Brexit Uncertainty and Trade Disintegration*

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ABSTRACT: We estimate the uncertainty effects of preferential trade disagreements. Increases in the probability of Britain's exit from the European Union (Brexit) reduce bilateral export values and trade participation. These effects are increasing in trade policy risk across products and asymmetric for UK and EU exporters. We estimate that a persistent doubling of the probability of Brexit at the average disagreement tariff of 4.5% lowers EU-UK bilateral export values by 15 log points on average, and more so for EU than UK exporters. Neither believed a trade war was likely.

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1 Introduction

Trade agreements have been a driving force toward economic integration (cf. Limão, 2016). That trend may be reversing in the face of recent trade policy disagreements, including threats to abandon or renegotiate long-standing trade commitments by the United States[1] and the United Kingdom's looming Brexit from the European Union (EU). Governments and firms worldwide are right to question whether policy commitments will be reversed and lead to trade disintegration. We examine how changes in beliefs about policy reversals impact trade in the context of Brexit.

Specifically, we estimate how shocks to the probability of Brexit affect bilateral export investments and trade flows between the UK and the EU. Our identification comes from monthly variation in exports as the political process unfolded prior to the June 2016 referendum. As a result, the estimates are unaffected by ex-post shocks — to financial markets, exchange rates, policy and politics — that might interact with and confound policy uncertainty analysis. The estimated elasticities of exports to uncertainty therefore allow us to isolate and quantify the trade effects of large permanent changes in the probability of Brexit. Standard sunk investment models predict that higher uncertainty reduces investment by increasing the option value of waiting to act (Dixit, 1989; Bloom, 2014). This mechanism implies that if trade agreements decrease trade policy uncertainty (TPU), then they can spur export investments and increase trade integration (Handley and Limão, 2015; Carballo et al., 2018). Conversely, the prospect of Brexit may lead to trade disintegration.

We find that increases in the probability of Brexit, as measured by prediction markets for the referendum outcome, reduce UK-EU exports and net export entry. The effect is largest in products with higher potential protection in the event of a trade disagreement, i.e. higher risk. We model alternative trade policy risk scenarios including one where UK and EU exporters face the current EU external tariff (the most favored nation rate, MFN) and another where they face non-cooperative tariffs: a trade war. Using each of these we construct model-based measures of tail risk: the share of lost profits if trade barriers increased to the MFN or the non-cooperative rates.

We find significant export uncertainty elasticities only for the MFN scenario, so exporters did not expect a trade war. At the mean MFN risk a persistent increase in the probability of Brexit by one standard deviation reduces UK-EU trade by 2.6 log points on average and the impact is twice as high for EU exporters to the UK than vice versa. A doubling in that probability reduces UK-EU trade by about 15 log points; it reduces the net entry of exported products by more than 10 percent. After the referendum this probability measure more than doubled relative to its pre-referendum mean. We also show that large persistent political shocks, such as polling swings in the voter exit share pre-referendum, are consistent with a doubling of this probability.

We focus on the impacts of potential exit from agreements and show their impacts even if the outcome does not materialize. Another approach is to compute the outcomes of actual changes in policy under possible scenarios. Using simulations, Dhingra et al. (2017) find a 1 percent welfare loss for the UK under a "soft Brexit" and 3 percent under a hard Brexit. A key driver of these welfare effects is a reduction in UK-EU bilateral trade. Mulabdic et al. (2017) use gravity estimates and conclude that a reversal of previous trade integration implies it will fall up to 30% if no trade deal is reached.[2] Steinberg (2018) also finds reductions in

[1] The US has left the Trans-Pacific Partnership (TPP), threatened to leave the World Trade Organization(WTO), and renegotiated the North American and Korea-US Free Trade Agreements.

[2] Kee and Nicita (2017) find smaller effects on UK exports to the EU because MFN tariffs are negatively correlated with demand elasticities. Baldwin et al.(2017) suggest the UK could form alternative, mutually beneficial trade agreements outside the negotiation constraints of the EU. On the other hand, the UK would lose preferential access to markets where the EU already has preferential trade agreements (PTAs) that generated more trade, better quality, and access to new varieties (Berlingieri et

trade and welfare using a calibrated, dynamic model. But in contrast to our empirical approach, his model simulations attribute a small role to uncertainty in accounting for the trade effects.

We build on Handley and Limão (2015, 2017) and a growing body of research that finds TPU is important in explaining trade outcomes.[3] Independent work by Crowley et al. (2018b) uses the framework in Handley and Limão (2017) with UK firm-level export data. They find lower UK exporter participation in high MFN products, but only when comparing post- and pre-referendum trade participation in the second semesters of 2016 and 2015. They find no impact for export values. Our approach and results differ from and complement the literature in several other important ways.

First, earlier work has identified trade effects using uncertainty reductions caused by a specific event such as accession to the EU or the WTO. We estimate export elasticities from time-varying policy uncertainty about trade policy regimes that may never materialize. A "leave" referendum result increases the likelihood of a regime change, but its timing and policies were (and remain) uncertain. In our approach, we combine monthly trade and prediction market data; we model the trade and belief processes in a way that allows for dynamic effects via lags and derive an estimable elasticity to persistent shocks.

Second, we provide a novel means to disentangle and quantify whether predictions about Brexit uncertainty are reflected in the pattern of trade flows and participation. Mapping political events into specific firm- or product-specific risk is difficult without the heterogeneity in risk exposure. Some recent papers handle this challenge using variation in the timing and competitiveness of elections to estimate the effects on investment and economic activity (Boutchkova et al., 2012; Julio and Yook, 2016).[4] Our approach exploits the time variation in prediction markets (as done by Zitzewitz and Wolfers, 2007; Snowberg et al. 2013) interacted with industry variation in trade policy.

Third, we estimate the differential effects of Brexit across UK and EU exporters. We find that the effects are qualitatively similar, but not symmetric: the uncertainty elasticities are larger for EU exports to the UK than in the opposite direction. We also estimate and confirm our baseline findings for UK trade with other countries with which new agreements would need to be negotiated following Brexit. We also find the results are present in sunk cost industries and reflected in asymmetric export entry and exit behavior. These findings lend additional credibility for the channels highlighted by the model.

Next, we discuss some background and motivation for our approach. In section 3, we outline the theory that we use in section 4 to derive an estimation equation linking the dynamic response of exporters to trade policy risks interacted with a measure of the Brexit probability. Section 5 provides the empirical estimates of Brexit uncertainty on trade value and entry-exit behavior. We quantify the impacts and perform robustness checks in section 6.2.

al., forth.).

[3]For example, Crowley et al. (2018a) show that "tariff scares" from anti-dumping actions against Chinese firms have spillover effects on trade and investment decisions by other firms. Greenland et al. (forth) show that economic policy uncertainty reduces trade and market entry in a cross-country panel gravity estimation. Shepotylo and Stuckatz (2018) find reductions in trade and FDI to a news-based measures of TPU surrounding Ukraine's scuttled effort to join the EU.

[4]Hassan et al., 2017; Handley and Li, 2018 obtain firm-level measures, by using textual measures from investor conference calls.

2 Brexit: Background and Motivation

An important component of our strategy is to estimate the relationship between exports and measures of UK and EU firms' beliefs about Brexit. Thus we provide some historical background on the latent historical support of UK voters for leaving the EU. We then show how more recent measures of such support relate to aggregate trade participation leading up the referendum. We also discuss business and media attitudes that explicitly point to the role of uncertainty that the model focuses on.

UK voter support for leaving the EU has been high since its accession in 1973. That support is well documented in surveys since 1977; it has averaged around 40%, fluctuating from 65% in 1980 to a low of 28% in 1991. The most recent upsurge occurred after the financial crisis to an above average 49%, but then receded by 2016.

As in many high income countries, parts of the UK were negatively affected by globalization, trade shocks to manufacturing employment, and the aftermath of the Euro crisis. The latter strengthened the standing of the eurosceptic UK Independence Party and was a factor leading to the 2013 promise by the Prime Minister Cameron to hold a referendum. Following the Conservative Party's general election victory in 2015, leaving the EU once again became a potential reality. The EU Referendum Bill was presented in May and approved in December 2015. The bill allowed the government to schedule a referendum vote before 2017. In February 2016, the vote was scheduled for June 23, 2016 and in that date 52% of voters agreed for '*the UK to leave the European Union*'.

The referendum was hotly debated by policymakers and business leaders in the media. A renegotiation of commitments need not be detrimental to trade, but an acrimonious dissolution of the EU agreement was certainly a risk. Perhaps with this in mind, Prime Minister Cameron used the vote as leverage to obtain a commitment to renegotiate aspects of the EU relationship before announcing the referendum date.

Nevertheless, there was evidence of rising uncertainty as the referendum approached. Survey results indicated that 83% of UK CFOs reported a high level of uncertainty in 2016Q1, up 11 points over the previous six months. Similar sentiments prevailed throughout Europe, especially among German and Irish CFOs, where the EU relationship is important (Deloitte, 2016).[5] The Deloitte chief economist noted that this was historically non-trivial for the UK: "A fog of uncertainty has descended on the corporate sector. Perceptions of financial and economic uncertainty are back to levels last seen in early 2013 as the euro crisis abated."[6]

UK business leaders largely supported remaining in the EU because of uncertainty concerns. On the eve of the vote, 1,200 business leaders wrote a letter to the *The Times* arguing that "Britain leaving the EU would mean uncertainty for our firms, less trade with Europe and fewer jobs. Britain remaining in the EU would mean the opposite: more certainty, more trade and more jobs."[7] However, some business leaders supported Brexit, and discounted the risks of an exit.[8]

[5] The specific question was "How would you rate the overall level of external financial and economic uncertainty facing your business?" and respondents chose either low, normal, or high. Most chief financial officers expected revenues to increase over the next 12 months. But 75% of those in the UK answered it was not a good time to take greater risk—a 44-point downward swing in a six-month period. Moreover, a majority of UK CFOs planned to decrease investment.

[6] UK finance chiefs delay hiring and investment as Brexit tops risk list. *The Guardian* (May 31, 2016).

[7] Letter to the editor. British business 'benefits massively from EU'. *The Times* (June 22, 2016).

[8] The entrepreneur James Dyson wrote: "There is a perception that having a seat at the EU table means Britain has influence. As David Cameron discovered in his recent attempt at renegotiation, we don't [. . .] There is a misplaced belief in the mythical powers of the single market and its influence on and importance to the UK economy [...] For Remain supporters to argue that the EU would impose trade tariffs is equally absurd." 'It's our last chance. To remain would be an act of self-harm'. *The Times*

There was substantial variation in polling data and prediction markets in the months leading up to the referendum. In Figure 1 we plot two time-series. First, polling data on the share of respondents planning to vote “Leave” plus undecided voters in the referendum. Second, the daily average price of a prediction market contract that pays \$1 if “Leave” wins the referendum and \$0 otherwise. There are a large swings in both measures, particularly around large events, such as the passage of the Referendum Bill itself and the setting of the election date.

Did the variation in the likelihood of Brexit in the months leading up to the vote affect trade? Simple inspection of the data does not yield an obvious answer, which is one reason we focus on estimating the elasticity of trade to Brexit uncertainty using high-frequency data. To underscore this point, we divide UK and EU bilateral exports into high and low risk products, defined by those with a post-Brexit tariff above the median MFN (high risk) and those below it. We then compute the export share of the low risk products. In Figure 2 we plot a smoothed local polynomial through these shares from August 2015 to June 2016 along with the 60-day moving average of the prediction market price shown in Figure 1. These two series visually co-move and have a simple correlation of 0.22. A regression of the low risk shares on the contract price moving average also indicates a positive relationship and allows us to control for bilateral importer-exporter fixed effects.

The relationship in Figure 2 is suggestive but may also reflect unobserved shocks and trends and fails to account for other dynamic factors. For example, the relationship appears more muted in the last four months before the referendum, when the prediction market price has several large trend reversals. We account for these factors and allow for dynamic effects of the Brexit probability in estimating trade outcomes in section 5. We handle other identification issues in disaggregated trade flow data using a rich set of controls where we can further explore how the impact is mediated by the degree of exposure to measurable trade policy risk factors rather than simple trade share indicators.

3 Theoretical Framework

We employ the theoretical framework in Handley and Limão (2015) and Carballo, Handley and Limão (2018, henceforth CHL) with some modifications to analyze Brexit. Here we describe only the basic elements and implications of the model. Firms requiring sunk investments to export will experience an increase in the option value of waiting if uncertainty increases, e.g. due to potential changes in trade barriers and product regulations. We derive a cutoff condition for exporting and show how it relates to export value and product entry and exit dynamics.

3.1 Environment

A firm v faces a standard CES demand in country i at time t,

$$q_{ivt} = \left[D_{it} \left(\tau_{it}\right)^{-\sigma}\right] p_{ivt}^{-\sigma} = a_{it} p_{ivt}^{-\sigma}, \tag{1}$$

where the **business conditions** term, a_{it}, reflects a purely economic demand shifter, D_{it}, and a policy component, the advalorem tax, $\tau_{it} \geq 1$, e.g. a tariff. The economic component can be further interpreted

2016, June 22.

as $D_{it} = \varepsilon Y_{it} \left(P_{it}\right)^{\sigma-1}$ where εY_{it} is the exogenous fraction of all country income spent on the differentiated goods and P_{it} the CES price aggregator. We assume the mass of exporters relative to domestic producers in the foreign destination is sufficiently small so that their entry decisions have a negligible impact on the price index in that destination.

A firm observes all relevant information before producing and pricing in a monopolistically competitive market each period, which leads to the standard constant mark-up rule over marginal cost, c_v, and results in the standard expression for export revenue $p_{ivt}q_{ivt} = a_{it}c_v^{1-\sigma}\rho^{\sigma-1}$ and operating profit $\pi_{ivt} = a_{it}c_v^{1-\sigma}\tilde{\sigma}$ where $\rho = \sigma/(\sigma-1)$ is the markup over marginal cost and $\tilde{\sigma} \equiv (1-\rho)\,\rho^{\sigma-1}$. We describe the main results in the context of policies that affect demand but they apply to other policies that affect profitability, e.g. certain product standards may increase costs and these may change after Brexit, as we later discuss.

The firm faces uncertainty about future values of business conditions; it believes that with probability γ_i a new a_i' is drawn from a distribution $\bar{H}_i\left(a\right)$, independent of the current a. The firm takes the demand regime $r_i = \{\gamma_i, \bar{H}_i\left(a\right)\}$ as time-invariant. This characterization encompasses a range of situations: if $\gamma_i = 0$ there is no uncertainty; if $\gamma_i = 1$ then demand is i.i.d. and otherwise there are imperfectly anticipated shocks of uncertain magnitude.

3.2 Firm Export Entry and Technology

The firm must incur a sunk cost, K_i, if it does not export in the previous period; it enters exporting if and only if the net expected value of exporting, $\Pi_e - K_i$, is at least as high as the expected value of waiting, Π_w. So at any given a_{it} the marginal entrant from a continuum of firms is the one with cost equal to the cutoff, c_{it}^U, defined by:

$$\Pi_e\left(a_{it}, c_{it}^U, r_i, \beta\right) - K_i = \Pi_w\left(c_{it}^U, r_i, \beta\right), \tag{2}$$

where β is the firm's discount rate for the next period's payoff. It reflects the probability of the survival of export capital to a given market at the end of each period.[9]

Using this framework we solve (2) using the value functions in Appendix A.2 to obtain the same equilibrium cutoff expression in CHL in country i at t:

$$c_{it}^U = c_{it}^D \times U_{it} = \left[\frac{a_{it}\tilde{\sigma}}{(1-\beta)K_i}\right]^{\frac{1}{\sigma-1}} \times \left[1 + \frac{\beta\gamma_i\left[\bar{\omega}_{it}-1\right]}{1-\beta\left(1-\gamma_i\right)}\right]^{\frac{1}{\sigma-1}} \tag{3}$$

$$\bar{\omega}_{it} - 1 = -\bar{H}_i(a_{it})\frac{a_{it} - \mathbb{E}(a_i' \leq a_{it})}{a_{it}} \;\in (-1, 0]. \tag{4}$$

The first term in equation (3) is the unit cost cutoff if business conditions were expected to permanently remain at a_{it} and reflects the present discounted value of the export investment without uncertainty. The uncertainty factor, U_{it}, captures how much more stringent the cutoff condition is under uncertainty. We see that $U_{it} \leq 1$ if conditions are expected to change, $\gamma_i > 0$, and there is some scenario where conditions deteriorate, $\bar{\omega}_{it} < 1$. The latter is defined in (4) and is a measure of profit tail risk: the product of the probability that business conditions deteriorate and the expected proportion of profits lost in that event.

Thus a firm with costs below c_{it}^U exports to i at t. A firm continues to export to a market as long its capital

[9]The firm's discount rate on its export decision is $\beta = (1-\delta)(1-d) < 1$, where the probability of firm and export capital death are δ and d, respectively. Since we take the active producers as given and do not model domestic entry or use firm data we abstract from domestic death and set $\delta = 0$.

survived and thus some exporters to i at t may have costs above c_{it}^U. CHL show that for any given a_{it} both entry and exports are reduced after an increase in uncertainty, which may be due to either unanticipated increases in γ or increases in the risk of the distribution $\bar{H}$ (in the second-order stochastic dominance sense). Below we map these shocks to the Brexit setting.

Uncertainty can also affect the intensive margin of exporting. This occurs if a firm can make additional sunk investments to lower its marginal export cost. Handley and Limão (2017) show this generates a cutoff rule with the same uncertainty factor as (3) applied to a deterministic cutoff corresponding to the technology decision. The resulting upgrade cutoff is $c_z^U = c^U \times \phi$, where ϕ reflects upgrading cost parameters. Thus both the export entry and upgrade cutoffs have the same elasticity with respect to the uncertainty factor. This implies that the industry export equation we estimate can reflect both intensive and extensive margin effects.

3.3 Industry Export Dynamics

In this subsection, we aggregate firm behavior up to the exporter-industry level—what we measure in the data—and derive the adjustment dynamics that arise from sunk costs.

