline{V_t}$, with variance $\omega_i^2(r) = \beta_i^2 \times \sigma^2(r) + \sigma_\xi^2$. Finally, the proceeds from disinvesting each existing project can be characterized as a MPS with distribution $s_{it} \sim R(\overline{s_{it}}, r)$ and mean $\overline{s_{it}} = \beta_i \times \overline{V_t}$, with variance $\psi_i^2(r) = \beta_i^2 \times \sigma^2(r) + \sigma_\zeta^2$. We note that we model the firm's income from the projects in this way, and not with an explicit characterization of the production function and demand equation, so as to abstract away from unnecessary assumptions about the firm's technology and market structure. The approach allows us to parsimoniously capture the effect of uncertainty on the timing of the firm's investment decisions and the moderating role played by input irreversibility.

4.1.2 Investment Costs

In order to undertake investment project n, the firm must incur a one-time fixed cost of capital, denoted by $F_{iK}(\kappa, n) = \kappa n$, and a one-time fixed cost of labor, denoted by $F_{iL}(\lambda, n) = \lambda n$. The parameters $\kappa > 0$ and $\lambda > 0$ capture the degree of irreversibility of the fixed costs, which scale with n.[12] If it chooses to invest in capital project n, the firm can either invest at $t = 0$ or $t = 1$. If it invests in n at $t = 0$, it incurs the fixed costs $\lambda n + \kappa n$ at $t = 1$, and earns the revenues $v_{i1} + v_{i2}$. If it does not invest at $t = 0$, choosing instead to invest at $t = 1$, it incurs the fixed costs $\lambda n + \kappa n$ at $t = 2$, earning the revenue v_{i2}. The negative effect of uncertainty on capital investment through a

[12] We choose to model the irreversibility of capital and labor investment decisions through fixed costs, and not through a "price discount" when the firm attempts to sell assets, for analytical tractability. In adopting this approach, we follow prior literature (see, e.g., Lee and Shin (2000)) and derive results that would remain qualitatively similar to those under the price discount approach.

real-options channel arises from the joint presence of the option to delay and irreversible fixed costs.

R&D-type projects, m, differ from capital investment projects, n, in two key ways. First, the option to invest in R&D projects is available only at $t = 0$. That is, the firm has only one chance to decide whether to invest. If it declines, these projects cease to become available in the future ($t = 1$ or 2). This means that the R&D investment decision cannot be delayed or postponed, unlike the decision to make standard-type investments. To a first-order approximation, this matches the reality of several types of R&D projects, including the "race to patent" a certain idea or bring a new technology or drug to the market, where the first-mover enjoys a substantial advantage (monopoly in the case of patents) over late-movers.

Second, investments in R&D projects are partially reversible. If the firm wishes to buy the option to invest in project m, it pays an upfront cost of m. In addition, it must pay a development cost d_t for each period in which the project remains alive. That is, in order to earn $t = 1$ revenue u_{i1}, it must pay d_1; similarly, in order to earn $t = 2$ revenue u_{i2}, it must pay d_2. However, at the end of $t = 1$, the firm may choose to scale back and recover a fraction, μm, of the initial investment cost, with $\mu \in (0, 1)$. In this case, it does not receive any revenue from the project at $t = 2$; i.e., $u_{i2} = 0$. On the other hand, if at the end of $t = 1$, it wishes to continue the project then it must pay the second period development cost, d_2, to receive u_{i2}. This, too, matches the reality of certain types of R&D projects (e.g., pharmaceutical trials), in which decisions are made in stages, and the firm does not need to pre-commit to follow through on all stages at once. Notably, the joint absence of (1) the option to delay and (2) irreversible, fixed costs generates a *positive* effect of uncertainty on R&D investment.

Finally, the firm can choose at time $t = 0$ or $t = 1$, to disinvest (sell) any of its existing endowment of projects, w. If the firm sells the project at time t, it must pay a scrapping cost δw, but receives the cash flow from disinvestment of s_{it}. Else, for each period t that the project remains alive, the firm earns a known x_{it} (this is akin, for example, to rent accruing from a real-estate holding).[13] The process of disinvesting a project is irreversible, and as in the case of capital investment, it is this irreversibility that generates a negative effect of uncertainty on disinvestment.

[13]The continuation revenue could also be characterized as random. However, we choose to keep its value deterministic for tractability and because such modeling choice would have no effect on the results.

4.2 Analysis and Results

4.2.1 Capital and Labor Investment Decisions

In solving the firm's capital investment problem, we first consider its decision at $t = 1$. If the firm had initiated any projects at $t = 0$, it obtains the second period revenue v_{i2} per project. Among those projects that were not undertaken at $t = 0$, the firm can choose to initiate any of them at $t = 1$ and earn $v_{i2} - (\kappa + \lambda)n$ per project. Else, it can discard any uninvested projects and earn 0. The firm will rationally discard a given project, $\tilde{n}$, when its revenue is less than the associated costs of investment and hiring. The firm ceases operations at the end of $t = 2$, thus any project that is not undertaken at either $t = 0$ or $t = 1$ has a value of 0 by the end of $t = 2$. The firm's investment decision at $t = 1$ will be guided by profit in the second period that is generated by project $\tilde{n}$. The profit function, π_{i2}, can be characterized as:

$$\pi_{i2}(\tilde{n}) = \begin{cases} v_{i2} & & (\textit{Early Investment}), \\ v_{i2} - (\kappa + \lambda)\tilde{n} & \text{if } v_{i2} > (\kappa + \lambda)\tilde{n} & (\textit{Delayed Investment}), \\ 0 & \text{if } v_{i2} \leq (\kappa + \lambda)\tilde{n} & (\textit{No Investment}). \end{cases} \tag{6}$$

Next, we consider the firm's decision at $t = 0$. The optimal total investment level at $t = 0$ can be expressed in terms of n^*, the breakeven project. The firm will optimally invest in all projects in the range $[0, n^*)$, and not invest in any projects in the range $[n^*, N]$, instead waiting until $t = 1$ to decide whether to undertake those projects. The firm's expected profit from investing in project $\tilde{n}$ at $t = 0$ is $v_{i1} + \mathbb{E}[v_{i2}] - (\kappa + \lambda)\tilde{n}$. Its expected profit from not investing in $\tilde{n}$ at $t = 0$, and choosing instead to wait till $t = 1$ to decide, is $\mathbb{E}\left[\max\left(v_{i2} - (\kappa + \lambda)\tilde{n}, 0\right)\right]$. The firm invests in project $\tilde{n}$ at $t = 0$ if:

$$\underbrace{v_{i1} + \mathbb{E}[v_{i2}]}_{\textit{Expected Revenue}} \geq \underbrace{(\kappa + \lambda)\tilde{n}}_{\textit{Cost of Investment}} + \underbrace{\mathbb{E}\left[\max\left(v_{i2} - (\kappa + \lambda)\tilde{n}, 0\right)\right]}_{\textit{Value of Waiting}}. \tag{7}$$

The breakeven condition for determining the optimal investment level n^* at $t = 0$ is:

$$v_{i1} + \mathbb{E}\left[v_{i2}\right] = (\kappa + \lambda)n^* + \mathbb{E}\left[\max\left(v_{i2} - (\kappa + \lambda)n^*, 0\right)\right] \tag{8}$$

In Lemma 1, we prove the existence of the optimal $t = 0$ investment level, n^*.

Lemma 1. *The optimal capital investment level n^* at $t = 0$ is given by (8) for sufficiently large N.*

Proof. See Appendix A. $\square$

The breakeven condition in (8) implies that the firm invests in all projects at $t = 0$ up to project n^*, for which the benefits are expected to exceed the costs. Notice that firm costs are made of two components: the cost of investing in capital and hiring, and the option value of waiting to choose whether to invest. The embedded optionality in the firm's investment decision is key in generating a negative relation between uncertainty and investment. In particular, while the addition of a zero-mean spread does not change the left-hand side of (7), it increases the right-hand side of that inequality given the firm's option to forgo investment in low income states. Differently put, an increase in uncertainty in the distribution of v_{it} reduces the breakeven project level n^*, and correspondingly, shrinks the set of projects the firm invests in at $t = 0$, namely the interval $[0, n^*)$. We establish this result in Proposition 1.

Proposition 1. *Increased uncertainty leads to less investment at $t = 0$. For $r' > r$, namely when $G(\cdot, r')$ is obtained by a mean-preserving spread of $G(\cdot, r)$, $n^*(r') < n^*(r)$. That is, $\frac{dn^*}{dr} < 0$.*

Proof. See Appendix A. $\square$

Given that the firm invests in n^* projects, the variance of its total income is $(n^* \times \sigma_i(r))^2$. Notice that $r' > r$ implies that variance of the firm's total income increases; i.e., $(n^* \times \sigma_i(r'))^2 > (n^* \times \sigma_i(r))^2$. In addition, for $\beta_i' > \beta_i$, it follows that $(n^* \times \sigma_i'(r))^2 = (n^*)^2 \times \left(\beta_i'^2 \times \sigma^2(r) + \sigma_\epsilon^2\right) > (n^*)^2 \times \left(\beta_i^2 \times \sigma^2(r) + \sigma_\epsilon^2\right) = (n^* \times \sigma_i(r))^2 \;\; \forall\, r$. That is, higher values of parameter β_i would imply greater increases of firm i's income variance for a given increase in uncertainty. This means that firms with higher β_i should reduce capital investment more in the face of higher uncertainty.

4.2.2 R&D Investment Decisions

Our model shows how the "growth options" nature of R&D-type investments generates a positive relation between uncertainty and investment. The argument is based on the idea that increased uncertainty increases the probability of both highly positive and highly negative outcomes. Provided there is sufficient investment reversibility, or the ability to scale back without incurring substantial sunk costs in the face of a negative realization ("downside limiting"), uncertainty only increases the incentive to invest in such projects.[14] Our model delivers a prediction that is consistent with this intuition.

In solving the firm's R&D investment problem, we consider its decision at $t = 0$, the time it may purchase the option to invest. The profits from project $\tilde{m}$ can be expressed as:

$$\pi_{i2}(\tilde{m}) = \begin{cases} 0 & (No\ Investment), \\ u_{i1} - d_1 + u_{i2} - d_2 - \tilde{m} & (Investment,\ No\ Scaling\ Back), \\ u_{i1} - d_1 + \mu\tilde{m} - \tilde{m} & (Investment,\ Later\ Scaling\ Back). \end{cases} \tag{9}$$

The firm will invest at $t = 0$ if:

$$\mathbb{E}[\max\left(\min\left(u_{i1} - d_1 + u_{i2} - d_2, u_{i1} - d_1 + \mu\tilde{m}\right), 0\right)] \geq \tilde{m}. \tag{10}$$

Since the firm may only scale back at $t = 1$ if $\mathbb{E}[u_{2t}] < \mu\tilde{m} + d_2$, it is clear that the firm will invest if:

$$\mathbb{E}[\max\left(u_{i1} - d_1 + \mu\tilde{m}, 0\right)] \geq \tilde{m}. \tag{11}$$

The breakeven R&D project, m^*, is determined by:

$$\mathbb{E}[\max\left(u_{i1} - d_1 + \mu m^*, 0\right)] = m^*. \tag{12}$$

In Lemma 2, we prove the existence of the optimal R&D investment level m^*.

Lemma 2. *The optimal R&D investment level m^* at $t = 0$ is given by (12) for sufficiently large M.*

Proof. See Appendix A. □

The breakeven condition (12) implies that the firm invests in all R&D projects up to the point at which benefits are expected to exceed costs. Since at $t = 1$ the firm can choose to scale back the project, and if so, partially recover the upfront cost, the decision to invest in the R&D projects at $t = 0$ is equivalent to the decision to buy a call option expiring at $t = 1$. At the breakeven R&D investment level, m^*, the price of the option equals its value. Increased uncertainty in the distribution of u_{it}

[14] This dynamic is believed to have played a part in the dot-com bubble (see Bloom (2014)).

increases the value of this option, thereby increasing the breakeven project threshold m^*, expanding the set of R&D projects the firm undertakes. This argument is formalized in Proposition 2.

Proposition 2. *Increased uncertainty leads to greater R&D investment at $t = 0$. For $r' > r$, namely when $G(\cdot, r')$ is obtained by a mean-preserving spread of $G(\cdot, r)$, $m^*(r') > m^*(r)$. That is, $\frac{dm^*}{dr} > 0$.*

Proof. See Appendix A. □

Proposition 2 states that an increase in uncertainty increases the set of R&D projects that the firm is willing to undertake, given that the potential upside has increased and the downside is capped by the ability to scale back, and partially recover upfront costs. It is important to stress the two key conditions that generate opposing predictions of the effect of uncertainty on capital investments *versus* R&D investments. The first condition is the firm's ability to delay capital investments ("wait and see"), but not R&D investments ("patent race").[15] The second relates to the irreversibility of investment. In the R&D setting, the firm has the ability to scale down investment freely at the end of $t = 1$. This is in contrast to capital investment, whose initial costs, once paid, are largely lost.

