Department of Economics Discussion Paper Series

The Brexit Vote and Labour Demand: Evidence from Online Job Postings

Beata Javorcik, Layla O'Kane, Benjamin Kett,
Katherine Stapleton

Number 878
August, 2019

Department of Economics
Manor Road Building, Manor Road
Oxford, OX1 3UQ

ISSN 1471-0498

The Brexit Vote and Labour Demand: Evidence from Online Job Postings

By Beata Javorcik, Layla O'Kane, Benjamin Kett and Katherine Stapleton *

This paper uses high frequency data on the universe of job adverts posted online in the UK to study the impact of the trade uncertainty caused by the Brexit referendum on labour demand. We develop measures of industry and regional exposure to the threat of potential most-favoured-nation (MFN) tariffs if the UK were to leave the EU without a trade deal. We show that industries and regions more exposed to the tariff threat differentially reduced online hiring in the period after the referendum. We also show that the magnitude of this negative effect varied with the time-varying perceived probability of a no-deal Brexit, proxied by the relative frequency of Google-searches for terms associated with a no-deal Brexit. The policy implications of this paper are that uncertainty around trade policy, not only enacted policy, have real economic impacts and governments should therefore strive for clarity and predictability in their actions to create a strong enabling environment for the private sector.

The consequences of trade barriers for economic outcomes is a long studied area of research, yet uncertainty about possible future barriers, as opposed to barriers themselves, is less well understood and currently an active area of research. The question of the future trading relationship between the United Kingdom and European Union, given its extended negotiation and as yet unclear resolution, provides a unique opportunity to study the impact of trade uncertainty.

We exploit the product-level variation in EU MFN tariffs that would be placed upon UK trade with the EU under a Brexit scenario without a trade deal, to explore how trade uncertainty affects online hiring and local labour markets. We study how the referendum result itself and changing expectations about the likelihood of future imposition of MFN tariffs during the three year period after the referendum, affected the posting of job adverts online. We use a high frequency dataset consisting of the near universe of online job adverts posted in the UK between 2014 and 2019, to track the real-time response of UK firms to tariff uncertainty as the political process evolved. This approach allows us to gauge how

* Javorcik: Department of Economics, University of Oxford and CEPR, Manor Road Building, Manor Road, Oxford OX1 3UQ, UK. E-mail: beata.javorcik@economics.ox.ac.uk. O'Kane: Burning Glass Technologies, One Lewis Wharf Boston MA 02110. Email: lokane@burning-glass.com. Kett: Department of Economics, University of Oxford, Manor Road Building, Manor Road, Oxford OX1 3UQ, UK. E-mail: ben.kett@economics.ox.ac.uk. Stapleton: Department of Economics, University of Oxford, Manor Road Building, Manor Road, Oxford OX1 3UQ, UK. E-mail: katherine.stapleton@economics.ox.ac.uk.
Acknowledgements

firms adjusted their hiring patterns in response to specific political events and time-varying measures of perceived tariff uncertainty.

Our results show that regions and sectors that were *ex ante* more exposed to the possible introduction of MFN tariffs in the future reduced online hiring after the referendum relative to less exposed regions and sectors. The most exposed UK Travel to Work Area (TTWA), relative to the least exposed, experienced a 17% decline in the posting of online job adverts in the period after the referendum. The relative decline in online hiring for more exposed regions and sectors continued in the period after the referendum and occurred when there was heightened uncertainty about future tariff arrangements with the EU. We develop a new measure of tariff uncertainty based on the Google search intensity for a composite of terms such as 'no deal Brexit'.

We show that the impact of tariff uncertainty was distinct from the impact of the exchange rate depreciation that followed the referendum and uncertainty about future immigration policy. While regions and sectors exporting more before the referendum with markets with which the pound experienced a greater depreciation experienced a relative increase in online hiring after the vote, trade uncertainty had an opposite, offsetting effect. There is some indicative evidence that regions with a higher *ex ante* employment share of EU and specifically EU8[1] nationals differentially increased hiring after the vote, but this effect disappears after controlling for regional exposure to the exchange rate depreciation, suggesting that regions with a high pre-vote employment share of EU nationals were also those that were most affected by the exchange rate depreciation.

Our results suggest that uncertainty around trade policy, and not only actual policy changes, has an important negative impact on labour markets. Our contribution to the literature consists of several elements. First, we offer novel evidence linking policy uncertainty to labour demand through online hiring. There is a substantial literature showing that uncertainty affects investment, growth and employment. Bloom (2009) for example, develops a theoretical model whereby macro uncertainty shocks produce a rapid drop and rebound in aggregate output and employment because higher uncertainty causes firms to temporarily pause their investment and hiring[2]. We demonstrate empirically that this holds for online hiring, and the response is relatively immediate.

We also contribute to the expanding literature looking specifically at trade policy uncertainty (Pierce and Schott (2016); Crowley, Meng and Song (2018); and Handley and Limo (2017). While these papers typically study the effect of trade policy uncertainty on trade and investment, we add to this literature by consid-

[1]The EU8, also referred to as A8, countries are a group of eight of the 10 countries that joined the European Union during its 2004 enlargement. They are commonly grouped together separately from the other two states that joined in 2004, Cyprus and Malta, because of their relatively lower per capita income levels in comparison to the EU average.They are the Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Slovakia and Slovenia.

[2]For a review of the theoretical literature, see Dixit and Pindyck (1994). For a recent review of some of the empirical literature, see Baker, Bloom and Davis (2016)

ering how trade and investment feed through to hiring and labour markets. Two recent papers that have studied the economic consequences of the uncertainty surrounding Brexit are Crowley, Exton and Han (2018) and Graziano, Handley and Limo (2018). The former paper studies firm entry and exit from foreign markets, using a difference in difference approach comparing firms that are differentially exposed to potentially high "threat-point" tariffs, before and after the referendum. The latter paper concentrates on uncertainty pre-referendum and its impact on the value of bilateral trade. Our approach adds a higher frequency of outcome variable, which stretches much closer to the present day (end of Q2 2019) and includes the whole of the renegotiation period.