An industry V is defined by the firms $v \in V$, which draw their productivity from a similar distribution, $G_V(c)$, and face similar trade barriers in exporting to country i. Thus the cutoff can depend on V via business conditions and tail risk. In **stationary periods**, defined as those where the cutoff and entry decisions are unchanged relative to the previous period, there is a set of active exporters Ω_{iV} in country x serving country-industry iV. This set is the endogenous fraction of the N_V potential exporters with costs below the current export entry cutoff. Thus bilateral industry exports are given by aggregating sales from all firms in x to i:

$$R\left(a_{itV}, c_{itV}^U\right) = a_{itV} N_V \rho^{1-\sigma} \int_0^{c_{itV}^U} c_v^{1-\sigma} dG_V(c). \tag{5}$$

This expression applies if entry is currently easier than ever before, i.e. $c_{itV}^U \geq \max_{T<t} c_{iTV}^U$. Otherwise we must account for the legacy of surviving exporters. These are firms that started exporting to i under better conditions and remain since operating profits are positive once the sunk cost is paid.

To fix ideas, consider starting from a stationary period with a cutoff c_{i0V}^U followed by a single permanent shock to c_{i1V}^U observed at the end of period $t = 0$ and a constant a_{iV}. The constant a_{iV} would prevail if uncertainty increased but current conditions were unchanged. In this case, total exports can be written as the sum of: (i) exports by firms that exited with probability $1 - \beta^t$ and re-enter at the new cutoff c_{i1V}; and (ii) export values given by equation (5) at the previous cutoff c_{i0V} multiplied by the survival probability β^t:

$$R\left(a_{iV}, \mathbf{c}_{itV}^U, \beta^t\right) = \begin{cases} R\left(a_{iV}, c_{i1V}^U\right), & \text{if } c_{i1V}^U \geq c_{i0V}^U \\ \left[R\left(a_{iV}, c_{i1V}^U\right)\left(1-\beta^t\right)\right] + \left[R\left(a_{iV}, c_{i0V}^U\right)\beta^t\right], & \text{if } c_{i1V}^U < c_{i0V}^U. \end{cases} \tag{6}$$

Thus the estimation must account for lags of negative uncertainty shocks since they work via attrition.[10]

[10] Each of these expressions applies to more general cases and allows for any history of shocks between $t = 0$ and $t-1$ provided that either $c_{itV}^U \geq c_{i0V}^U$, so the first line in equation (6) applies; or $c_{itV}^U \in [c_{iTV}^U, c_{i0V}^U)$ in the second line of (6) applies. So the history we need to consider empirically is not necessarily of all shocks since c_{i0V}^U. We denote this potential dependence of exports on past cutoffs by the vector $\mathbf{c}_{itV}^U = \{c_{i0V}^U, ...c_{itV}^U\}$.

3.4 Product Export Dynamics

The model can be applied to dynamics at the exporter-product level, if the sunk costs are product specific. To examine dynamics for a large set of countries in a recent period at the monthly level we are restricted to using product level data. Thus we must map the exporter-product to product dynamics. We do so by exploiting the fact that a zero value in an $ixVt$ cell implies that no firm $v \in V$ from country x exported to country i at time t. In that case, the cutoff must be lower than even the minimum cost (most productive) firm, $c^U_{ixVt} < c^{\min}_{xV}$. A positive value indicates that at least one firm exported either because the cutoff is sufficiently low at time t or because some firm survived from a prior export entry investment. In the appendix we show how this insight can be used to directly relate entry and exit to uncertainty factor. In the empirical section we explain how entry and exit are measured.

4 Identification and Uncertainty Measurement

To identify the impacts of uncertainty we decompose the export equation in (6) into shocks to uncertainty, demand, and supply factors and provide an approach to control for the latter two. We then discuss how to measure shocks to the probability of Brexit. Finally, conditional on Brexit, we describe how to measure the tail risk over products under different scenarios. To be clear about the level of variation of each variable we introduce x subscripts to denote export country.

4.1 Identification

4.1.1 Decomposition of Export Shocks

If there are any sales from x to i in industry V, then we can write exports in (6) as log deviations relative to a baseline stationary period value. Using a "$\frown$" to denote log changes, e.g. $\hat{a}^U_{ixVt} \equiv \ln \frac{a_{ixVt}}{a_{ixV}}$, we obtain the first-order decomposition of current exports relative to a stationary baseline evaluated at $\mathbf{r}_{ixV} = \{a_{ixV}, c^D_{ixV}, N_{xV}, \bar{b}^h_i\}$. In a stationary period t this is simply

$$\ln \frac{R_{ixVt}}{R\left(\mathbf{r}_{ixV}\right)} = \left(k_c \hat{c}^U_{ixVt} + \hat{a}_{ixVt} + \hat{N}_{xtV}\right) + o_{ixVt}, \tag{7}$$

where $k_c \equiv \frac{\partial \ln R(a,c)}{\partial \ln c} \geq 0$ is the export elasticity with respect to the cutoff around a deterministic steady state; under a standard Pareto productivity distribution with dispersion k, this export elasticity is equal to $k - (\sigma - 1)$ and $o_{ixVt} = 0$, i.e. there would be no approximation error.

If we do not start in a stationary period then we must approximate each of the terms in [] in the second line of equation (6). The expression in (7) shows how to approximate the stationary components in each t. However, we must also account for the fact that the relative weights on R_{ixVt} and R_{ixVt-T} depend on when the cutoffs changed, which may differ across destinations, i. We denote the dependence of those weights on prior shocks in i by the history coefficient, b^h_{it}, and approximate it around $\bar{b}^h_i$: interpreted as the average export death rate into i.[11] Thus the more general decomposition of (6) is:

$$\ln \frac{R_{ixVt}}{R\left(\mathbf{r}_{ixV}\right)} = \left(k_c \hat{U}_{ixVt} + k_a \hat{a}_{ixVt} + \hat{N}_{xtV}\right) \bar{b}_i^h + \left(k_c \hat{U}_{ixVt-T} + k_a \hat{a}_{ixVt-T} + \hat{N}_{xt-TV}\right)\left(1-\bar{b}_i^h\right) + o_{ixVt} \quad (8)$$

The first term in () in equation (8) is the same as in (7) after we use the definitions of c^U, c^D from (3) and define $k_a \equiv 1 + \frac{k_c}{\sigma-1}$. The second term in () is the approximation the stationary value in $t-T$. The average export death rate, $\bar{b}_i^h$, provides the relative weight and the history coefficient b_{it}^h has no first order effects since R_t and R_{t-T} are approximated around common values.

From (8) we can obtain an estimating equation focusing on the uncertainty shocks:

$$\ln R_{ixVt} = \bar{b}_i^h k_c \hat{U}_{ixVt} + \alpha_{ixV} + \alpha_{it} + o_{ixVt}. \quad (9)$$

We moved the stationary export value to the right in equation (9) where it is absorbed in the α_{ixV} fixed effects, which also control for selection. The structural interpretation of the coefficient on $\hat{U}_{ixVt}$ will be useful for counterfactuals and relies on the identification assumptions discussed below.

4.1.2 Identification Assumptions and Implications

The following four identification assumptions imply the set of fixed effects in (9) and control for all terms other than $\hat{U}_{ixVt}$.[12]

A1: Common, constant, deep parameters across exporters, time, and varieties, including: (a) the elasticity of substitution, σ; (b) the probability of policy shocks in i, γ_i, and; (c) the export entry elasticity in stationary state, k_c.

A2: Common shocks to the potential mass of exporting firms: $\hat{N}_{xtV} = \hat{N}_t$.

A3: Negligible changes in exporter- and industry-specific applied protection in the short-run: $\hat{\tau}_{ixVt} = \hat{\tau}_{it}$.

A4 Negligible or random variation over time in pre-sample policy uncertainty, i.e. $\hat{U}_{ixt-TV} \approx \hat{U}_{ixV}$.

Our four assumptions have the following implications. A1 is required to estimate the coefficient on $\hat{U}_{ixVt}$ and is maintained throughout the paper. A2 allows for exogenous shocks to the number of potential exporting firms but restricts them to be common across exporters and thus are captured by time effects or by importer-time effects, α_{it}, when interacted with importer specific shocks. A3 implies that import demand shocks in the period we consider, $\hat{a}_{ixVt} = \hat{D}_{it} - \sigma \hat{\tau}_{ixVt}$, can be captured by α_{it}. A4 is required given that prior to the announcement of the Brexit referendum there is no market probability data for the event. In the sample period we explicitly allow for lagged effects of $\hat{U}$.

We test the robustness of the results to some identification assumptions and approximation. The results focus on bilateral trade between the UK and the EU. For UK-EU bilateral trade, A1(b) is reasonable. We

[11] This coefficient is equal to $1-\beta^T$ if conditions have worsened in i for T periods before t, and 1 otherwise. We can allow for a more general history coefficient, b_{ixt}^h, that reflects bilateral variation in the history coefficient but the approximation would still be similar.

[12] $\alpha_{ixV} \equiv \ln R\left(a_{ixV}, c_{ixV}^D\right) + \left(1-\bar{b}_i^h\right)\tilde{k}_c \ln U_{ixV}$, controls the deterministic state exports in a stationary state and the pre-sample uncertainty under A4. $\alpha_{it} \equiv \bar{b}_i^h\left[\tilde{k}_a \ln \frac{a_{ixtV}}{a_{ixV}} + n_t\right] + \left(1-\bar{b}_i^h\right)\left[\tilde{k}_a \ln \frac{a_{ixt-TV}}{a_{ixV}} + n_{t-T}\right]$ as can be seen by using the definition of a, A1 and A3.

initially consider symmetric shocks γ and then allow for asymmetric shocks. We relax A2 and A3 by allowing variation in the exporter x through bilateral shocks α_{ixt} or different combinations of importer and exporter effects varying over time and sector. The quality of the approximation depends on how far the approximation point is and on the functional form. We test robustness to the history approximation point by approximating around bilateral history coefficients, $\bar{b}_{ix}^{h}$, and then controlling for bilateral-time effects, α_{ixt}.[13]

4.1.3 Timing of investment and export decisions

We use industry data at the monthly level and thus require certain timing assumptions to map between the theory and the data. First, we focus on lumpy sunk investments that we assume a firm makes annually for any given product destination. Taken literally, this implies that the relevant policy uncertainty in our sample relates to what will occur after the referendum, i.e. any firm investing between July 2015 and June 2016 need not make another investment in exporting to country-industry iV until after the referendum. Second, we assume that not all firms in an ixV cells make investment decisions in the same month; otherwise we could not explore variation over the year within any given ixV cell. Thus the identification requires investment decisions to be staggered over time across cohorts of firms. An export shipment may be recorded in the same month as the investment but it may also occur in later months, so we will include lags of $\hat{U}_{ixVt}$ to capture these dynamics.

4.2 Uncertainty Measurement

First, we describe how preferential trade disagreements can affect the uncertainty factor, U, by increasing the probability of riskier trade policies. Second, we model exporter beliefs about the probability of Brexit and how shocks to the latter are related to prediction markets. Third, we outline the measurement of potential trade policy risks conditional on Brexit.

4.2.1 Trade Disagreements

We model uncertainty in demand conditions, $a_{ixVt} = D_{it}\left(\tau_{ixVt}\right)^{-\sigma}$, by focusing on potential shocks to bilateral policy barriers, τ_{ixVt}, but recognizing that other sources exist. If all uncertainty is policy related then γ_i may capture the expected arrival rate of a (re)negotiation opportunity or a change in the government that is necessary for a policy change. More generally, γ captures the probability of any demand shock, so we keep this parameter constant throughout and describe how the uncertainty factor U varies over time due to tail risk shocks.

How do trade agreements affect uncertainty? We follow CHL in modeling an agreement as a choice of an initial policy vector and a distribution, $\bar{H}$, from which future policies are drawn. That distribution can be written as $\bar{H} = \Sigma_S m^S H^S$: a mixing distribution with probability weights m^S over S mutually exclusive uncertainty states, each with a fixed distribution, H^S, characterized by different risk. The EU aims to integrate the product markets of its members, which requires a credible and permanent reduction (or elimination) of trade barriers such that uncertainty is low. CHL provide conditions where governments

[13] In this case, the approximation in (8) will have $\bar{b}_{ix}^{h}$ and applying the identifying assumptions A1 and A3 we obtain a version of (9) where the fixed effects are $\alpha_{ixV} \equiv \ln R\left(a_{ixV}, c_{ixV}^{D}\right) + \left(1-\bar{b}_{ix}^{h}\right) k_c \ln U_{ixV}$, and $\alpha_{ixt} \equiv \bar{b}_{ix}^{h}\left[k_a \ln \frac{a_{ixtV}}{a_{ixV}} + \ln \frac{N_{xt}}{N}\right] + \left(1-\bar{b}_{ix}^{h}\right)\left[k_a \ln \frac{a_{ixt-TV}}{a_{ixV}} + \ln \frac{N_{xt-T}}{N}\right]$

that are export risk averse prefer higher weights on less risky distributions in a second-order stochastic dominance sense.

We apply this model in our context to two uncertainty states: $S = \{BR, EU\}$, so the policy is drawn from either H^{BR} with probability m or with probability $1 - m$ from the less risky distribution, H^{EU}. The tail risk is then given by the following weighted average:

$$\bar{\omega}_{ixVt} = m_{ixt}\omega_{ixV}^{BR} \; + (1 - m_{ixt})\,\omega_{ixV}^{EU}. \tag{10}$$

Increases in the likelihood of a trade disagreement such as Brexit can then be modeled as increases in m_{ixt}, i.e. in the probability of a draw from the riskier policy distribution, as perceived by exporting firms.

Three points are useful for the ultimate estimation equation and interpretation of results. First, the probability of staying in the EU is similar across industries. Second, the underlying distributions, H^S, can differ across industries and partners but are assumed to be time invariant; as discussed below. Third, increases in m increase tail risk if and only if H^{EU} SSD H^{BR}, so its impacts on exports depend on risk rather than mean effects.

4.2.2 Policy Risks

In Figure 3 we illustrate the scenarios the exporters consider. With probability $\gamma(1 - m)$ policy is drawn from H^{EU} at some level no higher than the current one, τ_{ix}^{EU}. Therefore by remaining in the agreement there is no tail risk, $\omega_{ixV}^{EU} = 1$, because exporters believe the current policy represents a credible commitment for the maximum barrier. If we take a narrow view and consider only tariffs, which have been eliminated, then $\tau_{ix}^{EU} = 1$. We can also allow for the possibility of non-tariff barriers so $\tau_{ix}^{EU} \geq 1$ captures a tariff equivalent factor of all bilateral trade policy barriers. One implication is that there is room for improved market access through negotiation.

With probability γm Brexit occurs and a new policy is drawn from H^{BR}. We discretize the Brexit distribution into mutually exclusive scenarios indexed by $s = \{W, M, F, R\}$: War, MFN, FTA and Renegotiation. These occur with probabilities η_{ix}^s, so $\sum_s \eta_{ix}^s = 1$, and each implies a policy factor defined by $\bar{\tau}_{ixV}^s = \tau_{ixV}^s \tau_{ix}^{EU}$. Policy in scenario s deteriorates relative to the EU if $\tau_{ixV}^s > 1$ and we assume this is the case under all except renegotiation, so the conditional Brexit tail risk reflects only the top three scenarios in Figure 3.

$$\omega_{ixV}^{BR} - 1 = \sum_{s=F,M,W} \eta_{ix}^s \left[\left(\tau_{ixV}^s\right)^{-\sigma} - 1 \right]. \tag{11}$$

Under the renegotiation scenario policy barriers remain at EU levels or lower, $\bar{\tau}_{ixV}^F \leq \tau_{ix}^{EU}$. If firms place a zero weight on this scenario then (11) remains unchanged. Allowing for $\eta_i^R \geq 0$, captures the possibility that a renegotiation can generate improvements and makes it clear that even if on average policy conditions were better under the renegotiation (if $\bar{\tau}_{ixV}^R$ was sufficiently low relative to τ_{ix}^{EU}) it would still lower entry and exports due to the higher risk.[14]

Replacing (11) and $\omega_{ixV}^{EU} = 1$ in (10) we obtain the unconditional trade policy tail risk before the referen-

[14]More broadly, this represents a post-Brexit scenario where business conditions for certain exporters have improved, $a_{ixV}^R \geq a_{ix}^{EU}$. This is possible if tariffs remain at EU levels and (i) certain restrictions are relaxed (e.g. product standards); or (ii) governments implement policies aimed at expanding exports such as export credit subsidies, reductions in profit taxes or a depreciated currency.

dum:

$$\bar{\omega}_{ixVt} - 1 = m_{ixt} \sum_{s=F,M,W} \eta^s_{ix} \left[(\tau^s_{ixV})^{-\sigma} - 1 \right] \tag{12}$$

We measure potential profit loss conditional on the MFN scenario by using observed EU MFN tariffs applied to non-members. For the trade war scenario we construct non-cooperative tariffs as described in the data section. We complement these with trade protection from four developed countries to address potential measurement error via an IV approach. We define the FTA scenario as one where tariffs remain at zero, so there is no product level variation, $\tau^F_{ixV} = \tau^F_{ix}$, but may reflect some non-tariff barriers so $\tau^F_{ix} \geq 1$. We control for any FTA risk using bilateral-time effects in the baseline; sector-time effects in section 6 and bringing in additional data in section 6.1.3. We will show that η^s_{ix} are absorbed in the estimated coefficients.

4.2.3 Firm's Brexit Beliefs and Prediction Market Shocks

Having modeled the variation across industries we turn to the variation over time. Our objective is to estimate the response to permanent changes in beliefs. Since we do not have direct information on exporter beliefs, we model how they depend on observables. Specifically, we map changes in m_{ixt}, the probability that a policy is drawn from a Brexit distribution, H^{BR}, to Brexit measures from prediction markets.

