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. We estimate that at the average disagreement tariff of 4.5% the increase in the probability of Brexit after the referendum lowered EU-UK bilateral export values between 11-20%. Neither the EU or UK exporters 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 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 most favoured nation tariff rate (MFN) and another where they enter 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 trade war rates.

We find significant export uncertainty elasticities only for the MFN scenario, so exporters did not expect a trade war. The estimated UK-EU export elasticity with respect to Brexit uncertainty, which is obtained using pre-referendum data, is about -0.2 at the mean MFN risk. We use this elasticity to compute counterfactuals. A permanent increase in Brexit uncertainty of magnitude similar to the post-referendum year implies reductions of 11-20 log points for UK-EU trade value. The reduction in net entry of exported products is about 9.4 percentage points and driven largely by lower entry, which is consistent with sluggish exit adjustment under sunk costs.

We focus on the impacts of potential exit from agreements and show their effects 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 percent if no trade deal is reached.[2] Steinberg (2019) also finds reductions in trade and welfare using a calibrated, dynamic model. But in contrast to our empirical

[1] The US has left the Trans-Pacific Partnership, threatened to leave the World Trade Organization, 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 trade agreements outside the negotiation constraints of the EU. But the UK would lose access to markets where the EU already has preferential trade agreements that generated more trade, better quality, and access to new varieties (Berlingieri et al., 2018).

approach, the uncertainty measure in his simulations has a negligible impact on trade.

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. (2018a) 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 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 before they occur and even if they may never materialize. A "leave" referendum result increases the likelihood of a regime change, but its timing and policies were uncertain and remained so for years. In our approach, we combine monthly trade and prediction market data and find it reflects polling and political event information related to the referendum. 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, our estimation closely follows the theoretical model and finds several pieces of consistent evidence. Brexit uncertainty only affects industries with sunk export costs and has a stronger effect on entry than exit (since the latter works mainly through attrition). Moreover, the uncertainty elasticity is significant for the subsample of UK exports to the EU and vice-versa; the theory predicts stronger impacts on exporters facing higher MFN risk — consistent with what we find for the EU exporters that had to predict new tariffs and regulations in the UK.

Third, we provide a novel approach to identify the effects of uncertainty shocks applicable beyond Brexit uncertainty and trade. Our approach measures time variation in probabilities using prediction markets (as done by Wolfers and Zitzewitz, 2004; Snowberg et al. 2013) matched with observable product-specific, counterfactual trade policies. This approach can be used to examine the ex-ante effects of other policies where the potential outcomes are known, e.g. tax rates, regulations, etc. Otherwise, mapping policy uncertainty into economic outcomes often requires both heterogeneity in firm- or industry-specific risk exposure observed before and after the resolution of a political event at a discrete point in time. [4]

Next, we discuss some background and motivation for our approach. In section 3, we outline the theory used 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. In section 5 we estimate the effect of Brexit uncertainty on trade and provide evidence for the mechanisms we model. We perform robustness checks in section 6 and quantify the impacts in section 7.

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 background on the latent historical support of UK voters for leaving the EU. We then show how recent measures of such support relate to aggregate trade

[3]For example, Crowley et al. (2018b) show that anti-dumping actions against Chinese firms have spillover effects on trade and investment decisions by other firms. See also Greenland et al. (2019) and Shepotylo and Stuckatz (2018).

[4]Recent papers in this vein include Boutchkova et al. (2012) and Julio and Yook (2016). An alternative is to construct firm measures based on investor calls or regulatory filings as in Hassan et al. (2019) and Handley and Li (2018).

participation leading up to the referendum. We also discuss how business leaders expressed concern with the type of uncertainty the model focuses on.

UK voter support for leaving the EU has been high since its accession in 1973. It averaged 47% between 1977-2014 among those with an opinion, fluctuating from a high of 71% in 1980 to a low of 30% in 1991. The most recent upsurge occurred after the financial crisis in 2011, 54%, and it then receded by 2016.[5]

After the Euro crisis there was increased support for the eurosceptic UK Independence Party, which was a factor leading to the 2013 promise by Prime Minister Cameron to hold a referendum in the case of a Conservative Party general election victory. That victory occurred in May 2015 and was followed by the introduction of the EU Referendum Bill in that month. The bill passed in December 2015 and allowed the government to schedule a vote before 2017. In February 2016, the referendum was scheduled for June 23, 2016, which was when 52% of voters agreed for *'the UK to leave the European Union'.*

The referendum was hotly debated by policymakers, business leaders, and the public. Uncertainty rose as the referendum approached, e.g. 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 CFOs of German and Irish companies (Deloitte, 2016).[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]

There was substantial variation in leave sentiment reflected in polling and prediction markets leading up to the referendum. In Figure 1, we plot two time-series. First, the polling fraction of those supporting "Leave" among voters with an opinion. Second, the daily probability of a "Leave" outcome in the referendum based on prediction markets, which we describe in the data section. There are large swings in both measures, particularly around large events, such as the passage of the Bill and setting the referendum date.

Did this variation in the probability of Brexit affect trade? A simple inspection of the data does not yield an obvious answer because of confounding shocks reflected in the aggregate data. This is one important reason why we focus on using an interaction of time varying uncertainty with variation in risk across industries to estimate the elasticity of trade to Brexit uncertainty. We check for prima facie evidence that increased uncertainty shifts exports away from riskier products as follows. We divide UK and EU bilateral exports into high and low risk products, defined by those with a potential 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 backward moving average of the prediction market price shown in Figure 1. These two series co-move and have a simple correlation of 0.22. A regression of the low risk shares on the prediction market price moving average also indicates a significant positive relationship even after we control for bilateral fixed effects and a time trend.

The relationship in Figure 2 is suggestive but may also reflect unobserved shocks and fails to account for

[5]See www.ipsos.com/ipsos-mori/en-uk/european-union-membership-trends (accessed November 11, 2018).

[6]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.

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

other dynamic factors. We account for these and other factors in estimating trade outcomes in section 5. The model we present next guides the measurement, identification and quantification of alternative uncertainty shocks on trade outcomes.

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 analyse 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 with elasticity $\sigma > 1$ 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 policy component, the advalorem tax, $\tau_{it} \geq 1$, e.g. a tariff, and economic demand shifters, $D_{it} = \varepsilon Y_{it}\left(P_{it}\right)^{\sigma-1}$ where εY_{it} is the exogenous fraction of all country income spent on the differentiated goods and P_{it} the CES price aggregator. Assuming the mass of exporters is small relative to domestic production in i implies their entry decisions have a negligible impact on P_{it}.

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. This 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 $\tilde{\sigma} \equiv (1-\rho)\,\rho^{\sigma-1}$.[8]

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

3.2 Firm Export Entry and Technology

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

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

[8]We describe the main results in the context of policies that affect demand but they apply to other policies that affect profitability, e.g. product standards that increase costs and change after Brexit.

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

We solve (2) using the value functions in Appendix A.1 to obtain the cutoff to export to 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 cutoff if a_{it} remained unchanged and reflects the present discounted value of the export investment without uncertainty. The **uncertainty factor**, U_{it}, captures the increased stringency in the cutoff under uncertainty; it is lower than one if $\gamma_i > 0$, and 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 a_{it} falls and the expected proportion of profits lost in that event.

Thus a firm with costs below c_{it}^{U} exports to country i at t. A firm continues to export to a market as long its capital 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 sunk investments to lower its marginal export cost. Handley and Limão (2017) show this generates a cutoff rule with the same U_{it} as (3) applied to a deterministic cutoff corresponding to the technology decision. Therefore the industry export equation we estimate can reflect both intensive and extensive margin effects.[10]

3.3 Industry Exports

The monthly data for a large set of countries is only available at the industry level, so we aggregate firm behaviour up to that level. An industry V from a given exporter is defined by the firms $v \in V$, which draw their productivity from a distribution, $G_V(c)$, and face similar trade barriers in i. Thus the cutoff can vary across V via a_{itV} and tail risk. In **stationary periods**, all exporters have costs below the current export entry cutoff and their mass is given by the product of the endogenous fraction, $G_V\left(c_{itV}^{U}\right)$, and potential exporters, N_V. Thus bilateral industry exports are given by aggregating sales from all firms in a given exporter to i:

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

This expression applies if the cutoff exceeds the historical maximum such that $c_{itV}^{U} \geq \max_{T<t} c_{iTV}^{U}$, i.e. entry is currently easier than ever before. 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. In Appendix A.2 we derive the general export expression for this case, which

[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 $\delta = 0$.

[10] 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.

underlies our estimation.

4 Identification and Uncertainty Measurement

To identify the impacts of uncertainty we decompose the export equation 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 include x subscripts to denote the export country.

4.1 Identification

If there are any exports from x to i in V, then we can write exports 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 $\theta_{ixV} = \{a_{ixV}, c^D_{ixV}, N_{xV}, \bar{b}^h_i\}$. In a stationary period t this is simply

$$\ln \frac{R_{ixVt}}{R\left(\theta_{ixV}\right)} = \left(k_c \hat{c}^U_{ixVt} + \hat{a}_{ixVt} + \hat{N}_{xtV}\right) + o_{ixVt}, \tag{6}$$

where $k_c \equiv \frac{\partial \ln R(a,c)}{\partial \ln c} \geq 0$ is the export elasticity of the cutoff around the deterministic equilibrium.[11]

In Appendix A.2 we use the definitions of c^U and c^D from (3) to derive the generalized version of (6) when there are legacy exporters. We obtain the following estimating equation focusing on the uncertainty shocks:

$$\ln R_{ixVt} = \bar{b}^h_i k_c \hat{U}_{ixVt} + \boldsymbol{\alpha}_{ixV} + \boldsymbol{\alpha}_{it} + o_{ixVt}. \tag{7}$$

We moved the stationary export value to the right; it is absorbed in the $\boldsymbol{\alpha}_{ixV}$ fixed effects, which also control for selection. The structural interpretation of the coefficient on $\hat{U}_{ixVt}$ is useful for counterfactuals. It reflects the export elasticity k_c and a history coefficient, $\bar{b}^h_i$, that is $1 - \beta^T$ if conditions have worsened in i for T periods before t or equal to one otherwise. The following structural identification assumptions imply that $\boldsymbol{\alpha}_{ixV} + \boldsymbol{\alpha}_{it}$ (defined in Appendix A.2) control for any terms other than $\hat{U}_{ixVt}$.