Our paper also contributes to a growing body of research on the economic impacts of the Brexit referendum. We add new evidence on another important way in which the Brexit vote affected the UK economy through its impact on labour markets. Costa, Dhingra and Machin (2019) also study the Brexit referendum and show that that devaluation of the pound sterling on the night of the referendum resulted in a negative effect on worker salaries and training post-referendum. We follow their method to control for the impact of exchange rate changes and confirm that the exchange rate depreciation has also had a meaningful impact on online hiring and this is distinct to the impact of tariff uncertainty. Our findings also support and explain the work of Bloom et al. (2019), who show that more productive, internationally exposed, firms have been more negatively impacted by the uncertainty caused by the anticipation of Brexit than less productive domestic firms.

Finally, we contribute to a growing literature using realtime labour market data, such as online job adverts, to study labour markets (Hershbein and Kahn (2018) Deming and Noray (2018), Deming and Kahn (2017)). This paper proceeds as follows: Section 1 provides background information on the referendum, Section 2 outlines the empirical strategy, Section 3 summarises the data sources used, Section 4 presents the results and Section 5 concludes.

I. Background on the Brexit Referendum

On the 23rd January 2013 David Cameron committed to hold a referendum on the UK's membership of the European Union if his party won the next general election. This promise introduced a period of uncertainty about the future trade policy between the UK and the EU. Table 1 outlines some of the key dates in the Brexit process. The referendum date was eventually announced in February 2016 and the UK electorate voted in the referendum over whether or not to leave the European Union on the 23rd June 2016. While the uncertainty began in 2013, the result of the referendum came as a big surprise to many observers: betting markets had placed the likelihood of a leave outcome at around 30% for most of the preceding year and in the 24 hours following the referendum the pound-dollar exchange rate fell by 8 percent, Sterling's biggest one day loss since the introduction of free-floating exchange rates in the 1970s, reflecting the adjustment of the markets to the outcome of the referendum.

In the event of Britain leaving the EU, UK firms trading with the EU faced two main potential future trade arrangements with different tariff schedules. One scenario was that the UK would retain tariff free access to the EU Customs Union, while on the other end of the spectrum there was the possibility that the UK would trade with the EU under the EUs WTO tariff schedule and pay MFN tariffs. Prior to the referendum, and indeed throughout the negotiation period, it was unclear which of these outcomes would be realised and so firms had to infer the probability of an MFN outcome from political signals. The EU is the UK's largest trade partner and so future MFN tariffs would have a non-trivial impact on UK firms: in 2014, the 27 other EU members accounted for 45 percent of exports and 53 percent of imports (Dhingra et al., 2017).

In the initial period after the referendum, it was proposed, although still with a substantial degree of ambiguity, that the UK would leave the single market and then trade on the basis of a new free trade agreement without regulatory alignment but with the majority of goods being traded without being subject to tariffs. The challenges of the Irish border subsequently came to the fore, specifically how to manage different regulatory regimes without having a physical (or "hard") border and potentially undermining key elements of the Good Friday Agreement. The EU insisted on introducing a "backstop" into the transition agreement, negotiated by Theresa May, to ensure that, in the absence of mutually agreed solution to managing the border, at least Northern Ireland would remain in the customs union of the EU. At this point the probability of an MFN outcome was therefore generally seeming low. However, this transition agreement failed three times to pass through parliament and Theresa May hence gave official notice of her resignation on the 24th May 2019.

Boris Johnson was subsequently elected as the new leader of the Conservative Party, showing strong support for a 'no deal' Brexit. On June 25th 2019 he stated "We are getting ready to come out on 31 October, do or die"[3], once again raising the perceived probability of an MFN outcome[4].

II. Empirical Strategy

A. Baseline specification

Our baseline specification estimates the impact of the uncertainty surrounding Brexit on online hiring in UK local labour markets as a function of a labour market's exposure to future MFN tariffs. Our analysis uses UK Travel to Work

[3]https://www.theguardian.com/politics/2019/jun/25/brexit-boris-johnson-britain-will-leave-eu-31-october-do-or-die

[4]Brexit also created uncertainty for services sectors. However, because we are unable to quantify it, we will not take it into account in our analysis. Thus our results could be considered to be a lower bound on the true effect.

Table 1—Brexit Timeline

Date	Event
23rd January 2013	David Cameron declares he is in favour of an EU referendum
14th April 2015	Launch of the Conservative Party Manifesto for the 2015 General Election, committing to hold an in-out referendum on our membership of the EU before the end of 2017
7th May 2015	Election of Cameron on Manifesto containing referendum promise
7th September 2015	European Union Referendum Act passed in parliament
20th Feb 2016	Date of referendum confirmed
23rd June 2016	EU Referendum
13th July 2016	Cameron steps down, Theresa May becomes Prime Minister
29th March 2017	Invocation of Article 50
8th June 2017	Snap General Election
15th January	First failed vote on withdrawal deal
16th January 2019	Government wins vote of no confidence
12th March 2019	Second failed vote on withdrawal deal
14th March 2019	Vote to request extension of Article 50 (to 12th April if no deal agreed or 22nd May if deal agreed)
29th March 2019	Third failed vote on withdrawal deal and originally planned leaving date
10th April 2019	The UK and EU27 agree to extend Article 50 until 31st October 2019
24th May 2019	Theresa May gave official notice of her resignation
24th June 2019	Boris Johnson elected Prime Minister by conservative party members

Source: Brexit timeline: events leading to the UKs exit from the European, Commons Briefing papers CBP-7960, Nigel Walker, https://researchbriefings.parliament.uk/ ResearchBriefing/Summary/CBP-7960

Areas (TTWAs)[5] as our statistical unit, which are areas that aim to reflect the geographic region where the population would generally commute to a larger town, city or conurbation for the purposes of employment. This work hence builds on the literature on local labour markets pioneered by Autor et al. (2014), who studied the exposure of US commuting zones to future Chinese imports. We estimate the following model:

$$postings_{rt} = \beta_0 + \beta_1 tariff\_threat_r \times post\_vote_t + \gamma_t + \gamma_r + \epsilon_{rt} \tag{1}$$

where $postings_{rt}$ are the total number of online job adverts posted in month-year t and region r, $post\_vote_t$ is a dummy variable for the time period after the referendum and $tariff\_threat_r$ is a measure of the exposure of TTWA r's labour force to future MFN tariffs with the EU, defined as:

$$tariff\_threat_r = \sum_{j \in r} \frac{employment_{rj,2015} \times tariff\_threat_{j,2014}}{\sum_{j \in r} employment_{rj,2015}} \tag{2}$$