The definition of Brexit at t is that at some future period $\mathcal{T}$ a policy shock arrives and a new trade barrier is drawn from H^{BR}. We denote a referendum at $\mathcal{T}$ where a majority votes to leave as $\mathcal{R}_{\mathcal{T}}$=1 and note it was a necessary condition for Brexit. Conditional on $\mathcal{R}_{\mathcal{T}}$=1 we define the probability of a policy draw from H^{BR} as p_{ix}. For firms exporting from x to i, with information set $\mathcal{I}_t$, the average belief that Brexit will occur can then be written as:

$$\gamma_i m_{ixt} = \gamma_i p_{ix} \Pr\left(\mathcal{R}_{\mathcal{T}} \mid \mathcal{I}_t\right). \tag{13}$$

Conceptually we are modeling the firm belief of Brexit as the product of an exogenous time varying shock: the probability of a leave referendum outcome, and an invariant component, $\gamma_i p_{ix}$. The latter represents the probability that a policy shock arrives and the policy is drawn from H^{BR} given a leave vote and will be reflected in the estimation coefficients.

We can approximate $\Pr\left(\mathcal{R}_{\mathcal{T}} \mid \mathcal{I}_t\right)$ by using observables in the information set $\mathcal{I}_t$ that are common to all firms. We let $\mathcal{I}_t$ be a function of information inputs that include data from prediction markets, polling or both. Changes in the unobserved beliefs relative to a baseline period can then be approximated using a first-order log change in information inputs, $\hat{m}_{t-l}$.

$$\widehat{\Pr\left(\mathcal{R}_{\mathcal{T}} | \mathcal{I}_t\right)} = \sum_{l=0,\ldots,L} r^m_l \hat{m}_{t-l} + e^r_t. \tag{14}$$

The parameters r^m_l represent the elasticity of firm beliefs with respect to a change in a specific component m_{t-l}. We allow the elasticity to vary depending on whether the information is current ($l = 0$) or lagged up to L periods. The sum $\sum r^m_l$ represents the long-run elasticity of firm beliefs with respect to a permanent change in the information input, m.

Our baseline information input is the Brexit contract price that at time t promises to pay $1 if a referendum is held by the end of 2016 and leave wins. We also consider alternative inputs that can shape firm beliefs and discuss how they are related.

4.3 Uncertainty Factor

To estimate (9) we combine the policy risk and probability shocks to provide an empirical measure of the uncertainty factor. Using $\hat{U} \equiv \ln U$ (log change relative to the deterministic); applying the definition of U in (3) and of $\bar{\omega}$ in (12) we obtain

$$\hat{U}_{ixVt} = \frac{1}{\sigma - 1} \ln\left(1 + \tilde{\beta}_i m_{ixt}\left(\omega_{ixV}^{BR} - 1\right)\right). \tag{15}$$

The term $\tilde{\beta}_i \equiv \frac{\beta\gamma_i}{1-\beta(1-\gamma_i)}$ represents the expected duration of an export spell to i under the current conditions.

To explore the interaction between industry variation in policy risk and the time variation in Brexit beliefs we derive a second order approximation to $\hat{U}_{ixVt}$ *around* $\omega_{ixV}^{BR} = 1$ and $\ln m_0$, i.e. around the EU scenario prior to the possibility of a referendum. In Appendix A.3 we show that this approximation combined with the empirical models we previously described for ω_{ixV}^{BR} and m_{ixt} yields

$$\hat{U}_{ixVt} = -\frac{\tilde{\beta}_i m_{ix0}}{\sigma - 1} \sum_{s=M,W} \eta_{ix}^s \sum_{l=0}^{L} r_l^m \left\{ mbv_{t-l}\left[1 - \left(\tau_{ixV}^s\right)^{-\sigma}\right]\right\} + \alpha_{ixt}^F + \alpha_{ixV}^U + e_{ixVt}^r \tag{16}$$

where the terms within {} are observable data: the ln contract price (mbv_{t-l}) and the expected proportion of profit losses from trade policy deteriorations in the two Brexit scenarios with product variation, $s = M, W$. The analogous term for the FTA scenario is captured by the bilateral-time effect, α_{ixt}^F, since it has no product variation.[15] The fixed effect α_{ixV}^u captures constant baseline uncertainty effects; and e_{ixVt}^r captures any error from approximating beliefs.

5 Estimation

We map the model components described thus far into estimable equations for export values, entry, and exit. We describe our main data sources and sample. We also discuss the results on export values and then turn to further evidence for the uncertainty mechanism by analyzing export entry, exit, and heterogeneity in high versus low sunk cost industries.

5.1 Export Values

Using the uncertainty factor in (16) in the export equation (9) and re-arranging we obtain the baseline estimating equation:

$$\ln R_{ixVt} = \sum_{s=M,W} \sum_{l=0}^{L} W_{ix}^s(l) \left\{ mbv_{t-l}\left[1 - \left(\tau_{ixV}^s\right)^{-\sigma}\right]\right\} + \alpha_{ixV,it,jt} + e_{ixVt}, \tag{17}$$

where the vector $\alpha_{ixV,it,jt}$ represents country-time (it, xt) and bilateral-industry effects; e_{ixVt} is an error term. The key coefficients of interest that we report are cross-partial derivatives of (17) with respect to the

[15]The FTA effect is negative if exporters place weight on an FTA, $\eta_{ix}^F > 0$, with increase in policy barriers, $\tau_{ix}^F > 1$; it is zero otherwise.

prediction market contract price, mbv, and risk terms:

$$\sum_l W_{ix}^s(l) \equiv \sum_l \frac{\partial^2 \ln R_{ixVt}}{\partial mbv_{t-l}\partial\left[1-\left(\tau_{ixV}^s\right)^{-\sigma}\right]} = -\bar{b}_i^h k_c \frac{\tilde{\beta}_i}{\sigma-1} m_{ix0}\eta_{ix}^s \sum_l r_l^m. \tag{18}$$

This sum of the estimated coefficients over the lags is what we define as the *permanent cross-elasticity of uncertainty and risk*, $\mathcal{E}^s = \left|\sum_l W_{ix}^s(l)\right|$. The parameters in this elasticity are positive according to the model, reflecting export elasticities to entry $\bar{b}_i^h k_c$, the baseline probability of Brexit conditional on a policy shock, m_{ix0}, and the expected export duration period under the next policy, $\tilde{\beta}_i$. Thus, $\mathcal{E}^s$ is zero only if $\eta_{ix}^s = 0$, so scenario $s = M, W$ was not believed by firms, or the measure used to capture changes in beliefs from the baseline is uninformative, in which case $\sum_l r_l^m \approx 0$.

We can learn about belief parameters of firms exporting to i such as the relative probability of post-Brexit scenarios by using $\mathcal{E}^M/\mathcal{E}^W = \eta_i^M/\eta_i^W$.

5.2 Export Entry and Exit

In Appendix A.5 we derive the relationship between the cutoff and the probabilities of product entry and exit. The basic insight we explore is that if we observe current but not lagged exports in an ixV cell then this implies an increase in the cost cutoff between t and some prior period, $t-12$, that induced the minimum cost firm to enter, and possibly other firms below the new cutoff as well. Analogously, if we observe lagged exports but no current exports then with probability, $1-\tilde{\beta}$, the firms exporting in $t-12$ lost their export capital and chose not to re-invest at the current cutoff. We estimate a linear probability model for the mutually exclusive samples depending on lagged export participation. Entry is estimated for a sample where $R_{ix,t-12,V} = 0$ and exit on the complementary sample as follows:

$$Entry_{ixVt} = \tilde{k}_c^E \hat{U}_{ixVt} + \alpha_{ixV,it,jt}^E + o_{ixVt}^E \text{ if } R_{ix,t-12,V} = 0 \tag{19}$$

$$Exit_{ixVt} = \tilde{k}_c^X \hat{U}_{ixVt} + \alpha_{ixV,it,jt}^X + o_{ixVt}^X \text{ if } R_{ix,t-12,V} > 0. \tag{20}$$

The binary variables are defined as $Entry_{ixVt} = 1$ if $R_{ixVt} = 1$ and $Exit_{ixVt} = 1$ if $R_{ixVt} = 0$; both are zero otherwise. The parameters for the uncertainty factor have a structural interpretation but the key predictions we test are whether uncertainty reduced export entry; increased exit; and whether the latter responds less strongly since $\text{abs}\left(\tilde{k}_c^X/\tilde{k}_c^E\right) = 1-\tilde{\beta} < 1$. We follow the approach in equation (17) and replace the approximation for $\hat{U}_{ixVt}$ in (16), and control for a similar set of fixed effects.

5.3 Data

5.3.1 Uncertainty

The main measure of Brexit uncertainty we use is a prediction market based variable. Specifically, we employ the average daily price of a contract traded in PredictIt.org paying \$1 if a majority voted for Brexit in a referendum held by December 2016 and zero otherwise. The market opened on May 27th 2015 and closed on June 24th 2016.

We interpret changes in the contract price as providing information that allows exporters to update their beliefs about the average probability of the event. In Figure 1 we plot this contract price until the day prior to the referendum. We see that on average it was about 30% and exhibited substantial variation. For example, there was an initial decline in the probability, which halted once the wording was approved. The probability declined again in the month before the bill authorizing a referendum was passed in December 2015. Another increase is clear after the referendum date was set. After the campaign started the probability of a majority Brexit vote declined initially, which tracks opinion polls, but then increased sharply in the month before the vote. The day after the referendum the price converged to 1 (not shown). Some of the daily variation will reflect noise trading but we expect this to be ameliorated by the monthly averages we employ and that still exhibit considerable variation.

The contract price is what the prediction market interprets from polls, political discussions, and other information sources. In Figure 1 we also plot a polling average for individuals that either intended to vote for "Leave", or were undecided (RHS axis). This co-moves closely with the contract price, particularly once the date of the referendum was set.[16] We examine the robustness of the results to alternative measures of uncertainty and further discuss some correlates of the contract price in Section 6.2 and in the Appendix.

5.3.2 Trade

We use bilateral monthly trade data from Eurostat at the 6-digit product level of the Harmonized System (HS). The baseline estimation employs trade values between the UK and the EU from August 2015 to June 2016. To measure entry and exit outcomes, we extend the data back to August 2014 in order to condition on export participation at $t-12$.

In Table 1 we summarize some key features of the data. First, the EU-27 countries account for about 42% of UK exports and 52% of its imports in 2015. For the EU the UK represented, 7% of total exports and 4% of imports. There is much less asymmetry in the data we employ for the estimation since it reflects bilateral exports between the UK and individual EU countries.

The export value regressions use the set of ixV observations with positive trade for all months in the sample. This is a strict subsample of the entry and exit set of bilateral-HS6 observations but still covers more than 90% of trade between the UK and EU. In Table 1 we provide summary statistics for the binary $Entry_{ixVt}$ and $Exit_{ixVt}$ measures defined in section 5.2. Average entry in this period is about 25% and exit is 14%; both variables have coefficients of variation above 1.75.

5.4 Trade Policy

We downloaded the simple average MFN tariffs in 2015 from the United Nations' TRAINS database. We construct tail risk factors at the HS6 level for 2015. This MFN tariff is the common external tariff that the EU applies to all non-members except those with which it has PTAs. We employ product codes in which the reported simple average does not include specific tariffs to minimize error coming from imputation methods (this covers 94% of 6-digit product codes for the EU). In many cases there is limited or no variation below the

[16] There are well known issues with the uses of specific voting intention polls. We use a polling average from Number Cruncher Politics that was used in this period to describe the evolution of voters' intention to vote for Brexit. Examples of its use are Bloomberg (`http://www.bloomberg.com/graphics/2016-brexit-watch/`) and LSE (`http://blogs.lse.ac.uk/politicsandpolicy/polling-divergence-phone-versus-online-and-established-versus-new/`). Its construction is detailed in `http://www.ncpolitics.uk/2016/04/faq-number-cruncher-politics-polling-average.html`.

6 digit level. We also use MFN tariffs for other developed countries (the US, Japan, Canada, and Australia) to construct instruments.

In Table 1 we summarize some key features of these policies in the regression samples we use. The EU MFN tariff is positive for over 75% of HS6 products; both the average and standard deviation of the log tariff factor are equal to 0.04. The MFN risk factor is computed as $1 - \left(\tau^{M}\right)^{-4}$; its average is 0.15 and the standard deviation is 0.125.

In Table A1 we provide policy risk statistics by sector (21 sections of the HS classification). Products face policy risk in all but two small sectors and for the remaining 19 sectors the average risk ranges from 0.014 to 0.34 and the coefficient of variation from 0.17 to 2. In one of the largest sectors, vehicles, the mean and standard deviation of this risk is similar to that of the overall sample.

We construct trade war risk measures using non-cooperative tariff estimates from Nicita et al. (2018). Their estimates are built using an optimal tariff formula from a theoretical prediction that non-cooperative tariffs are increasing in the importer's market power in a product. There is substantial evidence supporting this prediction and knowledge about how to address error in the measurement of this market power (cf. Broda et al., 2008) that we build on. The resulting average non-cooperative for the EU is 57% and the associated tail risk is 0.73. The latter is five times higher than the MFN risk average.

5.5 Export Value Estimates

We first estimate (17) constraining the cross elasticities, W_{ix}^{s}, to be symmetric between EU and UK; and subsequently show the results are qualitatively similar but quantitatively different if we allow for asymmetries.

5.5.1 UK-EU MFN Risk

In Table 2 we find evidence that increases in the probability of Brexit lowered UK-EU export values for products where MFN tariffs would be applied. This effect is statistically significant at standard levels. The first specification employs OLS and controls for importer-exporter-HS6 (ijV) as well as monthly effects by importer (it) and exporter (jt). Since the sample includes EU exports only to the UK and vice versa, the it and jt effects are equivalent to bilateral monthly effects, ijt, so they control for any risk factor that is not product specific, as defined in the FTA scenario, as well as other unobserved bilateral aggregate shocks (e.g. exchange rates, FDI, etc.).

The MFN risk measure is potentially subject to measurement error, which may attenuate its estimated effect. Under a hard Brexit where the UK raises tariffs on the rest of the EU, the resulting tariff schedule may differ from the current EU common external tariffs. In that case, the EU may also choose to change its common external tariff and/or apply certain additional trade barriers on the UK.

We address this source of measurement error by instrumenting the MFN risk factors. We do so by computing the median HS6-specific MFN risk across the US, Japan, Canada, and Australia. The rationale is that even if exporters are uncertain about the exact future protection level in the UK and EU, they know that protection in certain products tends to be correlated across developed countries and use this information to predict UK-EU MFN risk.[17] The point estimates from this IV procedure in column 2 is -1.5, which is about 1.8 times larger than the corresponding OLS estimate.

[17]In appendix A.6 we describe the IV procedure and the high explanatory power of the first stage.

5.5.2 UK-EU Trade War Risk

If exporters believed that a trade war was likely after Brexit, then we should find lower exports in industries with higher tail risk under that scenario. We construct $1 - \left(\tau_{iV}^{W}\right)^{-\sigma}$ using the non-cooperative tariffs described in the data section 5.4. The elasticities used to construct these tariffs are subject to two sources of measurement error. First, they can take on extreme values, so we drop products with non-cooperative tariffs above 180%.[18] Second, there is idiosyncratic measurement error across importer-industry products, iV, which we address via instrumental variables. Similarly to the MFN risk, we use other developed countries (US, Japan, Canada, Australia), compute trade war risk measures for each, and take the median for each product.

The OLS estimates in column 3 of Table 2 indicate there is no effect from a trade war risk. The IV point estimate in column 4 is negative and the implied trade war risk is about one-third of the MFN, although it is not statistically significant. Additional controls can improve the magnitude of this coefficient but it remains imprecisely estimated.[19]

In sum, the trade war risk effect is negative but too imprecise to determine whether exporters placed any significant weight on the probability of such an event. Moreover, since this additional control does not significantly affect the MFN risk estimate, we will omit it from subsequent regressions.

5.6 Mechanism Evidence: Sunk Costs, Entry, and Exit

We provide evidence for the role of export sunk costs and entry and exit behavior, which are consistent with the theoretical model.

5.6.1 Export Sunk Costs

The export entry predictions apply to industries with significant export sunk costs. Thus we examine if the estimates so far are present in those industries and not others.

We apply the approach in Handley and Limão (2017) to identify high sunk cost industries. Specifically, we run an export probability model at the HS-8 level and estimate the impact of lagged exporting conditional on standard participation determinants of current exporting. We estimate separate models for each HS 4-digit industry and use significance in lagged participation as an indicator for sunk costs in that industry. We use semi-annual exports of non-EU countries to the EU (and UK) from the first semester of 2012 to 2016. The estimation details are in Appendix A.8. We base these estimates on exports of non-EU countries to the UK so these flows are distinct from the dependent variable in the baseline UK-EU bilateral trade estimation. There is considerable overlap in the resulting classification if we base it on exports to the UK or to other large EU countries, which suggests an important industry component. Given this congruence in classifications we use the UK-based classification and note the baseline results are similar with alternative classifications.

Table 3 shows estimates based on subsamples under the respective high or low column heading. The

[18] The threshold criteria is based on a statistical test of outliers based on sufficiently large distance from the interquartile range and the restriction applies to about 6% of the baseline sample.

[19] For example, the estimated elasticities used to construct τ_{iV}^{W} are a function of the elasticity of substitution, σ (Broda et al., 2008). If goods with higher σ are responding differently to Brexit shocks then this omitted variable would bias the trade war risk estimates. When we control for this by adding section-month effects in column 4 we obtain a higher trade war risk coefficient (and of MFN), but it remains imprecisely estimated.

high sunk cost represent about 88% of all observations in the baseline, which is re-assuring since we expect that continuously traded industries will have high sunk costs. We find marginal increases in the absolute value and statistical significance of the high sunk cost sample coefficients relative to the baseline in Table 2. Conversely, we find positive and insignificant risk effects for low sunk cost industries.

5.6.2 Export Entry and Exit

In the presence of export sunk costs, the model predicts that uncertainty lowers exports via firm entry and exit. The estimated export value coefficients reflect that behavior, but focus on continuously traded products in this period and thus do not allow us to directly test them. Thus we now use a sample of intermittently traded products to estimate export entry and exit using the specifications in equations (19) and (20).