A1: Common deep parameters across exporters, time, and varieties, including: (a) the elasticity of substitution, σ; (b) the probability of shocks in i, γ_i, and; (c) the export entry elasticity, 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. $\hat{U}_{ixt-TV} \approx \hat{U}_{ixV}$.

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 the shocks are restricted to be common

[11] 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.

across industries in the exporting country and thus captured by time effects or by importer-time effects, $\boldsymbol{\alpha}_{it}$, 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 $\boldsymbol{\alpha}_{it}$. A4 is required because prior to the announcement of the Brexit referendum there is no 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.[12]

We use industry data at the monthly level and thus require certain timing assumptions to map the theory to 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 export investment in country-industry iV until after the referendum. Second, we assume that not all firms in an ixV cell make investment decisions in the same month; otherwise we could not explore variation over the year within any such 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 two lags of $\hat{U}_{ixVt}$ to capture these dynamics.

4.2 Uncertainty Measurement

First, we describe how preferential trade disagreements can affect U by increasing the probability of riskier trade policies. Second, we model exporter beliefs about the probability of Brexit and how it relates 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 $a_{ixVt} = D_{it}\left(\tau_{ixVt}\right)^{-\sigma}$ by focusing on potential shocks to bilateral policy barriers but recognizing that other sources exist. If all uncertainty is policy-related then γ would capture the expected arrival rate of a (re)negotiation opportunity or a change in the government necessary for a policy change. More generally, γ captures the probability of any demand shock, so we keep it constant and focus on how U varies over time due to tail risk shocks.

How do trade agreements affect uncertainty? We follow CHL in modelling an agreement as a choice of an initial policy vector and a distribution, $\bar{H} = \Sigma_S m^S H^S$. This mixing distribution has probability weights m^S over S mutually exclusive uncertainty states, each with a fixed distribution, H^S. The EU aims to integrate the product markets of its members, which requires a credible and permanent reduction of trade barriers such that uncertainty is low. CHL provide conditions where governments that are export risk averse prefer higher weights on distributions that are less risky in a second-order stochastic dominance (SSD) sense.

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

[12] The results focus on bilateral trade between the UK and the EU. For UK-EU bilateral trade, A1(b) is reasonable. We initially consider common shocks γ and then allow for heterogeneous shocks. We relax A2 and A3 by allowing variation in the exporter x through bilateral shocks $\boldsymbol{\alpha}_{ixt}$ 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.

$$\bar{\omega}_{ixVt} = m_{ixt}\omega_{ixV}^{BR} + (1 - m_{ixt})\,\omega_{ixV}^{EU}. \tag{8}$$

We model increases in the likelihood of a trade disagreement such as Brexit as increases in m_{ixt}, which increases tail risk for exporting firms.

Three points are useful for the estimation and interpretation of results. First, the probability of staying in the EU is similar across industries. Second, increases in m increase tail risk if and only if H^{EU} SSD H^{BR}, so its impacts on exports are fully captured by its interaction with tail risk. Third, the underlying distributions, H^S, can differ across industries and partners but are assumed to be time invariant, which we discuss below.

4.2.2 Firm's Brexit Beliefs and Prediction Market Shocks

We model the time varying components of the Brexit probability and map them into observable measures of beliefs. We illustrate the potential scenarios exporters consider (omitting the time and country subscripts for clarity) in Figure 3.

With probability $\gamma(1-m)$ a 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.[13]

Brexit occurs with probability γm and a new policy is drawn from H^{BR}. 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} in equation (8) to Brexit measures from prediction markets.

The definition of Brexit is that 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}^{BR}. For exporters from x to i, with information set $\mathcal{I}_t$, the probability of Brexit after the referendum is:

$$\gamma_i m_{ixt} = \gamma_i p_{ix}^{BR} \Pr(\mathcal{R}_{\mathcal{T}} \mid \mathcal{I}_t). \tag{9}$$

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

We can approximate $\Pr(\mathcal{R}_{\mathcal{T}} \mid \mathcal{I}_t)$ 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, $\hat{B}_{t-l}$.

$$\Pr\widehat{(\mathcal{R}_{\mathcal{T}}|\mathcal{I}_t)} = \sum_{l=0,\ldots,L} r_l^B \hat{B}_{t-l} + e_t^r. \tag{10}$$

[13] 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.

The parameters r_l^B represent the elasticity of firm beliefs with respect to a change in a specific component B_{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 $\sum r_l^B$ represents the long-run elasticity of firm beliefs with respect to a permanent change in the information input.

Our baseline information input is the probability of a leave outcome in a referendum held by the end of 2016 from prediction markets. In data section 5.2 we discuss this and alternative inputs we consider.

4.2.3 Policy Risks

We now turn to measures of the industry variation in policy under the alternative scenarios in Figure 3.

We discretise the Brexit distribution into mutually exclusive scenarios indexed by $s = \{\text{M,W,F}\}$: (**M**)FN, Trade (**W**)ar, and (**F**)TA. 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.

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

Under (**R**)enegotiation barriers remain at EU levels or lower, $\bar{\tau}_{ixV}^R \leq \tau_{ix}^{EU}$. 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. Under a Brexit threat average barriers could be lower ex-ante (if $\bar{\tau}_{ixV}^R$ was sufficiently low relative to τ_{ix}^{EU}), but even in that case exports would be depressed by the higher risk until a renegotiation was actually implemented. Regardless of whether renegotiation was likely or not—and thus whether or not the ex-ante mean was higher—the model implies that the tail risk measure is a sufficient statistic to capture the impact of changes in the Brexit probability.[14]

By substituting (11) and $\omega_{ixV}^{EU} = 1$ into (8), the unconditional trade policy tail risk before the referendum is:

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

where the scenario probabilities η_{ix}^s are estimated coefficients. 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. In the FTA scenario the tariffs remain at zero and there is no product level tariff variation that we need to control for. We control for possible FTA changes in non-tariff barriers provided they are either (i) uniform across all products (e.g. costlier customs procedures), $\tau_{ixV}^F = \tau_{ix}^F \geq 1$, by using bilateral-time effects in the baseline; or (ii) uniform across products within sectors, using sector-time effects in section 6.

4.2.4 Uncertainty Factor

To estimate (7) we combine the probability shocks and policy risk from above to provide an empirical measure of the uncertainty factor. Using $\hat{U} \equiv \ln U$ (log change relative to the deterministic); applying the definition

[14] More broadly, renegotiation can represent 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.

of U in (3) and of $\bar{\omega}$ in (12) we obtain

$$\hat{U}_{ixVt} = \frac{1}{\sigma - 1} \ln \left(1 + \tilde{\beta}_i m_{ixt} \left(\omega^{BR}_{ixV} - 1\right)\right). \tag{13}$$

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 future conditions.

To explore the interaction between industry variation in risk and time variation in Brexit beliefs we derive a second order approximation to $\hat{U}_{ixVt}$ around both $\omega^{BR}_{ixV} = 1$ 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^{BR}_{ixV} and m_{ixt} yields

$$\hat{U}_{ixVt} = -\frac{\tilde{\beta}_i m_{ix0}}{\sigma - 1} \sum_{s=M,W} \eta^s_{ix} \sum_{l=0}^{L} r^B_l \left\{ mbv_{t-l} \left[1 - \left(\tau^s_{ixV}\right)^{-\sigma}\right] \right\} + \boldsymbol{\alpha}^F_{ixt} + \boldsymbol{\alpha}^U_{ixV} + e^r_{ixVt} \tag{14}$$

where the terms within {} are observable data. The Brexit probability is measured by the ln contract price (mbv_{t-l}). The expected proportion of profit losses from trade policy deteriorations in the two Brexit scenarios with product variation in tariffs, $s = M, W$. We refer to these observable profit loss terms, $1 - \left(\tau^s_{ixV}\right)^{-\sigma}$, as the MFN and trade war risk factors. The analogous term for the FTA scenario is captured by the bilateral-time effect, $\boldsymbol{\alpha}^F_{ixt}$, since it has no product variation.[15]

5 Estimation

We map the components described thus far into estimable equations and describe the data. We then present the export values and further evidence on the uncertainty mechanism by analysing export entry, exit, and heterogeneity in high versus low sunk cost industries.

5.1 Export Value Specification

Substituting U in (14) into the export equation (7) and rearranging we obtain the baseline estimating equation:

$$\ln R_{ixVt} = \sum_{s=M,W} \sum_{l=0}^{L} W^s_{ix}(l) \left\{ mbv_{t-l} \left[1 - \left(\tau^s_{ixV}\right)^{-\sigma}\right] \right\} + \boldsymbol{\alpha}_{ixV,it,xt} + e_{ixVt}. \tag{15}$$

The vector $\boldsymbol{\alpha}_{ixV,it,xt}$ represents bilateral-industry and country-time (it, xt) effects; e_{ixVt} is an error term. The key coefficients of interest that we report are cross-partial derivatives of (15) with respect to the Brexit probability and risk terms:

$$\sum_l W^s_{ix}(l) \equiv \sum_l \frac{\partial^2 \ln R_{ixVt}}{\partial mbv_{t-l} \partial \left[1 - \left(\tau^s_{ixV}\right)^{-\sigma}\right]} = -\bar{b}^h_i k_c \frac{\tilde{\beta}_i}{\sigma - 1} m_{ix0} \eta^s_{ix} \sum_l r^B_l. \tag{16}$$

This sum of the estimated coefficients over the lags is what we define as the *permanent cross-elasticity of uncertainty and risk*, denoted $\mathcal{E}^s = \left|\sum_l W^s_{ix}(l)\right|$. The parameters in this elasticity are positive according to the model, reflecting export elasticities to entry, $\bar{b}^h_i k_c$, the baseline probability of Brexit conditional on

[15] The fixed effect $\boldsymbol{\alpha}^U_{ixV}$ captures constant baseline uncertainty and e^r_{ixVt} is any error from approximating beliefs.