[5]Travel to Work Areas are defined by the Office for National Statistics using census data for commuting between wards, based on the different locations of individuals' home and work addresses. See here: https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/articles/traveltoworkareaanalysisingreatbritain/2016

where $employment_{rj,2015}$ is aggregate employment in TTWA r in industry j in 2015 and $tariff\_threat_{j,2014}$ is a measure of SIC4 industry j's exposure to future EU MFN tariffs based upon the level of these tariffs in 2014. In other words, we use the pre-referendum industrial structure of a region to infer the potential impact of trade policy changes.[6] The total employment within each TTWA (the denominator) is calculated to include service sectors where each service sector is allocated a value of zero for the tariff threat.[7] The construction of this industry level tariff exposure measure is outlined in the Data section below.

B. Time-varying trade policy uncertainty

The outcome of the referendum introduced a large overnight increase in uncertainty about future trade policy between the UK and EU. However, the degree of uncertainty continued to vary substantially in the period after the referendum as political events unfolded. We therefore also explore how time-varying measures of uncertainty surrounding tariff arrangements with the EU affected online hiring in regions more, relative to less, exposed to the future MFN tariffs. We consider the following specification:

$$postings_{rt} = \beta_0 + \beta_1 tariff\_threat_r \times tariff\_uncertainty_t + \gamma_t + \gamma_r + \epsilon_{rt} \tag{3}$$

where $tariff\_uncertainty_t$ is a of MFN tariff uncertainty, defined based on a composite of Google Trends results and explained in the Data section below.

C. Immigration policy uncertainty

The Brexit referendum also introduced uncertainty surrounding other areas of engagement with the EU. Immigration was a central theme of the Leave campaign and was one of the policy areas given priority during the negotiation period. The referendum result introduced substantial uncertainty surrounding freedom of movement of people between the UK and EU and the ability of UK firms to employ EU nationals. We therefore introduce an additional control for a TTWA's share of employment of EU nationals and EU8[8] nationals in the pre-referendum period, interacted with the post referendum dummy. We hypothesise that firms relying on EU workers may react to increased uncertainty about the ability to import

[6] Ideally we would like to use 2014 for both, but the regional data at our disposal start only in 2015.

[7] Although Brexit created uncertainty about future treatment of UK services providers by the EU, we are unable to quantify the magnitude of this threat and therefore it does not enter our analysis.

[8] 1The EU8, also referred to as A8, countries are a group of eight of the 10 countries that joined the European Union during its 2004 enlargement. They are commonly grouped together separately from the other two states that joined in 2004, Cyprus and Malta, because of their relatively lower per capita income levels in comparison to the EU average.They are the Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Slovakia and Slovenia.

workers in the future by hiring more aggressively in advance of the referendum date.

D. Accounting for the exchange rate depreciation

One of the most notable immediate impacts of the EU referendum was the large overnight depreciation of the pound with respect to the dollar and euro, the magnitude of which speaks to the unexpected nature of the referendum results. UK firms are likely to have been affected by this depreciation, both through increased cost of imported inputs, and through increased competitiveness of export products. The depreciation was also not equal with respect to different currencies, for example, the pound-dollar exchange rate fell by 8 percent overnight on June 23/24 while the pound-euro exchange rate fell by 6 percent. Since imports and exports differ in their source and destination countries, industries trading in different world markets faced a different sterling depreciation. The differential cost and revenue shocks from these country specific variations in the unexpected sterling depreciation therefore affected industries differentially (Costa, Dhingra and Machin, 2019). If these sector-specific changes across time are correlated with the threat of MFN tariffs then we may be concerned that our key estimated impact is biased.

Following Costa, Dhingra and Machin (2019), we include controls for the sector-specific (2-digit SIC) exposure to the exchange rate depreciation both in terms of exports and imported inputs,[9] interacted with a post_vote dummy. These controls are constructed as follows:

Intermediate import weighted exchange rate change (where the depreciation corresponds to a *negative* value):

$$\hat{E}_o^M \equiv \sum_i \sum_{s \neq uk} S_{sio} \hat{E}_s$$

Export weighted exchange rate change (where the depreciation corresponds to a *positive* value):

$$\hat{E}_o^X \equiv - \sum_{d \neq uk} S_{dxo} \hat{E}_d$$

Where s indexes the source country for imported inputs, d the destination country for exports, o the sector, i imports, and x exports. $\hat{E}_s$ is the change in the exchange rate between the pound sterling and source country currencies, and $\hat{E}_d$ is similarly defined but for destination country currencies. S_{sio} and S_{dxo} are the sector-specific shares of imports and exports respectively coming from specific sources/destinations. A depreciation of the pound with respect to any currency would lead to a negative value for $\hat{E}_s$ or $\hat{E}_d$ and, as long trade is concentrated

[9] We are very grateful to Swati Dhingra for sharing the data with us.

among partner countries for which there was indeed a depreciation, this should lead to a negative value for $\hat{E}_s^M$ (more expensive imported inputs) and a positive value for $\hat{E}_d^X$ (more competitive exports). We would therefore expect a positive coefficient for both variables when they are included as controls in our baseline sector specification.

E. Alternative approach

In addition to looking at local labour markets, we also consider the impact of trade policy uncertainty on online hiring at the industry level. The local labour market approach relies on using the sectoral composition of employment in each TTWA in 2015. While we shouldn't expect much change in the composition of employment prior to the referendum because the result was largely unanticipated, there is a chance that labour markets adjusted in the wake of the announcement to hold the referendum in February 2015. Ideally we would use the sectoral composition from prior to 2015, but as discussed in the data section, the coverage of the data is less comprehensive prior to 2015. Given we are studying relatively small regional units, this could lead to inaccurate results. We therefore also conduct the analysis at the SIC4 industry level and explore whether the same results hold. The quality of the industry classification of the job adverts is lower than the classification by TTWA, however, and so we do not use the analysis at the industry level as our baseline approach.