In Table 4, we find that entry decreased with MFN risk, as predicted. The estimates triple in magnitude when we move from OLS (column 1) to IV (column 2). Exit increased with MFN risk, as predicted, and the estimates double in magnitude when we move from OLS (column 3) to IV (column 4).

Export entry is more responsive to MFN risk than exit in all comparable specifications. Firms can immediately respond by entering when conditions improve but when they deteriorate firms choose to wait. The more sluggish exit response occurs because it operates through foregone re-entry decisions. Existing exporters at $t-12$ face a new entry choice at time t only if they are hit by an exogenous shock to their export capital. These shocks occurs with annual probability $1-\beta$, which is the model's interpretation of the ratio of medium run elasticity of exit to MFN risk relative to entry.

Similarly to the export value specifications in Table 2, we find no significant impact of the trade war scenario for entry and exit. The point estimates on MFN risk do not change substantially when controlling for trade war risk . Also, similarly to the value estimation in Table 3, we find the impacts of MFN risk are driven by the high sunk cost industries. Both sets of results are available on request.

6 Quantification and Robustness

We quantify the impacts of Brexit uncertainty on export values and participation via MFN risks. We start with the baseline symmetric UK-EU estimates and then extend the estimation to allow these to differ for the UK and EU. We also extend the estimation to capture an average of all Brexit risk effects (FTA, MFN, War), which we find is driven by the MFN risk. Thus the full Brexit uncertainty elasticity is close to the lower bound implied by MFN alone.

We conclude the section by showing that the baseline results are robust to alternative specifications, different measures of Brexit likelihood, and additional controls.

6.1 Quantification

The permanent cross-elasticities of exports with respect to Brexit uncertainty under different scenarios, defined by equation (18) depend on constant parameters; we now use our estimates to quantify the uncertainty elasticity of exports at alternative policy levels. The predicted average change in exports evaluated at the mean risk from a shock to uncertainty captured by the log change in contract prices, $\Delta mbv = mbv_1 - mbv_0$, is given by the first line in this equation:

$$\begin{aligned}\mathbb{E}\left(\ln \frac{R_{ixV}(mbv)}{R_{ixV}(mbv_0)}\right) &= -\sum_{s=F,M,W} \mathcal{E}^s \times \left(\overline{1-(\tau^s)^{-\sigma}}\right) \times \Delta mbv \\ &\leq -\mathcal{E}^M \times \left(\overline{1-(\tau^M)^{-\sigma}}\right) \times \Delta mbv. \end{aligned} \tag{21}$$

Recall that the $\mathcal{E}^s$ represent the cross-elasticity of uncertainty and risk under scenario s — the cumulative effect of a shock in the current period plus two lags. We focus on quantifying the impact from the MFN risk alone, which is given by the second line and understates the full negative uncertainty effect according to the model since $\mathcal{E}^s \geq 0$.

Using the IV estimates from Table 2, column 2 we have $\mathcal{E}^M = 1.45$ and the mean MFN risk is denoted by $\overline{1-(\tau^M)^{-\sigma}} = 0.15$ (Table 1). Thus we obtain the uncertainty elasticity at the mean MFN risk to be $\mathcal{E}^M \times \left(\overline{1-(\tau^M)^{-\sigma}}\right) = 1.45 \times 0.15 = 0.22$. This implies that for a 10 log point Brexit uncertainty shock exports fall by at least 2.2 log points. If we use the estimate from column 4 (which controls for any trade war effect) we obtain a larger impact.

6.1.1 Symmetric Effects

Table 5 provides the quantification of the effects using the baseline estimates of $\mathcal{E}^M$ for export values and participation. That table includes both OLS and IV estimates for the formula given by the expression in (21) but our discussion focuses on the IV unless specified.

Export Values

A persistent increase in mbv_t by one standard deviation lowers average exports by at least 2.6 log points due to the MFN risk, as shown in Table 5, panel A. A standard deviation shock is equivalent to an interquartile range increase in the sample.[20]

In panel B of Table 5 we consider a doubling of Brexit uncertainty, so $\Delta mbv = 0.69$. This results in at least a 15 log point decrease in bilateral exports (IV). In section 6.1.4, we map this uncertainty change to specific political and polling shocks.

We illustrate the magnitudes of these shocks by plotting the export response to changes in Brexit uncertainty and changes in MFN risk in Figure 4. For a given MFN risk the response of log exports to changes in mbv_t is linear. Figure 4(a) shows the change in exports at the mean MFN risk for mbv shocks ranging from zero to 0.69, the shaded area represents 95% confidence intervals for the prediction.

In Figure 4(b) we plot the impacts of doubling uncertainty at different MFN risks, specifically the predicted value $-\mathcal{E}^M \times 0.69 \times \left(1-\left(\tau^M\right)^{-\sigma}\right)$ over a tariff range: $100 \times \ln \tau^M \in [0, 22.5]$. The effect at the mean is 15 log points, as reported in Table 5. We note that 40% of observed tariffs in the sample are above the mean and thus have larger impacts. For products with tariffs one standard deviation above the mean, or 15% of the sample, the export reduction is 30 log points.

[20]The overall effect is the average of the effect on *treated* industries with positive MFN risk factors and those with no MFN risk. The effect for the subset of industries with positive MFN risk factors is 3.3 log points.

Export Participation

We perform the same quantification exercise for the entry and exit regressions in columns 3-6 of Table 5. Permanently doubling Brexit uncertainty (Panel B) would reduce entry by almost 6 percent due to MFN risk (column 5), and increase exit by about one third of that, 2% (column 6). This amounts to a net entry reduction of doubling Brexit uncertainty of at least 8 percent. Even the smaller standard deviation shock in Panel A implies a net entry reduction of about 1.4 percent.

Summary and implications

These estimates indicate that the effects of Brexit can be inferred from the responsiveness of trade patterns to the probability of measurable policy outcomes. The latter is a novel contribution to ex-ante analysis of the impact of trade renegotiations. The effects for large political shocks that we identify seem reasonable. The average MFN tariff in the EU is 4.5%. Using tariff elasticities from the literature, which range from 4 to 7 (Limão, 2016), the average trade response of exports to a permanent increase in those applied tariffs would be 18 to 32 log points.[21]

A further implication of our results that Brexit uncertainty pre-referendum lowered exports is that subsequent analysis must account for this pre-referendum dip, particularly for industries with high MFN risk. Results may vary depending on whether the initial period used for the analysis included mostly months with high uncertainty, such as April or June 2016, or low uncertainty.

6.1.2 Asymmetric Effects

Thus far we presented cross elasticity estimates assuming they are symmetric for both the UK and EU exporters. When we allow for asymmetries we find qualitatively similar results for the baseline export values and thus restricted them to be symmetric for exposition purposes. However, for quantitative purposes, we now present the asymmetric elasticities.

In Table 6, we find larger elasticities for EU export values to the UK, i.e. $\mathcal{E}_{EU}^{M} > \mathcal{E}_{UK}^{M}$. The structural interpretation of this asymmetry is that, conditional on a leave referendum outcome, the EU exporters placed a considerably higher probability on an MFN reversion than UK exporters. We estimate these effects across UK and EU export subsamples for convenience. A stacked regression obtains the same results due to the set of fixed effects. In columns 3-6 we find the same pattern for entry and exit.

Exports

The lower panel in Table 6 reports the quantification for Brexit uncertainty shocks. Panel A reports the standard deviation shock in *mbv*, which is -3.6 log points for EU exports (column 2) and about half for the UK (column 1). The counterfactual doubling of Brexit uncertainty inherits the same asymmetric patterns: a reduction in EU exports of 21 log points and about half that for the UK.

The large effects for the EU are not due to trade composition. As we noted in the data section, the bilateral trade shares of the UK with each EU country are very similar in our sample and the average MFN risk factor is roughly the same for each subsample.

[21] This partial equilibrium range of deterministic export changes due to tariffs is in line with magnitudes in calibrated general equilibrium models (e.g. Dhingra et al., 2017, predict a 35% reduction one year after hard Brexit).

Entry and Exit

There are also substantial asymmetries in export participation effects, as seen in columns 3-6 of Table 6. The exit elasticity for the EU is almost twice the UK's, a ratio similar to the export value estimates. The entry elasticities display an even stronger differential, with the EU export response being about three times larger than the UK's.

The resulting effect of a doubling of Brexit uncertainty via MFN risk is for an average reduction in entry of 2.3% for the UK and 10% for the EU. Exit increases by 1.6% for the UK and 2.8% for the EU. In sum, a doubling of Brexit probability would reduce net entry by 4% for UK exporters and 13% for EU exporters.

Summary and Implications

This strong asymmetry of Brexit uncertainty for UK and EU exports has interesting implications. One interpretation of $\mathcal{E}^M_{EU} > \mathcal{E}^M_{UK}$ is that the EU exporters believed there was a higher probability of an MFN scenario, $m_{ix}\eta^M_{ix}$, than their UK counterparts. Alternatively, their underlying beliefs about these probabilities can be the same but they may face different losses conditional on the MFN state. Our measure of MFN tail risk is identical for the EU and UK but if EU exporters expect uniformly higher risk than UK exporters then this would be reflected in higher estimates of $\mathcal{E}^M_{EU}/\mathcal{E}^M_{UK}$. One reason for this is that under the MFN scenario the UK would have to set new tariff schedule whereas the EU is more constrained due both to its large membership and negotiated MFN tariffs with other countries.[22]

6.1.3 Average uncertainty effects and third countries

We now examine how much of the uncertainty effect is attributable to the MFN risk component and whether it is offset (or exacerbated) by exports to third countries.

To estimate the average impact of mbv_t over all sources of risks we require additional data. The baseline estimates condition on importer and exporter by time effects—thus absorbing any aggregate country shocks including the average effect of mbv_t. Thus, to condition on the same fixed effects but now identify the average uncertainty impact, we extend the sample to include EU and UK exports to the rest of the OECD plus Brazil, Russia, India and China. This extended sample accounts for over 85% of EU and UK exports in 2015.

We consider two alternative measures of ex-ante risk the EU and UK may face in these third countries:

$$\bar{\omega}_{ixtV} - 1 = \left\{ \begin{array}{l} \bar{\omega}_{ixV} - 1 \\ m_t \eta_{ix} \left[(\tau_{ix})^{-\sigma} - 1 \right] \end{array} \right| \quad \text{if } i = row; x = \{EU, UK\}. \tag{22}$$

The top one assumes that the risk does not vary systematically with Brexit probabilities. The bottom alternative is more similar to (12): the exporters in x believe that after a policy change there is a probability $m_t\eta_{ix}$ they will face barriers $\tau^r_{ix} \geq 1$ higher than the current ones. The key difference relative to (12) is that we do not know what the exact risk an EU (or UK) exporter will face in the rest of the world under each Brexit scenario; therefore we use a uniform increase across products and scenarios, τ^r_{ix}. This is without loss of generality when considering only the average uncertainty effect across all s.[23]

[22] Another reason is that UK firms may expect relatively more relief in the form of lower taxes on profits or a depreciated currency.

[23] In section 6.3 we allow for an exception to this: countries with PTAs with the EU where the UK risks losing preferences.

The export estimates in Table 7 use this extended sample. In column 1 we include fixed effects (ixV, it, xt) and the *mbv* variable, which has a significant effect equal to $-.23$. This represents the differential average uncertainty for UK and EU exporters selling to each other relative to their sales to third countries. If the risk in third countries does not vary with Brexit probabilities, $\bar{\omega}_{ixtV} = \bar{\omega}_{ixV}$, then the magnitude of the coefficient in column 1 has the following structural interpretation: $\sum_{s=F,M,W} \mathcal{E}^s \times \left(\overline{1-(\tau^s)^{-\sigma}}\right) = 0.23$, i.e. the average uncertainty elasticity over all s scenarios. Note that this is just above the 0.22 estimate using only the MFN risk for the EU-UK sample.[24]

In columns 2 and 3 we estimate the cross-elasticity $\mathcal{E}^M$ (OLS and IV). These are identical to the ones we obtain in the baseline Table 2. Importantly, conditional on that EU-UK MFN risk, the average uncertainty effect decreases considerably. It is close to zero and insignificant in the IV specification.

In sum, we draw two implications from Table 7. First, the MFN risk is the driving force through which uncertainty reduces exports in this setting. Second, the resulting export reduction between the EU and UK is not mitigated by higher exports to third countries.

6.1.4 Political Shocks

The uncertainty elasticities can be used to compute the impact of any reasonable log change in the contract price. Our description and headline numbers focus on a doubling of that price and associated growth in the Brexit probability it models. Here we address two questions: is that a reasonable magnitude and what types of political shocks are commensurate with it.

Pre-referendum increases in *mbv* include one instance where it doubled (from before the bill was passed to after the referendum date was set) but this increase was not persistent, until the referendum vote. After the referendum outcome is realized the contract price was one, which more than doubled its daily average of 0.28. Thus the doubling counterfactual is a conservative estimate of the impact of the referendum vote.

In Table 8 we provided direct evidence that changes in shares of exit and undecided voters interacted with MFN risk reduced exports.[25] We interpret the result as a reduced form estimate of how political shocks can have uncertainty effects. In Table A2 we provide direct evidence at the daily level of how the contract price depends on measures of voter intentions and other political events. The shares of exit and undecided voters have a positive effect, which becomes stronger after the referendum bill is passed. This model predicts that the daily MBV average doubles if, after the bill is passed, the exit share increases by about 10 percentage points. Is this type of swing in the exit share plausible? In the pre-referendum period the exit share ranges from 0.38 to 0.48. Moreover, the mean exit share was 0.40 and the actual vote was 0.52 so it is clear that this magnitude of voter sentiment change did occur.

Our estimates also suggest that post-referendum events that increase exporter beliefs of Brexit may continue to dampen their exports. These events include the triggering of article 50 to start formal Brexit negotiations in March of 2017. Changes in Brexit prediction market prices post-referendum could be applied to more recent trade data as it becomes available to test how well the pre-referendum relationship we estimate holds.

[24] The interpretation under Brexit-varying risk in third countries is $\sum_{s=F,M,W} \mathcal{E}^s \times \left(\overline{1-(\tau^s)^{-\sigma}}\right) - \mathcal{E}^{\text{row}} \times \left(\overline{1-(\tau^{\text{row}})^{-\sigma}}\right)$, where $\mathcal{E}^{\text{row}}$ is defined similarly to $\mathcal{E}^s$ but reflects the beliefs of increased protection in third countries, η_{row}.

[25] In order to achieve the same export outcome as a doubling of contract prices, the results in Table 8 show we require about a 9 percentage point increase in the exit plus undecided share.

6.2 Robustness

We provide additional evidence on our prediction market measure of the probability of Brexit and examine some alternative measures in a regression context. We also provide a number of robustness checks against our structural assumptions on trade policy risk measures and other potential threats to identification.

6.2.1 Uncertainty Measurement

In the baseline estimation, we use a simple average of the (ln) daily contract prices. In this section, we examine robustness to alternative measures.

There is heavier trading volume in contracts for specific days, which may represent an update in information after a significant event. Thus we weight (ln) daily prices by the square root of the daily number of trades. We use this weighted measure in OLS estimates and report the results in column 2 of Table 8. These results are similar to the baseline (replicated in column 1 of Table 8 for comparison).

Shocks to polls measuring Brexit voting intentions can also affect exporter beliefs. The share of respondents stating they are undecided or will vote for Brexit varies considerably over time. Interestingly, the sum of exit and undecided voters never falls below 52%. This series co-moved closely with the contract price, particularly once the date of the referendum was set. Using this polling average to replace the *mbv* in the baseline specification we find similar qualitative results (column 3 of Table 8). The magnitude of the coefficient differs since the variables are not normalized to have similar moments.

We perform the same robustness exercises for the export entry and exit regressions in Appendix Table A6. Using contract weighted averages or polling data directly does not change our main entry and exit results.

Using the prediction market contract price to measure beliefs remains more attractive empirically. First, it is available starting from an earlier date. The average polling series starts only in September 2015. We have to impute the previous two months using the September value to match the time frame of the baseline. Second, polls can have non-linear effects on exporter beliefs since a 5 percent change can have a large effect if polls are around 50% and no effect when far from that value. We see this effect clearly in the fractional response margins in Figure A1. In contrast, a change in the probability measured through the contract price has a clear structural interpretation that we use to compute the counterfactuals. Third, as we show in the daily regressions in Appendix Table A2, the contract price does respond to observable polling data, so it reflects a key piece of information, but it can also reflect other economic and political information that firms use to form their beliefs that may not be fully reflected in polls.

6.2.2 Trade Policy Risk Measurement

For the baseline estimation trade policy tail risk measure, we use a common value for the elasticity of substitution, $\sigma = 4$. We test robustness to this choice in Table 9. In columns 1-4 we show that the results are robust to using $\sigma = 2$ or 3. In columns 5 and 6 we confirm they are robust to keeping only the HS6 industries with $\sigma \in [2, 6]$ based on estimates of σ from Broda and Weinstein (2006). In columns 7 and 8 we avoid using any model specific functional form for risk or imposing a value of σ by approximating U with respect to $\ln \tau_V^M$ directly. We verify the negative and significant MFN risk effect from the baseline. The magnitude of the tariff coefficient is larger since it reflects the effect of σ but the overall impact of a one standard deviation change in the probability measure on exports is similar.

In Appendix Table A7 we find that the baseline export entry and exit results are also robust to these issues.

6.2.3 Specification and Identification

We check several alternative specifications and sub-samples.

Alternative Distributed Lag: The baseline uses the current monthly value plus two lags and we report the sum of those coefficients. In Table A4 we show that the result is not sensitive to dropping the second lag, which is often small and insignificant (column 2) or to adding a third lag (column 4). When only the current value is used the cross elasticity is about half. This suggests there is up to two months between export investments and shipments and/or there is a delayed exit response to bad news (as predicted with sunk costs).