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 $\eta^s_{ix} = 0$ (i.e. scenario s was not believed by firms) or the measure used to capture changes in beliefs from the baseline is uninformative, in which case $\sum_l r^B_l \approx 0$. We can learn about belief parameters of firms exporting to i such as the relative probability of post-Brexit scenarios by using $\mathcal{E}^M/\mathcal{E}^W = \eta^M_i/\eta^W_i$.

To estimate (15), we require data on the Brexit probability and we need to construct measures of the policy risk $1 - (\tau^s_{ixV})^{-\sigma}$. In the baseline, we choose a lag length of two and cluster standard errors at the bilateral-product level (ixV). We discuss the data next, in section 5.2, and alternative lags and standard errors in section 6.

5.2 Data

5.2.1 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). While some of the daily variation will reflect noise trading, we expect this to be ameliorated by the monthly averages we employ, which still have 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 the share of likely voters that intended to vote for "Leave" (RHS axis). This co-moves with the contract price, particularly once the date of the referendum was set.[16] We examine the robustness of the results to using refined measures of this contract price (e.g. accounting for volume within and across months) and alternatives such as polls in Section 6.

5.2.2 Trade

We use bilateral monthly trade data from Eurostat at the 6-digit product level of the Harmonized System (HS). The baseline 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 $t - 12$. The robustness includes post-referendum data.

In Table 1 we summarize some key features of the data. First, the EU-27 countries account for about 42%

[16] The reported share is leave/(leave+stay). In the working paper we show a similar relationship is present if we add undecided voters to leave. Snowberg et al. (2013) review the uses of this type of prediction markets for forecasting outcomes including evidence that they are more accurate than polls the farther out the election is.

of UK exports and 52% of its imports in 2015. The UK represented 7% of total exports and 4% of imports for EU-27 members in aggregate. 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 subsample of the entry and exit 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 5.4.2. Average entry in this period is about 25% and exit is 14%; both variables have coefficients of variation above 1.75.

5.2.3 Trade Policy

We use the simple average MFN tariffs from the United Nations' TRAINS database to 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. In many cases there is limited or no variation below the 6 digit level. We also use MFN tariffs for other developed countries (the US, Japan, Canada, and Australia) to construct instruments and test their robustness.[17]

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(1 + tariff) factor are equal to 0.04. We compute MFN risk using $\sigma = 4$ as $1 - \left(\tau^M\right)^{-4}$; its average is 0.15 and the standard deviation is 0.125. We explain our choice of elasticity and consider alternative values in section 6.2.

In Table A1 we provide policy risk statistics by sector (defined as the 21 sections of the HS classification). Products face policy risk in all but two small sectors. For the other 19 sectors the average risk ranges from 0.014 to 0.34 and the coefficient of variation from 0.17 to 2. In vehicles, one of the largest sectors, 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 tariff for the EU is 57% and the associated tail risk is 0.73. The latter is five times higher than the MFN risk average.

5.3 Export Value Estimates

We first estimate (15) constraining the cross elasticities to be homogeneous between the UK and the EU; and subsequently show the results are qualitatively similar for each separately.

5.3.1 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

[17] 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.

first specification employs OLS and controls for importer-exporter-HS6 (ixV) as well as monthly effects by importer (it) and exporter (xt). Since the sample includes EU exports only to the UK and vice versa, the it and xt effects are equivalent to bilateral monthly effects, ixt, 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.). In section 6 we show these results are robust to various unobserved shocks by including sector by time effects and product trends.[18]

The MFN risk measure is potentially subject to measurement error because the tariffs we do observe may differ from exporters' true beliefs. This may attenuate the estimated cross elasticity. 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 MFN risk. We do so by computing the median HS6-specific MFN risk across the US, Japan, Canada, and Australia. The rationale is that exporters are uncertain about the exact future protection level in the UK and EU, but they know that protection in certain products tends to be correlated across developed countries and use this information to predict UK-EU MFN risk. The IV point estimate in column 2 is -1.45, which is about 1.8 times larger than the OLS estimate.[19]

5.3.2 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 $1 - \left(\tau_{iV}^{W}\right)^{-\sigma}$ as described in section 5.2.3 and note that 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 implied non-cooperative tariffs above 180%.[20] Second, there is idiosyncratic measurement error across importer-industry products, iV, which we address via instrumental variables. Similarly to the MFN risk, we use tariffs for other developed countries, compute trade war risk measures for each, and take the median for each product.

The IV estimate in column 4 is negative and the implied trade war risk is about one-third of the MFN, but it is not statistically significant. Additional controls increase the magnitude of this coefficient but it remains imprecisely estimated.[21] Moreover, since this additional control does not significantly affect the MFN risk estimate, we omit it from subsequent regressions.

5.4 Mechanisms: Sunk Costs, Entry, and Exit

We provide evidence for export sunk costs and entry and exit behaviour that is consistent with the model.

[18] We cluster standard errors at the bilateral-HS6 level; using more aggregated industries, e.g. HS4, or two-way clusters by importer and exporter, increases the errors slightly but the coefficients remain significant.

[19] In Appendix A.6 we describe the IV procedure and the high explanatory power of the first stage. The correlation of EU MFN risk and the excluded instrument is high, as shown in Table A3. It is highest with the US and Japan. If we only use these two countries to construct the instrument, we obtain a similar uncertainty elasticity.

[20] 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.

[21] 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.

5.4.1 Sunk Costs

To examine if the estimates so far are present only in high sunk cost industries as predicted by the model we apply the approach in Handley and Limão (2017) to identify high sunk cost industries.

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 industry sunk costs. We use semi-annual exports of non-EU countries to the UK from the first semester of 2012 to 2016. So these flows are distinct from the dependent variable in the baseline UK-EU trade estimation. The estimation details are in Appendix A.8.[22]

Table 3 shows estimates for the high and low cost subsamples. The high sunk cost represent about 88% of all observations in the baseline, which is re-assuring since we expect that continuously traded industries 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.

5.4.2 Entry and Exit

In the presence of export sunk costs, the model predicts that uncertainty lowers exports via lower firm net entry. The estimated export value coefficients reflect that behaviour, but focus on continuously traded products in this period and thus do not allow us to directly test those predictions.

In Appendix A.5 we derive the relationship between the cutoff and the probabilities of product-level 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:

$$Entry_{ixVt} = \tilde{k}_c^E \hat{U}_{ixVt} + \boldsymbol{\alpha}^E_{ixV,it,xt} + o^E_{ixVt} \text{ if } R_{ix,t-12,V}=0 \tag{17}$$

$$Exit_{ixVt} = \tilde{k}_c^X \hat{U}_{ixVt} + \boldsymbol{\alpha}^X_{ixV,it,xt} + o^X_{ixVt} \text{ if } R_{ix,t-12,V}>0. \tag{18}$$

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 $\left|\tilde{k}_c^X/\tilde{k}_c^E\right| = 1-\tilde{\beta} < 1$. We follow the approach in equation (15) and replace the approximation for $\hat{U}_{ixVt}$ in (14), and control for a similar set of fixed effects.

In Table 4, we find that net entry decreased with MFN risk, as predicted. We use a sample of intermittently traded products to estimate export entry and exit using equations (17) and (18). The entry estimates triple

[22] 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.

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). In Table 5, we re-estimate the entry and exit IV regressions on samples of high and low sunk cost industries. We find the impacts of MFN risk on entry and exit are only significant for the high sunk cost industries.

Export entry is more responsive to MFN risk than exit. Firms can immediately respond by entering when conditions improve but when they deteriorate firms can 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 occur with annual probability $1-\beta$. Interpreted through the model, that latter probability is reflected in the ratio of the exit to the entry cross-elasticity coefficients.[23]

6 Robustness and Additional Evidence

We provide a number of robustness checks on our structural assumptions, the trade policy risk measures, and other potential threats to identification. We also provide additional evidence including (i) heterogeneous elasticities across exporters and (ii) average impacts of Brexit uncertainty over all sources of EU-UK risk—trade policy and otherwise—that shows most of its impact is accounted for by the MFN risk.

6.1 Uncertainty Measurement

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

Trading Volume Information. There is heavier trading volume in contracts for specific days, which may represent an update in information after a significant event. Thus we weight (log) daily prices by the square root of the daily number of trades.[24] We use this weighted measure in columns 4 and 5 of Table 6 and find results similar to the respective baseline (replicated in columns 1 and 2 for comparison). To compare the magnitudes across specifications with alternative measures mbv^r we report the coefficient adjusted by the standard deviation relative to the baseline measure.[25] Trading volume in prediction markets also varies across months and increases closer to the referendum. We re-estimate the baseline to examine if results are sensitive to increased contract volume yields by running a weighted regression, i.e. assigning higher weights to observations in months with more transactions. The results in columns 6 and 7 are similar to the baseline.[26]

Polling Information. Shocks to Brexit voting intentions can also affect exporter beliefs. The poll share of respondents stating they will vote for Brexit varies over time and co-moves with the contract price, particularly once the date of the referendum was set, as we see in Figure 1. In Table A2 we provide direct evidence at the daily level of how the contract price varies with measures of voter intentions and other political events. The share of exit voters has a positive effect, which becomes stronger after the referendum

[23]Similarly to the export value specifications in Table 2, we find no significant impact of the trade war scenario for entry and exit and its inclusion does not change the MFN risk substantially. The results are available on request.

[24]We take a weighted average within months using the square root of transactions volume. The intuition is that days within a month with higher transactions volume are more precise measures of the implied leave probability on those days.

[25]Specifically, $W^{adj} = W^r\left[std\left(mbv^r\right)/std\left(mbv\right)\right]$, e.g. in column 5 $-1.56 = -1.29\,(.146/.121)$.