F. Threats to identification

The primary threat to identification is omitted variable bias, that is to say region-time varying factors that affect job postings and are correlated with both $post\_vote_t$ and $tariff\_threat_r$. Any shared trends or time invariant regional factors are of course controlled for with the region and time fixed effects.

A potential concern is the the EU MFN tariffs are high in declining industries because the EU is trying to slow down the process of job losses. If some UK regions in our analysis are dominated by such declining industries, we might mistakenly attribute their worsened job market performance to the Brexit shock. This concern is attenuated by the fact that these tariffs are negotiated at the supranational level, the UK doesn't have direct control over the specific industries that get protected, although it may be able to achieve protection either through effective negotiation, or through shared interests with other EU states.

We focus on the 2014 tariffs for two reasons. First, we want to avoid the unlikely possibility that the EU might be strategically adjusting its MFN tariffs in anticipation of the possibility of Brexit. Second, as our analysis will also use a trade-weighted tariff measure hence we want to avoid the possibility of trade flows being affected by the referendum results.[10]

[10]We could also be worried about other time varying factors that may be impacting sectors in different

III. Data

A. Online job adverts

We use data collected by Burning Glass Technologies (BGT), a private sector firm that scrapes what they claim to be the quasi-universe of UK online job postings on a daily basis.[11] These postings are sourced from more than 40,000 online job boards and company websites, with a total over over 60 million UK job adverts over the period 2012-2019. BGT classify the job adverts by TTWA, Local Authority District, and region. They also use machine learning techniques to classify the adverts by SIC (Standard Industrial Classification) codes, SOC (Standard Occupational Classification) codes and skill clusters. In addition they clean the data and remove duplicate posts.

Over the period January 2014 to June 2019, a total of 43,910,278[12] postings are observed in the data, which translates into an average of 7,983,686 per year. The postings cover 641 different SIC codes at the 4-digit level, and 225 travel to work areas across the UK. Of the total sample of job postings 76% are classified with a TTWA.

The dotted blue line in Figure 1 displays a three-month running average of the monthly postings, with a vertical red dotted line indicating the month of the referendum. The change in gradient between the pre- and post-referendum trend provides a stark motivating visual for the impact of Brexit vote on private sector job postings. Of course, the exact placement of the change in trend can be disputed and there were many other concurrent changes in the British economy over this period, however we take this as a reasonable starting point for our investigation.

B. UK Regional Employment Composition

We use data from the UK Business Register and Employment Survey (BRES) for 2015 that contains a breakdown of employment by SIC4 industry within each TTWA in the UK. The UK has 228 travel to work areas (TTWA).[13] The current criteria for defining TTWAs are that at least 75% of the area's resident workforce

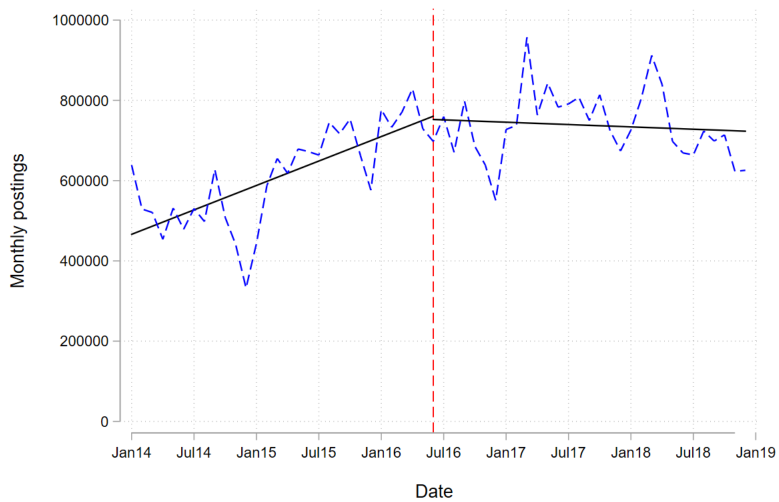
ways such as exchange rate fluctuations, global market trends, declining or emerging sectors, interest rates etc. A priori, however, it's not obvious that these factors should be meaningfully correlated with both the sectoral tariff threat and the pre/post vote timeline.

[11]Carnevale, Smith and Strohl (2013) have shown that online job vacancy data is strongly correlated with data on total vacancies. Hershbein and Kahn (2018) estimate, for the United States, that approx. 85% of all jobs posted online and those posted online are biased to higher skilled and white collar jobs. Online job adverts therefore do not provide a complete picture of the entire labour market, but can provide a useful barometer on labour market demand.

[12]Only 14,367,642 have non-missing SIC codes however, equivalent to 2,612,299 postings on average per year.

[13]A Travel to Work Area or TTWA is a statistical unit used by UK Government agencies and local authorities, especially by the Department for Work and Pensions and Jobcentres, to indicate an area where the population would generally commute to a larger town, city or conurbation for the purposes of employment.

Figure 1. Monthly Job Postings



Note: Three-month moving average of number of job postings including all postings recorded by BGT.
Source: Job postings data: Burning Glass Technologies (BGT).

work in the area and at least 75% of the people who work in the area also live in the area. The area must also have an economically active population of at least 3,500. TTWAs range in population size from 6,800 to 8.4 million. BRES collects employment information from businesses across the whole of the Great Britain economy for each site that they operate. The Department of Finance and Personnel Northern Ireland (DFPNI) collects the same BRES information independently in Northern Ireland. Both data sources are then combined to produce estimates on a UK basis.