4.2.3 Disinvestment Decisions

In solving a firm's disinvestment problem, we first consider its decision at $t = 1$. If the firm had disinvested any of its endowed projects at $t = 0$, then it earns 0 for those projects. Among projects that were not disinvested at $t = 0$ (i.e., remain alive a $t = 1$), the firm can choose to sell any of them at $t = 1$ and receive cash flows of $s_{i2} + x_{i2} - \delta w$ per project. Else, it can choose not to sell and receive x_{i2} per project. As in the case of the investment decision, the firm's disinvestment policy is guided by the cash flows at $t = 2$ generated by project $\tilde{w}$. These cash flows can be characterized as:

$$\pi_{i2}(\tilde{w}) = \begin{cases} 0 & & (\textit{Early Disinvestment}), \\ s_{i2} + x_{i2} - \delta\tilde{w} & \text{if } s_{i2} > \delta\tilde{w} & (\textit{Delayed Disinvestment}), \\ x_{i2} & \text{if } s_{i2} \leq \delta\tilde{w} & (\textit{No Disinvestment}). \end{cases} \tag{13}$$

[15] The present approach assume that the cost of delaying an R&D project is infinite for analytical simplicity. If we were to relax this assumption and allow the cost of delay to vary, Proposition 2 would continue to obtain provided the cost of delay is sufficiently high.

Next, we consider the firm's disinvestment decision at $t = 0$. The optimal level of disinvestment at $t = 0$ can be expressed in terms of w^*, the breakeven project. The firm will optimally disinvest (sell) all projects in the range $[0, w^*)$, and not disinvest (choose to retain) any projects in the range $[w^*, W]$, instead of waiting until $t = 1$ to decide whether or not to disinvest. The firm's cash flows from disinvesting project $\tilde{w}$ at $t = 0$ is $s_{i1} + x_{i1} - \delta\tilde{w}$. Its expected cash flows from not disinvesting project $\tilde{w}$ at $t = 0$, and choosing instead to wait till $t = 1$ to decide, is $x_{i1} + \mathbb{E}\left[\max\left(s_{i2} + x_{i2} - \delta\tilde{w}, x_{i2}\right)\right]$. Simplifying these two expressions, the firm disinvests project $\tilde{w}$ at $t = 0$ if:

$$s_{i1} - \delta\tilde{w} \geq x_{i2} + \mathbb{E}\left[\max\left(s_{i2} - \delta\tilde{w}, 0\right)\right]. \tag{14}$$

The breakeven condition for determining the optimal disinvestment level w^* at $t = 0$ is:

$$s_{i1} - \delta w^* = x_{i2} + \mathbb{E}\left[\max\left(s_{i2} - \delta w^*, 0\right)\right]. \tag{15}$$

In Lemma 3, we prove the existence of the optimal $t = 0$ investment level, w^*.

Lemma 3. *The optimal disinvestment level w^* at $t = 0$ is given by (15) for sufficiently large W.*

Proof. See Appendix A. □

The breakeven condition in (15) implies that the firm disinvests all projects at $t = 0$ up to project w^*, for which the benefits, s_{i1}, are expected to exceed the costs. The costs are made of two components: the cost of selling the project, δw, and the option value of waiting to choose whether to disinvest. The embedded optionality in the firm's disinvestment decision is key in generating a negative relation between uncertainty and disinvestment, as is the case with investment. As before, while the addition of a zero-mean spread does not change the left-hand side of (14), it increases the right-hand side of that inequality given the firm's option to forgo disinvestment in high income states. An increase in uncertainty in the distribution of s_{it} reduces the breakeven project level w^*, and correspondingly, shrinks the set of projects the firm disinvests at $t = 0$, namely the interval $[0, w^*)$. We establish this result in Proposition 3.

Proposition 3. *Increased uncertainty leads to less disinvestment at $t = 0$. For $r' > r$, namely when $G(\cdot, r')$ is obtained by a mean-preserving spread of $G(\cdot, r)$, $w^*(r') < w^*(r)$. That is, $\frac{dw^*}{dr} < 0$.*

Proof. See Appendix A. □

Taken together, the results of Proposition 1 and 3 imply that by increasing the value of the option to wait, greater uncertainty leads to decreases in *both* investment and disinvestment.

4.2.4 Effect Duration

While a richer model is needed to fully characterize the dynamics of investment under uncertainty over time, our model provides intuition for the fact that the drop in investment induced by increased uncertainty is temporary.

Consider two $t = 0$ breakeven investment levels n^* and n^{**} associated with two degrees of uncertainty, r and r' respectively, with $r' > r$. From Proposition 1, we know that this implies $n^* > n^{**}$. This means that at $t = 1$, the firm has the option to invest in projects $[n^*, N]$ and $[n^{**}, N]$, respectively, having chosen to invest in projects $[0, n^*)$ and $[0, n^{**})$ at $t = 0$. At $t = 1$, uncertainty regarding v_{i1} has been resolved, and the firm must determine which of the remaining projects $[n^*, N]$ or $[n^{**}, N]$, it will invest in. The interval $[n^{**}, n^*]$ represents the projects that the firm has foregone investing in at $t = 0$ due to increased uncertainty. As the firm loses the option to invest in these projects at the end of $t = 2$, the firm will choose to invest in them at $t = 1$ provided the benefits exceed the costs. In Proposition 4 we show that even under the higher level of uncertainty, r', the firm invests in all projects on the interval $[n^{**}, n^*]$ at $t = 1$.

Proposition 4. *The firm will invest in the set of projects $[n^{**}, n^*]$ at future time $t = 1$ regardless of the level of uncertainty, r.*

Proof. See Appendix A. □

The intuition behind this proposition can be seen as follows. The projects on the interval $[n^{**}, n^*]$ are profitable projects, which are not undertaken at $t = 0$ due to increased uncertainty. However, since the firm loses the ability to invest in any project $[0, N]$ at the end of $t = 2$, it will invest in any profitable projects on this interval at $t = 1$ (when uncertainty regarding v_{i1} has been resolved). As the projects $[n^{**}, n^*]$ continue to remain profitable, the firm will undertake them. This implies that the firm returns its investment levels to normalcy by $t = 1$, despite the reduction in investment levels at $t = 0$ induced by uncertainty. The effect of uncertainty on investment is, thus, temporary.

4.2.5 The Effect of Input Irreversibility

We now address the role played by the degree of irreversibility of capital and labor, as captured by their associated fixed costs. We do so by way of two propositions.

Proposition 5. *An increase in the degree of irreversibility of capital leads to less investment for higher levels of uncertainty in the first period; i.e.,* $\frac{dn^*}{d\kappa} < 0$.

Proof. See Appendix A. □

Proposition 6. *An increase in the degree of irreversibility of labor leads to less investment for higher levels of uncertainty in the first period; i.e.,* $\frac{dn^*}{d\lambda} < 0$.

Proof. See Appendix A. □

Combining the last two propositions with Proposition 1, we have that for an increase in uncertainty in the MPS sense (i.e., $r' > r$) and for greater degree of input irreversibility ($\kappa' > \kappa$ and $\lambda' > \lambda$), the following conditions hold with respect to capital investment:

$$
\begin{aligned}
&n^*(r, \kappa, \lambda) > n^*(r', \kappa, \lambda) > n^*(r', \kappa', \lambda), \\
&n^*(r, \kappa, \lambda) > n^*(r', \kappa, \lambda) > n^*(r', \kappa, \lambda').
\end{aligned} \tag{16}
$$

The above conditions state that an increase in uncertainty reduces the set of capital projects the firm is willing to invest in at $t = 0$, electing to wait until uncertainty is partially resolved at $t = 1$ before deciding whether to invest. Notably, when the firm faces higher irreversible costs, it invests even less at $t = 0$. Differently put, an increase in uncertainty reduces investment in the first period, and the effect is modulated by the degree of irreversibility of capital or labor.

It is worth concluding our theoretical model with a discussion contrasting "uncertainty" about future cash flows and "expectations" about future cash flows. In our model, we do not explicitly derive the effects of a decline in expected cash flows (i.e., $\overline{V_t}$), focusing instead on the effects of an increase in uncertainty (i.e., r). Notably, a decline in expected cash flows would produce similar implications in terms of a decline in capital investment and employment. A decline in expected cash flows would, however, provide contrasting implications in terms of an increase in disinvestment (provided the decline in expected salvage value is not too substantial) and a decline in R&D, counter to the predictions of Propositions 2 and 3.

4.3 Testable Hypotheses

Our model implies that an increase in aggregate uncertainty reduces firm investments in capital projects, and that the effect is moderated by the degree of exposure to uncertainty, β_i. In the context of the impact of UK-born uncertainty onto US-based firms, we state our first testable hypothesis.

Hypothesis 1. *American firms with a higher exposure to UK uncertainty (High UK-Exposure firms) will disproportionately reduce their investment in capital and labor in response to Brexit.*

Our model also indicates that an increase in aggregate uncertainty increases firm investment in R&D projects, and the effect is moderated by the degree of exposure to uncertainty, β_i. Under our test setting, we state our second testable hypothesis.

Hypothesis 2. *American firms with a higher exposure to UK uncertainty (High UK-Exposure firms) will disproportionately increase their investment in R&D in response to Brexit.*

Our model also implies that an increase in aggregate uncertainty reduces firm disinvestment, and the effect is moderated by the degree of firm-level exposure to uncertainty. This translates to our third testable hypothesis.

Hypothesis 3. *American firms with a higher exposure to UK uncertainty (High UK-Exposure firms) will disproportionately reduce their disinvestment in response to Brexit.*

Finally, our model results are shaped by fixed costs F_{iK} and F_{iL}, which capture the degree of irreversibility of capital and labor, respectively. It implies that higher input adjustment costs in each factor modulates the effect of uncertainty in investment in that input. This gives rise to the fourth and fifth testable hypotheses.

Hypothesis 4. *American firms with a higher exposure to UK uncertainty (High UK-Exposure firms) facing higher capital adjustment costs reduce their fixed capital investment more pronouncedly in response to Brexit.*

Hypothesis 5. *American firms with a higher exposure to UK uncertainty (High UK-Exposure firms) facing higher labor adjustment costs reduce their hiring more pronouncedly in response to Brexit.*

4.4 Empirical Counterparts

The implementation of the proposed tests calls for identifying empirical counterparts to the constructs of the model. We first introduce an empirical counterpart to the sensitivity parameter β_i, which represents the intensity of firms' responses to changes in uncertainty. We adopt two approaches to derive empirical measures of β_i. The first follows the model very closely, using a construct that comes from the capital market. The second approach measures expectations of corporate decision-makers regarding uncertainty by looking into mentions of relevant keywords in firms' regulatory disclosures. After defining the empirical counterparts to β_i, we present measures of capital and labor irreversibility, corresponding to κ and λ in our model respectively.

4.4.1 Model-Based Measure of Uncertainty

We first derive a model-based measure of American firms' exposure to UK uncertainty by translating the constructs of our model into their closest empirical counterparts. In our context, the increase in aggregate uncertainty, V_t, comes from the spike in uncertainty associated with Brexit. Accordingly, we take variances on both sides of Eq. (1) (alternatively, Eq. (2)), to capture the notion of uncertainty in the MPS framework:

$$Var(v_{it}) = \beta_i^2 Var(V_t) + \sigma_\epsilon^2. \tag{17}$$

Next, we employ a regression-like approach to identify an empirical counterpart to β_i. Taking square-roots of both sides of (17) we obtain:

$$Vol(v_{it}) = \beta_i Vol(V_t) + \sigma_\epsilon - \sqrt{2 \times \beta_i Vol(V_t) \times \sigma_\epsilon}. \tag{18}$$

Following Bloom (2014), we then use stock volatility as a metric of aggregate uncertainty and estimate (18) for each firm i as:[16]

$$Vol(r_{it}) = \alpha_i + \beta_i^{UK} Vol(FTSE100_t) + Controls_t + \epsilon_{it}. \tag{19}$$

Eq. (19) uses the volatility of firm equity returns, $Vol(r_{it})$, to capture the volatility of firm income, $Vol(v_{it})$. It also uses the volatility of the *FTSE100* index as a proxy for uncertainty in the UK — the relevant source of aggregate uncertainty in our setting.[17] We include control variables consisting of $Vol(SP500)$ and $Vol\left(FX^{\$/£}\right)$ into (19) to absorb effects arising through firms' exposure to the US market and exchange rate fluctuations between the US dollar and the British pound. For each firm, we take the estimated value of β_i^{UK} from the above regression as the empirical counterpart to β_i in our model.[18] Consistent with our model, we restrict attention to firms for which $\beta_i^{UK} \geq 0$.