[26]We run weighted least squares, or weighted IV regressions, where the weights are a vector of the *monthly* total trading volume, e.g. $\hat{\beta} = (X'WX)^{-1}X'Wy$ with diagonal elements for W of $w_{it} = \text{Volume}_t$. In practice, we run the regression $\sqrt{w_{it}}y_{it} = \beta\sqrt{w_{it}}x_{it}$, which is implemented in STATA using the analytical weights option.

bill is passed. The impact of increasing the share of exit from the mean in the pre-referendum sample, 0.47, to its maximum, 0.52, is a 32 log point increase in *mbv*. Using this polling average to replace the *mbv* in the baseline specification we find similar qualitative results (columns 8 and 9 of Table 6). A one standard deviation increase in the poll measure reduces exports by more than one standard deviation in *mbv*.[27]

We can also use the polling data as an instrument for *mbv* to address potential measurement error in the latter. Assuming polls affect exports only through the referendum probability if we control for the latter then polls are excludable from the second stage. We already showed there is a strong effect of polls on *mbv* and so if changes in each of these variables contains information about the true probability plus some idiosyncratic error then we can instrument *mbv* with polls, essentially using the econometric argument described for instrumenting risk. In column 3 of Table 6 we find that the resulting coefficient is almost twice as large, which suggests some attenuation bias of the baseline estimates.

The fact that our measure is strongly correlated with polls and both yield qualitatively similar results is reassuring. Using this prediction market contract price to measure beliefs remains more attractive empirically. First, it is available 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 1 percentage point change can have a large effect if polls are around 50% and no effect when far from that value. 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, the daily regressions in Appendix Table A2 show the contract price responds 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. Nonetheless, we will see that the quantitative implications using polls are reasonably similar.

Betting Market Probability. An alternative measure of the probability of leave in the referendum is available from betting markets such as Betfair.com. The restrictions and participants in the betting and prediction market differ so the probabilities need not be the same.[28] Relative to PredictIt, the Betfair measure underpredicts leave until the wording of the referendum, over predicts it from 10/15 until shortly after the Bill is passed and subsequently the two line up better and their correlation becomes positive and equal to 0.23 from the passage of the bill (December 17) to the referendum, and 0.70 when measured from when the referendum date was determined (February 22). The latter may reflect a reduction in arbitrage opportunity as more trading took place throughout 2016. While *mbv* is strongly positively correlated with the exit share in polls after the bill was passed (0.67), the Betfair measure is not. In fact, the daily regression equivalent to Table A2 using Betfair implies it is decreasing in the poll exit share.[29] With these caveats in mind we re-run the baseline using the Betfair measure and continue to find a negative effect on export values but with a smaller magnitude (Table 6 columns 10 and 11).[30] Since volume data is not available for Betfair

[27] We perform the same robustness exercises for the export entry and exit regressions in Appendix Table A4. Using contract weighted averages or polling data directly does not change our main entry and exit results.

[28] Arbitrage opportunities across these markets existed during the 2016 US presidential election http://blog.predictwise.com/2016/05/betfair-v-predictit/. Possible motives include: different currencies (pound for Betfair, $US for PredictIt); a PredictIt limit per contract of 5,000 active traders and $850 in value per trader at the time of purchases (balances can exceed that amount thereafter); transaction and withdrawal fees; and the need for US residents to have foreign account to trade in Betfair. Betfair predictions have also diverged relative to those in other prediction markets, e.g. the implied probability of its contract price for an Obama win in 2012 was consistently higher than the same contract offered by Intrade (Rothschild and Sethi, 2016).

[29] Specifically, the coefficient is 2.69 for PredictIt in Table A2 column 2 whereas the equivalent one is -1.08 for Betfair. Unlike PredictIt, Betfair does not restrict bet amounts and can potentially be manipulated by a small number of large trades.

[30] The Betfair measure has no impact on exit (OLS) and impacts with sign opposite to the predicted for entry and exit (IV).

we are unable to correct for any measurement error arising from low trading in certain periods in the way we do for *mbv*. Given this data limitation of Betfair and its unexpected negative relation to exit polling, *mbv* remains our preferred measure.

Alternative Lag and Lead Structure. To test robustness to alternative timing structures we focus on the specification that addresses potential measurement error in risk (using the risk IV) and in the probability by weighting *mbv* by the volume of transactions within a month shown in column 5 of Table 6. The corresponding coefficients for the current and last two months are in column 1 of Table 7. The sum of the coefficients is qualitatively similar if we use only one lag or none but smaller in magnitude in the latter case (column 3). 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).

We also test robustness to including leads. In principle it is possible to find some effect of leads, e.g. if *mbv* increases at the end of a month t and remains at that level in $t + 1$ then this will only increase mbv_t slightly but the export reaction may be large at the end of t and thus correlated with mbv_{t+1}. However, any such effect should be smaller than the current and lagged impacts. To test this we use the same sample period and set the probability to 1 for July and August 2016 (the two leads that enter in May and June). The cumulative effect for $t = 0, -1, -2$ is qualitatively similar to what we find without leads whereas the cumulative effect for the two leads is very small, -0.004 (and insignificantly different from zero).

The conclusions are similar for entry and exit as shown in Table 7. Specifically, at least one lag is necessary to reflect most of the impact, the baseline coefficient is similar after controlling for leads and the cumulative lead effects are small in magnitude.[31]

6.2 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 8. 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). Moreover, those estimates of σ are uncorrelated with tariffs in our sample (-0.02) so the average effect in our baseline should not be biased by the omission of heterogeneous effects across σ.

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 A5 we find that the baseline export entry and exit results are also robust to these issues.

6.3 Entry and Exit Measurement

We relax the assumptions on the timing of entry and exit and find our results are robust.

The precise measurement of entry requires we observe when and at what level a firm incurs the export

[31] We reject the equality of the average of the leads compared to the remaining ones at 1% for exit and value and 1.5% for entry.

sunk cost. Because this is not available in our data, we need to make some assumptions. First, we assume that cost is at the destination-variety level, iv, possibly even at the buyer level (firm or retailer).[32] Second, we assume each firm has some export window in a year. If the firm does not export, then it will have to incur a sunk cost to export in that same window the following year. In the baseline we assume a narrow window of one single month, i.e. $Entry_{ixvt} = 1$ if $\min_n\{q_{ivt-n}\} > 0$ and $\max_n \{q_{ivt-12-n}\} = 0$ for $n = 0$. One interpretation is that this variety is subject to seasonality or that it ships to a similar set of buyers at t each year (and potentially to another set in another month).

We now relax the second assumption and allow for wider export windows so $n = 0, 1, 2$ in defining entry. Recall that we can not observe the flow for individual $v \in V$, only V so what we can measure is entry of the most productive variety into a market in a given window.[33] In Table A13, the first column replicates the baseline entry defined with $n = 0$. When that window is extended to either $n = 1$ or 2 in columns 2 and 3, the uncertainty elasticity is significant and similar to the baseline. We adopt a similar strategy for exit, so it occurs when $\max_n\{q_{ivt-n}\} = 0$ and $\min_n \{q_{ivt-12-n}\} > 0$. The elasticity with wider windows in column 5 or 6 is similar to the baseline in column 4.

6.4 Specification and Identification

We check several alternative specifications and sub-samples.

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 (7) 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 A3. We do so in Table 9 and find that uncertainty elasticities of the export value and participation are larger.

The results are robust to allowing these unobserved sector shocks to be bilateral as shown for exports by comparing columns 1 and 2 in Table A6. With the current data if we include more detailed industry-time effects we absorb most of the variation in the variable of interest (since it does not vary across countries). But we can control for linear trends for each HS-6 at the bilateral level and find results that are very similar to the baseline (column 4).

Seasonality and Longer-run Trends. Seasonality could bias the results if it implied differential exports for riskier products in months with higher Brexit probability. To the extent that seasonality is common across industries in a section then this issue is addressed by the results in Table 9. By extending our data we can further test robustness to this issue and allow for unobserved seasonal effects at the HS6–month-bilateral level. Suppose that the true model (15) includes a seasonal (or any other unobserved effect) that takes the form $\boldsymbol{\alpha}_{ixVM}$ where M indexes months. In the baseline sample there is a single observation for each $ixVM$ and thus we are unable to control for fixed effects at this level. Thus we extend the sample backwards to include the same months in earlier years and take the difference $\ln R_{ixVtM} - \ln R_{ixVTM}$ such

[32] It should be clear that more detailed firm data for the UK or other EU members could identify this channel more directly.
[33] That is $Entry_{ixVt} = 1$ if $\min_{n,v}\{q_{ivt-n}\} > 0$ and $\max_{n,v} \{q_{ivt-12-n}\} = 0$ and the latter can be observed as $\min_n\{q_{iVt-n}\} > 0$ and $\max_n \{q_{iVt-12-n}\} = 0$

that we difference $\boldsymbol{\alpha}_{ixVM}$ since tM and TM are in the same calendar month. We rely on A4 since we do not have information on the probability measure in T prior to the baseline sample, which implies that $mbv_T \sim mbv_0$ (negligible variation over the months in T) and so when we difference the RHS of (15) we will have a term $(mbv_t - mbv_0)\left[1 - (\tau^s_{ixV})^{-\sigma}\right]$. We separate the time invariant component, which captures the uncertainty in T, and control for it using an $\boldsymbol{\alpha}_{ixV}$ effect. In Table A7 we show the IV coefficients on the time varying component, which reflect the cross elasticity. Each column corresponds to a different period from 4 years prior (column 1) to one year (column 4). We continue to find negative and significant impacts. The magnitude is smaller, which may reflect some attenuation error from assuming constant mbv_0. Note that by including $\boldsymbol{\alpha}_{ixV}$ this differenced specification also controls for any possible long-run *trends*.

Selection in Continuously Traded and Heterogeneous Margin Effects. The baseline sample criteria for export values requires continuous trade, i.e. $R_{ixVt} > 0$ in all months in 8/15-6/16. We discuss this criteria and provide some robustness. The criteria is satisfied as long as there is one firm in x producing some variety in V for each t sufficiently productive to export to i, so the estimated elasticity reflects both intensive margin responses (e.g. incumbent firm investments to maintain or upgrade technology or distribution) and extensive (entry of firms crossing the threshold as uncertainty changes). In certain settings the two elasticities will be identical at the ixV level as shown in Handley and Limão (2017). If they are heterogeneous then our current estimate will reflect a trade weighted average of the two.