BRES surveys approximately 85,000 businesses. As it is a business survey, the quality of the industry classifications is preferable to industry data from household surveys such as the Annual Population Survey, which we use for the immigration controls. We ideally would like to use the employment composition before there was any possibility of Brexit. However, the sampling of BRES changed in 2015 so substantially improve its coverage by including business units with a single Pay As You Earn (PAYE) code for which no Value Added Tax (VAT) data are available. Prior to 2015, such units were excluded from the sampling frame and thus we choose to use 2015 data for the employment weights. We consider all employed individuals in a TTWA. An employee is defined as anyone aged 16 years or over that is paid directly from the payroll, in return for carrying out a full-time or part-time job or being on a training scheme. Employment includes employees plus the number of working owners who receive drawings or a share of the profits. For 2015 the BRES data includes 28.5 million employees, 91% of the total UK labour force as estimated by the ONS.[14]

C. Exposure to MFN Tariffs

The tariffs used in the analysis are taken from World Integrated Trade Solution (WITS), and we select the applied Most Favoured Nation (MFN) tariffs that the EU applies to imports coming from the rest of the world (excluding countries with which the EU has preferential trading arrangements). The data are aggregated at the 6-digit level of the Harmonised System (HS6) and contain the simple average of tariffs across higher levels of disaggregation as well as the number of sub-tariff lines. We match these tariffs to imports of the EU-27[15] from the UK at the HS6 level and then match the combined dataset with SIC codes at the 4-digit level using a crosswalk provided by WITS.[16]

From there we can aggregate the tariffs to the sectoral level using both a simple average across tariff lines, and a trade weighted average.

Simple average tariff threat:

$$tariff\_threat_{j,2014} = \frac{1}{n_j} \sum_{p \in j} \tau_{p,2014}$$

Trade weighted average tariff threat:

$$tariff\_threat_{j,2014} = \sum_{p \in j} \frac{X_{p,2014}\tau_{p,2014}}{\sum_{p \in j} X_{p,2014}}$$

Where j indexes sectors, p products at the HS6 level, n_j the number of HS6 level products associated to production in sector j, $\tau_{p,2014}$ represents the simple average 2014 tariff rate at the HS6 level (as a percentage), and $X_{p,2014}$ exports from the UK to the EU-27 of a particular HS6 product in 2014.

The tariff data aggregates up to 442 sectors, all except one of which provide positive exports to the EU. Figure 2 displays histograms of both average tariff measures across sectors. Taking the simple average, 19% of sectors have an average tariff of zero, 56% have tariffs greater than zero and smaller than or equal to

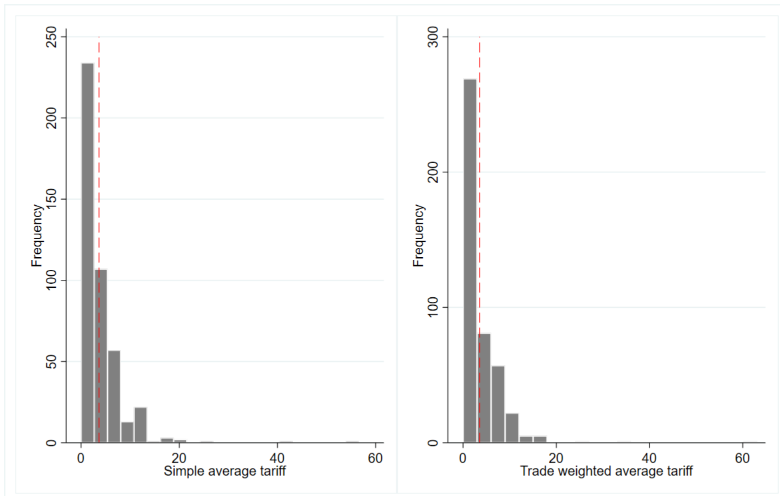
[14] https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/bulletins/uklabourmarket/2015-07-15

[15] Excluding the UK. This analysis could be extended to include UK exports to countries with preferential trade agreements with the EU although this significantly complicates the analysis and the figures are second order relative to trade with other EU members. We focus on imports are they are likely to be more reliably recorded than exports.

[16] The H2007 to SIC crosswalk can be found here: http://wits.worldbank.org/WITS/WITS/Support%20Materials/CMTNomenclatureandConcordancesList.aspx?Page=ProductNomenclatureandConcordances. This must be connected to the H2012 nomenclature in order to match the trade and tariff data. We therefore use a H2007 to H2012 crosswalk available here: https://unstats.un.org/unsd/trade/classifications/correspondence-tables.asp. We use pre-determined data from 2014 to avoid endogeneity concerns.

5, 18% have tariffs between 5 and 10, and 8% of sector have rates greater than 10. The mean tariff rate across all sectors is 3.7, with a maximum of 56.6 and a standard deviation of 4.8. These descriptive statistics are broadly similar for the trade weighted average.

Figure 2. Sectoral distribution of average tariffs



Note: 442 SIC sectors at the 4-digit level. Mean across sectors denoted by vertical red dotted line.
Source: Tariff data: World Integrated Trade Solution (WITS). Trade data: UN Comtrade. HS6-SIC crosswalk from WITS and UN.

D. *Combining TTWA Job Postings and Tariff Data*

The job postings data can be mapped to the tariff threat data either through TTWAs or sectors. We map the job postings to BRES data based on TTWA name. When mapping to TTWAs, there are 3 TTWAs in the BRES data that have no job postings in the BGT data and so we do not include these in the analysis. In addition our analysis excludes job postings that have not been possible to classify by TTWA.

E. *Combining Sectorsl Job Postings and Tariff Data*

When mapping by sectors the job postings data covers 805 sectors at the SIC 4-digit level, whereas the tariff data covers 442 sectors. There are 81 sectors that are present in both datasets, 724 that are present in the BGT data but not in the tariff data, and 361 that are present in the tariff data but not in the BGT data. The first of these categories represents sectors for which there is positive hiring over the period and the associated goods produced are in principal tradable. The second category can be considered as non-tradables with positive job postings. The third category contains sectors that can be traded but for which there are no associated job postings. This last category may include products that are exported from the UK to the EU but which are not produced in the UK, and hence are dropped from our sample. Non-tradable sectors are assigned a value of zero for the average tariff threat as they should not be directly affected by the tariffs (although they may be indirectly affected).

F. Measures of Trade Policy Uncertainty

Our objective is to estimate the response to changes in beliefs about the likelihood that UK firms will be subject to MFN tariffs when trading with the EU. Since we do not directly observe firm-level beliefs about tariffs, we develop proxies that reflect uncertainty about the future tariff arrangements with the EU.