4.4.2 Text-Based Measure of Uncertainty

As an alternative measure of US firms' exposure to Brexit-induced UK uncertainty, we develop a text-based metric that is constructed by parsing firms' 2015 10-K filings. In particular, we look for the number of entries of keywords related to Brexit-triggered uncertainty ("Brexit", "Great Britain", and "Uncertainty") and classify firms with a "high" number of entries as *High UK-Exposure* firms, and those with zero entries as control firms.[19] By computing these wordcounts from firms' 10-K disclosures — before the vote takes place — we are able to construct a measure of exposure to the UK based on what firms consider relevant to communicate to their investors.

Most firms cite concerns about Brexit a half dozen times or more in their 10-Ks or not at all. As such, we arbitrarily set a cut-off for high Brexit cites at more than 5 entries. There are 807 firms citing Brexit more than 5 times in their 10-Ks. On the other hand, 433 never cite any Brexit-related terms. While the five-entries cut-off is arbitrary, results are robust to many alternative choices.

[16] Bloom (2014) shows that stock market volatility exhibits a high degree of commonality with other observed proxies for uncertainty including those derived from bond markets, exchange rates, and GDP forecasts.

[17] The third term in (18) is subsumed by the idiosyncratic volatility term, ϵ_{it}, in (19).

[18] One could look at firm sales to the UK from standard sources like COMPUSTAT Historical Segments. However, close examination of 10-K forms of a number of firms indicates that such data are often incomplete. As such, we opt for the approach of extracting that information from market-based data. The use of stock market information also benefits from the availability of higher-frequency data, unlike accounting data.

[19] Entries like "Referendum", "Uncertain", "United Kingdom", "UK", "U.K.", "G.B.", etc. are subsided by the above choices.

4.4.3 Capital and Labor Irreversibility Measures

Our model results are modulated by fixed costs F_{iK}, which captures the degree of irreversibility of capital. In order to empirically measure capital irreversibility, we use a measure of capital redeployability proposed by Kim and Kung (2016). That measure classifies fixed capital liquidity in terms of salability of assets in secondary markets.[20] The premise is that when firms operate assets that are used across several industries, there are more potential buyers should firms decide to revert investment decisions by selling their assets. The same is not true for firms that operate highly-specialized assets. Higher values of the Kim and Kung (2016) asset redeployability index are associated with a lower degree of capital irreversibility, corresponding to a lower value of F_{iK} in our model.

Our next task is to find an empirical proxy for the irreversibility of labor, F_{iL}. We resort to the use of unionization as an empirical proxy for frictions in labor input. We do so as ample research in labor economics highlights the significant difficulties firms with unionized employees face in adjusting their workforce in response to change in aggregate conditions (e.g., Nickell (1986) and Bloom (2009)). In using this strategy, we measure the percentage of total employees who are unionized at the 4-digit SIC level using data from the BEA. We expect firms with a greater share of unionized workforce to have lower flexibility and incur greater costs in adjusting the size of their workforce.

5 Firm-Level Empirical Analysis

This section assesses the impact of Brexit on the US economy at the firm level. We first describe the data. Next, we set up our event study by identifying key event dates as well as treatment and control groups. Finally, we present results on investment, employment, R&D, cash holdings, and inventory.

5.1 Data

We use COMPUSTAT Quarterly to gather basic information on firm investment and financial data. We consider US companies with complete statements from the first calendar quarter of 2010 through the fourth calendar quarter of 2016. We drop utility and financial firms, as well as companies whose

[20] The asset redeployability index is derived from the capital flow table constructed by the Bureau of Economic Analysis (BEA). The BEA breaks down fixed capital expenditures into several categories of assets for a broad cross-section of industries. Kim and Kung (2016) compute the asset-level redeployability index as a function of the proportion of firms that use a given asset in an industry.

market value or book assets are lower than \$10 million. The sample used in our baseline firm investment tests consists of 41,630 observations (firm-quarters). For additional analysis on firms' investment in the US, we obtain subsidiary-level investment data from the Bureau van Dijk's Orbis dataset. We use Orbis's company search tool to match parent firms in our COMPUSTAT sample to ultimate owner firms in Orbis, and gather all available data on their US- and UK-based subsidiaries.

Firm-level data on employment is available only at lower frequency, taken from COMPUSTAT's Annual Fundamentals. We construct our measure of employment growth as the percent change in the number of employees. Our firm employment sample consists of 11,345 observations (firm-years). COMPUSTAT data includes firms' foreign operations, and therefore its employment count comprises foreign employees. We obtain the geographical location of firm employment using the COMPUSTAT Historical Segments dataset.

We use CRSP stock price data and Bloomberg equity index and currency returns data to construct our model-based measure of exposure to the UK (and in robustness tests, exposures to other major economies), using monthly data from 2010:M1 through 2014:M12 so that such exposure is measured before any major Brexit-related events. For our text-based measure of exposure to the UK, we obtain firms' 2015 10-K filings from SEC's EDGAR platform. Macroeconomic variables are taken from the Federal Reserve Bank of St. Louis' FRED data base, except for the 12-month forecast of GDP growth, which is taken from the Federal Reserve Bank of Philadelphia's website.

5.2 Identification Strategy and Empirical Specification

We use a DID approach to assess the impact of Brexit on US firms. We employ alternative empirical measures of UK-exposure to assign firms to treated and control groups. Following our model framework, in our base analysis, we consider non-negative values of β_i^{UK} and partition the sample into terciles, labeling treated (control) firms as those firms in the upper (bottom) tercile of the range of the β_i^{UK} distribution.[21] The sample β_i^{UK} ranges from 0 to 3.2, with a total of 449 unique firms being assigned to the treated category ($\beta_i^{UK} > 0.68$). In contrast, three hundred and sixty unique firms are

[21]For the purpose of empirical contrasting, one may not include firms that *benefit* from uncertainty in the UK in the control group; firms with negative β_i^{UK}. Nevertheless, in specifications where we use β_i^{UK} as a continuous treatment variable, we relax this restriction and include all values of β_i^{UK}. In unreported checks, we also label only those firms with statistically significant positive β_i^{UK} estimates as treated firms, and those with β_i^{UK} statistically indistinguishable from zero as control firms. Our results continue to obtain across a broad range of statistical significance thresholds.

assigned to the control category ($\beta_i^{UK} < 0.28$).

We also consider an alternative, text-based measure of exposure to Brexit that takes into account the number of times Brexit-related key words are mentioned in 2015 10-Ks. Under this approach, a total of 807 firms are assigned to the treated category (2015 10-K mentions of Brexit terms > 5). Four hundred and thirty three firms in the control category have no mentions of Brexit-related terms in their 2015 10-Ks.

5.2.1 Timeline

Once firms are identified as exposed and non-exposed, we need to set the time dimension of our proposed DID analysis. We make this determination by relating key events of our institutional setting and market-based measures of perceived uncertainty. In Figure 4, we plot three point-in-time snapshots of the term structure of implied volatility for the FTSE100 Index.[22]

The first (dotted blue) curve represents the term structure as of December 31, 2014, which is the last date of our β_i^{UK} estimation period. We use this curve as a benchmark since expectations at that time were uncontaminated by Brexit-related events. As is typically observed for equities during normal economic conditions, the term structure is upward sloping, indicating the market expects greater volatility at longer horizons. The term structure curve hovers smoothly around the 16% line, suggesting that no abrupt changes are expected by options market participants over a maturity horizon of one week up to two years.

The second (continuous red) curve is the term structure as of February 22, 2016, the first trading day following David Cameron's announcement of the Brexit vote date. Upon news that the Referendum would be held on June 23, the term structure exhibits a U-shape at short-end of maturities — in the window leading up to this newly-revealed date — with a peak occurring at 5 months. This pattern is striking since the options with 5 months to maturity are the very first FTSE100 derivatives to mature after the Brexit vote. The graphed structure suggests that resolution regarding the exact

[22]The implied volatility term structure serves as a metric of market uncertainty over time as it expresses the range of movements in the FTSE100 that market participants expect over various horizons. The values in Figure 4 reflect the market's expectation of the volatility of the FTSE100 over different maturities. For example, if annualized implied volatility for 2 years is 15%, the market expects that prices will move over the next 2 years within a band $\left[-(15 \times \sqrt{2}\%), +(15 \times \sqrt{2})\%\right]$ with 68% probability (one standard deviation). The term structure at each of the dates in the graph is constructed from average Black-Scholes implied volatilities derived from quoted prices of at-the-money options on the FTSE100 Index on that date.

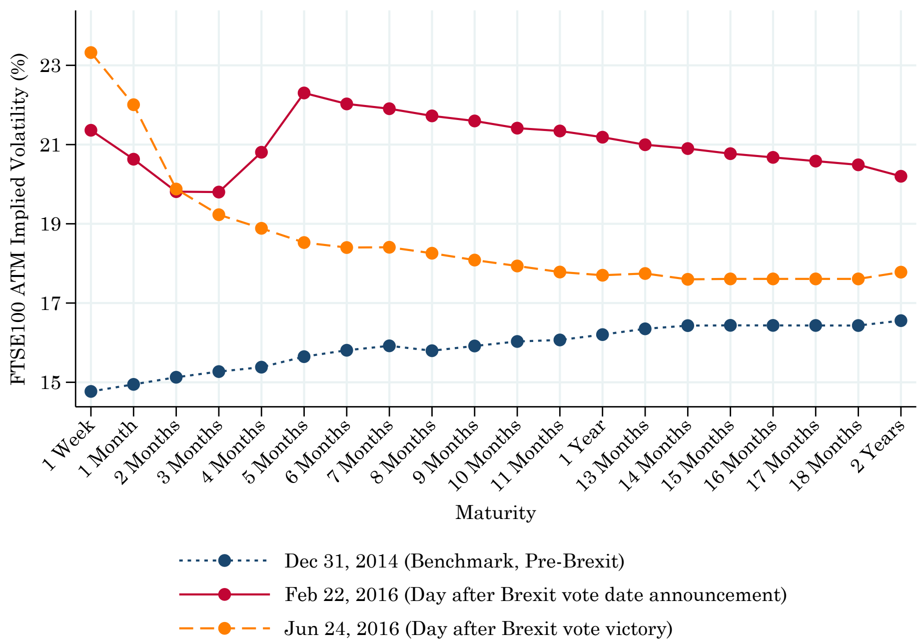

Figure 4. Term Structure of FTSE100 Implied Volatility. This figure shows the term structure of the FTSE100 Index at three different moments. The term structure at each of the dates is constructed from average Black-Scholes implied volatilities derived from quoted prices of at-the-money options on the FTSE100 Index (Ticker: UKX) on that date. The values plotted reflect the market's expectation of the volatility of the FTSE100 index over various maturities considered.

Referendum date had a soothing effect on the market expectations of volatility implied by the prices of options maturing before the Brexit vote, yet introduced a spike in the volatility implied by option prices written on the same underlying asset but maturing right after the vote.

The third (dashed yellow) curve depicts the term structure as of June 24, 2016, the first trading day following the "leave" victory. The term structure becomes downward-sloping, pointing to substantial uncertainty in the immediate aftermath of the Brexit vote, relative to longer maturity horizons. This curve also shows that the volatility implied by option prices converges to a similar level of longer-term uncertainty (several years out) compared to the pre-Brexit levels.