If the elasticity for a subsample where firms are known to have exported some variety in ixV differed substantially from the one in a sample that also includes entrants this would be evidence of heterogeneity. Our data does not allow us to identify this subsample directly but we can provide indirect evidence by estimating the elasticity for subsamples of ixV that were traded in previous years and thus excludes the ixV that are more likely to include entry.

The results in Table A8 show the baseline in the first column and compare them to subsamples of products also traded in other $T < t$. We note three points about the elasticity. First, its magnitude falls as we restrict the sample for longer trading periods, which suggests the impact for ixV entrants is slightly higher. Second, the difference in the coefficients across columns is small (statistically identical). Third, while the share of observations for continuers falls (to 86% of baseline by the last column) their share of trade is very large, e.g. 0.96 of trade in the baseline sample is done by HS6-countries continuously trading for at least 3 years. Thus even if the elasticity for entrants was significantly different and twice as high, the aggregate effect (weighted by trade) would still be dominated by the impact on continuing observations.

This evidence suggests that for our purpose of estimating the impact of Brexit uncertainty on overall trade, separating out the firm intensive and extensive elasticities is not essential.[34]

6.5 Heterogeneous Exporter Effects

We estimated the pooled, average cross elasticity for the UK and EU thus far. We now allow them to differ and discuss the reasons for a differential effect.

We find significant effects for both the UK and the EU that are qualitatively similar to the average but with some heterogeneity. Namely, the elasticity is higher for EU exporters in the baseline IV, i.e. $\mathcal{E}^M_{EU} > \mathcal{E}^M_{UK}$.

[34] Relatedly, if an approach such as PPML were feasible with the current set of fixed effects then we do not expect the new information in the 10% of trade represented by the non-continuously traded ixV would generate a significantly different trade weighted elasticity.

While this finding may seem counterintuitive a priori, it actually has a natural structural interpretation: EU firms believed MFN reversion was more likely and/or costly. We provide evidence that is consistent with differential policy beliefs and information.

Before presenting and interpreting the results we note two points regarding the identification. First, recall that our observations are at the bilateral-month-HS6 level, e.g. Portuguese widget exports to the UK each month and vice-versa. Thus our estimate of $\mathcal{E}^M_{UK}$ captures the average for the UK across each of those countries and $\mathcal{E}^M_{EU}$ captures the average elasticity for each of those individual EU countries exporting to the UK, so they do not necessarily represent aggregate EU elasticities. Second, our baseline controls for aggregate bilateral shocks (with bilateral-month effects) and unobserved heterogeneity in export size and composition (with bilateral-HS6 effects). So the residual variation in bilateral exports that identifies these elasticities should be comparable across the EU and UK sample. Moreover, the MFN risk average and variability is similar for each subsample so that is not the source of the heterogeneous result.

Columns 1 and 2 of Table 10 apply the OLS specifications in Table 2 to the UK and EU exporter subsamples respectively. Those OLS cross elasticities are statistically similar to their average in Table 2. The ratio $\mathcal{E}^M_{EU}/\mathcal{E}^M_{UK}$ is 1.5 but the difference is not statistically significant.

The MFN risk is constructed from the current EU external tariff and is subject to measurement error, which leads to attenuation bias (as we noted in explaining the IV approach). The IV estimates in Table 10 show this attenuation is larger for EU exporters. The elasticity in column 4 doubles relative to OLS. It is significantly different and 1.9 times larger than the UK estimate. We interpret this as evidence that EU exporters perceived higher MFN risk because they had to predict UK tariffs, and regulations, after a hard Brexit. In contrast, the EU is more constrained due to its large membership and negotiated tariffs with other countries.

Differential expectations about non-MFN protection may also affect the MFN elasticity. Suppose that UK exporters face higher risk under a trade war, e.g. because the EU is larger. If MFN and trade war tariffs are correlated and we omit trade war risk then this will differentially affect the UK MFN elasticity. To test this we add trade war risk to the IV specifications. In column 5 we find trade war risk has a negative effect for both the UK and EU but it is insignificant. Once we condition for this scenario the UK MFN elasticity increases relative to the EU MFN elasticity. Thus we now have $\mathcal{E}^M_{EU}/\mathcal{E}^M_{UK} = 1.7$ and reject equality at the 6% level.

In Appendix A.10 and Table A10 we show that some alternatives can explain part of the heterogeneity under IV in columns 3 and 4, (e.g. addressing error in the probability of Brexit), while others exacerbate it (e.g. controlling for omitted bilateral-industry trends and composition). Overall, the evidence suggests $\mathcal{E}^M_{EU} > \mathcal{E}^M_{UK}$, which is consistent with the model if EU exporters faced higher MFN risk, as seems plausible. The relative elasticity responds to how we measure and control for uncertainty in sensible ways, which suggests that it is capturing some differential policy beliefs and information. It may also reflect additional forces such as government relief for UK industries facing higher protection in the EU.[35]

[35] The entry and exit effects are also significant for both the UK and the EU and the IV elasticity for the EU is higher, as seen in Table A11.

6.6 Average Uncertainty Effects

We now extend the sample and analysis with two objectives: (1) to address 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; and (2) to allow controls for additional, unobserved heterogeneity.

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 trade with the rest of the OECD plus Brazil, Russia, India and China.[36] We also include EU-27 exports to itself. This extended sample accounts for over 70% of all EU and UK trade in 2015.

We consider two alternative measures of ex-ante risk between the EU or UK and third countries, i.e. with any countries other than each other:

$$\bar{\omega}_{ixtV} - 1 = \begin{cases} \bar{\omega}_{ixV} - 1 \\ m_t \Sigma_s \eta_{ix}^s \left[(\tau_{ix}^s)^{-\sigma} - 1 \right]. \end{cases} \tag{19}$$

The top expression assumes that the risk does not vary systematically with Brexit probabilities and is thus captured by ixV effects. The bottom alternative is more similar to (12): the exporters in x believe that after a policy change there is a probability $m_t \eta_{ix}^s$ they will face barriers $\tau_{ix}^s \geq 1$ higher than current levels. The key difference relative to (12) is that we do not know what the exact risk is and therefore we use a uniform increase across products and scenarios, τ_{ix}^s. This is without loss of generality when considering only the average uncertainty effect across all scenarios s.

The export estimates in Table 11 on the extended sample suggest that MFN risk is the main driver of our baseline results. In column 1 we include fixed effects (ixV, it, xt) and the mbv variable, which has a significant effect equal to -0.24. This represents the differential average uncertainty impact between the UK and EU relative to their exports to third countries. In columns 2 and 3 we estimate the cross-elasticity $\mathcal{E}^M$ (OLS and IV). These are identical to the estimates we obtain in the baseline Table 2.[37] Importantly, conditional on that EU-UK MFN risk, the average uncertainty effect for a product with no MFN risk is close to zero and insignificant in the IV specification.[38] If the third country risk in (19) is constant, $\bar{\omega}_{ixtV} = \bar{\omega}_{ixV}$, then the coefficient in column 1 has the following structural interpretation: $\sum_{s=F,M,W} \mathcal{E}^s \times \left(\overline{1 - (\tau^s)^{-\sigma}} \right) = 0.24$, i.e. the average elasticity over all scenarios with tail risk. This estimate is just above the corresponding impact obtained using the estimate in Table 2, 1.45, at the average MFN risk (0.15): $0.22 = 1.45 \times 0.15$.[39]

By including EU and UK trade with other countries, the extended sample also provides additional identifying variation to test the robustness of the baseline elasticity estimate. Using the same set of fixed effects as the baseline on the extended sample , we obtain a similar IV elasticity (column 3 of Table 11). We can go further and control for additional unobserved heterogeneity. For example, there may be unobserved product shocks at the importer or exporter level, including any seasonality effects. The extended sample allows us

[36] We exclude Israel, Chile, Turkey, South Korea and Mexico because they have PTAs with the EU and thus face Brexit risk.

[37] The results in Table 11 are also robust to allowing heterogeneous coefficients. Both the EU and UK have significant cross-elasticities and the uncertainty elasticity at average MFN is larger for EU exports.

[38] The IV results are robust to dropping the four countries used for the construction of the instrument.

[39] The interpretation under Brexit-varying risk 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 pairs other than EU-UK.

to address these by including iVt and xVt fixed effects. In Table A9 of the appendix, we include these extra controls and confirm uncertainty reduces exports and that the average impact of a change in probability is very similar to the baseline.

In sum, we draw two implications from Table 11. 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.

7 Quantification

7.1 Export Values

The permanent cross-elasticities of exports with respect to Brexit uncertainty, defined by equation (16) depend on constant parameters; we now use our estimates to quantify the uncertainty elasticity of exports at alternative policy levels. We focus on the average effect for the UK and EU but similar calculations can be applied to the exporter-specific estimates.

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:

$$\begin{aligned}\mathbb{E}\left(\ln \frac{R_{ixV}(mbv)}{R_{ixV}(mbv_0)}\right) &= -\sum_{s=M,W,F} \mathcal{E}^s \times \left(\overline{1-(\tau^s)^{-\sigma}}\right) \times \Delta mbv \\ &\leq -\mathcal{E}^M \times \left(\overline{1-(\tau^M)^{-\sigma}}\right) \times \Delta mbv. \end{aligned} \tag{20}$$

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 $\mathcal{E}^s \geq 0$.