Our first approach is to use Google searches that reflect public attention and concern surrounding the form and consequences of Brexit. Google Trends[17] provides public information on the Google searches conducted within a given region over time. The tool adjusts search data to make comparisons between terms easier, with search results being proportionate to the time and location of a query according to the following process: Each data point is divided by the total searches of the geography and time range it represents to compare relative popularity (otherwise, places with the most search volume would always be ranked highest). The resulting numbers are then scaled on a range of 0 to 100 based on a topics proportion to all searches on all topics. Different regions that show the same search interest for a term dont always have the same total search volumes.

We use searches within the UK for four specific terms: 'no deal Brexit', 'hard Brexit', 'Brexit tariffs' and 'EU trade'. We use the composite of these terms because the vocabulary used to describe Brexit evolved over the course of the period following the referendum as the political events unfolded. The term 'hard Brexit' first appeared in Google searches in 2015 and search intensity peaked in June 2016. 'No deal Brexit', on the other hand, first appeared in Google searches in March 2017 and peaked in March 2019. We also use the term 'Brexit tariffs' to reflect general concern surrounding changing tariffs after Brexit and 'EU trade' to encompass broader concern about trade with the EU.[18]

[17]https://trends.google.com/trends

[18]We considered other options for measuring trade policy uncertainty under Brexit. One option was to follow the approach in papers such as that by Graziano, Handley and Limo (2018) and use prediction markets to gauge uncertainty. These authors use the average daily price of a contract traded in PredictIt.org paying $1 if a majority voted for Brexit in the referendum as a measure of pre-referendum trade policy uncertainty. However, betting markets tend to release contracts on narrowly defined questions over a limited period of time. Since we aim to measure the perceived probability of firms facing MFN tariffs over the entire pre-and post-Brexit period, this type of measure was not feasible. Public polling was an additional option, but few polls asked the same question over time.

G. *Immigration data*

To measure the employment share of EU and EU8 nationals in a TTWA we use data from the Annual Population Survey (APS). The APS is a continuous household survey, covering the UK, with the aim of providing estimates between censuses of main social and labour market variables at a local area level. The APS is not a stand-alone survey, but uses data combined from two waves of the main Labour Force Survey (LFS) with data collected on a local sample boost. The datasets comprise 12 months of survey data and are disseminated quarterly. The achieved sample size is approximately 320,000 respondents. The APS is the most comprehensive source of data on employment by nationality of workers and is typically used for research on immigration in the UK. The data provide a breakdown of the share of employment of EU and EU8 nationals in each region and SIC2 industry. We use data on the SIC2 employment composition of each TTWA in a given region to construct the employment share measures.

IV. Baseline Results

Table 2 displays the results from specifications (1) and (2) for local labour markets. Columns 1 and 5 display the coefficients on the interaction term between the post vote dummy variable and the TTWA simple average and trade weighted tariff exposure measures, respectively. The coefficients are negative and strongly significant, showing that online hiring decreased differentially more in regions more exposed to future MFN tariffs after the referendum. For example, for the simple average tariffs, a one standard deviation (5.85 percentage points) increase in a TTWA's employment weighted pre-referendum exposure measure is associated with a decrease in postings by approximately 1.7% in the post-referendum period relative to the pre-referendum period. For the trade-weighted exposure measure the results are very similar: a one standard deviation (6.4 percentage points) increase in the exposure measure is associated with a 1.86% decrease in job postings in the post-referendum period relative to the pre-period.

Table 2 also displays results using the trade uncertainty proxy. Columns 2 and 6 display the interaction between the combined measure of monthly google searches for the four terms of 'no deal Brexit', 'EU trade', 'Brexit tariffs' and 'hard Brexit' and the MFN exposure meaures. These columns also show a negative (weakly) significant effect. In terms of magnitude, for the combined search effect for simple average tariffs, a one standard deviation (15 percentage point) increase in search intensity was associated with a 3.2% decrease in postings for TTWAs with a one standard deviation (5.8 percentage points) higher exposure measure.

A. *Controlling for the exchange rate depreciation*

Columns (3), (4), (7) & (8) in Table 2 also show the results when also controlling for the impact of the exchange rate. The coefficients increase in size and remain negative and statistically significant. As is expected, sectors which face

Table 2—Local labour markets: uncertainty measures plus exchange rate changes.

A: Simple average tariff	(1)	(2)	(3)	(4)
tariff exposure * post vote	-0.298***		-0.404***	
	(0.079)		(0.086)	
tariff exposure * combined searches		-0.372*		-0.410*
		(0.211)		(0.214)
import appreciation * post vote			72.728***	44.311**
			(20.877)	(19.477)
export depreciation * post vote			77.495***	48.695**
			(20.982)	(19.556)
Observations	11,880	12,100	11,556	11,556
Adjusted R-squared	0.984	0.984	0.984	0.984
TTWA & Month FE	YES	YES	YES	YES

B: Trade weighted average tariff	(5)	(6)	(7)	(8)
tariff exposure * post vote	-0.292***		-0.379***	
	(0.070)		(0.075)	
tariff exposure * combined searches		-0.374**		-0.400**
		(0.182)		(0.185)
import appreciation * post vote			70.548***	44.187**
			(20.581)	(19.455)
export depreciation * post vote			75.328***	48.574**
			(20.684)	(19.534)
Observations	11,880	12,100	11,556	11,556
Adjusted R-squared	0.984	0.984	0.984	0.984
TTWA & Month FE	YES	YES	YES	YES

Note: Robust standard errors in parentheses, ***p<0.01, ** p<0.05, * p<0.1. 11,880 observations covering 220 TTWAs over a period of 54 months.