The dynamics of options markets depicted in Figure 4 are useful in guiding our testing strategy. Responses to official news about the exact Referendum vote date suggest that market participants were quick to incorporate uncertainty embedded by Brexit in their trading activity — this, before the actual outcome of the vote. In particular, options trading taking place on February 22, 2016 were priced to reflect a significant drop in market volatility for the period leading up to the Brexit vote date (on June 23), only to show a spike in volatility right after the vote. At the time the vote takes place, market uncertainty seems unusually high. The vote, however, seems to quell uncertainty

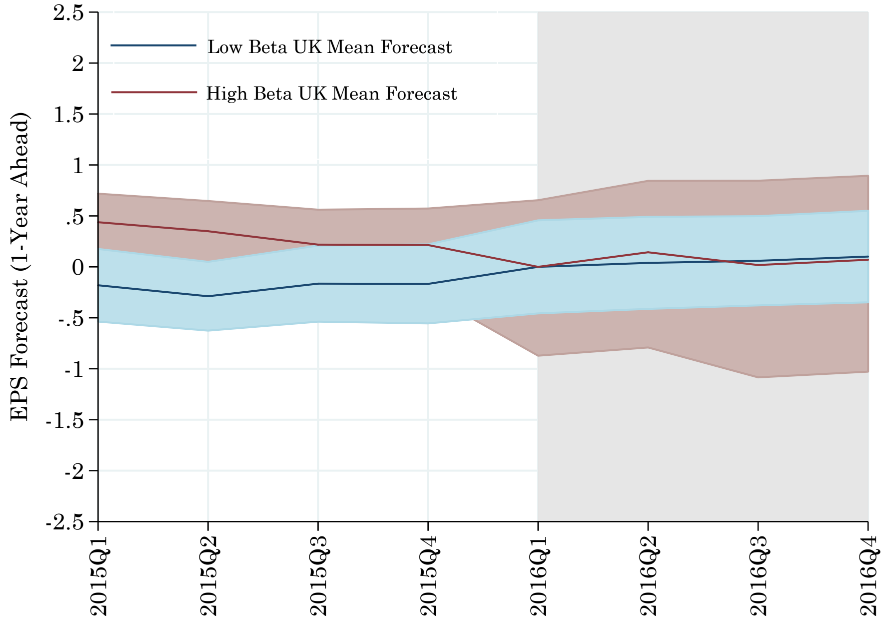

Figure 5. Analysts' Earnings Per Share Forecasts around Brexit. This figure shows how analyst Earnings Per Share (EPS) forecasts behaved around Brexit's key dates. Confidence intervals are calculated as ±1.5 standard deviations from the mean forecast. Each line represents a group of firms sorted by exposure to the UK economy as measured by β_i^{UK}. The shaded area marks the beginning of Brexit-related events with the announcement of the date of the UK–EU Referendum by PM David Cameron (2016:Q1). Both series are normalized to take the value of 0 in 2016:Q1.

forecasts. In particular, as of June 24, 2016, the one-year ahead implied volatility is not significantly different from that registered in December 2014.

Having set the treatment window based upon options market expectations, we set out to verify in the data if this period coincided with increased uncertainty for *High UK-Exposure* firms. We do so using data on analysts' forecasts from the I/B/E/S database. Beginning in 2015:Q1, we obtain the 1-year ahead earnings per share (EPS) forecast for each firm in our sample and compute the mean and standard deviation of forecasts. We quantify forecast uncertainty for firms in the high and low β_i^{UK} groups by constructing ±1.5 standard-deviation intervals around the mean forecasts in Figure 5. Two facts stand out. First, the period that we identified based on the increase in market expectations of uncertainty from options markets is associated with a remarkable increase in earnings forecast dispersion for *High UK-Exposure* firms, but not for firms with low β_i^{UK}. The figure implies that it is precisely during the first two quarters of 2016 that equity analysts begin incorporating the possibility of Brexit-induced uncertainty affecting US firms that are more exposed to the UK. Second, there is no discernible difference in mean forecasted earnings between high and low β_i^{UK} firms, suggesting analysts did not expect UK-exposed American firms to do any worse in

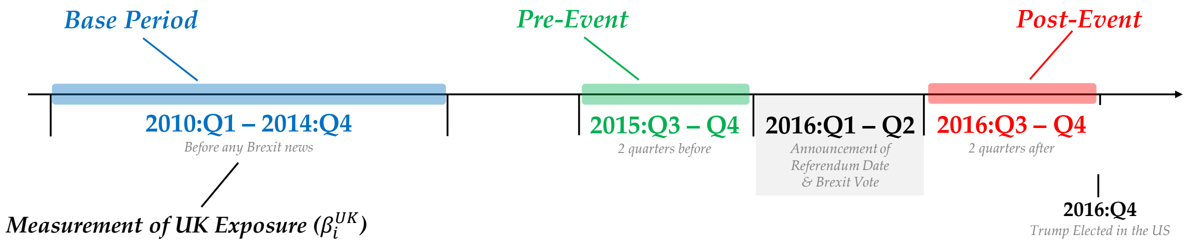

Figure 6. Event Study Timeline. This figure is a timeline of the main events related to Brexit along with dating definitions used in the DID analysis. The grey box in 2016:Q1–Q2 marks the beginning of Brexit-related events, with the announcement of the date of the UK–EU Referendum by PM David Cameron (2016:Q1) and the victory of the Brexit vote (2016:Q2). Colored shaded areas indicate, chronologically: (1) the sample period used to measure firm-level exposure to the UK (β_i^{UK}); (2) the period before Brexit-related events; and (3) the period after Brexit-related events.

terms of earnings. The evidence from earnings forecasts point to Brexit having a "second-moment" effect in terms of increased uncertainty regarding exposed firms' expectations formed in 2016:Q1–Q2, consistent with evidence from the options markets. Notably, the fact that mean EPS forecasts stay virtually the same over the 2-year window considered for *both* high and low β_i^{UK} firms suggests that there is no clear sign of a "first-moment" (negative) effect of Brexit on corporate earnings.

Figure 6 shows the timeline of our testing strategy. We compare two quarters before (2015:Q3–Q4) *versus* two quarters after (2016:Q3–Q4) the two key Brexit events we have described.[23] We limit our analysis to 2016:Q4 due to another political uncertainty event with global reach — the start of the Trump administration. We, however, show in robustness checks that results also hold for a narrower window excluding 2016:Q4.

5.2.2 Empirical Model

Our empirical analysis is centered around a Difference-in-Differences estimation, where we compare the difference in the outcome variable between treated (*High UK-Exposure*) and control (*Low UK-Exposure*) firms. Differences in outcomes over the 2016:Q3–Q4 period are taken relative to the same two quarters in the previous year, 2015:Q3–Q4. This is equivalent to estimating the following model:

$$\begin{aligned} Y_{it} = {} & \alpha + \delta\,[Post_t \times High\ UK\text{-}Exposure_i] \\ & + \theta \boldsymbol{Controls}_{it} + \sum_i Firm_i + \sum_j \sum_t [Industry_j \times Quarter_t] + \epsilon_{it}. \end{aligned} \tag{20}$$

[23]Comparing the last two quarters of 2016 with the same quarters in the prior year is meant to minimize the impact of seasonal effects.

The outcomes of interest, Y_{it}, are fixed capital investment, employment growth, R&D expenditures, divestitures, cash holdings, and non-cash working capital. $High\ UK\text{-}Exposure_i$ is a dummy variable equal to 1 if firm i is UK-exposed and zero otherwise. A firm is considered UK-exposed based on two measures: (1) if it belongs to the top tercile of β_i^{UK} (market-based measure); or (2) if it has a high number of Brexit-related entries in its 2015 10-K form (text-based measure). $Post_t$ equals 1 if the time period is in the 2016:Q3–Q4 window. $\boldsymbol{Controls}_{it}$ is a vector of macroeconomic- and firm-level control variables. Macro controls include the US dollar/British pound exchange rate, the lagged VIX implied volatility index, the lagged mean GDP growth 1-year-ahead forecast from the Federal Reserve Bank of Philadelphia's Livingstone Survey, the lagged Consumer Sentiment Index from the University of Michigan, and the lagged Leading Economic Indicator from the Federal Reserve Bank of Philadelphia. Firm-level controls are lagged Tobin's Q, cash flow, sales growth, and logged assets. $Firm_i$ represents firm-fixed effects, $Industry_j$ is a dummy for each industry category j of the Hoberg and Phillips (2016) classification (FIC 100),[24] and $Quarter_t$ are calendar-quarter dummies. Standard errors are double-clustered by firm and calendar quarters.

5.3 Descriptive Statistics

Table 1 presents our sample summary statistics. Firm-level accounting variables are normalized by lagged total assets. All variables are winsorized at the 1% level to avoid the impact of outliers. We begin with Panel A describing the statistics for the universe of COMPUSTAT firms in the pre-Brexit sample period (2010:Q1–2015:Q4). Using our baseline market-based β_i^{UK} criterion, Panel B summarizes the data for treated firms as defined by β_i^{UK} (top tercile of β_i^{UK}), while Panel C reports statistics for control firms as defined by β_i^{UK} (bottom tercile of β_i^{UK}). Panels D and E report summary statistics for treatment and control firms, respectively, as defined by mentions of Brexit-related words in firms' 2015 10-K filings (our text-based approach).

Table 1 About Here

[24] This industry classification is formed by grouping firms with textually similar product descriptions in their 10-Ks. Hoberg and Phillips (2016) argue that the resulting industry classification is more granular and captures the locus of product-market competitors of a given firm better than the standard SIC or NAICS industry schemes.

Our summary statistics are in line with prior studies on the impact of uncertainty that consider publicly-traded companies, such as Gulen and Ion (2016). Treated firms do not display salient discrepancies relative to the universe of COMPUSTAT firms, suggesting that our sample is standard in terms of observable variables. Comparisons across groups suggest that treated and control firms (as defined by β_i^{UK}) differ across a few characteristics: firms in the treatment group are smaller as measured by total assets and invest more than control firms. However, firms in the treated group as defined by 10-K mentions of Brexit-related words are, if anything, larger than those in control firms, while their investment appears to be substantially similar. Across both treatment assignment schemes, the two groups of firms share similarities on a number of dimensions, nonetheless. They display economically similar R&D expenditures, cash holdings, Tobin's Q, and employment growth.

6 Empirical Results

6.1 The Impact of Brexit on US Firms' Investment, Labor, R&D, and Divestiture Decisions

Results from our baseline regression model for investment and employment are shown in Table 2. We begin with a basic OLS firm-fixed effects estimation in which β_i^{UK} enters the specification as a linear continuous-treatment variable in column (1), including both non-negative and negative values of β_i^{UK}. The $Post \times \beta_i^{UK}$ interaction coefficient is negative and highly significant, consistent with Hypothesis 1 of our model. In short, it points to the interpretation that a higher exposure to UK uncertainty is related to lower investment spending following Brexit. We move to our baseline specification in column (2), which considers positive values of β_i^{UK} partitioned in terciles. We now add time-varying industry-fixed effects by interacting Hoberg and Phillips (2016) industry (FIC 100) and calendar-quarter dummy variables. As a result, macroeconomic controls are dropped due to multi-collinearity. A complete set of dynamic fixed effects is important to mitigate concerns as to whether results are driven by variation within certain industries and time periods. The $Post \times High\ \beta_i^{UK}$ coefficient is negative and highly significant. Finally, we consider our text-based approach to measure firm-level exposure to the UK in column (3). Treatment assignment is now a result of the frequency of words "Brexit", "Great Britain", and "Uncertainty" in the 10-K reports from firms in our sample. The DID coefficient is again negative and highly significant.

Critically, the investment spending reductions identified by our estimations in Table 2 are not only statistically, but also economically significant. Given that pre-Brexit (2015) average investment was 1.1% of firms' assets, our upper bound DID estimate of –0.074 implies a drop of up to 6.7% in investment rates. Columns (1) through (3) show that following Brexit's victory, UK-exposed American firms significantly cut their investment vis-à-vis non-UK-exposed firms. The dollar magnitude of aggregate investment cuts implied by our DID estimate is $934 million.[25]

Table 2 About Here

The impact of Brexit on employment is also reported in Table 2. Using the specifications previously adopted, columns from (4) through (6) display negative and significant DID coefficients for corporate employment growth. The estimated DID coefficients imply a drop of between 3.0 and 3.4 percentage points. Given that pre-Brexit (2015) average employment growth was 3.4%, our results suggest that Brexit contributed to a measurable slowdown in net job creation in some segments of the US economy, with the upper bound estimate suggesting a stagnation in job growth for UK-exposed firms. This is a startling finding given the steady growth in employment observed across the economy since 2010.

Next, we analyze the effects of Brexit on UK-exposed firms' innovation policies by looking at how R&D expenditures changed in the face of Brexit. Columns (1) through (3) of Table 3 show that, for all specifications of UK-exposure, there is a positive and highly significant response of R&D investment to Brexit. This result is consistent with the growth-options channel discussed in our model. Notably, results for R&D are also economically significant, reaching an increase of 0.38 percentage points vis-à-vis the pre-Brexit (2015) average of 3.2% of assets.

Table 3 About Here

Finally, we look into the effects of Brexit on UK-exposed American firms' disinvestment policies (the sales of plant, property and equipment divided by lagged total assets). Columns (4) through (6) of Table 3 suggest that Brexit-induced uncertainty led to substantial reductions in divestitures for

[25]The 449 firms in the top tercile of β_i^{UK} had assets of $2.81B on average in 2016:Q2. Accordingly, a decline in their investment-to-assets ratio of 0.074 percentage points implies a drop in investment of $2.08 million per firm, or $934 million in total.