We base the quantification on the estimates that address measurement error in the MFN and contract variables in Table 6, column 5: $\mathcal{E}^M = 1.29$ (the unstandardised coefficient) and the mean MFN risk is denoted by $\overline{1-(\tau^M)^{-\sigma}} = 0.15$ (Table 1). Thus the uncertainty elasticity at the mean MFN risk is $\mathcal{E}^M \times \left(\overline{1-(\tau^M)^{-\sigma}}\right) = 1.29 \times 0.15 = 0.19$, as shown in the first column of Table 12. This implies that a persistent uncertainty increase by one standard deviation lowers average exports by 2.8 log points due to MFN risk.[40]

Permanent Uncertainty Impacts. In Figure 4(a) we plot the predicted export response to Brexit uncertainty shocks. These range from zero to 121 log points, where the latter represents a move from the pre-referendum mean to its value immediately after. Any Bregret—what we later define precisely as the fraction of post referendum regret about leaving—would place the impact below that maximum and here we focus on 1/3 of Bregret. For Brexit uncertainty of 0.81 (2/3 of 121 log points), this implies an export reduction of 16 lp. Below we provide evidence that this is a reasonable prediction for the average yearly change in the 12 months after the referendum.

[40] A standard deviation shock is equivalent to an interquartile range increase in the sample. The overall effect is the average of the effect on *treated* industries with positive MFN risk and those with no MFN risk.

MFN Tariff Impacts. In Figure 4(b) we plot the same post-referendum scenario at different MFN risks on the x-axis. We set Brexit uncertainty to 0.81, as above, and plot the predicted value $-\mathcal{E}^M \times 0.81 \times \left(1-\left(\tau^M\right)^{-\sigma}\right)$ over a tariff range: $100 \times \ln \tau^M \in [0, 22.5]$. The effect at the mean is 16 lp, as reported in Table 12. About 40% of products have tariffs above the mean and thus have larger impacts.

Non-tariff Barriers (NTBs) and MFN Tariff Impacts. It is possible that Brexit leads to NTBs between the EU and UK similar to those they set against the rest of the world. These are hard to measure by industry, which is why our identification relies on tariffs. However, we have estimates of the average advalorem equivalent reflecting those NTBs plus tariffs, $\tilde{\tau} = 1.097$ (Kee et al, 2009). This implies a combined risk of 0.31, about twice that of MFN tariffs alone, which doubles the uncertainty elasticity and the associated export impact moves from 16 to 32 lp.[41]

Export Entry and Exit We perform the same quantification exercise for the entry and exit regressions in columns 2 and 3 of Table 12. Under our post referendum scenario Brexit uncertainty reduced entry by 7 percentage points due to MFN risk and increased exit by 2.4: a net entry impact of over 9 percentage points.

7.2 Post Referendum Uncertainty and Bregret

The uncertainty elasticities can be used to compute the impact of any reasonable log change in the contract price. In panel B of Table 12 we focused on a particular scenario and we now interpret it as the predicted impact of the referendum under Brexit regret, i.e. Bregret. We also show there is a similar impact when we use polls instead of prediction markets. We find these predictions are within the range of estimated changes we obtain using pre and post-referendum data.

Recall that in (9) we modelled the growth in the probability of Brexit prior to the referendum such that it is equal to the growth in the probability of a leave vote. If this assumption continues to hold after a leave referendum outcome, then we say there is **no Bregret** because the Brexit probability conditional on such a vote, p_{ix}^{BR}, remained unchanged. If this assumption fails and p_{ix}^{BR} falls at some $T > \mathcal{T}$, then we say there is **Bregret**. We can measure the degree of Bregret from none to full relative to the pre-referendum average. Specifically, we define $Bregret_T \equiv -\frac{\ln p_T^{BR}/p_{\mathcal{T}}^{BR}}{\ln[1/\Pr(\mathcal{R}_{\mathcal{T}}|\mathcal{I}_t)]} \in [0,1]$, which we obtain by rearranging (9):

$$\begin{aligned} \ln m_T/m_t &= \ln\left[1/\Pr\left(\mathcal{R}_{\mathcal{T}} \mid \mathcal{I}_t\right)\right] - \ln p_T^{BR}/p_{\mathcal{T}}^{BR} \\ &= \ln\left[1/\Pr\left(\mathcal{R}_{\mathcal{T}} \mid \mathcal{I}_t\right)\right] \cdot \left(1 - Bregret_T\right) \end{aligned} \tag{21}$$

To make an out-of-sample prediction incorporating Bregret, we rely on two alternative measures that suggest a similar degree of Bregret: about 1/3 between July 2016-June 2017. First, we use the fact that voter support grew from 46.7% to the final referendum result of 51.9%. Support fell to only 50.1% in the subsequent year and thus reversed by about one-third: $-\frac{\ln(0.501/0.519)}{\ln(0.519/0.467)} = 0.33$. Second, other events suggest the *conditional* probability of Brexit fell after the vote. For example, Article 50 was a necessary condition for implementing Brexit and the government had promised to follow through in case of a leave referendum. However, we now know that after the referendum the probability of Article 50 being triggered by the end

[41] Our preferred estimate for the average impact uses only tariff risk because it was used for the coefficient estimate and lines up better with the average effect in section 6.6.

of March 2017 was far below one. Using that average over July 2016-June 2017 also yields Bregret of about one third.[42]

Combining the uncertainty elasticity at mean risk estimated on pre-referendum data in Table 12 with the change in probability implied by equation (21) we obtain the predicted changes in exports in column 1 of Table 13, which under 1/3 of Bregret implies the 16 log point reduction we described above. We interpret this as the average predicted change in August 2016-June 2017 relative to the same period in the previous year due to increased MFN uncertainty. The alternative in column 2 uses the IV estimate from using polls obtained in Table 6. The latter implies a smaller reduction that is still within the 95% confidence interval of 11-20 lp.

We can compare these out-of-sample predictions with estimates that use the actual changes in the period. In Appendix A.11 we describe the latter estimation in detail using the difference of equation (15) over 12 months. The contract price post-referendum is set to one. Thus, when we compute the change $mbv_{t-l} - mbv_{t-12-l}$ we set the log value of the contract price at the end point to $mbv_{t-l} = 0$. If there is positive and constant Bregret, then the estimated coefficient from a regression in changes will reflect $\mathcal{E}^s \times (1 - Bregret)$. The resulting estimates imply an average reduction in exports of 10 lp. The lower magnitude of the point estimate relative to the prediction in columns 1 and 2 may be caused by attenuation from measurement error as the post-referendum Brexit probability varied over time (i.e. Bregret was not constant). The measurement error is reflected in the higher confidence intervals, which include the estimates in columns 1 and 2.

7.3 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 along two dimensions. First, the out of sample predictions are in line with ex-post estimated changes. Second, the uncertainty effect is is smaller than a permanent actual increase in tariffs, which in this case would imply an export reduction between 18-32 log points.[43]

Our results also indicate there is a pre-referendum dip in exports due to uncertainty and ignoring it will bias standard estimates that focus on changes before and after the referendum. This is a broader cautionary point for studies examining the impact of discrete events as a proxy for uncertainty shocks.

8 Conclusion

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. We show that just the possibility of such regime shifts can substantially lower trade. In short, increased uncertainty about an existing agreement's policies or its survival may lead to disintegration.

[42] This uses $Bregret_T = -\ln(0.67/1)/\ln(1/0.3) = 0.33$, where 0.3 is the average weighted contract probability before the referendum and 1 its value after the referendum. We assume that at the referendum date the probability of triggering Article 50 by the end of June 2017 was expected to be 1 but its observed annual average from July 2016 to 2017 was 0.67, as measured by prediction contracts from Predictwise.

[43] This uses the average MFN tariff in the EU, 4.5%, times the tariff elasticities from the literature, which range from 4 to 7 (Limão, 2016). 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).

We find that shocks to the probability of Brexit reduce trade flows and trade participation. The effects are largest in products where the reversion to MFN tariffs under WTO 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 as predicted: larger in industries with high sunk costs, at the entry margin and for exporters potentially facing higher risk.

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 before any actual policy change, a finding that is relevant in this setting and more generally when evaluating ex-post impacts of actual changes.

Trade disagreements and renegotiation have halted and possibly reversed the most recent era of global trade integration in the UK, the EU, and elsewhere.[44] We anticipate future research will continue to illuminate and quantify the important of uncertainty relative to other mechanisms as more firm-level data for the UK and other EU member countries becomes available and the process of disintegration unfolds.

[44] Graziano et al. (2020) apply our framework and find Brexit uncertainty also reduced its trade with some non-EU PTA partners.

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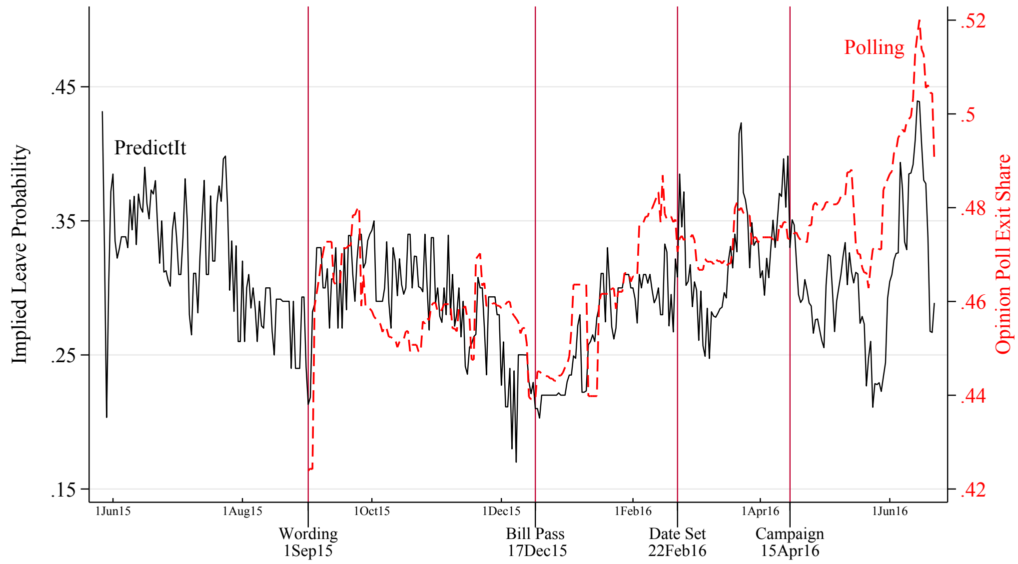
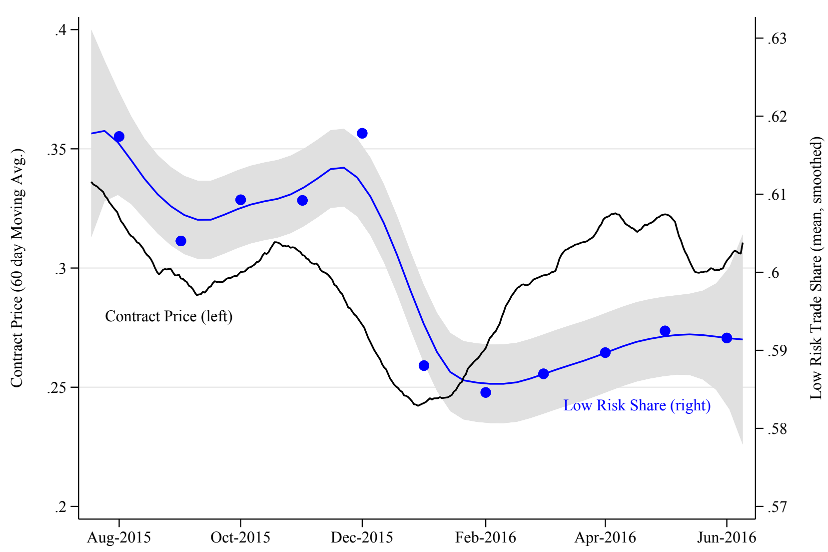
Figure 1: Brexit Average Daily Contract Price and Opinion Polling
5/27/15 to 6/22/16