Other Time-varying Export Shocks and Beliefs: Under our baseline identifying assumptions, the history coefficients are approximated around an average importer level. This implies those history effects are log separable in (9) into *it* and *xt* effects and are thus controlled for. Since the UK and EU are the only trading partners in our baseline sample, the *it* and *xt* effects are equivalent to *ixt* effects and thus control for *all* unobserved aggregate bilateral shocks that are common across industries (e.g. exchange rates, FDI, migration, corporate taxes, etc.). Exporters may have believed that governments would intervene to counteract ex-post uncertainty in the hardest hit sectors. We can control for unobserved sector shocks, which also relaxes assumption 3. We do so in Table 10 and find that uncertainty elasticities of the export value and participation are larger.[26]

6.3 External Validity: Brexit beyond the EU

Under a hard Brexit any trade preferences the UK grants to and receives from non-EU countries could also revert to MFN tariffs. We examine this risk for Turkey, Mexico, and South Korea—the three largest non-European economies (by GDP) that the EU had a PTA with in our sample period. All three apply negligible tariffs on most of the goods imported from the EU and vice versa. The long-standing agreements with Turkey and Mexico have withstood the pressure of large shocks and potential trade wars, such as the great trade collapse. Moreover, Turkey has a customs union with the EU since 1995, which would require it to apply the EU tariff to UK products in the case of a hard Brexit.

The specification in Table 11 is identical to Table 2, but it uses these three PTA countries instead of the EU-27. We construct risk measures for each country. The estimates in Table 11 are qualitatively and quantitatively similar to those in Table 2. The quantification of uncertainty shocks for the PTA sample shows they are also similar to the EU-27 baseline. The common factor between the EU-27 and those PTA countries is that their trade policy with the UK is exposed to similar uncertainty shocks, which provides further evidence for the mechanism in our model.[27]

Given the large number and types of trade agreements the EU has, a thorough examination of this question requires a separate paper but the evidence thus far indicates that Brexit uncertainty impacts extend beyond

[26] We define sectors using the standard 21 sections that group related HS-6 digit codes.

[27] In Appendix Table A7 we show that similar results hold for the entry and exit regressions, but they are less precise than for the larger EU sample.

the UK-EU.

7 Conclusion

Trade disagreements and renegotiation have halted and possibly reversed the most recent era of global trade integration. Brexit could result in the UK and EU increasing tariffs on a wide scale for the first time since 1973. Potential scenarios include a reintroduction of MFN tariffs or even higher levels in the case of sharp disagreements or an economic crisis.

While minor renegotiations on specific products are a normal part of the process of managed trade (Bagwell and Staiger, 1990), little is known about the impacts of sharp reversals when countries abandon agreements or threaten to do so. One of our contributions is to show that just the possibility of such large regime shifts can have large negative impacts on trade flows and trade participation. In short, substantial policy uncertainty over trade agreements that threatens their very existence may lead to disintegration.

We find that shocks to the probability of Brexit reduce trade flows and trade participation. The effects are largest where the reversion to MFN tariffs under WTO rather than PTA rules are highest. Brexit uncertainty has already induced a net exit of traded products and a reduction in UK-EU bilateral trade flows. These effects vary by country, industry characteristics and trade margins. We find larger negative effects of Brexit uncertainty on EU exports relative to UK exports, in industries with high sunk costs, and at the product entry margin.

Our methodology measures the responsiveness of trade to increases in the likelihood of Brexit. So we can model the counterfactual effect on trade flows of large political uncertainty shocks. Large, sustained shocks during the renegotiation period that increase the likelihood of a "hard Brexit" could have substantial effects in the interim. A doubling of that probability is predicted to lower exports by 10 to 20 log points and lower export participation by as much as 10 percent.

The effects of large policy reforms may be uncertain and difficult for firms to ascertain ex-ante (Pastor and Veronesi, 2013) but quite important as several investment decisions rely on worst case scenarios and tail risks (Kozlowski et al., 2017). Despite these difficulties, our research indicates that such uncertainty is important in shaping firm export decisions well in advance of any actual policy change, a finding that is relevant in this setting and more generally when evaluating ex-post impacts of actual changes.

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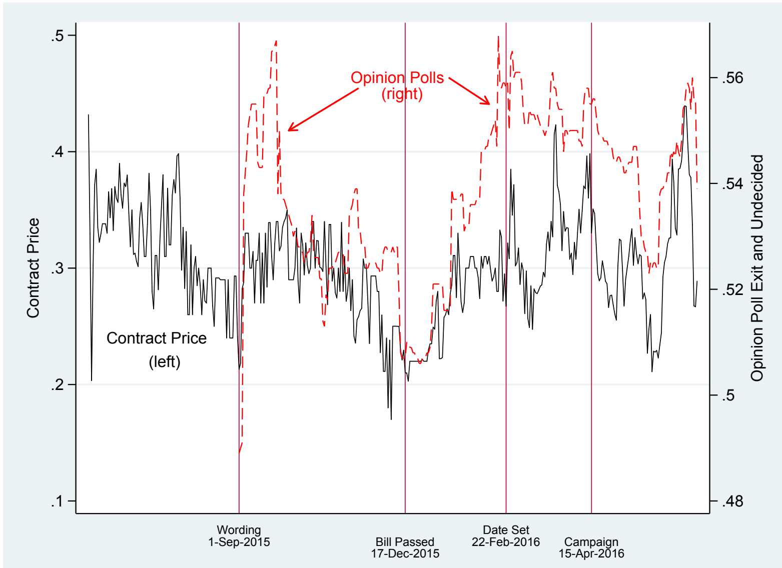
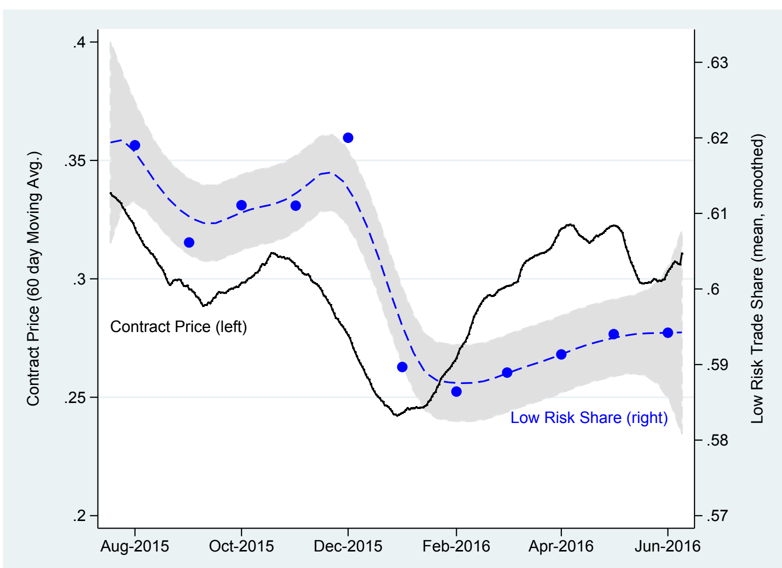
Figure 1: Brexit Average Daily Contract Price and Opinion Polling – 5/27/15 to 6/22/16



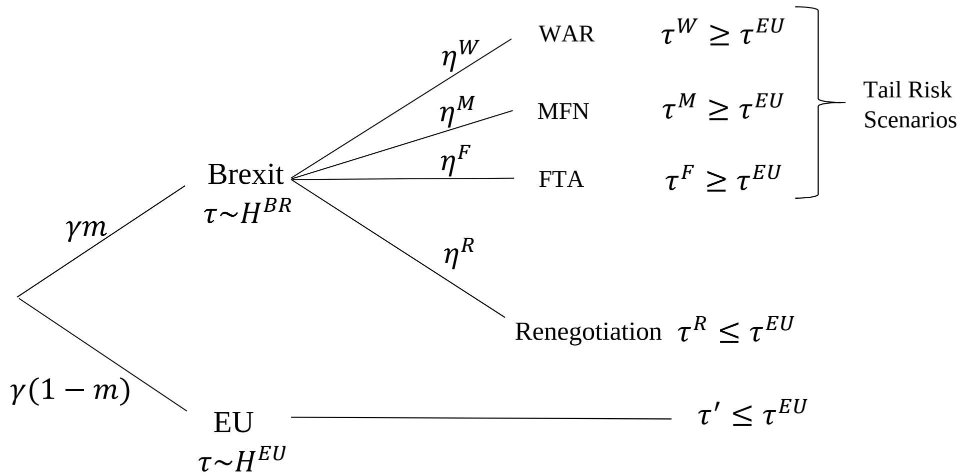
Notes: The solid black line is the daily average price of a contract on PredictIt.org that pays $1 if Britain votes to Leave the EU and zero otherwise. The dashed red line is share of respondents in opinion polls that say they will vote leave or "undecided". Major legislative and political events are denoted by the vertical red lines.

Figure 2: Brexit 60-day Moving Average Contract Price and Low MFN Risk Trade Shares – 8/15-6/16



Notes: The solid black line is the 60-day moving average of the price of a contract on PredictIt.org that pays $1 if Britain votes to Leave the EU and zero otherwise. The dashed blue line is a local, first degree polynomial through the monthly trade share of low MFN risk products in bilateral UK and EU exports with a shaded 95% confidence interval. Solid blue dots plot the average low MFN risk share for each month (centered on the 15th of the month).

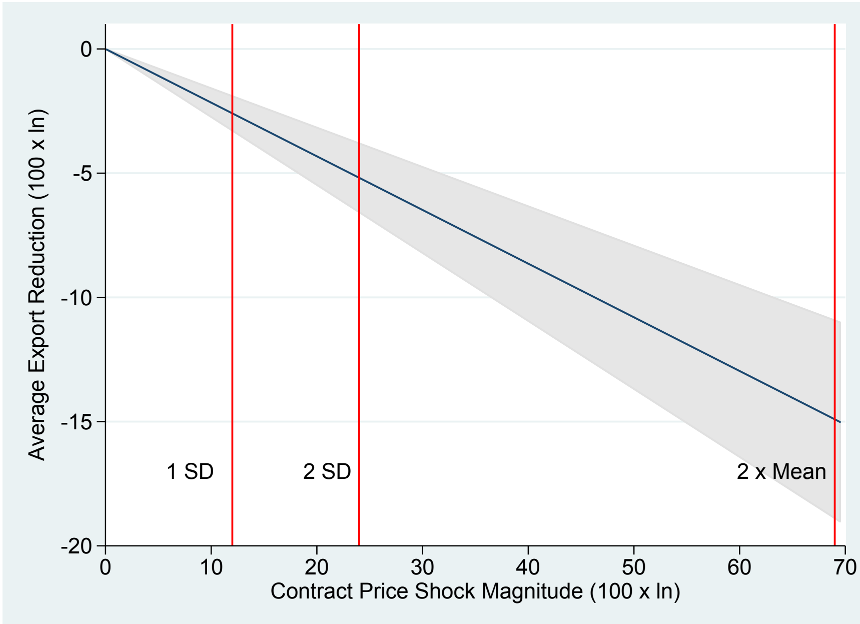
Figure 3: Event Space and Probability Tree for Brexit and EU Trade Policy Distributions



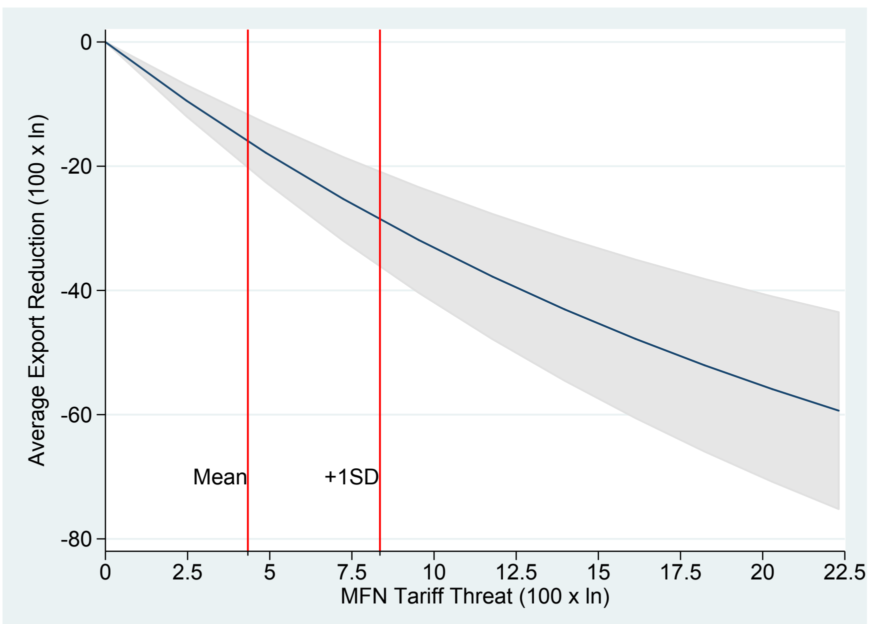
Notes: A shock arrives with probability γ and firms expect that a new trade policy factor τ is drawn from a distribution $\bar{H}$. We model $\bar{H}$ as a mixture over a Brexit distribution H^{BR} with probability weight m and an EU distribution H^{EU} with weight $1-m$. We assume that H^{EU} SSD H^{BR} such that increases in m increase risk. We assume tariffs drawn from the EU distribution are no higher than τ^{EU}, which represents a credible commitment so that $\tau' \leq \tau^{EU}$. We discretize the trade policy outcomes from a Brexit distribution into scenarios with tariffs higher than τ^{EU} — Trade War, MFN, and FTA — and a Renegotiation scenario where tariffs could possibly be lower. The scenarios that are worse than the EU tariff generate tail risk that affect export investment and re-entry decisions as described in the text.

Figure 4: Average Export Response to Changes in Contract Price and MFN Risk

(a) Changes in Contract Price at Mean MFN Risk



(b) Changes in MFN Risk at Large Political Shock



Notes: Panel (a) uses the IV estimate of the cross-elasticity from Table 2 to compute the change in exports at the mean MFN risk factor over the range of a log change in the contract price ($100 \times \Delta mbv$) from 0 to 70. Panel (b) holds the change in the log contract price fixed at $\Delta mbv = ln(2)$, i.e. a large sustained political shock, and increases the MFN tariff. Grey shaded areas indicate 95% confidence intervals.

Table 1: Summary Statistics - Regression Samples
8/15-6/16

	Mean	SD	Median	Min	Max	N
Aggregate Bilateral Exports and Within EU Trade Shares: Continuously Traded Sample						
	Mean	SD	Median	Min	Max	N
UK import value (Bn. €)	7.95	2.33	13.92	0.04	65.01	27
EU import value (Bn. €)	5.03	1.22	7.51	0.13	30.78	27
Export Values: UK-EU Continuously Traded Sample						
	Mean	SD	Median	Min	Max	N
ln(exports)	10.29	2.62	10.45	0.00	20.60	637,263
ln Pr(Brexit)	-1.23	0.12	-1.19	-1.50	-0.98	637,263
Trans. Vol. Weighted	-1.21	0.15	-1.19	-1.48	-0.85	637,263
ln Poll Share (Exit+Und. %)	3.99	0.02	4.00	3.94	4.01	637,263
ln Tariff	0.04	0.04	0.03	0	0.56	637,263
MFN risk	0.15	0.13	0.12	0	0.89	637,263
MFN Risk IV	0.10	0.11	0.08	0	0.49	637,263
Trade War Risk	0.73	0.19	0.77	0.03	0.98	533,258
Trade War Risk IV	0.67	0.25	0.70	0.00	1.00	533,258
Extensive Margin: UK-EU Entry and Exit Samples						
	Mean	SD	Median	Min	Max	N
Entry sample: Conditional on Non-Traded Status (Exports=0) at t-12						
Entry (binary)	0.245	0.430	0.000	0	1	647,488
MFN risk	0.141	0.121	0.118	0	0.893	647,488
Trade War Risk	0.718	0.204	0.762	0.03	0.984	528,916
Exit sample: Conditional on Traded Status (Exports>0) at t-12						
Exit (binary)	0.141	0.348	0.000	0	1	977,177
MFN risk	0.148	0.124	0.118	0	0.893	977,177
Trade War Risk	0.731	0.192	0.767	0.029	0.984	813,349
UK-PTA subsample						
	Mean	SD	Median	Min	Max	N
ln(exports)	11.72	1.77	11.67	6.84	18.69	27,709
MFN risk	0.153	0.133	0.132	0	0.995	27,709

Notes: ln(exports) defined at the exporter-importer-HS6-month level for UK and EU (2015 membership). Entry sample is defined as exporter-importer-HS6 products not traded in the same month of the previous year, and exit sample is defined as exporter-importer-HS6 products traded in the same month of the previous year. Entry(t)=1 if Export(t)>0 and Export(t-12)=0 for the exporter-importer-HS6 observation in month t from 8/15-6/16. Exit(t)=1 if Export(t)=0 and Export(t-12)>0. Pr(Brexit) defined as the monthly average (ln) MBV, the leave referendum prediction market contract price. MFN risk defined as $1-(\tau^{MFN})^{-\sigma}$, where σ=4 and τ^{MFN}=1+MFN advalorem/100. Trade War risk constructed similarly using τ^{WAR} and the latter is constructed using estimated export supply elasticities at HS-6 (see text for full discussion). The number of observations relative to MFN risk is lower due to unavailability of elasticity estimates for certain country-HS6 (-10%) and removal of outlier elasticity estimates implying tariffs higher than 180% (another -6%).

Table 2: UK and EU MFN and Trade War Risk - Export Values

	Monthly Export Value (ln) 8/15-6/16			
	1	2	3	4
	OLS	IV	OLS	IV
Pr(Brexit)×MFN Risk	-0.793	-1.450	-0.900	-1.661
	(0.149)	(0.198)	(0.16)	(0.225)
Pr(Brexit)×Trade War Risk	-	-	0.169	-0.595
			(0.108)	(0.748)
Exporter-Importer-HS6 FE	Yes	Yes	Yes	Yes
Exporter-Month FE	Yes	Yes	Yes	Yes
Importer-Month FE	Yes	Yes	Yes	Yes
N	637,263	637,263	533,258	533,258
R2	0.875	n/a	0.875	n/a

Notes: Dependent variable ln(exports) defined at the exporter-importer-HS6-month level for UK and EU (2015 membership). All estimations include exporter-importer-HS6, exporter-month and importer-month fixed effects. Pr(Brexit) defined as the monthly average (log) MBV, and MFN risk defined as $1-(\tau^{MFN})^{-\sigma}$, where $\sigma=4$ and $\tau^{MFN}=1+\text{MFN advalorem}/100$. Trade War risk constructed similarly using non-cooperative trade war tariffs from estimated export supply elasticities at HS-6 (see text for full discussion). The number of observations relative to MFN risk in columns 3 and 4 is lower due to unavailability of elasticity estimates for certain country-HS6 (-10%) and removal of outlier elasticity estimates implying tariffs higher than 180% (another -6%). Columns 1 and 3 employ OLS. In columns 2, 4 we instrument the risk variables by their respective median HS6-specific risk across four large countries (Australia, Canada, Japan and US). Coefficients report the sum of current and two monthly lags. Robust standard errors clustered at the exporter-importer-HS6 level in parenthesis.