Table 3—Local labour markets: Uncertainty measures plus immigration and exchange rate measures

A: Simple average tariff	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
tariff exposure * post vote	-0.296***		-0.405***		-0.304***		-0.404***	
	(0.079)		(0.085)		(0.080)		(0.085)	
tariff exposure * combined searches		-0.327		-0.411*		-0.332		-0.410*
		(0.214)		(0.215)		(0.214)		(0.214)
EU national share * post vote	0.876***	0.777**	0.331	0.320				
	(0.316)	(0.316)	(0.316)	(0.316)				
Eastern EU national share * post vote					1.181**	0.912*	-0.063	-0.087
					(0.492)	(0.488)	(0.525)	(0.526)
import appreciation * post vote			69.086***	40.749**			73.581***	45.498**
			(21.335)	(19.936)			(22.870)	(21.516)
export depreciation * post vote			73.607***	44.894**			78.378***	49.924**
			(21.492)	(20.069)			(23.077)	(21.702)
Observations	11,556	11,556	11,556	11,556	11,556	11,556	11,556	11,556
Adjusted R-squared	0.984	0.984	0.984	0.984	0.984	0.984	0.984	0.984
TTWA & Month FE	YES	YES	YES	YES	YES	YES	YES	YES
B: Trade weighted average tariff	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**	**(15)**	**(16)**
tariff exposure * post vote	-0.286***		-0.379***		-0.294***		-0.379***	
	(0.070)		(0.075)		(0.070)		(0.075)	
tariff exposure * combined searches		-0.326*		-0.399**		-0.331*		-0.400**
		(0.185)		(0.185)		(0.184)		(0.185)
EU national share * post vote	0.854***	0.774**	0.300	0.316				
	(0.316)	(0.316)	(0.316)	(0.316)				
Eastern EU national share * post vote					1.147**	0.908*	-0.108	-0.093
					(0.489)	(0.488)	(0.526)	(0.526)
import appreciation * post vote			67.155***	40.656**			72.024***	45.453**
			(21.087)	(19.918)			(22.669)	(21.503)
export depreciation * post vote			71.710***	44.807**			76.856***	49.886**
			(21.245)	(20.051)			(22.877)	(21.690)
Observations	11,556	11,556	11,556	11,556	11,556	11,556	11,556	11,556
Adjusted R-squared	0.984	0.984	0.984	0.984	0.984	0.984	0.984	0.984
TTWA & Month FE	YES	YES	YES	YES	YES	YES	YES	YES

Note: Robust standard errors in parentheses, ***p<0.01, ** p<0.05, * p<0.1. 11,880 observations covering 220 TTWAs over a period of 54 months.

particularly high increases in imported input prices, and were less impacted in the increasing attractiveness of their export products, employed fewer workers post referendum. Taking column (2), for example, a one s.d. increase in the import appreciation measure (0.004) increased postings by approximately 29%.

B. *Immigration policy uncertainty*

We also explore how uncertainty about immigration policy with the EU affected online hiring. Table 3 displays the results for tariff uncertainty when also including the interaction term between the post referendum dummy and a TTWA's pre-vote employment share of EU and EU8 (here we denote EU8 as EEU since all of the EU8 nations were in Eastern Europe) nationals and additionally when adding the exchange rate controls. The coefficients on the tariff uncertainty-post vote interactions (columns (1), (5), (9) & (13)) remain statistically significant and negative in all of these specifications and controlling for immigration does not have much impact on the magnitude of the coefficients. Columns (1)=(2) and (9)-(10) show the results when adding the interaction term between the post vote dummy and the EU national share of a TTWA in 2015. The coefficients on this interaction term are positive, suggesting that TTWA's with a higher share of EU nationals employed in 2015 differentially increased hiring after the referendum relative to TTWA's employing a lower share of EU nationals. The magnitude of these coefficients is quite substantial, taking column (1) as an example, a 1 s.d. increase in thee EU national share (1.3%) led to a 1.4% increase in hiring. Columns 2 and 6 show the results including this interaction term but only for employment of EU8 nationals. The coefficients are even higher and remain strongly significant.

These results are consistent with at least two possible interpretations. First, firms are attempting to employ more immigrant workers before the UK leaves the EU so that these workers with be able to stay longer term under pre-settlement status (designed for EU national working in the UK for less than 5 years at the date the UK leaves the EU)[19]. Alternatively, firms could be replacing immigrant workers from the EU who are leaving the UK in reaction to the Brexit vote (perhaps due to uncertainty, or a change in their experience in the UK). Unfortunately we are not able to tell whether immigrant works or UK nationals are being hired into the jobs being posted online.

Columns (3), (4), (7), (8), (11), (12), (15) & (16) additionally include the exchange rate controls. Adding these controls leads to the immigration measures losing significance, suggesting that areas with high EU immigration are also those affected by the exchange rate depreciation and it is perhaps not immigration that is having the effect on online hiring but the exchange rate.

[19]The cutoff seems to be the day of leavings so any workers migrating right up until the final day with be afforded these rights. https://www.gov.uk/settled-status-eu-citizens-families

V. Alternative Approach - Sectoral Analysis

A. Baseline sectoral results

An alternative to the regional analysis is to focus on the sectoral impact of trade uncertainty. The specification is very similar to that used in the regional analysis, however the variation now is at the sector-time level, with sector fixed effects replacing the regional fixed effects. These results should be viewed as an additional check to the TTWA results because of the limited accuracy of the sectoral classification of the job adverts, resulting in a high proportion of missing values for sectors.

The results using postings by sector rather than TTWA are similar with similar implications. The coefficients are negative and significant (except in column (9)), supporting the hypothesis that uncertainty over the possibility of facing MFN tariffs has affected firms' hiring decisions. In terms of magnitude, taking column (1) as an example, a one standard deviation increase in tariff exposure (2.88 percentage points) reduced monthly sectoral job postings by an average of 7.8 relative to the pre-referendum level. To put this in context, the mean number of monthly sectoral job postings over the period was 270.4 so this impact represents roughly a 2.88% decrease.

As in the section using TTWA variation, we can interact the tariff threat with a time varying measure reflecting uncertainty about future tariff levied on UK trade with the EU. The results are presented in Table 4, remains negative and significant for the OLS and PPML specifications, but not for the log specification.

The results in Table 5 show that sectors which faced particularly high increases in imported input prices, and were less impacted in the increasing attractiveness of their export products, employed fewer workers post referendum. Our main results on tariff exposure are robust to the inclusion of exchange rate effects.

VI. Conclusion

In this paper we exploit the product-level variation in EU MFN tariffs that would be placed upon UK trade with the EU under a Brexit scenario without a trade deal, to explore how trade policy uncertainty affects online hiring and local labour markets. We use a high frequency dataset consisting of online job adverts posted in the UK between 2014 and 2019, to track the real-time response of UK firms to tariff uncertainty as the political events unfolded. We show that areas more exposed to the threat of future tariffs on their trade with the EU decreased online hiring substantially more than regions less exposed, after the referendum result. The most exposed TTWA, relative to the least exposed, experienced a 17% decrease in online job adverts in the period after the vote.