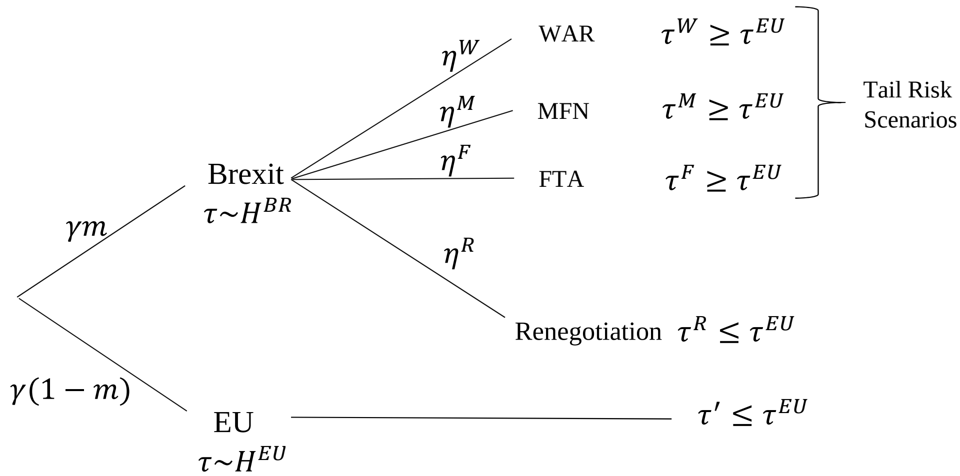
Notes: The solid black line is the daily average price of a contract on PredictIt.org that pays $1 if Britain votes to leave the EU and zero otherwise. The dashed red line is share of respondents in opinion polls that say they will vote leave excluding undecided voters. Major legislative and political 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).

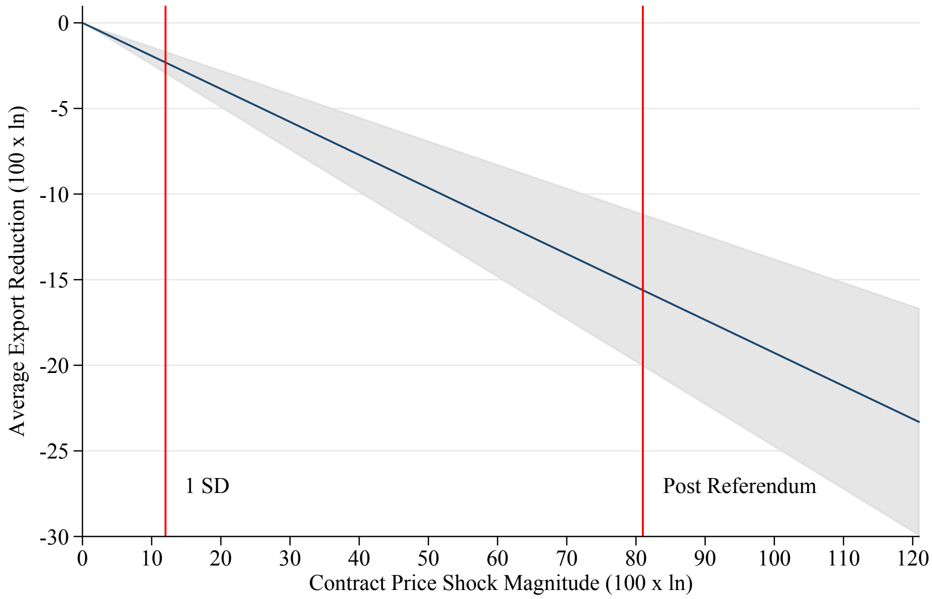
Figure 3: Event Space and Probability Tree for Brexit and EU Trade Policy Distributions



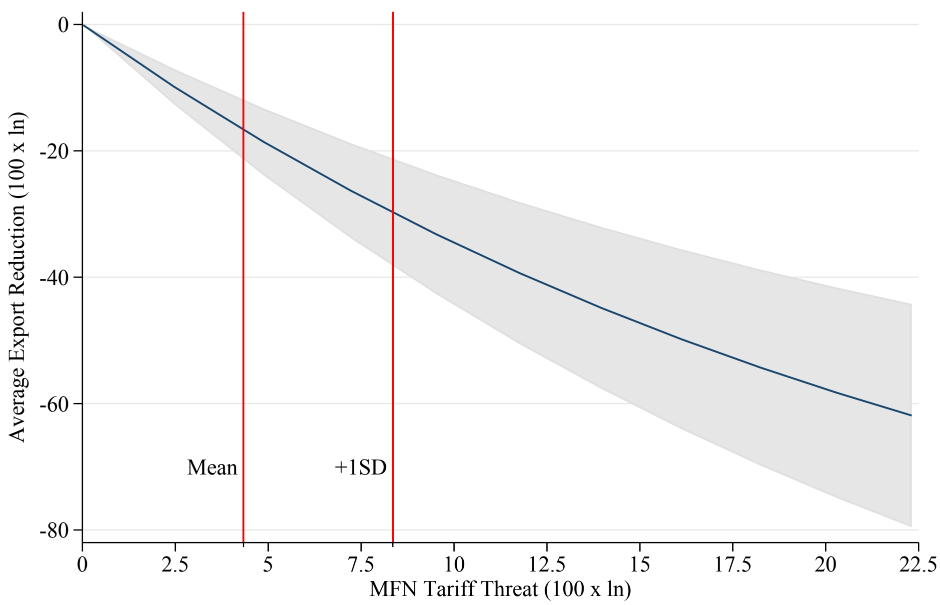
Notes: A shock arrives with probability γ and firms expect that a new trade policy factor τ is drawn from a distribution $\bar{H}$. We model $\bar{H}$ as a mixture over a Brexit distribution H^{BR} with probability weight m and an EU distribution H^{EU} with weight $1-m$. We assume that H^{EU} SSD H^{BR} 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 0.81, i.e. the implied shock assuming 1/3 Bregret as explained in Table 13, and increases the MFN tariff. Grey shaded areas indicate 95% confidence intervals.

Table 1: Summary Statistics

8/15-6/16

	Mean	SD	Median	Min	Max	N
Aggregate Bilateral Export Values: Continuously Traded Sample						
UK import value (Bn. €)	7.95	13.9	2.33	0.0448	65.0	27
EU import value (Bn. €)	5.03	7.51	1.22	0.131	30.8	27
Export Values: UK-EU Continuously Traded Sample						
	Mean	SD	Median	Min	Max	N
ln(exports)	10.30	2.62	10.50	0	20.60	637,263
Pr(Brexit)	-1.23	0.121	-1.19	-1.50	-0.985	637,263
Transaction Vol. Weighted	-1.21	0.146	-1.19	-1.48	-0.854	637,263
Poll Share (Exit)	-0.760	0.0293	-0.769	-0.801	-0.691	637,263
ln Tariff (τ^{MFN})	0.0433	0.0402	0.0315	0	0.559	637,263
MFN Risk	0.149	0.125	0.12	0	0.893	637,263
MFN Risk IV	0.103	0.107	0.08	0	0.491	637,263
Trade War Risk	0.734	0.188	0.768	0.0292	0.984	533,258
Trade War Risk IV	0.666	0.247	0.696	0.00481	1	533,258
Extensive Margin: UK-EU						
	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	0	1	647,488
MFN risk	0.141	0.121	0.118	0	0.893	647,488
Exit sample: Conditional on Traded Status (Exports>0) at t-12						
Exit (binary)	0.141	0.348	0	0	1	977,177
MFN risk	0.148	0.124	0.118	0	0.893	977,177

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) leave prediction market contract price. 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 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

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

	1	2	3	4
	OLS	IV	OLS	IV
Pr(Brexit) × MFN Risk	-0.793	-1.45	-0.900	-1.660
	(0.149)	(0.198)	(0.16)	(0.225)
Pr(Brexit) × Trade War Risk			0.169	-0.595
			(0.108)	(0.748)
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). Pr(Brexit) defined as the monthly average (ln) leave prediction market contract price, and MFN risk defined as $1\text{-}(\tau^{MFN})^{-\sigma}$, 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 in columns 3 and 4 is lower due to data availability (details in Table 1 notes). 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. All estimations include exporter-importer-HS6, exporter-month and importer-month fixed effects.