Table 3: UK and EU MFN Risk in High vs. Low Sunk Cost Industries

8/15-6/16

	Monthly Export Value (ln)			
	1	3	1	2
	OLS		IV	
Sunk Cost Sample:	High	Low	High	Low
Pr(Brexit)×MFN Risk	-0.929	0.203	-1.681	0.835
	(0.156)	(0.524)	(0.204)	(0.812)
N	559,889	57,915	559,889	57,915
R2	0.876	0.868	n/a	n/a

Notes: Dependent variable ln(exports) defined at the exporter-importer-HS6-month level for UK and EU (2015 membership). Pr(Brexit) defined as the monthly average (ln) MBV, and MFN risk defined as $1-(\tau^{MFN})^{-\sigma}$, where $\sigma=4$ and $\tau^{MFN}=1+\text{MFN advalorem}/100$. High sunk cost sample: HS4 codes with significant semi-annual persistence of exporter-HS8 codes over 2013-2016 where UK is the importer (details in appendix). We instrument the MFN risk by the median HS6-specific MFN risk across four large countries (Australia, Canada, Japan and US). Coefficients report the sum of current and two monthly lags. Robust standard errors clustered at the exporter-importer-HS6 level in parenthesis. All estimations include exporter-importer-HS6, exporter-month and importer-month fixed effects.

Table 4: UK and EU MFN Risk - Entry and Exit Probability

8/15-6/16

	Entry		*Exit*	
	1	2	3	4
	OLS	IV	OLS	IV
Pr(Brexit)×MFN Risk	-0.191	-0.606	0.107	0.204
	(0.055)	(0.09)	(0.029)	(0.038)
N	647,488	647,488	977,177	977,177
R2	0.406	n/a	0.586	n/a

Notes: Entry sample is defined as exporter-importer-HS6 products not traded in the same month of the previous year, and exit sample is defined as exporter-importer-HS6 products traded in the same month of the previous year. Dependent variable Entry(t)=1 if Export(t)>0 and Export(t-12)=0 for the exporter-importer-HS6 observation in month t from 8/15-6/16. Exit=1 if Export(t)=0 and Export(t-12)>0. Pr(Brexit) defined as the monthly average (log) MBV, and MFN risk defined as1-$(\tau^{MFN})^{-\sigma}$, where σ=4 and τ^{MFN}=1+MFN advalorem/100. Columns 1, 3 employ OLS. In columns 2, 4 we instrument the MFN risk by the median HS6-specific MFN risk across four large countries (Australia, Canada, Japan and US). Coefficients report the sum of current and two monthly lags. Robust standard errors clustered at the exporter-importer-HS6 level in parenthesis. All estimations include exporter-importer-HS6, exporter-month and importer-month fixed effects.

Table 5: Quantification Results

8/15-6/16

	1	2	3	4	5	6
	(ln) Exports		**Entry**	**Exit**	**Entry**	**Exit**
	OLS	IV	OLS	OLS	IV	IV
Uncertainty Elasticity at Mean MFN Risk						
	-0.118	-0.216	-0.027	0.016	-0.086	0.030
A. One SD shock to ln(MBV) at mean risk						
	-0.014	-0.026	-0.003	0.002	-0.010	0.004
B. Doubling ln(MBV) at mean risk						
	-0.082	-0.150	-0.019	0.011	-0.059	0.021

Notes: Calculations employ OLS and IV coefficients from Table 2 and 3, and summary statistics from Table 1. Columns 1-2: change in (ln) exports, columns 3-6: change in probability of entry/exit.

Table 6: Asymmetric UK and EU MFN risk

8/15-6/16

	Export Value (ln)		*Entry*		*Exit*	
	1	2	3	4	5	6
	IV		IV		IV	
Exporter:	UK	EU	UK	EU	UK	EU
Pr(Brexit)×MFN Risk	-1.051	-2.012	-0.239	-1.011	0.153	0.275
	(0.253)	(0.315)	(0.125)	(0.13)	(0.049)	(0.059)
N	369,589	267,674	373,946	273,542	584,559	392,618
Uncertainty Elasticity at Mean MFN Risk						
	-0.156	-0.300	-0.033	-0.145	0.022	0.041
A. One SD shock to ln(MBV) at mean risk						
	-0.019	-0.036	-0.004	-0.018	0.003	0.005
B. Doubling ln(MBV) at mean risk						
	-0.108	-0.208	-0.023	-0.100	0.016	0.028

Notes: IV regressions. Dependent variable ln(exports) defined at the exporter-importer-HS6-month level for UK and EU (2015 membership). Entry sample is defined as exporter-importer-HS6 products not traded in the same month of the previous year, and exit sample is defined as exporter-importer-HS6 products traded in the same month of the previous year. Entry(t)=1 if Export(t)>0 and Export(t-12)=0 for the exporter-importer-HS6 observation in month t from 8/15-6/16. Exit=1 if Export(t)=0 and Export(t-12)>0. Pr(Brexit) defined as the monthly average (ln) MBV, and MFN risk defined as $1-(\tau^{MFN})^{-\sigma}$, where $\sigma=4$ and $\tau^{MFN}=1+\text{MFN advalorem}/100$. We instrument the MFN risk by the median HS6-specific MFN risk across four large countries (Australia, Canada, Japan and US). In columns 1, 3 and 5 the sample is UK exports to EU, and in columns 2, 4 and 6 the sample is EU exports to UK. Coefficients report the sum of current and two monthly lags. Robust standard errors clustered at the exporter-importer-HS6 level in parenthesis. All estimations include exporter-importer-HS6, exporter-month and importer-month fixed effects. Statistics employed in quantitative calculations are from Tables A2 and A3.

Table 7: UK and EU MFN and Overall Risk

Monthly Export Value (ln) 8/15-6/16

	1	2	3
Sample (rel. to baseline):	+ Exports to OECD & BRICs		
	OLS	OLS	IV
Pr(Brexit)	-0.233	-0.114	0.000
	(0.049)	(0.054)	(0.058)
Pr(Brexit)×MFN Risk		-0.803	-1.569
		(0.148)	(0.199)
N	6,778,816	6,778,816	6,778,816
R2	0.872	0.872	n/a

Notes: Dependent variable ln(exports) defined at the exporter-importer-HS6-month level for UK and EU (2015 membership). All estimations include exporter-importer-HS6, exporter-month and importer-month fixed effects. Pr(Brexit) defined as the monthly average (ln) MBV, and MFN risk defined as $1-(\tau^{MFN})^{-\sigma}$, where $\sigma=4$ and $\tau^{MFN}=1+\text{MFN advalorem}/100$. UK is a binary indicator for UK exports and EU is a binary indicator for EU exports. The sample includes all exports of the UK and EU to the OECD and four large developing countries: Brazil, Russia, India and China (BRIC). Coefficients report the sum of current and two monthly lags. Robust standard errors clustered at the exporter-importer-HS6 level in parenthesis. All estimations include exporter-importer-HS6, exporter-month and importer-month fixed effects.

Table 8: UK and EU Alternative Brexit Measures

Monthly Export Value (ln) 8/15-6/16

	1	2	3
	Prediction Probability		
	Unweighted Average	Contract Weighted Average	Polls
Pr(Brexit)×MFN Risk	-0.793	-0.707	-3.55
	(0.149)	(0.142)	(0.675)
N	637,263	637,263	637,263
R2	0.875	0.875	0.875

Notes: OLS regressions. Dependent variable ln(exports) defined at the exporter-importer-HS6-month level. Pr(Brexit) defined as the monthly average (ln) MBV, and MFN risk defined as $1-(\tau^{MFN})^{-\sigma}$, where σ=4 and τ^{MFN}=1+MFN advalorem/100. Column 1 uses the baseline unweighted monthly average of daily Pr(brexit), column 2 weights the daily probabilities with the squared root of the volume of daily transactions. Column 3 defines Pr(Brexit) as the average (ln) share of exit plus undecided voters. The poll data for July and August 2015 is imputed to be the same as in September due to lack of data. Coefficients report the sum of current and two monthly lags. Robust standard errors clustered at the exporter-importer-HS6 level in parenthesis. All estimations include exporter-importer-HS6, exporter-month and importer-month fixed effects.

Table 9: UK and EU Alternative MFN Risk Measures

Monthly Export Value (ln) 8/15-6/16

	1	2	3	4	5	6	7	8
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Parametric Assumptions:	σ=2		σ=3		industries with σ ϵ [2, 6]		(ln) MFN tariff threat	
Pr(Brexit)×MFN Risk	-1.425	-2.670	-1.003	-1.857	-1.000	-1.610	-2.517	-4.873
	(0.264)	(0.353)	(0.187)	(0.249)	(0.185)	(0.235)	(0.461)	(0.626)
N	637,263	637,263	637,263	637,263	368,984	368,984	637,263	637,263
R2	0.875	n/a	0.875	n/a	0.876	n/a	0.875	n/a

Notes: Dependent variable ln(exports) defined at the exporter-importer-HS6-month level. All estimations include exporter-importer-HS6, exporter-month and importer-month fixed effects. Pr(Brexit) defined as the monthly average (ln) MBV, and MFN risk defined as $1-(\tau^{MFN})^{-\sigma}$, where σ=4 and τ^{MFN}=1+MFN advalorem/100. Columns 5-6 exclude industries with sigmas higher than 6 and lower than 2 based on estimations using US import data in Broda and Weinstein (2006). Column 7-8 uses (ln) τ^{MFN} as the MFN risk measure. Coefficients report the sum of current and two monthly lags. Robust standard errors clustered at the exporter-importer-HS6 level in parenthesis.

Table 10: UK and EU MFN risk and Sector Trends

8/15-6/16

	Export Value (ln)		*Entry*		*Exit*	
	1	2	3	4	5	6
	OLS	IV	OLS	IV	OLS	IV
Pr(Brexit)×MFN Risk	-1.081	-2.161	-0.278	-0.728	0.098	0.303
	(0.226)	(0.423)	(0.074)	(0.152)	(0.044)	(0.08)
N	637,263	637,263	647,488	647,488	977,177	977,177
R2	0.875	n/a	0.406	n/a	0.586	n/a

Notes: Dependent variable ln(exports) defined at the exporter-importer-HS6-month level for UK and EU (2015 membership). Entry sample is defined as exporter-importer-HS6 products not traded in the same month of the previous year, and exit sample is defined as exporter-importer-HS6 products traded in the same month of the previous year. Entry(t)=1 if Export(t)>0 and Export(t-12)=0 for the exporter-importer-HS6 observation in month t from 8/15-6/16. Exit(t)=1 if Export(t)=0 and Export(t-12)>0. Pr(Brexit) defined as the monthly average (log) MBV, and MFN risk defined as $1-(\tau^{MFN})^{-\sigma}$, where σ=4 and τ^{MFN} =1+MFN advalorem/100. Columns 1, 3 and 5 employ OLS. In columns 2, 4 and 6 we instrument the MFN risk by the median HS6-specific MFN risk across four large countries (Australia, Canada, Japan and US). Coefficients report the sum of the included lags. Robust standard errors clustered at the exporter-importer-HS6 level in parenthesis. All estimations include exporter-importer-HS6, exporter-month, importer-month and section-month fixed effects. We define sectors using the 21 sections of the HS that group related HS-6 digit codes.

Table 11: UK and Other PTAs MFN risk

Monthly Export Value (ln) 8/15-6/16

	1	2
	OLS	IV
Pr(Brexit)×MFN Risk	-0.932	-1.937
	(0.629)	(0.869)
N	27,709	27,709
R2	0.796	n/a
Uncertainty Elasticity at Mean MFN Risk		
	-0.143	-0.297
A. One SD shock to ln(MBV) at mean risk		
	-0.017	-0.036
B. Doubling ln(MBV) at mean risk		
	-0.099	-0.206

Notes: Dependent variable ln(exports) defined at the exporter-importer-HS6-month level for UK and the three largest PTA countries in terms of GDP (Turkey, Mexico and South Korea). All estimations include exporter-importer-HS6, exporter-month and importer-month fixed effects. Pr(Brexit) defined as the monthly average (ln) MBV, and MFN risk defined as $1-(\tau^{MFN})^{-\sigma}$, where σ=4 and τ^{MFN}=1+MFN advalorem/100. In columns 2 we instrument the MFN risk by the median HS6-specific MFN risk across four large countries (Australia, Canada, Japan and US). Coefficients report the sum of current and two monthly lags. Robust standard errors clustered at the exporter-importer-HS6 level in parenthesis.

A Appendix

A.1 Data Details and Sources

- Trade flows: Monthly exports and imports between EU and OECD countries plus Brazil, Russia, India and China at the HS 8-digits level. Source: Eurostat.[28]
  - August 2015 to June 2016 at the HS 6-digits level used for value regressions.
  - August 2014 to June 2015 at the HS 6-digits level used for determining entry and exit same month the next year.
  - 2012 to 2016: Used to identify industries with sunk costs.
- Probability of Brexit: Daily price of a contract from May 27, 2015 to June 23, 2016 paying \$1 if "Leave" wins in the referendum. Monthly average of the log of the price used in regressions. Source: PredicitIt.org.
- Polls: Daily average of published opinion polls from September 1, 2015 to June 22, 2016. Monthly average of the log of the share of exit plus undecided voters used in regressions. Source: Number Cruncher Politics.
- MFN tariffs: One plus MFN ad-valorem tariffs of 2015 used to construct MFN risk measures. Source: TRAINS.
- Non-Cooperative (NC) tariffs: one plus NC ad-valorem tariffs of 2006 (last available) used to construct Trade War risk measures. Source: Nicita et al. (2018).

A.2 Value Functions

The following derivation is adapted from Carballo et al. (2018). The export investment decision is ixV specific for each firm so we omit these subscripts without loss of generality. The expected value of starting to export at time t conditional on observing current conditions a_t, the firm's own unit costs c, and the demand regime r, is:

$$\Pi_e(a_t, c, r) = \pi(a_t, c) + \beta[\underbrace{(1-\gamma)\Pi_e(a_t, c, r)}_{\text{No Shock}} + \underbrace{\gamma \mathbb{E}\Pi_e(a', c, r)}_{\text{Shock}}]. \tag{A.1}$$

This includes current operating profits upon entering and the discounted future value. Without a shock the firm value next period remains $\Pi_e(a_t, c, r)$. If a shock arrives then a new a' is drawn, so the third term is the ex-ante expected value of exporting following a shock, $\mathbb{E}\Pi_e(a', c, r) = \mathbb{E}\pi(a', c)/\,(1-\beta)$, where $\mathbb{E}$ denotes the expectation operator.

The expected value of waiting is

$$\Pi_w(c, r) = 0 + \beta \underbrace{\left(1 - \gamma + \gamma \bar{H}(a_t)\right) \Pi_w(c, r)}_{\text{Wait}} + \beta \underbrace{\gamma \left(1 - \bar{H}(a_t)\right) \left(\mathbb{E}\Pi_e\left(a' \geq \bar{a}, c, r\right) - K\right)}_{\text{Enter}}. \tag{A.2}$$

A non-exporter at t receives zero profits from that activity today. The continuation value remains at Π_w if either demand is unchanged, with probability $1-\gamma$, or changes to some level that is not sufficiently high to induce entry, with probability $\gamma\bar{H}(a_t)$. If demand changes and is above some endogenous trigger level, $a' \geq \bar{a}$, then we obtain the third term, reflecting the expected value of exporting net of the sunk cost,

[28] For intra-EU trade each member state imposes its own customs declaration thresholds for imports values to reduce respondent burdens. Imports (or exports) below the thresholds are estimated or obtained from invoices and VAT filings. In practice the statistical discrepancies are small. The extra-EU threshold is €1000 or 1000 kg. See the "Quality Report on International Trade Statistics", Eurostat (2010) at https://ec.europa.eu/eurostat/documents/3888793/5848021/KS-RA-10-026-EN.PDF

K, conditional on the new demand being high enough to trigger entry. The conditional expected value of exporting if $a' \geq \bar{a}$ is given by

$$\mathbb{E}\Pi_e \left(a' \geq \bar{a}, c, r\right) = \mathbb{E}\pi \left(a' \geq \bar{a}, c, r\right) + \beta(1-\gamma)\mathbb{E}\Pi_e \left(a' \geq \bar{a}, c, r\right) + \beta\gamma\mathbb{E}\Pi_e(a', c, r). \tag{A.3}$$

A firm with costs c_v is indifferent between entering or waiting if demand is at a threshold level $a_{c_v} = \bar{a}\left(c_v\right)$. Instead, of solving for $\bar{a}\left(c_v\right)$ we characterize the marginal exporting firm at any current demand, which is characterized by a cost parameter c_t^U defined by $a_t = \bar{a}\left(c_t^U\right)$.[29] If a firm has costs equal to this threshold, then in that period all other firms in that industry with lower costs also export to that particular destination.

We obtain an expression for this cutoff by using the entry condition in (2); the value functions in (A.1), (A.2) and (A.3), and the expression for $\mathbb{E}\Pi_e(a', c, r)$.