The relative decline in online hiring in tariff exposed regions occurred during periods when there were peaks in google searches for terms such as 'no deal

Table 4—Baseline results for sectoral analysis.

VARIABLES	OLS		ln(postings+1)		PPML	
A: simple average tariff exposure						
	(1)	(2)	(3)	(4)	(5)	(6)
tariff exposure* post_vote	-2.705***		-0.002*		-0.026***	
	(0.223)		(0.001)		(0.009)	
tariff exposure* combined searches		-0.023***		0.000		-0.001***
		(0.009)		(0.000)		(0.000)
Observations	52,325	47,495	52,325	47,495	41,470	37,524
Adj R-squared	0.924	0.932	0.961	0.963	0.951	0.957
Sector & Month FE	Y	Y	Y	Y	Y	Y
B: trade weighted tariff exposure						
	(7)	(8)	(9)	(10)	(11)	(12)
tariff exposure* post_vote	-2.561***		-0.001		-0.021**	
	(0.226)		(0.001)		(0.009)	
tariff exposure* combined searches		-0.024***		0.000		-0.002***
		(0.009)		(0.000)		(0.000)
Observations	52,325	47,495	52,325	47,495	41,470	37,524
Adj R-squared	0.924	0.932	0.961	0.963	0.951	0.957
Sector & Month FE	Y	Y	Y	Y	Y	Y

Note: Robust standard errors in parentheses, ***p<0.01, ** p<0.05, * p<0.1.

Table 5—Sector results with exchange rate controls

	OLS		ln(postings+1)		PPML	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
simple average tariffs* post_vote	-2.819***		-0.002**		-0.023**	
	(0.230)		(0.001)		(0.009)	
trade weighted tariffs* post_vote		-2.652***		-0.001		-0.018*
		(0.230)		(0.001)		(0.009)
import appreciation* post_vote	4,437***	4,429***	1.441	1.450	11.126***	11.121***
	(1,048)	(1,048)	(2.078)	(2.078)	(2.838)	(2.838)
export appreciation* post_vote	2,222***	2,216***	1.737***	1.731***	1.155	1.091
	(343.9)	(343.8)	(0.505)	(0.505)	(0.802)	(0.819)
Observations	47,645	47,645	47,645	47,645	39,260	39,260
Adj R-squared	0.920	0.920	0.957	0.957	0.953	0.953
Sector & Month FE	YES	YES	YES	YES	YES	YES

Note: Robust standard errors in parentheses, ***p<0.01, ** p<0.05, * p<0.1.

Brexit' and 'hard Brexit'. Additionally, the negative effect happened after key political events that signalled a greater chance of the UK leaving the EU without a trade deal. We show that these results are distinct from the impact of the exchange rate depreciation and uncertainty about future immigration policy. We therefore conclude that tariff uncertainty caused by the Brexit referendum and the renegotiation period has been an important factor in affecting the hiring decisions of UK firms. In addition to affecting trade flows and investment, trade policy uncertainty can evidently have a substantial negative effect on local labour markets.

REFERENCES

Autor, David H., David Dorn, Gordon H. Hanson, and Jae Song. 2014. "Trade Adjustment: Worker-Level Evidence*." *Quarterly Journal of Economics*, 129(4): 1799–1860.

Baker, Scott R., Nicholas Bloom, and Steven J. Davis. 2016. "Measuring Economic Policy Uncertainty." *The Quarterly Journal of Economics*, 131(4): 1593–1636.

Bloom, Nicholas. 2009. "The Impact of Uncertainty Shocks." *Econometrica*, 77(3): 623–685.

Bloom, Nicholas, Philip Bunn, Scarlet Chen, Paul Mizen, Pawel Smietanka, Greg Thwaites, and Garry Young. 2019. "Brexit and uncertainty: insights from the Decision Maker Panel." *Bank of England, Staff Working Paper No. 780*.

Carnevale, Anthony, Nicole Smith, and Jeff Strohl. 2013. "Recovery: Job Growth and Education Requirements Through 2020." *Georgetown Public Poliocy Institute, Center of Education and the Workforce*.

Costa, Rui, Swati Dhingra, and Stephen Machin. 2019. "Trade and Worker Deskilling." *CEP Discussion Paper Series*.

Crowley, Meredith, Ning Meng, and Huasheng Song. 2018. "Tariff scares: Trade policy uncertainty and foreign market entry by Chinese firms." *Journal of International Economics*, 114: 96–115.

Crowley, Meredith, Oliver Exton, and Lu Han. 2018. "Renegotiation of Trade Agreements and Firm Exporting Decisions: Evidence from the Impact of Brexit on UK Exports." 35.

Deming, David, and Kadeem Noray. 2018. "STEM Careers and the Changing Skill Requirements of Work." *NBER Working Paper Series*.

Deming, David, and Lisa B Kahn. 2017. "Skill Requirements across Firms and Labor Markets: Evidence from Job Postings for Professionals." *NBER Working Paper Series*, 33.

Dhingra, Swati, Hanwei Huang, Gianmarco Ottaviano, Joo Paulo Pessoa, Thomas Sampson, and John Van Reenen. 2017. "The costs and benefits of leaving the EU: trade effects." *Economic Policy*, 32(92): 651–705.

Dixit, Avinash K, and Robert S Pindyck. 1994. *Investment under uncertainty.* Princeton, N.J.:Princeton University Press. OCLC: 777593629.

Graziano, Alejandro, Kyle Handley, and Nuno Limo. 2018. "Brexit Uncertainty and Trade Disintegration."

Handley, Kyle, and Nuno Limo. 2017. "Policy Uncertainty, Trade, and Welfare: Theory and Evidence for China and the United States." *American Economic Review*, 107(9): 2731–2783.

Hershbein, Brad, and Lisa B. Kahn. 2018. "Do Recessions Accelerate Routine-Biased Technological Change? Evidence from Vacancy Postings." *American Economic Review*, 108(7): 1737–1772.

Pierce, Justin R., and Peter K. Schott. 2016. "The Surprisingly Swift Decline of US Manufacturing Employment." *American Economic Review*, 106(7): 1632–1662.