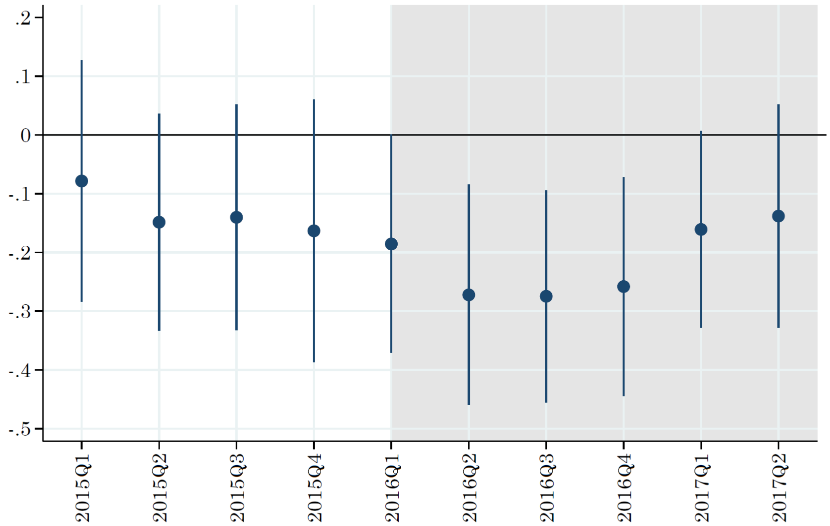

Figure 7. Corporate Investment Trends around Brexit-related Events. This figure displays coefficients of investment regressions for the timeline of the main events related to Brexit. The shaded area marks the beginning of Brexit-related events, with the announcement of the date of the UK–EU Referendum by PM David Cameron (2016:Q1).

highly UK-exposed firms. The magnitudes here are striking, with a decline of up to 0.04 percentage points, representing 44% of the unconditional average divestiture rate of 0.09% in the pre-Brexit (2015) period. Confirming the intuition of our model, we find that Brexit-induced uncertainty led to a reduction in *both* investment and disinvestment by affected US firms.

Effect Duration

We also look at the duration of Brexit's impact. Figure 7 extends the period of our baseline sample from 2015:Q1 through 2017:Q2, one whole year after the Referendum. The figure plots the difference between investment regression coefficients (and 95% confidence intervals) from UK-exposed *versus* non-exposed firms (refer to the model under column (2) of Table 2). The significant difference in the investment of both groups of firms occurring between 2016:Q2–Q4 confirms our previous findings. Moreover, as predicted by our model, Brexit-induced uncertainty led to a significant, yet temporary, drop in investment for affected American firms for a period of three quarters, followed by a rebound to near normalcy in the next two quarters. Notably, this "drop and rebound" behavior also matches a pattern of *domestic* uncertainty shocks discussed in Bloom (2009). Conveniently, the figure also illustrates the presence of parallel pre-trends in the investment of both groups of firms. This is a reassuring finding for our proposed DID testing framework.

6.2 Result Characterization

6.2.1 The Effect of Input Irreversibility

We turn to the analysis of adjustment costs in modulating the effect of uncertainty on investment and employment as a way to more finely characterize our results (cf. Hypotheses 4 and 5 from our model). We begin by looking at capital adjustment costs. We do so introducing a firm-level proxy of how irreversible investment decisions are, namely the Kim and Kung (2016) asset redeployability index. Columns (1) through (3) of Table 4 show results on the amplification effect of capital adjustment costs. In column (1), we run the same baseline DID estimation that considers firms in the top tercile of β_i^{UK} as the treatment group. In this first run, we restrict the sample to firms with high irreversibility, as defined by the bottom tercile of the Kim and Kung (2016) index. The DID coefficient is negative and highly significant. The same exercise is repeated in column (2), but for the subsample of firms in the top tercile of asset redeployability; that is, firms with plausibly less irreversible investment decisions. As one could expect for this group of firms, the DID coefficient is non-significant. The estimation under column (3) uses the entire sample of firms, introducing a dummy variable *High Irreversibility* that equals one if the firm is in the high irreversibility group. The coefficient on this variable can be interpreted as a third difference in a DID framework, that is, as a Difference-in-Difference-in-Differences (DIDID) estimate. It identifies whether the response of investment to β_i^{UK} is significantly different across the different capital irreversibility groups. As the coefficient for the triple interaction in column (3) is negative and highly significant, we conclude that these responses are indeed quite different.

Table 4 About Here

We next turn to the impact of labor adjustment costs. We adopt an empirical proxy for these costs, namely industry-level unionization rates. Columns (4) through (6) of Table 4 show that the response of firms in more unionized industries is significantly different from the response of firms in less unionized industries. In all, this analysis suggests that the effect of uncertainty on corporate employment was modulated by a real-options channel of input irreversibility, such as the one emphasized by our model's Hypothesis 5. These two sets of results suggest that capital and labor adjustment costs played an important role in modulating firms' responses to Brexit-induced uncertainty.

6.2.2 Mapping Investment and Labor Declines

We next delve deeper into the characteristics of the investment and employment declines as a result of Brexit-induced uncertainty as reported in Table 2. Since we are looking at global firms, it is important that we identify if investment and job losses occur in the US, or stem from cuts in foreign operations, such as those in the UK. First, we investigate whether the investment cuts observed among UK-exposed American firms took place in the United States. We then look at the location of hiring cuts. Finally, we look into the cross-sectional heterogeneity in employment declines among UK-exposed American firms in industries with predominantly low *versus* high skilled workers, and states with high *versus* low degree of labor protection laws.

The Location of Investment Cuts

We determine the location of investment cuts by exploiting data from Orbis on the investment rates of US subsidiaries of US-domiciled companies identified by our β_i^{UK} treatment assignment scheme. With these data, we are able to identify operations of these global firms that are domiciled in the US, and thus are able to conduct our baseline analysis on investment, restricted to US subsidiaries. Among the set of firms in our baseline sample, we are able to match 1,035 of them to parent firms (Global Ultimate Owners, GUO) with at least one subsidiary in which the GUO has a 49% or higher ownership stake. These US-based parents have complete data on investment, as well as the control variables used in our analysis. The total number of US-domiciled subsidiaries associated with these parent firms is 51,750. For each parent firm, in each year, we aggregate investment by summing across these subsidiaries. We then repeat the analysis of Table 2. Results in columns (1) and (2) of Table 5 indicate that American UK-exposed firms *systematically cut* investment in their US-located subsidiaries in response to Brexit. The magnitudes of the investment cuts are larger than those reported in Table 2 (annualized), suggesting that effects on investment measured at the parent firm level are likely to be largely driven by investment declines in their US-based subsidiaries.

TABLE 5 ABOUT HERE

As a further check, we investigate whether these American UK-exposed firms cut their investment in UK-based subsidiaries as well. Using the Orbis dataset, we identify 660 US parent firms with UK subsidiaries with non-missing data on investment. We partition these firms into treatment and control units based on our two metrics. Results in columns (3) and (4) of Table 5 suggest that American UK-exposed firms cut investment in their UK-based subsidiaries even more than they do across their US-based subsidiaries — consistent with a direct effect of Brexit-induced uncertainty on local UK operations.

The Location of Employment Cuts

We identify the location of employment cuts made by American firms in 2016 by utilizing the COMPUSTAT Historical Segments database.[26] We note that because firms are not mandated to disclose employment disaggregated by geographical segments, the COMPUSTAT Historical Segments data may suffer from a particular type of sample selection bias. Prior work has argued that firms are less likely to disclose geographical employment breakdowns when they are concerned about negative responses from the US government, business media, and employees. It finds, in particular, that firms whose foreign activity affects US employment negatively (e.g., through outsourcing) are less likely to report geographical employment information (Beatty and Liao (2013)). This reporting distortion is likely to work against us finding significant cuts in US employment, as firms which engage in such hiring reductions are less likely to disclose this information in the first place.

Table 6 About Here

We repeat the analysis of Table 2 in the sample of firms who report US segment employment. Results in Table 6 indicate that American UK-exposed firms reduced their employment in the US following Brexit. The magnitudes of the employment cuts reported in columns (1) and (2) are substantially larger than those reported in columns (4) and (5) of Table 2, suggesting that effects on employment measured at the aggregate firm level are likely to be primarily driven by employment declines in their US segments. Notably, the incentives of firms to not disclose disaggregated employment information when engaging in domestic employment cuts suggest that our baseline results in Table 2 likely *underestimate* the true effect of Brexit-induced uncertainty on US employment.

[26]We are unable to utilize the more comprehensive Orbis subsidiary-level data as information on employment is largely missing. We also run our tests on investment using COMPUSTAT Historical Segments data, and find results similar to those reported in Table 5.

Labor Skills and Protection Laws

Labor skill levels is said to have played a key role in moderating the impact of increased manufacturing competition from China on the US labor force (Autor et al. (2013)). Given the importance of labor skills in shaping the response of employment to shocks to the US economy, we examine whether they played a similar role in moderating employment cuts by American firms exposed to Brexit-induced uncertainty. As a proxy for labor skill levels, we utilize an industry-level labor skill index (LSI), which we construct following Ghaly et al. (2017). The LSI is based on data from the Occupational Employment Statistics (OES) compiled by the Bureau of Labor Statistics (BLS) and the US Department of Labor's O*NET program classification of occupations according to skill level. The O*NET classification allocates occupations into five categories where scores of 1 (5) correspond to the lowest (highest) skilled occupations, based on the extent of education, experience, and training required to perform each occupation. The LSI for a given industry is calculated as the weighted average O*NET classification across all occupations in that industry, where the weights correspond to the fraction of workers engaged in each occupation in the industry.

Relatedly, labor protection laws have been shown to have a marked effect on corporate employment policies (Autor et al. (2006)). Wrongful-discharge laws (WDLs) refer to a set of labor protection laws that were adopted by US states from 1967 through 1995. These laws were enacted to curtail at-will employment, or the ability of employers to terminate employees without reason or notice, without facing legal penalties. Three major sets of WDLs contain various exceptions to employers' at-will right to terminate employees. The Good Faith Exception gives terminated employees legal recourse in case of "bad faith" by the employer. The Implied Contract Exception protects workers from termination when there is an implicit agreement between the employer and employee suggesting that the worker will only be terminated with good cause. The Public Policy Exception protects employees from termination for refusal to violate public policy. Firms subjected to WDLs face greater firing costs as they face potential legal damages for violating any of the exceptions stated above. Following previous studies, we construct an state-level index which takes the value of 0, 1, 2, or 3 based on how many of the three exceptions are in force in the state a firm is incorporated (see, e.g., Acharya et al. (2013b) and Serfling (2016)).

Table 7 About Here

Table 7 reports results on the effect of Brexit on employment in subsamples of firms partitioned into two groups based on the 2015 (pre-Brexit) LSI. Firms in the *Low Skill* subsample are in industries which fall within the lowest tercile of LSI and firms in the *High Skill* subsample are in industries which fall within the highest tercile of LSI. The results in columns (1) and (2) clearly indicate that UK-exposed American firms in *Low Skill* industries (including food, chemical, and primary metal manufacturing, mining, and clothing retail) cut their employment substantially more (relative to control firms), while such firms in *High Skill* industries (including computer and electronic product manufacturing, telecommunications and information services and professional, technical and scientific services) show no statistically significant effect. The DIDID coefficient in column (3) confirms that the effects across these two groups are significantly different. These results are striking in that they suggest that the negative employment effects of Brexit-induced uncertainty were borne largely by workers in low-skill occupations, the very demographic group among which support for populist policies (including the "leave" vote in the Brexit referendum) have been argued to be the strongest.

Results on the cross-sectional effects of wrongful-discharge laws are shown in columns (4) through (6). The results indicate that firms incorporated in states with higher labor protection laws observed a more pronounced negative impact on their employment decisions in the face of Brexit. They are also consistent with prior literature which finds a contraction in employment in states following the adoption of such laws (Autor et al. (2006)).

6.3 Other Firm Policies and Outcomes

We also study how Brexit affected other firms' policies, especially regarding their liquidity management. We do so using our previous testing methods to look at how firms adjusted their cash holdings and non-cash working capital (NWC). The positive and highly significant coefficients in columns (1) and (2) in Table 8 imply that UK-exposed firms increased their cash savings in the face of higher uncertainty induced by Brexit. Negative and highly significant coefficients in columns (3) and (4) imply that firms concomitantly accumulated less inventory by adjusting their NWC downwards in the face of uncertainty. Although not modeled in our framework, this behavior is consistent with the theoretical underpinnings from the liquidity management literature (see, e.g., Acharya et al. (2013a)). In particular, precautionary behavior will lead firms to change the composition of assets in their balance sheets, leading to the accumulation of the most liquid assets available to them.