A.3 Uncertainty Factor Derivation

To obtain (16) we start with (15) and take a second order approximation wrt $\mathbf{u} = \left(\omega^{BR}, \ln m\right)$ and around $\mathbf{u}_0 = (1, \ln m_0)$. We treat the observed policy risk measures as the true beliefs. The general form of the approximation is

$$\ln U\left(\mathbf{u}\right) = \ln U\left(\mathbf{u}_0\right) + \left(\mathbf{u} - \mathbf{u}_0\right) \cdot \bigtriangledown \ln U\left(\mathbf{u}_0\right) + \frac{1}{2}\left(\mathbf{u} - \mathbf{u}_0\right)^T \left(\mathbf{H} \ln U\left(\mathbf{u}_0\right)\right)\left(\mathbf{u} - \mathbf{u}_0\right) + r,$$

where $\bigtriangledown$ is the gradient function and $\mathbf{H} \ln U\left(\mathbf{u}_0\right)$ is the hessian matrix and r the approximation error. We evaluate around no tail policy risk, which implies that the following terms are zero: $\ln U\left(\mathbf{u}_0\right)$, the first and second derivatives wrt $\ln m$. The tail risk derivatives and cross effects evaluated at $\mathbf{u}_0$ are

$$\begin{aligned}
(\sigma - 1)\frac{\partial \ln U}{\partial \omega^{BR}}|_{\mathbf{u}_0} &= \frac{\partial \ln\left(1 + \tilde{\beta} m\left(\omega - 1\right)\right)}{\partial \omega^{BR}}|_{\mathbf{u}_0} = \tilde{\beta} m_0 \\
(\sigma - 1)\frac{\partial^2 \ln U}{\partial\left(\omega^{BR}\right)^2}|_{\mathbf{u}_0} &= \frac{\partial^2 \ln\left(1 + \tilde{\beta} m\left(\omega - 1\right)\right)}{\partial\left(\omega^{BR}\right)^2}|_{\mathbf{u}_0} = -\left(\tilde{\beta} m_0\right)^2 \\
(\sigma - 1)\frac{\partial^2 \ln U}{\partial \ln m \partial \omega}|_{\mathbf{u}_0} &= \frac{\partial^2 \ln\left(1 + \tilde{\beta} m\left(\omega - 1\right)\right)}{\partial \ln m \partial \omega^{BR}}|_{\mathbf{u}_0} = \tilde{\beta} m_0
\end{aligned}$$

$$\ln U\left(\mathbf{u}\right) = \frac{\tilde{\beta} m_0}{\sigma - 1}\left(\omega^{BR} - 1\right)\left[1 - \tilde{\beta} m_0 \frac{\left(\omega^{BR} - 1\right)}{2} + \ln\frac{m}{m_0}\right] + r \tag{A.4}$$

where the first two terms in [] represent the first and second order effects of $\partial\omega^{BR}$ and the third represents the cross effect.

Re-introducing the subscripts in (A.4) that indicate the level of variation and replacing $\ln\frac{m_t}{m_0} = \widehat{\Pr\left(\mathcal{R}_\mathcal{T}|\mathcal{I}_t\right)}$

[29] We can do so since a is common to all firms exporting to a given market in a given industry and the marginal cost is the only source of heterogeneity among such firms. Assuming a continuum of firms in any given industry with productivity that can be ranked according to a strictly increasing CDF, we can find the marginal export entrant for any a_t.

from (13) and use (14) to map to the estimation we have

$$
\begin{aligned}
\ln U_{ixVt} &= \frac{\tilde{\beta}_i m_{ix0}}{\sigma-1}\left(\omega_{ixV}^{BR}-1\right)\left[1-\tilde{\beta}_i m_{ix0}\frac{\left(\omega_{ixV}^{BR}-1\right)}{2}+\sum_l r_l^m \hat{m}_{t-l}+e_t^r\right]+r_{ixVt} \\
&= \frac{\tilde{\beta}_i m_{ix0}}{\sigma-1}\left(\omega_{ixV}^{BR}-1\right)\left[\sum_l r_l^m\left(mbv_{t-l}-mbv_0\right)+1-\tilde{\beta}_i m_{ix0}\frac{\left(\omega_{ixV}^{BR}-1\right)}{2}+e_t^r\right]+r_{ixVt} \\
&= \frac{\tilde{\beta}_i m_{ix0}}{\sigma-1}\left(\omega_{ixV}^{BR}-1\right)\sum_l r_l^m mbv_{t-l}+\alpha_{ixV}^U+e_{ixVt}^r \\
&= \frac{\tilde{\beta}_i m_{ix0}}{\sigma-1}\sum_{s=F,M,W}\eta_{ix}^s\left[\left(\tau_{ixV}^s\right)^{-\sigma}-1\right]\sum_l r_l^m mbv_{t-l}+\alpha_{ixV}^U+e_{ixVt}^r \\
&= \frac{\tilde{\beta}_i m_{ix0}}{\sigma-1}\sum_{s=M,W}\eta_{ix}^s\left[\left(\tau_{ixV}^s\right)^{-\sigma}-1\right]\sum_l r_l^m mbv_{t-l}+\alpha_{ixt}^F+\alpha_{ixV}^U+e_{ixVt}^r,
\end{aligned}
$$

where the third line uses α_{ixV}^U and e_{ixVt}^r defined below. The fourth replaces ω_{ixV}^{BR} using (11) over all $s = F, M, W$ and the last one separates out the bilateral-time effect from the FTA scenario and defines it as α_{ixt}^F, so we obtain (16) in the text.

$$
\begin{aligned}
\alpha_{ixt}^F &\equiv \frac{\tilde{\beta}_i m_{ix0}}{\sigma-1}\eta_{ix}^F\left[\left(\tau_{ix}^F\right)^{-\sigma}-1\right]\sum_l r_l^m mbv_{t-l} \\
\alpha_{ixV}^U &\equiv \frac{\tilde{\beta}_i m_{ix0}}{\sigma-1}\left(\omega_{ixV}^{BR}-1\right)\left[\left(1-\tilde{\beta}_i m_{ix0}\frac{\left(\omega_{ixV}^{BR}-1\right)}{2}\right)-mbv_0\sum_l r_l^m\right] \\
e_{ixVt}^r &\equiv r_{ixVt}+\frac{\tilde{\beta}_i m_{ix0}}{\sigma-1}\left(\omega_{ixV}^{BR}-1\right)e_t^r
\end{aligned}
$$

A.4 Export Estimation Equation Derivation

We obtain equation (17) by replacing the uncertainty factor in equation (9) with eq. (16). Below we show the steps to re-arrange and redefine the parameters to arrive at our estimating equation:

$$
\ln R_{ixVt} = \bar{b}_i^h k_c\left[-\frac{\tilde{\beta}_i m_{ix0}}{\sigma-1}\sum_{s=M,W}\eta_{ix}^s\sum_{l=0}^{L} r_l^m\left\{mbv_{t-l}\left[1-\left(\tau_{ixV}^s\right)^{-\sigma}\right]\right\}+\alpha_{ixt}^F+\alpha_{ixV}^U+e_{ixVt}^r\right]+\alpha_{ixV}+\alpha_{it}+o_{ixVt} \tag{A.5}
$$

$$
= \sum_{s=M,W}\sum_{l=0}^{L} W_{ix}^s(l)\left\{mbv_{t-l}\left[1-\left(\tau_{ixV}^s\right)^{-\sigma}\right]\right\}+\left(\bar{b}_i^h k_c\left(\alpha_{ixt}^F+\alpha_{ixV}^U\right)+\alpha_{ixV}\right)+\alpha_{it}+\left(\bar{b}_i^h k_c e_{ixVt}^r+o_{ixVt}\right) \tag{A.6}
$$

$$
= \sum_{s=M,W}\sum_{l=0}^{L} W_{ix}^s(l)\left\{mbv_{t-l}\left[1-\left(\tau_{ixV}^s\right)^{-\sigma}\right]\right\}+\alpha_{ixV,it,jt}+e_{ixVt} \tag{A.7}
$$

In the second line we rearrange terms and define $W_{ix}^s(l) \equiv -\bar{b}_i^h k_c \frac{\tilde{\beta}_i m_{ix0}}{\sigma-1}\eta_{ix}^s r_l^m$. In the third, we collect terms into groups of estimated coefficients, a set of terms absorbed by fixed effects $\alpha_{ixV,it,jt}$, and the error term, where the latter two are given by:

$$
\alpha_{ixV,it,jt} \equiv \left(\bar{b}_i^h k_c\left(\alpha_{ixt}^F+\alpha_{ixV}^U\right)+\alpha_{ixV}\right)+\alpha_{it}, \quad e_{ixVt} \equiv \bar{b}_i^h k_c e_{ixVt}^r+o_{ixVt}.
$$

A.5 Product Export Dynamics

Similar to the value estimation we illustrate the results based on starting at some stationary state at $t-12$ and then considering two alternative types of shock: a deterioration or improvement in business conditions.

We do not directly observe whether the unit cost of the most productive firm is below the cutoff, but we do observe whether a product is traded at each point in time. We use $\bar{r}_{ixVt}$ to denote the sales of the most productive firm in the cohort of firms in the cell xiV productivity distribution at a point in time. It need not identify the same firm across time periods due to churning in trade participation. We drop the xV subscripts to simplify notation and define a latent variable that is a function of the sales of the most productive firm and sales at the cutoff:

$$Z_{it} = \frac{\bar{r}_{it}}{r(c_{it}^U)} = \left(\frac{\bar{c}_{it}}{c_{it}^U}\right)^{1-\sigma}. \tag{A.8}$$

If $Z_{it} > 1$, then at least one firm will export and trade is observed. However, trade may be observed even if $Z_{it} \leq 1$ because a firm survived from a prior export spell T periods ago when conditions were better. If a firm survives with probability β^T, then it will continue to have positive export sales even if these sales are below what is implied by the cutoff, $r_{it}(c_v) < r(c_{it}^U)$. Alternatively, all firms from a previous period may be hit by the death shocks with probability $1-\beta^T$. In that case, exit will occur but it will be unobservable to the econometrician if re-entry occurs, i.e. $Z_{it} > 1$.

We model entry and exit of product trade separately by conditioning on lagged trade participation. First, we take the log of equation (A.8) so that $z_{it} = \ln(Z_{it}) = (\sigma-1)\ln\frac{c_{it}^U}{\bar{c}_{it}}$ is a latent variable that is a function of the cutoff condition and the minimum unit cost draw from the cohort $\ln\bar{c}_{it}$. Second, we let $\mathbf{1}_{it}^{Trade} = 1$ if trade is observed. That latter always occurs when $z_{it} > 0$. But we also observe trade if firms survive from a previous export spell, even if they are below the cutoff, or if all firms exit and at least one re-enters in the same period. So we must track lagged trade participation in period $t-12$ as well. Rather than include a lagged dependent variable as a regressor, we use it to condition the sample. This method is sometimes called a restricted transition model.

If we condition on a sample of products that were non-traded in $t-12$ then we can model the probability of entry as

$$\Pr(\mathbf{1}_{it}^{Trade} = 1 \mid \mathbf{1}_{it-12}^{Trade} = 0) = Probit\left[z_{it}\right] \tag{A.9}$$

where *Probit* is a standard unit normal distribution with index function z_{it}. We know in this case that no firm was exporting in the previous period, so we do not need to consider deterioration relative to previous conditions that include a legacy of surviving firms. We can then estimate parameters on observable determinants of z_{it} that relate to the cutoff level.

For exit, we condition on the sample of traded products in $t-12$. If the export capital of at least one firm survives until time t, then a product will continue to be traded regardless of business conditions. But there is another possibility that all legacy firms from a previous spell exogenously exit with probability $1-\beta^T$. Even in this case, we may still observe continuing export participation in the product-level data. If at least one firm is productive enough to *re-enter* after making a sunk investment, i.e. $z_{it} > 0$, then we won't observe exit. The latter could occur if business conditions have not deteriorated at all or if they have deteriorated but there is still some subset of firms that is below the cost cutoff.

An observable exit only occurs in the event of death to the export capital of all firms exporting a product. The probability of exit is therefore:

$$\Pr(\mathbf{1}_{it}^{Trade} = 0 \mid \mathbf{1}_{it-12}^{Trade} = 1) = Probit\left[-(1-\beta^T)z_{it}\right]. \tag{A.10}$$

The index function of the exit probability has the opposite sign from entry and it is re-scaled downward in magnitude by $(1-\beta^T)$. We ultimately include the same regressors on the RHS of the exit regression equations. So all coefficients should have the opposite sign of the entry equation (and the export value equation). The coefficients and marginal effects are adjusted downward relative to the entry coefficients to a degree that declines in the rate of survival β^T.

A.6 Measurement Error in Policy Risks

The trade policy tail risk factors may contain errors relative to the true exporter beliefs of the policy barriers that could prevail following Brexit. This is clear for the non-cooperative tariffs, which rely on inverse export supply elasticities. But it could also be the case for MFN tariffs. While the EU would mostly likely apply its extant MFN tariff schedule to UK imports if no deal is reached, the UK may negotiate new commitments with WTO that are different from the current EU levels.

We use a multiple indicators method to address the measurement error. If exporters did not expect the MFN scenario to be exactly the current EU common external tariff, then we measure their beliefs with error. Suppose τ_V^M is the true tariff level exporters believe would prevail in a hard Brexit, but we measure the EU tariff, $\tau_V^{M,EU}$. We can relate the measured and true risk factors by $(1-(\tau_V^{M,EU})^{-\sigma}) = (1-(\tau_V^M)^{-\sigma}) + e_V^{EU}$, where e_V^{EU} is classic measurement error.

To address this measurement error we compute the median MFN tariff $\tilde{\tau}_V^M$ of the U.S., Canada, Japan and Australia for each 6-digit HS industry code, assuming that $(1-(\tilde{\tau}_V^M)^{-\sigma}) = (1-(\tau_V^M)^{-\sigma}) + \tilde{e}_V$. While both measures are correlated with the true belief, we assume the measurement errors are uncorrelated, $\text{Cov}(e_V^{EU}, \tilde{e}_V) = 0$. We interact our alternative measure $(1-(\tilde{\tau}_V^M)^{-\sigma})$ with mbv_t. We then include these as instrumental variables for $(1-(\tau_V^M)^{-\sigma})$, their interactions, and their lags that could be measured with error. We use the same approach and exogenous set of countries to construct instruments for the non-cooperative tariffs.

In the main text we report the overall weak identification F-stats of the full set of instrument variables. These statistics are inflated by the fact that a product tariff appears multiple times for every time period and country-product trade flow. In Table A3 we report F-statistics and coefficients of the zero-th stage regression at the highest level of aggregation for our policy data: the HS 6 digit product level. The F-statistic on the MFN and non-cooperative tariff estimates are above the threshold to rule out weak instruments concerns. Moreover, the coefficients on the instruments are positive and significant, which is sensible given their construction. We also note that the predicted regressors do not require an adjustment to standard errors because the IV procedure already handles this issue. Further discussion of measurement error correction in panel data is found in Griliches and Hausman (1986).

A.7 Contract Price Determinants

In this section, we explore the determinants of the contract price used in the econometric analysis to capture the probability of Brexit. In order to do so, we exploit the daily variation of the contract price and polling data along key dates in the year leading up to the referendum.

In Table A2 we present the results of different specifications to explain the contract price. In column 1 the results shows that the average contract price over this period is 0.301 when we include only a constant in the regression. We interpret this value as the average probability of a trade policy event that could cause a profit loss for firms.

A naive approach to understanding the determinants of the contract price is exploring the marginal effect of the share of exit voters. We add this variable to the specification along with an indicator for the pre-wording period in which we do not have opinion polls data. The marginal effect of the share of exit voters on the contract price in column 2 is significant and statistically indistinguishable from 1. Moreover, the explanatory power of this model is 0.143. As expected, the share of exit voters is a relevant variable to explain the contract price.

The share of undecided voters remained relatively high over the pre-referendum period with an average value of 0.132. In fact, the sum of exit and undecided voters remained above 0.5 for most of the period. We add the share of undecided voters in column 3 and find that both the share of exit and undecided voters have a positive predictive power on the contract price.

In column 4 we interact the share of exit and undecided voters by an indicator for the period in which the Brexit bill gained Royal Assent (December 17, 2015) and became the European Union Referendum Act of 2015. Results show that the marginal effect of both the share of exit and undecided voters are significantly higher after that date. We interpret this as a key institutional step towards the actual possibility of a trade policy event.

In column 5, we estimate a fractional response model using a logit link function for the dependent variable and a binomial distribution following Papke and Wooldridge (1996). We plot the response relative to the exit share of voters on $[0, 1]$. In the range for which we estimate the model, the relationship is nearly linear. The average marginal effects in column 5 are nearly identical to the linear model for most regressors.

In Figure A2 we show that the actual monthly average of the contract price in logs and the predicted one based on opinion polls and the aforementioned political events are highly correlated. For this figure we estimate a more complete model in logs in which we include a second order polynomial of the share of exit and undecided voters, which allows coefficients to differ after the bill is passed. The simple monthly correlation of this predicted variable and the one from the more parsimonious model in Table A2, column 4, is higher than 0.95.

A.8 Sunk Cost Industries Estimation

Only industries with positive sunk costs to export are affected by trade policy uncertainty. To identify these industries, we follow Handley and Limão (2017). We estimate the persistence of export participation at the product level conditional on a set of controls. Significant correlation of lagged and current participation can be interpreted as evidence of sunk costs.

We use UK HS-8 product import data from 2012-2016 from the non-EU OECD exporters plus Brazil, Russia, India, and China. This country set minimizes the risk of endogeneity that may arise from EU countries over the period before the referendum. We define a variety $\tilde{V}$ as a HS-8 product observation and the corresponding HS-4 product code as a industry V. This yields 1,217 industries with an average of 7.7 varieties per industry and a standard deviation of 10.5. We use semester-level frequency data.