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

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

	1	2	3	4
	OLS		IV	
Sunk Cost Sample:	High	Low	High	Low
Pr(Brexit) × MFN Risk	-0.929	0.203	-1.68	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) leave prediction market contract price, and MFN risk defined as $1\text{-}(\tau^{MFN})^{-\sigma}$, where σ=4 and τ^{MFN}=1+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

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	-0.191	-0.606	0.107	0.204
	(0.0553)	(0.0898)	(0.0286)	(0.0375)
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 (ln) leave prediction market contract price, and MFN risk defined as$1-(\tau^{MFN})^{-\sigma}$, where $\sigma=4$ and $\tau^{MFN}=1+$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: UK and EU MFN Risk in High vs. Low Sunk Cost Industries - Entry and Exit Probability

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

	1	2	3	4
Sunk Cost Sample:	High	Low	High	Low
Pr(Brexit) × MFN Risk	-0.610	-0.333	0.198	0.262
	(0.094)	(0.376)	(0.039)	(0.163)
N	557,734	63,596	854,494	90,202

Notes: IV regressions. Entry and Exit defined in Table 4 and sunk export cost samples as in Table 3. Pr(Brexit) defined as the monthly average (ln) leave prediction market contract price, and MFN risk defined as $1-(\tau^{MFN})^{-\sigma}$, where $\sigma=4$ and $\tau^{MFN}=1+$MFN advalorem/100. In all specifications 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 6: UK and EU Alternative Brexit Measures

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

	1	2	3	4	5	6	7	8	9	10	11
	Prediction Market Leave Probability Measure										
	Unweighted Average Contract Price			Weighted Average Contract Price				Opinion Polling Averages		Betfair Average Leave Percentage	
	OLS	IV Risk	IV Risk+Polling Avg	OLS	IV Risk	OLS Vol. Weighted	IV Risk Vol. Weighted	OLS	IV Risk	OLS	IV Risk
Pr(Brexit) × MFN Risk	-0.793	-1.45	-3.19	-0.851	-1.56	-0.764	-1.76	-1.31	-2.68	-0.479	-1.09
Standardized Coeff.	(0.149)	(0.198)	(0.263)	(0.171)	(0.227)	(0.143)	(0.194)	(0.166)	(0.225)	(0.11)	(0.149)
N	637,263	637,263	637,263	637,263	637,263	637,263	637,263	637,263	637,263	637,263	637,263
R2	0.875	n/a	n/a	0.875	n/a	0.988	n/a	0.875	n/a	0.875	n/a

Notes: Dependent variable ln(exports) defined at the exporter-importer-HS6-month level. Pr(Brexit) defined as the monthly average of the indicator in the column headings (unweighted and weighted (ln) contract price, Betfair implied leave percent, and polling averages). MFN risk defined as $1\text{-}(\tau^{MFN})^{-\sigma}$, where σ=4 and τ^{MFN}=1+MFN advalorem/100. Column 1-3 uses the baseline unweighted monthly average of daily Pr(brexit), where in column 2 the risk is instrumented as in Table 2, and in column 3 Pr(Brexit) is instrumented by monthly exit polling average. Column 4-7 weights the daily probabilities with the square root of the volume of daily transactions within month. Columns 8-9 are the average (ln) share of exit voters adjusted by 1 - undecided share of voters. Columns 10-11 defines Pr(Brexit) as the average (ln) Betfair implied leave percent. The poll data for July and August 2015 is imputed to be the same as in September when polls begin. Coefficients report the sum of current and two monthly lags and columns 4-11 are standardized to have the same standard deviation units as the unweighted contract price for comparison. 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 7: UK and EU MFN Risk - Lag/Lead Robustness

8/15-6/16

	Export Value (ln)				*Entry*				*Exit*			
	1	2	3	4	5	6	7	8	9	10	11	12
monthly lags	2	1	no	2	2	1	no	2	2	1	no	2
monthly leads	no	no	no	2	no	no	no	2	no	no	no	2
Pr(Brexit)×MFN Risk	-1.294	-1.488	-0.840	-0.908	-0.589	-0.517	-0.173	-0.444	0.192	0.197	0.0450	0.253
	(0.189)	(0.163)	(0.0986)	(0.213)	(0.0854)	(0.0739)	(0.043)	(0.100)	(0.036)	(0.0308)	(0.0178)	(0.0419)
Pr(Brexit_lead)×MFN Risk				-0.00410				-0.0836				-0.028
				(0.0638)				(0.0307)				(0.0131)
N	637,263	637,263	637,263	637,263	647,488	647,488	647,488	647,488	977,177	977,177	977,177	977,177

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(t)=1 if Export(t)=0 and Export(t-12)>0. Pr(Brexit) defined as the monthly average (ln) leave prediction market contract price and the coefficient reflects the sum of impact of current month and the number of lags listed in the column above it. Pr(Brexit_lead) reflects the sum of the coefficients on the lead of the same variable for the months listed and is set to 0 for July and August 2016. MFN risk defined as $1\text{-}(\tau^{MFN})^{-\sigma}$, where σ=4 and τ^{MFN} =1+MFN advalorem/100. All specifications use the transaction weighted probability measure and instrument the MFN risk by the median HS6-specific MFN risk across four large countries (Australia, Canada, Japan and US). Robust standard errors clustered at the exporter-importer-HS6 level in parenthesis. All estimations include exporter-importer-HS6, exporter-month, importer-month.

Table 8: 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	-1.42	-2.67	-1.00	-1.86	-1.00	-1.61	-2.52	-4.87
	(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. Pr(Brexit) defined as the monthly average (ln) leave prediction market contract price, and MFN risk defined as $1-(\tau^{MFN})^{-\sigma}$, where σ=4 in columns 5-6, and τ^{MFN}=1+MFN advalorem/100. Columns 5-6 exclude industries with σ 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. All estimations include exporter-importer-HS6, exporter-month and importer-month fixed effects.

Table 9: UK and EU MFN Risk and Sector Specific Shocks

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	-1.08	-2.16	-0.278	-0.728	0.0982	0.303
	(0.226)	(0.423)	(0.0735)	(0.152)	(0.0435)	(0.0803)
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 (ln) leave prediction market contract price, 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 10: UK and EU MFN and Trade War Risk by Exporter

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

	1	2	3	4	5	6
	OLS		IV		IV	
Exporter:	UK	EU	UK	EU	UK	EU
Pr(Brexit)×MFN Risk	-0.658	-0.976	-1.05	-2.01	-1.29	-2.17
	(0.191)	(0.236)	(0.253)	(0.315)	(0.283)	(0.372)
Pr(Brexit)×Trade War Risk					-0.61	-0.52
					(0.912)	(1.28)
H0: Identical MFN cross-elasticity (p-value)	0.295		0.017		0.060	
EU/UK elasticity ratio	1.48		1.91		1.68	
N	369,589	267,674	369,589	267,674	308,836	224,422
R2	0.863	0.885	n/a	n/a	n/a	n/a

Notes: Dependent variable ln(exports) defined at the exporter-importer-HS6-month level for UK and individual EU 2015 members. The source of exports is labelled on top of the columns. Pr(Brexit) defined as the monthly average (ln) leave prediction market contract price, and MFN risk defined as $1-(\tau^{MFN})^{-\sigma}$, where $\sigma=4$ and $\tau^{MFN}=1+$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), which limits the sample as described in Table 2 where we also describe how we instrument risk. Coefficients report the sum of current and two monthly lags. EU/UK elasticity reports the ratio between the two coefficients. 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 11: UK and EU MFN and Average Risk

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

	1	2	3
Sample (rel. to baseline):	+ Imports from/Exports to OECD, BRICs and w/in EU-27		
	OLS	OLS	IV
Pr(Brexit) × *UK-EU*	-0.238	-0.118	-0.00525
	(0.0373)	(0.0432)	(0.048)
Pr(Brexit) × MFN Risk × *UK-EU*		-0.805	-1.56
		(0.148)	(0.199)
N	7,447,011	7,447,011	7,447,011
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). Pr(Brexit) defined as the monthly average (ln) leave prediction market contract price, and MFN risk defined as $1-(\tau^{MFN})^{-\sigma}$, where $\sigma=4$ and $\tau^{MFN}=1+$MFN advalorem/100. The sample includes all exports and imports of the UK and EU to the OECD (excluding countries that have a PTA with EU: Chile, Israel, Korea, Mexico and Turkey) and four large developing countries: Brazil, Russia, India and China (BRIC). *UK-EU* is a binary indicator for UK exports to the EU and EU exports to the 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.

Table 12: Brexit Uncertainty Impacts at Average MFN Risk

8/15-6/16

	1	2	3
	Export	**Entry**	**Exit**
Uncertainty Elasticity	-0.193	-0.0878	0.0295
A. One SD shock	-0.0282	-0.0128	0.00431
B. Referendum shock (1/3 Bregret)	-0.156	-0.0711	0.0239

Notes: Calculations employ IV coefficients using the weighted leave prediction market contract price measure from Table 6, column 5 and summary statistics from Table 1. Column 1: change in (ln) exports, columns 2 and 3: change in probability of entry and exit respectively. Panel B uses a shock of (2/3) the change in average ln contract price in the pre-referendum period to its post referendum value assumed to be zero.

Table 13: Predicted Export Value Changes

	1	2	3
Estimation period	Pre-referendum		Pre vs post difference
Uncertainty variable	Contract (weighted)	Polls	Contract (weighted)
No Bregret	**-0.234**	**-0.172**	n/a
95% CI	(-0.301 , -0.167)	(-0.200 , -0.144)	
Bregret (1/3)	**-0.156**	**-0.115**	**-0.0960**
95% CI	(-0.201 , -0.111)	(-0.134 , -0.0960)	(-0.181 , -0.0108)

Notes: Calculations employ IV coefficients of estimation of (ln) exports and summary statistics from Table 1. The pre-referendum data is used with the weighted contract price in column 1 and exit share in column 2. Column 3 uses the 12 month ln difference in exports between June 2017 and June 2016. The no Bregret counterfactual uses the change in the average uncertainty variable between the year before the referendum and the referendum date assumed to be zero. The Bregret scenario in columns 1 and 2 assumes 1/3 of that change was reversed. The estimation approach in column 3 reflects any actual Bregret in the data as described in the text.