Table 8 About Here

We use Table 8 to report results on profit growth. The estimates in columns (5) and (6) are not statistically significant, suggesting that Brexit did not affect the profits of UK-exposed American firms relative to those of non-exposed firms. These findings are important in validating some of the underpinnigs of our proposed analysis. They confirm the premise that the investment and employment drops previously reported are arguably due to a "second-moment" shock to uncertainty, rather than a negative "first-moment" shock to firms' cash flows.

6.4 Robustness

6.4.1 Examining Trumpit

One could be concerned about confounding effects associated with the election of President Donald Trump in the US. We address this concern in two different ways. First, we consider an alternative event window in examining the robustness of our DID analysis. We run a specification that excludes 2016:Q4 from the treatment evaluation period. This narrower time window helps mitigate concerns that forward-looking behavior of firms regarding Trump's election in the US could influence our results. Accordingly, we compare the third quarter of 2016 with the same quarter of 2015. As shown in columns (1) and (2) of Table 9, results are quantitatively and qualitatively similar to our baseline estimates in Table 2.

Table 9 About Here

Second, we look at the recent literature on the effect of Trump's election on US firms. Wagner et al. (2018) detail a methodology identifying what the authors label as "winners" and "losers" from the recent US presidential election. We use their method, which is based on 10-day cumulative CAPM-adjusted abnormal returns of firms surrounding the election date to cross-check the presence of either of these sets of firms in our sample (see Figure 1 in their paper). Our treatment group based on β_i^{UK} contains 57 "loser" firms, while our treatment group based on 10-K mentions contains 23 "loser" firms. In columns (3) and (4) of Table 9, we replicate our baseline tests on investment omitting firms labeled as "losers" by Wagner et al. (2018); that is, firms that might invest less following Trump's election. The estimates make it clear that our results are not influenced by the presence of these firms in our sample.

6.4.2 Falsification Tests

We also run our baseline DID specification for dates unrelated to high volatility in the UK economy to address concerns that our base results are not necessarily tied to Brexit-generated uncertainty. In doing so, we select two treatment periods that occur prior to Brexit: (1) the period after David Cameron's election as Prime Minister (2015:Q3); and (2) the US Debt Ceiling Crisis of 2011 (2011:Q2–2011:Q4). The first falsification test mitigates concerns that firms already anticipated the process leading to Brexit at the time of Cameron's election, and a similar decline in investment occurred at that moment as a result. The second addresses concerns that our investment results could also be driven by uncertainty in the US (and not the UK), that affects global firms in general. As shown in columns (5) through (8) of Table 9, the DID coefficients are statistically non-significant in all cases. These falsification tests provide supporting evidence that the most likely driver behind our results is UK-related uncertainty induced by Brexit.

We conduct further falsification tests to rule out the possibility that our observed results on investment declines are driven by coincident, potentially uncertainty-inducing events in other major global economies. We construct metrics analogous to our baseline UK-exposure measure, β_i^{UK}, by re-estimating equation (19) for five economies comprising advanced and emerging markets: EU, China, Japan, India, and Canada. In other words, we repeat our experiment classifying firms based on each criterion — β_i^{EU}, β_i^{China}, β_i^{Japan}, β_i^{India}, and β_i^{Canada} — according to the sensitivity of their equity returns volatility to the respective region's main equity index returns volatility. In this estimation, performed over the same pre-Brexit sample period of 2010:M1 through 2014:12, we control for *FTSE100* volatility, US dollar/British pound exchange rate volatility, and the volatility in the exchange rate of the US dollar and the currency of each region.

TABLE 10 ABOUT HERE

Results are reported in Table 10. Column (1) repeats our baseline estimate from Table 2 for comparison purposes. In column (2), we find that American firms exposed to EU-born uncertainty, too, experience significant declines in investment. This is consistent with the fact that Brexit-related events induced political uncertainty in the EU as well as the UK. Results in columns (3) through (6) indicate that American firms exposed to uncertainty in several other global economies (and US trading partners) experienced no significant change in investment in the coincident quarters following the announcement of the Brexit referendum. Our main results are unlikely to be driven by American firms' exposures to events other than Brexit.

7 Concluding Remarks

We exploit the strong economic ties between the US and the UK to show how the uncertainty created by Brexit ended up shaping the behaviors of American firms. We provide firm-level evidence of transmission of uncertainty shocks generated by the British political system onto US firms exposed to the UK economy. Perhaps the most important implication of our analysis is shedding light on the fact that politicians and regulators can hurt the economy not only through policies they enact, but also by introducing uncertainty in the process of making policy decisions. Such uncertainty has real and financial consequences not only for the country that originates it, but also for the global economy as other countries may be ultimately affected by exogenously-born events.

The case of Brexit can be seen as a warning to the major economies in the world. To the extent countries are ever more connected into the global economy, domestic political uncertainty becomes internationally relevant. The strong negative effects we identify on capital investment and employment decisions of UK-exposed American firms is only one of the many channels through which uncertainty is transmitted across borders. Our paper adds to the contagion and uncertainty branches of the literature, but several other channels remain unexplored as avenues for future research. As discussed, Brexit may affect even the longer-run aspects of the British and EU economies, and should be studied further to deepen our understanding of events of similar nature.

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Table 1. Summary Statistics

This table reports summary statistics for the main variables used in our empirical analyses. The final sample is a match between COMPUSTAT Quarterly North America Fundamentals and the estimated β_i^{UK} sample for the period from 2010:Q1 to 2015:Q4. Each panel reports the mean, standard deviation, median, interquartile range (IQR), and the number of observations conditional on firms belonging to each subsample. Investment is defined as capital expenditures divided by lagged total assets. Employment growth is defined as the percent change in the number of employees (annual). R&D is defined as R&D expenditures divided by lagged total assets, considering only firms with non-missing R&D expenditures. Divestitures is defined as the value of sale of plant, property, and equipment divided by lagged total assets. Cash holdings is defined as cash and short-term investments divided by lagged total assets. Non-cash working capital is defined as working capital (net of cash) divided by lagged total assets. Tobin's Q is defined as the market value of assets divided by the book value of assets, and is calculated as the market value of equity plus the book value of assets minus book value of equity plus deferred taxes, all divided by book value of assets. Cash flow is defined as operating income before depreciation divided by lagged total assets. Size is defined as the logarithm of total assets. Sales growth is defined as the year-on-year percent change in quarterly sales. All variables are winsorized at the 1% level. Panel A summarizes data for the universe of COMPUSTAT firms. Panel B shows summary statistics for the sample of treated firms as defined by β_i^{UK} (top tercile of β_i^{UK}). Panel C shows summary statistics for the sample of control firms as defined by β_i^{UK} (bottom tercile of β_i^{UK}). Panel D shows summary statistics for the sample of treated firms as defined by mentions of Brexit-related words in their 2015 10-K filings (more than five 10-K entries). Panel E shows summary statistics for the sample of control firms as defined by mentions of Brexit-related words in their 2015 10-K filings (zero 10-K entries).

	Panel A. COMPUSTAT Universe					**Panel B. Treated Firms: Market-Based Approach (Top Tercile of β_i^{UK})**					**Panel C. Control Firms: Market-Based Approach (Bottom Tercile of β_i^{UK})**				
Firm-Level Variables	Mean	SD	Median	IQR	N	Mean	SD	Median	IQR	N	Mean	SD	Median	IQR	N
Investment	0.01	0.02	0.01	0.01	76,094	0.02	0.02	0.01	0.02	11,083	0.01	0.01	0.01	0.01	12,067
Employment Growth (Annual)	0.08	0.28	0.03	0.16	17,620	0.08	0.29	0.03	0.19	2,659	0.06	0.20	0.03	0.11	2,965
R&D	0.03	0.04	0.02	0.04	40,864	0.03	0.04	0.02	0.04	5,019	0.02	0.03	0.01	0.02	6,200
Divestitures (×100)	0.06	0.28	0.00	0.00	61,151	0.10	0.38	0.00	0.00	8,604	0.08	0.32	0.00	0.01	9,422
Cash Holdings	0.22	0.25	0.12	0.27	78,044	0.20	0.24	0.11	0.26	11,176	0.17	0.18	0.11	0.19	12,097
Non-Cash Working Capital	0.04	0.19	0.03	0.20	76,323	0.05	0.18	0.04	0.19	10,846	0.08	0.16	0.07	0.20	11,738
Tobin's Q	2.11	1.59	1.57	1.26	73,353	1.92	1.51	1.41	1.01	11,090	1.98	1.25	1.62	1.07	12,055
Cash Flow	0.01	0.06	0.03	0.04	75,287	0.01	0.06	0.02	0.04	10,972	0.03	0.04	0.03	0.03	11,871
Size (Log Assets)	6.19	2.08	6.15	3.08	78,062	6.11	1.87	6.12	2.86	11,176	7.25	1.99	7.25	2.65	12,097
Sales Growth	0.16	0.62	0.06	0.23	71,637	0.18	0.71	0.06	0.31	10,624	0.10	0.36	0.06	0.16	11,969

	Panel D. Treated Firms: Text-Based Approach (More Than Five 10-K Entries on Brexit)					**Panel E. Control Firms: Text-Based Approach (Zero 10-K Entries on Brexit)**				
Firm-Level Variables	Mean	SD	Median	IQR	N	Mean	SD	Median	IQR	N
Investment	0.01	0.02	0.01	0.01	35,828	0.01	0.02	0.01	0.01	9,389
Employment Growth (Annual)	0.08	0.30	0.03	0.17	8,004	0.08	0.30	0.03	0.16	2,248
R&D	0.03	0.04	0.02	0.04	19,988	0.03	0.04	0.01	0.03	4,745
Divestitures (×100)	0.05	0.26	0.00	0.00	29,009	0.05	0.24	0.00	0.00	7,377
Cash Holdings	0.23	0.25	0.13	0.29	36,985	0.22	0.24	0.12	0.26	9,533
Non-Cash Working Capital	0.01	0.20	0.02	0.20	36,292	0.06	0.19	0.04	0.21	9,260
Tobin's Q	2.10	1.59	1.55	1.29	34,108	2.06	1.54	1.55	1.17	9,138
Cash Flow	0.01	0.07	0.02	0.04	35,432	0.01	0.07	0.02	0.04	9,240
Size (Log Assets)	6.08	2.06	6.02	3.12	37,002	5.95	2.15	5.86	3.23	9,533
Sales Growth	0.17	0.66	0.06	0.25	33,647	0.17	0.67	0.05	0.22	8,835

Table 2. The Impact of Brexit on US Investment and Employment: Baseline Specification

This table reports output from Eq. (20). The dependent variables are investment and employment. Investment is defined as capital expenditures divided by lagged total assets (quarterly). Employment growth is the percentage change in the number of employees (annual). In the first specification, the measure of UK-exposure (β_i^{UK}) enters the regression as a linear continuous variable. In the second specification, the treatment group is composed by the top tercile of β_i^{UK}, while the control group is composed by firms in the bottom tercile of β_i^{UK}. The third specification is a text-based measure of UK-exposure that sums up the number of Brexit-related words in firms' 2015 10-K forms. The treatment group is made of firms with more than five entries, whereas the control group are firms with zero entries. The time dimension of the DID estimator is set so as to compare the two quarters following the announcement of the Brexit Referendum victory (2016:Q3–Q4) *versus* the two quarters preceding the announcement of the Referendum vote date (2015:Q3–Q4).

	Investment			Employment		
	Linear Model	Treatment is Top Tercile of β_i^{UK}	Treatment is > 5 Brexit Entries in 10-Ks	Linear Model	Treatment is Top Tercile of β_i^{UK}	Treatment is > 5 Brexit Entries in 10-Ks
	(1)	(2)	(3)	(4)	(5)	(6)
Post	–0.048**			–1.909		
	(0.020)			(1.974)		
$Post \times \beta_i^{UK}$	–0.034***			–5.315***		
	(0.010)			(1.408)		
$Post \times High\ \beta_i^{UK}$		–0.074***			–3.419**	
		(0.012)			(1.316)	
$Post \times High$ 10-K *Entries*			–0.064***			–3.020**
			(0.009)			(1.135)
Controls						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Macroeconomic	Yes	No	No	Yes	No	No
Fixed Effects						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Time	No	Yes	Yes	No	Yes	Yes
Observations	49,326	19,961	25,143	10,280	4,048	5,037
R-squared	0.64	0.72	0.70	0.31	0.44	0.43

Statistical significance levels: *** p-value<0.01, ** p-value<0.05, * p-value<0.10.