We estimate the following equation for the period ranging from the first semester of 2013 to the first semester 2016 for each V:

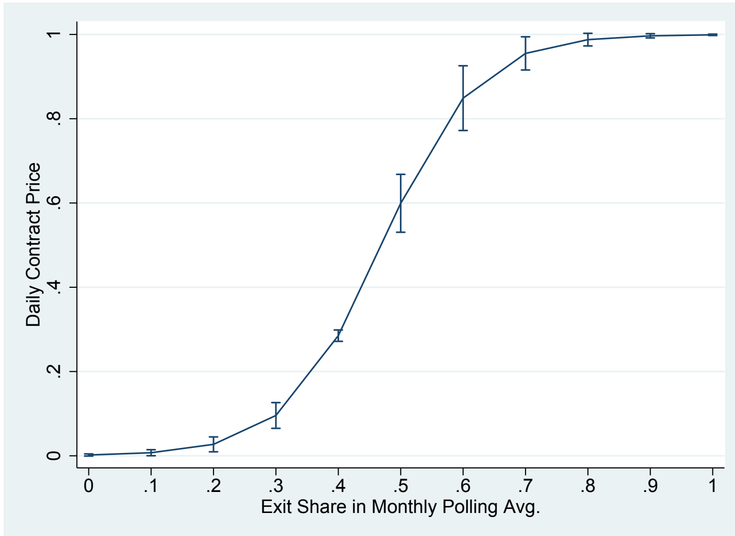
$$T_{\tilde{V}xt} = b_V^{sunk} \max\left\{T_{\tilde{V}xt-1}, T_{\tilde{V}xt-2}\right\} + b_{V,2012} T_{\tilde{V}x2012} + \alpha_{Vxt} + \alpha_{\tilde{V}} + \eta_{\tilde{V}xt}.$$

The dependent variable $T_{\tilde{V}xt}$ is an indicator taking the value of one if product $\tilde{V}$ is exported from country x at semester t to the UK. We control for initial conditions by $T_{\tilde{V}x2012}$, which is an indicator taking the value of one if product $\tilde{V}$ is exported by x at semester t to the UK in 2012. The terms α_{Vxt} and $\alpha_{\tilde{V}}$ are fixed effects capturing demand conditions, tariffs and transport costs, and industry conditions respectively. We interpret positive and significant estimates of b_V^{sunk} as evidence of sunk costs.

We estimate 1,032 of a possible 1,217 coefficients. We define as sunk cost (SC) industries those where the estimated coefficient has a t-statistic greater than 1.96. The t-statistic criterion provides a natural rank ordering of industries that is superior to using the estimated level of the persistence coefficient. In some cases, the estimated coefficients may be high, but they are imprecisely estimated. There are 809 industries we classify as high sunk cost (78%).

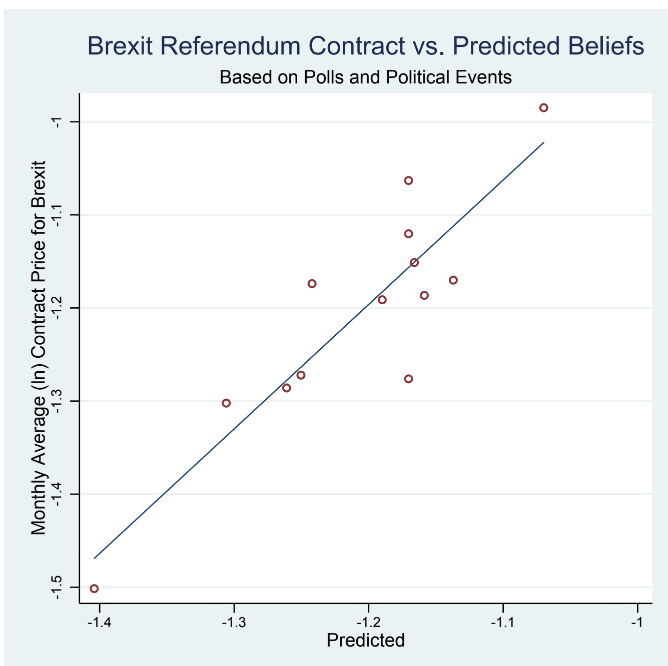
In Figure A3, we show the relation between the persistence coefficient and the t-statistic where the red line denotes a t-stat value of 1.96. It shows the same pattern as in Handley and Limão (2017) with all the significant coefficients between 0 and 1, as expected. The average significant persistence coefficient is 0.33 with a standard deviation of 0.11.

Figure A1: Estimated Response of Prediction Market Daily Contract Price Relative to Polling Share of Exit Voters



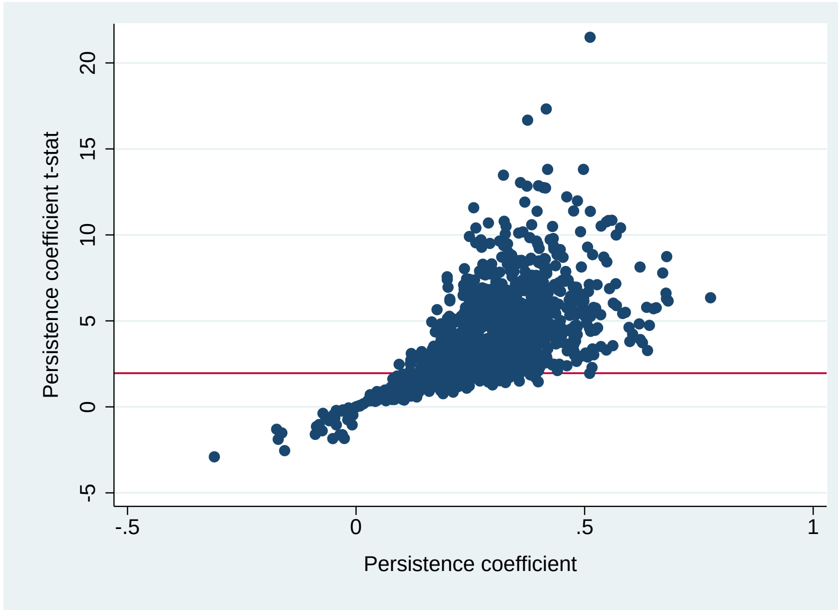
Notes: Fractional response model of contract price relative to polling share of exit voters, undecided, and interactions of indicators for referendum bill passage and wording. Full set of average marginal effects in Table A5, column 6.

Figure A2: Brexit Referendum Contract vs. Predicted Beliefs



Notes: Average monthly contract price is the same as the variable we used in our baseline sample. The average of predicted monthly contract is based on model a model in natural logs including a second order polynomial of the share of exit and undecided voters allowing coefficients to be different after the bill is passed.

Figure A3: Sunk Cost Estimates. t-statistics vs Persistence Coefficient.



Notes: t-statistics on persistence coefficient by HS-4 industry headings relative to estimated persistence coefficient. Red line is a t-statistic of 1.96.

Table A1: MFN Risk by Sector - UK and EU Trade

Sector	Exporter Shares (2015)	Mean	Median	SD
1 Animals	0.007	0.271	0.317	0.150
2 Vegetables	0.015	0.160	0.145	0.152
3 Fats & Oils	0.002	0.182	0.210	0.103
4 Prepared Foodstuffs	0.024	0.341	0.382	0.222
5 Minerals	0.072	0.014	0.000	0.028
6 Chemicals	0.164	0.160	0.193	0.078
7 Plastics, Rubber & Articles	0.053	0.164	0.217	0.079
8 Hides, Leather, & Articles	0.006	0.127	0.129	0.075
9 Wood, Straw & Articles	0.008	0.090	0.061	0.098
10 Pulp, Paper & Articles	0.023	0.000	0.000	0.000
11 Textiles & Articles	0.034	0.271	0.265	0.088
12 Footwear, Headgear, other	0.010	0.230	0.168	0.149
13 Stone, Plaster, Cement, other	0.010	0.127	0.112	0.098
14 Precious stones, Metals, Jewellery	0.017	0.029	0.000	0.051
15 Base Metals & Articles	0.053	0.073	0.065	0.077
16 Machinery; Elec. Equip.; Electronics	0.224	0.074	0.065	0.062
17 Vehicles, Aircraft, Vessels	0.218	0.154	0.135	0.116
18 Optical, Medical & other instruments	0.036	0.086	0.100	0.060
19 Arms and Ammunition	0.000	0.100	0.101	0.017
20 Miscellaneous Manufactures	0.022	0.097	0.101	0.058
21 Art and Antiques	0.001	0.000	0.000	0.000
Overall	1.000	0.145	0.123	0.125

Notes: EU-UK subsample. Exporter shares calculated for 2015. MFN risk defined as $1-(\tau^{MFN})^{-\sigma}$, where $\sigma=4$ and $\tau^{MFN}=1+\text{MFN advalorem}/100$. HS6 codes within each section included if present in the baseline sample of continuing country-product HS-6 varieties for 8/15-6/16.

Table A2: Market Based Variable Daily Determinants

Daily Contract Price 5/27/15 - 6/22/16

	1	2	3	4	5
Share of Exit Voters		0.922	2.063	1.06	1.102
		(0.159)	(0.181)	(0.395)	(0.418)
Share of Undecided Voters			1.59	1.032	1.057
			(0.136)	(0.199)	(0.203)
Bill Passed (BP)				-0.805	0.0160
				(0.188)	(0.00744)
BP×Exit Voters				1.634	1.672
				(0.439)	(0.460)
BP×Undecided Voters				1.008	1.070
				(0.247)	(0.254)
Pre-Wording		0.035	0.02	0.017	0.0169
		(0.005)	(0.005)	(0.006)	(0.00587)
Constant	0.301	-0.080	-0.752	-0.271	
	(0.002)	(0.064)	(0.083)	(0.166)	
N	393	393	393	393	393
R2	0.000	0.143	0.347	0.391	N/A

Notes: OLS regressions in columns 1-4. Average marginal effects of fractional response model in column 5 estimated by ML using logit link function and binomial distribution. Contract price is the daily average price defined between 0 and 1 of the Brexit shares in predicitit.com (pays 1$ if the Brexit option wins the referendum), share of exit and undecided voters is a daily average of different opinion polls constructed by Number Cruncher Politics (shares between 0 and 1), Bill Passed is an indicator that takes the value of one after the European Union Referendum Bill was given Royal Assent on 12/17/15, Pre-Wording is an indicator that takes the value of one before 9/1/15, when the final wording of the referendum question was established. Share of exit and undecided voters not available before 9/1/15 and imputed to 9/15 monthly average. Robust standard errors in parenthesis.

Table A3: MFN and Trade War Risk

	1 OLS MFN risk	2 OLS MFN risk	3 OLS Trade War risk
Median MFN risk	0.832	0.82	-0.050
	(0.015)	(0.016)	(0.034)
Median Trade War risk		0.007	0.114
		(0.007)	(0.014)
Constant	0.075	0.073	0.656
	(0.002)	(0.005)	(0.010)
N	4,128	3,390	3,390
R2	0.387	0.383	0.023
F-statistic	3192	1311	36.39

Notes: OLS regressions. Columns 1: MFN risk regressed on median HS6-specific MFN risk across four large countries (Australia, Canada, Japan and US). MFN risk defined as $1\text{-}(\tau^{MFN})^{-\sigma}$, where σ=4 and τ^{MFN} =1+MFN advalorem/100. Columns 2 and 3: MFN risk and Trade War risk regressed on median HS6-specific MFN risk and Trade War defined across the same four large countries. Only HS6 products traded between EU and UK over the baseline sample included. Column 1 corresponds to IV results in all tables other than and column 4 of Table 2. Robust standard errors in parenthesis.

Table A4: UK and EU MFN risk under Alternative Lags

Monthly Export Value (ln)

	1	2	3	4	5
	2 lags	1 lag	0 lags	2 lags	3 lags
	8/15-6/16	8/15-6/16	8/15-6/16	9/15-6/16	9/15-6/16
Pr(Brexit)×MFN Risk	-0.793	-0.866	-0.455	-1.382	-1.23
	(0.149)	(0.126)	(0.088)	(0.157)	(0.188)
N	637,263	637,263	637,263	579,330	579,330
R2	0.875	0.875	0.875	0.878	0.878

Notes: OLS regressions. Dependent variable ln(exports) defined at the exporter-importer-HS6-month level, Pr(Brexit) defined as the monthly average (ln) MBV, and MFN risk defined as $1-(\tau^{MFN})^{-\sigma}$, where $\sigma=4$ and τ^{MFN} =1+MFN advalorem/100. Column 1 replicates the baseline from Table 2 for comparison where coefficients report the sum of current and two monthly lags. Column 2 does not include the second lag and column 3 only includes the current lag. Column 5 adds an extra lag relative to the baseline and thus drops 8/15 observations. For comparison we use the same sample with the baseline 2 lag structure in column 4. Coefficients report the sum of the included lags. Robust standard errors clustered at the exporter-importer-HS6 level in parenthesis. All estimations include exporter-importer-HS6, exporter-month and importer-month fixed effects.

Table A5: UK and EU Alternative Brexit Measures and Entry/Exit

Annual Product Entry and Exit Indicators, 8/15-6/16 relative to 8/14-6/15

	Entry			*Exit*		
	1	2	3	4	5	6
	Prediction Probability			Prediction Probability		
	Unweighted Average	Contract Weighted Average	Polls	Unweighted Average	Contract Weighted Average	Polls
Pr(Brexit)×MFN Risk	-0.191	-0.186	-0.766	0.107	0.100	0.400
	(0.055)	(0.053)	(0.237)	(0.029)	(0.027)	(0.122)
N	647,488	647,488	647,488	977,177	977,177	977,177
R2	0.406	0.406	0.406	0.586	0.586	0.586

Notes: OLS regressions. Entry sample is defined as exporter-importer-HS6 products not traded in the same month of the previous year, and exit sample is defined as exporter-importer-HS6 products traded in the same month of the previous year. Dependent variable Entry(t)=1 if Export(t)>0 and Export(t-12)=0 for the exporter-importer-HS6 observation in month t from 8/15-6/16. Exit(t)=1 if Export(t)=0 and Export(t-12)>0 for the exporter-importer-HS6 observation in month t from 8/15-6/16. Pr(Brexit) defined as the monthly average (ln) MBV, and MFN risk defined as1-(τMFN)-σ, where σ=4 and τMFN=1+MFN advalorem/100. Columns 1 and 4 use the baseline unweighted monthly average of daily Pr(brexit), columns 2 and 5 weight the daily probabilities with the squared root of the volume of daily transactions. Columns 3 and 6 define Pr(Brexit) as the average (ln) share of exit voters plus (ln) undecided. The poll data for July and August 2015 is imputed to be the same as in September due to lack of data. Coefficients report the sum of the included lags. Robust standard errors clustered at the exporter-importer-HS6 level in parenthesis. All estimations include exporter-importer-HS6, exporter-month and importer-month fixed effects.

Table A6: UK and EU Alternative MFN Risk Measures and Entry/Exit

Annual Product Entry and Exit Indicators, 8/15-6/16 relative to 8/14-6/15

	Entry				*Exit*			
	1	2	3	4	5	6	7	8
	σ=2	σ=3	industries with σ ϵ [2, 6]	(ln) MFN tariff threat	σ=2	σ=3	industries with σ ϵ [2, 6]	(ln) MFN tariff threat
Pr(Brexit)×MFN Risk	-0.326	-0.236	-0.249	-0.525	0.194	0.136	0.0923	0.346
	(0.098)	(0.07)	(0.074)	(0.171)	(0.051)	(0.036)	(0.035)	(0.089)
N	647,488	647,488	344,915	647,488	977,177	977,177	555,850	977,177
R2	0.406	0.406	0.410	0.406	0.586	0.586	0.585	0.586

Notes: OLS regressions. Entry sample is defined as exporter-importer-HS6 products not traded in the same month of the previous year, and exit sample is defined as exporter-importer-HS6 products traded in the same month of the previous year. Dependent variable Entry(t)=1 if Export(t)>0 and Export(t-12)=0 for the exporter-importer-HS6 observation in month t from 8/15-6/16. Exit(t)=1 if Export(t)=0 and Export(t-12)>0 for the exporter-importer-HS6 observation in month t from 8/15-6/16. Pr(Brexit) defined as the monthly average (ln) MBV and MFN risk defined as$1-(\tau^{MFN})^{-\sigma}$, where σ=4 and τ^{MFN}=1+MFN advalorem/100. Columns 1 and 5 use sigma=2, columns 2 and 6 use sigma=3 and columns 3 and 7 exclude industries with sigmas higher than 6 and lower than 2 based on estimations using US import data in Broda and Weinstein (2006). Columns 4 and 8 use (ln) τ^{MFN} as the MFN risk measure. Coefficients report the sum of current and two monthly lags. Robust standard errors clustered at the exporter-importer-HS6 level in parenthesis. All estimations include exporter-importer-HS6, exporter-month and importer-month fixed effects.

Table A7: UK and Other PTAs MFN risk and Entry/Exit

Annual Product Entry and Exit Indicators, 8/15-6/16 relative to 8/14-6/15

	Entry		***Exit***	
	1	2	3	4
	OLS	IV	OLS	IV
Pr(Brexit)×MFN Risk	-0.182	-0.419	0.024	0.154
	(0.1)	(0.181)	(0.139)	(0.211)
N	99,480	99,480	67,634	67,634
R2	0.336	n/a	0.553	n/a

Notes: Entry sample is defined as exporter-importer-HS6 products not traded in the same month of the previous year, and exit sample is defined as exporter-importer-HS6 products traded in the same month of the previous year. Dependent variable Entry(t)=1 if Export(t)>0 and Export(t-12)=0 for the exporter-importer-HS6 observation in month t from 8/15-6/16. Exit(t)=1 if Export(t)=0 and Export(t-12)>0 for the exporter-importer-HS6 observation in month t from 8/15-6/16. Pr(Brexit) defined as the monthly average (ln) MBV and MFN risk defined as $1-(\tau^{MFN})^{-\sigma}$, where σ=4 and τ^{MFN}=1+MFN advalorem/100. Sample includes the UK and the three largest PTA countries in terms of GDP (Turkey, Mexico and South Korea). Columns 1 and 3 employ OLS. In columns 2, 4 we instrument the MFN risk by the median HS6-specific MFN risk across four large countries (Australia, Canada, Japan and US). Coefficients report the sum of current and two monthly lags. Robust standard errors clustered at the exporter-importer-HS6 level in parenthesis. All estimations include exporter-importer-HS6, exporter-month and importer-month fixed effects.