Table 3. The Impact of Brexit on R&D Expenditures and Divestitures: Baseline Specification

This table reports output from Eq. (20). The dependent variables are R&D and divestitures. R&D is defined as total R&D expenditures divided by lagged total assets. Divestitures are defined as the value of SPP&E (*Sale of Plant, Property, and Equipment*) divided by lagged total assets. In the first specification, the measure of UK-exposure (β_i^{UK}) enters the regression as a linear continuous variable. In the second specification, the treatment group is composed by the top tercile of β_i^{UK}, while the control group is composed by firms in the bottom tercile of β_i^{UK}. The third specification is a text-based measure of UK-exposure that sums up the number of Brexit-related words in firms' 2015 10-K forms. The treatment group is made of firms with more than five entries, whereas the control group are firms with zero entries. The time dimension of the DID estimator is set so as to compare the two quarters following the announcement of the Referendum and Brexit's victory (2016:Q3–Q4) *versus* the two quarters preceding the announcement (2015:Q3–Q4).

	R&D			Divestitures		
	Linear Model	Treatment is Top Tercile of β_i^{UK}	Treatment is > 5 Brexit Entries in 10-Ks	Linear Model	Treatment is Top Tercile of β_i^{UK}	Treatment is > 5 Brexit Entries in 10-Ks
	(1)	(2)	(3)	(4)	(5)	(6)
Post	0.026			0.007		
	(0.139)			(0.005)		
$Post \times \beta_i^{UK}$	0.205***			–0.013***		
	(0.034)			(0.003)		
$Post \times High\ \beta_i^{UK}$		0.147***			–0.041**	
		(0.041)			(0.017)	
$Post \times High$ 10-K *Entries*			0.378***			–0.013***
			(0.026)			(0.001)
Controls						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Macroeconomic	Yes	No	No	Yes	No	No
Fixed Effects						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Time	No	Yes	Yes	No	Yes	Yes
Observations	18,609	6,091	11,781	45,930	18,740	26,289
R-squared	0.86	0.88	0.85	0.21	0.30	0.26

Statistical significance levels: *** p-value<0.01, ** p-value<0.05, * p-value<0.10.

Table 4. Amplification Mechanism: The Impact of Capital and Labor Adjustment Costs on Corporate Investment and Employment

This table reports the results of the amplification effect of capital and labor adjustment costs on investment and employment respectively. The proxy for capital adjustment costs is the asset redeployability index of Kim and Kung (2016). The proxy for labor adjustment costs is the labor unionization rate from the Bureau of Economic Analysis (BEA). The treatment group is composed by firms in the top tercile of β_i^{UK}, the measure of UK-exposure, while the control group is composed by firms in the bottom tercile of β_i^{UK}. High capital irreversibility is defined as the top tercile of the Kim and Kung (2016) index of asset redeployability (at the firm-level). High labor irreversibility is defined as the top tercile of the labor unionization rate (at the industry-level). The time dimension of the DID estimator is set so as to compare the two quarters following the announcement of the Referendum and Brexit's victory (2016:Q3–Q4) *versus* the two quarters preceding the announcement (2015:Q3–Q4).

	Investment			Employment		
Irreversibility measure:	Asset Redeployability			Labor Unionization		
	High Irreversibility Subsample	Low Irreversibility Subsample	Pooled Sample	High Irreversibility Subsample	Low Irreversibility Subsample	Pooled Sample
	(1)	(2)	(3)	(4)	(5)	(6)
$Post \times High\ \beta_i^{UK}$	–0.238***	–0.027	–0.018	–4.542***	–0.455	–1.478**
	(0.038)	(0.016)	(0.043)	(1.009)	(0.374)	(0.503)
$Post \times High\ \beta_i^{UK}$			–0.184***			–4.249***
$\times$ *High Irreversibility*			(0.025)			(0.584)
Controls						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
Firm	Yes	Yes	Yes	No	No	No
Industry	No	No	No	Yes	Yes	Yes
Time	No	No	No	Yes	Yes	Yes
Industry $\times$ Time	Yes	Yes	Yes	No	No	No
Observations	6,183	7,255	14,000	1,512	1,094	2,789
R-squared	0.73	0.74	0.73	0.20	0.27	0.22

Statistical significance levels: *** p-value<0.01, ** p-value<0.05, * p-value<0.10.

Table 5. Result Characterization: The Impact of Brexit on Investment of US and UK-based Subsidiaries

This table reports output from Eq. (20) considering only US-based and UK-based subsidiaries of the parent firms in the baseline sample. The dependent variable is investment. In the first and third specifications, the treatment group is composed by the top tercile of β_i^{UK}, while the control group is composed by firms in the bottom tercile of β_i^{UK}. In the second and fourth specifications, we consider a text-based measure of UK-exposure that sums up the number of Brexit-related words in firms' 2015 10-K forms. The treatment group is made of firms with more than five entries, whereas the control group are firms with zero entries. The first two columns consider only US-based subsidiaries and the last two columns consider only UK-based subsidiaries. The time dimension of the DID estimator is set so as to compare the two quarters following the announcement of the Referendum and Brexit's victory (2016:Q3–Q4) *versus* the two quarters preceding the announcement (2015:Q3–Q4).

	Investment			
Subsidiaries located in:	US	US	UK	UK
	Treatment is Top Tercile of β_i^{UK}	Treatment is > 5 Brexit Entries in 10-Ks	Treatment is Top Tercile of β_i^{UK}	Treatment is > 5 Brexit Entries in 10-Ks
	(1)	(2)	(3)	(4)
$Post \times High\ \beta_i^{UK}$	–0.265**		–0.367**	
	(0.088)		(0.134)	
$Post \times High$ 10-K $Entries$		–0.282***		–0.508**
		(0.054)		(0.140)
Controls				
Firm	Yes	Yes	Yes	Yes
Fixed Effects				
Firm	Yes	Yes	Yes	Yes
Industry × Time	Yes	Yes	Yes	Yes
Observations	4,135	4,135	2,940	2,940
R-squared	0.83	0.85	0.78	0.79

Statistical significance levels: *** p-value<0.01, ** p-value<0.05, * p-value<0.10.

Table 6. Result Characterization: The Impact of Brexit on Employment in the US

This table reports output from Eq. (20) considering only employment reported for the US geographical segment by firms in the baseline sample. The dependent variable is employment. In the first specification, the measure of UK-exposure (β_i^{UK}) enters the regression as a linear continuous variable. In the second specification, the treatment group is composed by the top tercile of β_i^{UK}, while the control group is composed by firms in the bottom tercile of β_i^{UK}. The third specification is a text-based measure of UK-exposure that sums up the number of Brexit-related words in firms' 2015 10-K forms. The treatment group is made of firms with more than five entries, whereas the control group are firms with zero entries. The time dimension of the DID estimator is set so as to compare the two quarters following the announcement of the Referendum and Brexit's victory (2016:Q3–Q4) *versus* the two quarters preceding the announcement (2015:Q3–Q4).

	Employment		
	Linear Model	Treatment is Top Tercile of β_i^{UK}	Treatment is > 5 Brexit Entries in 10-Ks
	(1)	(2)	(3)
$Post$	5.124		
	(5.579)		
$Post \times \beta_i^{UK}$	–9.501**		
	(3.845)		
$Post \times High\ \beta_i^{UK}$		–7.197**	
		(2.736)	
$Post \times High$ 10-K $Entries$			–2.284
			(1.877)
Controls			
Firm	Yes	Yes	Yes
Macroeconomic	Yes	No	No
Fixed Effects			
Firm	Yes	Yes	Yes
Industry × Time	No	Yes	Yes
Observations	3,245	1,313	1,506
R-squared	0.35	0.54	0.53

Statistical significance levels: *** p-value<0.01, ** p-value<0.05, * p-value<0.10.

Table 7. Result Characterization: The Impact of Labor Skills and Labor Protection Laws on Corporate Employment

This table reports the results of the cross-sectional effect of labor skills and labor protection laws. The dependent variable is employment. Labor skills are measured by the labor skills index (LSI). The LSI is constructed as the weighted average O*NET occupational skills classification (1 to 5 scale), weighted by the fraction of employees in a given industry engaged in a given occupation, averaged across all occupations in that industry. Labor protection laws are measured by the number (1, 2, or 3) of wrongful discharge laws (WDL) that are in force in the state of a given firm's incorporation. The treatment group is composed by firms in the top tercile of β_i^{UK}, the measure of UK-exposure, while the control group is composed by firms in the bottom tercile of β_i^{UK}. Low (high) skills firms are similarly defined as firms in the bottom (top) tercile of the 2015 LSI (at the industry-level). High (low) WDL firms are defined as having 0 or 1 (2 or 3) WDL at the state-of-incorporation level. The time dimension of the DID estimator is set so as to compare the two quarters following the announcement of the Referendum and Brexit's victory (2016:Q3–Q4) *versus* the two quarters preceding the announcement (2015:Q3–Q4).

	Labor Skills			Labor Protection Laws		
	Low Labor Skills Subsample	High Labor Skills Subsample	Pooled Sample	High WDL Subsample	Low WDL Subsample	Pooled Sample
	(1)	(2)	(3)	(4)	(5)	(6)
$Post \times High\ \beta_i^{UK}$	–5.861***	–2.333	–1.746	–3.228***	–0.957	–1.041
	(0.370)	(1.689)	(1.533)	(0.477)	(1.968)	(1.151)
$Post \times High\ \beta_i^{UK}$			–4.077**			
$\times$ Low Labor Skills			(1.186)			
$Post \times High\ \beta_i^{UK}$						–2.145*
$\times$ High WDL						(0.999)
Controls						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
Firm	No	No	No	No	No	No
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes	Yes
Industry $\times$ Time	No	No	No	No	No	No
Observations	1,323	1,568	2,892	3,919	354	4,273
R-squared	0.10	0.14	0.10	0.09	0.19	0.08

Statistical significance levels: *** p-value<0.01, ** p-value<0.05, * p-value<0.10.

Table 8. The Impact of Brexit on Cash Holdings, Non-Cash Working Capital, and Profitability

This table reports output from Eq. (20). The dependent variables are cash holdings, non-cash working capital, and profit growth. Cash is defined as total cash holdings divided by lagged total assets net of cash holdings. Non-cash working capital is defined as working capital (net of cash) divided by lagged total assets. Profit growth is defined as the quarterly percentage change in profits (operating income before depreciation divided by sales). In the first specification, the treatment group is composed by the top tercile of β_i^{UK}, while control group is composed by firms in the bottom tercile of β_i^{UK}. The second specification is a text-based measure of UK-exposure that sums up the number of Brexit-related words in firms' 2015 10-K forms. The treatment group is made of firms with more than five entries, whereas the control group are firms with zero entries. The time dimension of the DID estimator is set so as to compare the two quarters following the announcement of the Referendum and Brexit's victory (2016:Q3–Q4) *versus* the two quarters preceding the announcement (2015:Q3–Q4).

	Cash		NWC		Profits	
	Treatment is Top Tercile of β_i^{UK}	Treatment is > 5 Brexit Entries in 10-Ks	Treatment is Top Tercile of β_i^{UK}	Treatment is > 5 Brexit Entries in 10-Ks	Treatment is Top Tercile of β_i^{UK}	Treatment is > 5 Brexit Entries in 10-Ks
	(1)	(2)	(3)	(4)	(5)	(6)
$Post \times High\ \beta_i^{UK}$	11.781***		–0.970***		0.020	
	(3.078)		(0.158)		(0.044)	
$Post \times High$ 10-K $Entries$		11.054***		–0.227***		–0.147
		(4.402)		(0.059)		(0.094)
Controls						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Industry× Time	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,000	25,614	19,255	32,338	19,852	34,917
R-squared	0.28	0.77	0.88	0.87	0.15	0.80

Statistical significance levels: *** p-value<0.01, ** p-value<0.05, * p-value<0.10.

Table 9. Robustness and Falsification Tests

This table reports output from Eq. (20) under alternative treatment windows and alternative treatment samples. The dependent variable is investment. In the first specification, the treatment group is composed by the top tercile of β_i^{UK}, while control group is composed by firms in the bottom tercile of β_i^{UK}. The second specification is a text-based measure of UK-exposure that sums up the number of Brexit-related words in firms' 2015 10-K forms. The treatment group is made of firms with more than five entries, whereas the control group are firms with zero entries. In the first two columns, the time dimension of the DID estimator is set so as to compare 2016:Q3 *versus* 2015:Q3. In the second two columns, the time dimension of the DID estimator is set so as to compare 2016:Q3–Q4 *versus* 2015:Q3–Q4, excluding firms deemed as "losers" from Trump's election as in Wagner et al. (2018). In the next two columns, the time dimension of the DID estimator is set so as to compare 2015:Q3 *versus* 2014:Q3. In the final two columns, the time dimension of the DID estimator is set so as to compare 2011:Q2–Q4 *versus* 2010:Q2–Q4.

Treatment Window:	2016:Q3 *vs.* 2015:Q3		2016:Q3–Q4 *vs.* 2015:Q3–Q4		2015:Q3 *vs.* 2014:Q3		2011:Q2–Q4 *vs.* 2010:Q2–Q4	
Event:	Excluding Trumpit		Excluding Trumpit Losers		Cameron's Election		US Debt Ceiling Crisis	
	Treatment is Top Tercile of β_i^{UK}	Treatment is > 5 Brexit Entries in 10-Ks	Treatment is Top Tercile of β_i^{UK}	Treatment is > 5 Brexit Entries in 10-Ks	Treatment is Top Tercile of β_i^{UK}	Treatment is > 5 Brexit Entries in 10-Ks	Treatment is Top Tercile of β_i^{UK}	Treatment is > 5 Brexit Entries in 10-Ks
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Post \times High\ \beta_i^{UK}$	–0.105***		–0.096***		–0.060		0.007	
	(0.015)		(0.014)		(0.191)		(0.040)	
$Post \times High$ 10-K *Entries*		–0.060***		-0.059***		0.029		N/A
		(0.010)		(0.012)		(0.021)		
Controls								
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Fixed Effects								
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Industry × Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Observations	20,685	25,143	18,642	24,461	20,685	25,143	20,685	
R-squared	0.71	0.70	0.72	0.69	0.71	0.70	0.71	

Statistical significance levels: *** p-value<0.01, ** p-value<0.05, * p-value<0.10.

Table 10. Robustness and Falsification Tests

This table reports output from Eq. (20) under alternative treatment assignments. The dependent variable is investment. In the first column, we report our baseline estimates as in Table 2. In the next columns, treated firms are in the highest tercile of positive values of exposure of firm-level volatility to equity index volatility in the EU, China, Japan, India, and Canada respectively. The time dimension of the DID estimator is set so as to compare the two quarters following the announcement of the Referendum and Brexit's victory (2016:Q3–Q4) *versus* the two quarters preceding the announcement (2015:Q3–Q4).

	Baseline	Robustness	Falsification			
	Treatment is Top Tercile of β_i^{UK}	Treatment is Top Tercile of β_i^{EU}	Treatment is Top Tercile of β_i^{China}	Treatment is Top Tercile of β_i^{Japan}	Treatment is Top Tercile of β_i^{India}	Treatment is Top Tercile of β_i^{Canada}
	(1)	(2)	(3)	(4)	(5)	(6)
$Post \times High\ \beta_i$	–0.074***	–0.046***	–0.008	0.008	0.012	–0.029
	(0.012)	(0.005)	(0.018)	(0.022)	(0.019)	(0.065)
Controls						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Time	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19,961	14,515	10,504	10,466	16,155	19,672
R-squared	0.72	0.73	0.73	0.68	0.67	0.73

Statistical significance levels: *** p-value<0.01, ** p-value<0.05, * p-value<0.10.

Appendix A Proofs

A.1 Proof of Lemma 1

Proof. Let us define

$$H(n^*) = v_{i1} + \mathbb{E}\left[v_{i2}\right] - (\kappa+\lambda)n^* - \mathbb{E}\left[\max\left(v_{i2} - (\kappa+\lambda)n^*, 0\right)\right].$$

To guarantee the existence of n^* as characterized by (8), it suffices to show that $H(n^*) = 0$ for some $n^* \in [0, N]$. Since $H(\cdot)$ is a sum of continuous functions, it is itself continuous. Since $v_{i1} > 0$ and $v_{i2} > 0$, it follows that:

$$H(0) = v_{i1} + \mathbb{E}\left[v_{i2}\right] - \mathbb{E}\left[\max(v_{i2}, 0)\right] = v_{i1} > 0.$$

Finally, for $N \to \infty$, we have that:

$$\begin{aligned}\lim_{N\to\infty} H(N) &= \lim_{N\to\infty} \left(v_{i1} + \mathbb{E}\left[v_{i2}\right] - (\kappa+\lambda)N\right) + \lim_{N\to\infty}\left(\mathbb{E}\left[\max\left(v_{i2} - (\kappa+\lambda)N, 0\right)\right]\right)\\ &= -\infty + 0 = -\infty.\end{aligned}$$

Thus, there must exist an $\bar{N} \in \mathbb{R}$ such that, for $N > \bar{N}$, $H(\bar{N}) < 0$. Putting these conditions together with the continuity of $H(\cdot)$ over $[0, N]$, the Intermediate Value Theorem guarantees that there exists an $n^* \in [0, N]$ such that $H(n^*) = 0$. □

A.2 Proof of Proposition 1

Proof. Let us define

$$H(n^*; r) = v_{i1} + \mathbb{E}\left[v_{i2}\right] - (\kappa+\lambda)n^* - \mathbb{E}\left[\max\left(v_{i2} - (\kappa+\lambda)n^*, 0\right); r\right] = 0$$

By the Implicit Function Theorem,

$$\frac{dn^*}{dr} = -\frac{\partial H/\partial n^*}{\partial H/\partial r}.$$

Considering first the derivative of H with respect to n^*, we have:

$$\begin{aligned}\frac{\partial H(n^*; r)}{\partial n^*} &= -(\kappa+\lambda) - \frac{\partial}{\partial n^*}\mathbb{E}\left[\max\left(v_{i2} - (\kappa+\lambda)n^*, 0\right); r\right]\\ &= -(\kappa+\lambda) - \mathbb{E}\left[\frac{\partial}{\partial n^*}\max\left(v_{i2} - (\kappa+\lambda)n^*, 0\right); r\right]\\ &= -(\kappa+\lambda) - \mathbb{E}\left[\max\left(v_{i2} - (\kappa+\lambda), 0\right); r\right]\\ &< 0.\end{aligned}$$

Next, considering the derivative of H with respect to r, we have:

$$\frac{\partial H(n^*; r)}{\partial r} = -\frac{\partial}{\partial r}\mathbb{E}\left[\max\left(v_{i2} - (\kappa+\lambda)n^*, 0\right); r\right].$$

Because $G(\cdot, r')$ is a MPS of $G(\cdot, r)$, for any convex function $J(\cdot)$,

$$\begin{aligned}\mathbb{E}\left[J(v_{i2}); r'\right] &= \int J(v_{i2})dG(v_{i2}, r')\\ &\geq \int J(v_{i2})dG(v_{i2}, r)\\ &= \mathbb{E}\left[J(v_{i2}); r\right].\end{aligned}$$

Since $\max\left(v_{i2} - (\kappa+\lambda)n^*, 0\right)$ is convex in v_{i2}, it follows that:

$$\mathbb{E}\left[\max\left(v_{i2} - (\kappa+\lambda)n^*, 0\right); r'\right] \geq \mathbb{E}\left[\max\left(v_{i2} - (\kappa+\lambda)n^*, 0\right); r\right] \forall r' > r.$$

This implies

$$\frac{\partial}{\partial r}\mathbb{E}\left[\max\left(v_{i2} - (\kappa+\lambda)n^*, 0\right); r\right] \geq 0.$$

Thus,

$$\begin{aligned}\frac{\partial H(n^*; r)}{\partial r} &= -\frac{\partial}{\partial r}\mathbb{E}\left[\max\left(v_{i2} - (\kappa+\lambda)n^*, 0\right); r\right]\\ &\leq 0.\end{aligned}$$

Putting these conditions together, we have:

$$\frac{dn^*}{dr} = -\frac{\partial H/\partial n^*}{\partial H/\partial r} < 0.$$

$\square$

A.3 Proof of Proposition 4

Proof. Let us define

$$H(n^*; \kappa) = v_{i1} + \mathbb{E}[v_{i2}] - (\kappa + \lambda)n^* - \mathbb{E}[\max(v_{i2} - (\kappa + \lambda)n^*, 0)] = 0.$$

By the Implicit Function Theorem,

$$\frac{dn^*}{d\kappa} = -\frac{\partial H/\partial n^*}{\partial H/\partial \kappa}.$$

Considering first the numerator, we know from Proposition 1 that:

$$\frac{\partial H}{\partial n^*} < 0.$$

Next, considering the denominator,

$$\begin{aligned}
\frac{\partial H}{\partial \kappa} &= -n^* - \frac{\partial}{\partial \kappa}\mathbb{E}[\max(v_{i2} - (\kappa + \lambda)n^*, 0)] \\
&= -n^* - \mathbb{E}\left[\frac{\partial}{\partial \kappa}\max(v_{i2} - (\kappa + \lambda)n^*, 0)\right] \\
&= -n^* - \mathbb{E}[\max(v_{i2} - n^*, 0)] \\
&< 0.
\end{aligned}$$

Putting these together, we have:

$$\frac{dn^*}{d\kappa} = -\frac{\partial H/\partial n^*}{\partial H/\partial \kappa} < 0.$$

$\square$

A.4 Proof of Proposition 5

Proof. Symmetric to the case of capital. $\square$

Appendix B VAR Alternative Specifications

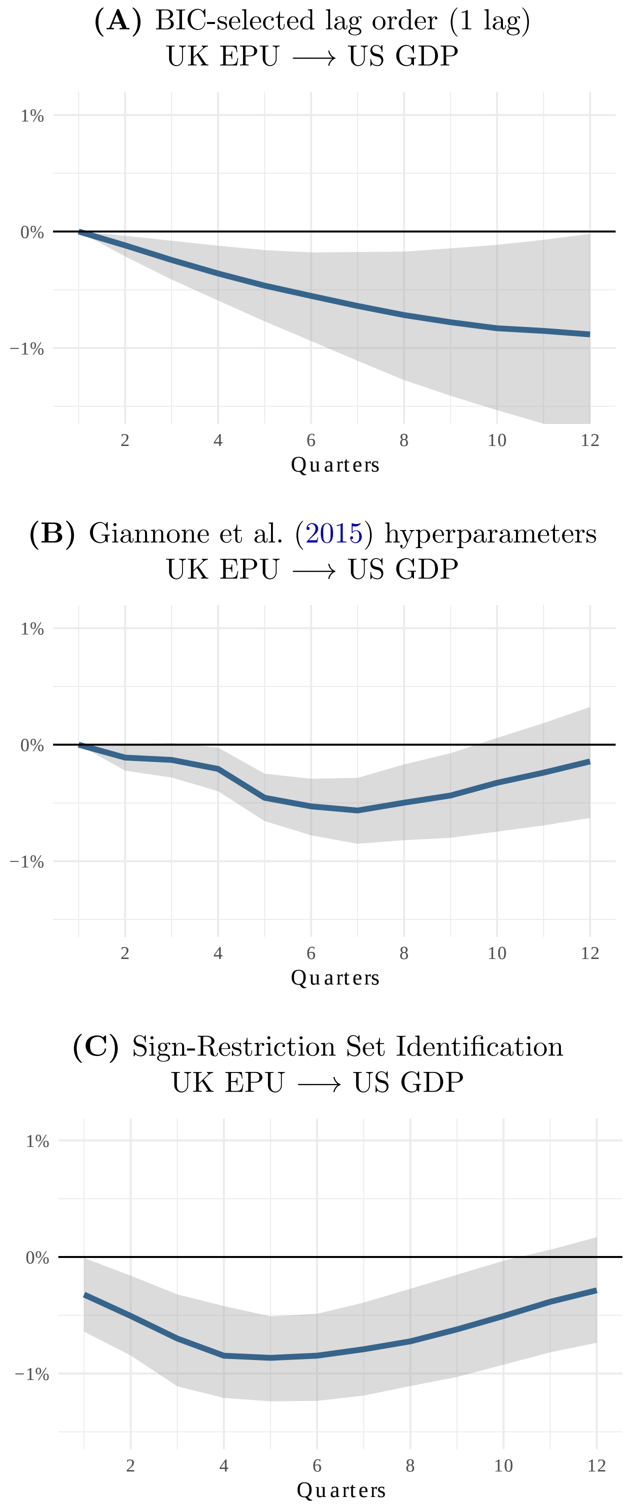

Figure B.1. Robustness Impulse-Response Functions of US GDP. Each figure shows the impulse-response function of a 3.4-standard deviations shock to UK Economic Policy Uncertainty and its response on US GDP along with 68% confidence intervals.