Online appendix

A. Data sources

1. Data used in the construction of Brexit exposure measures

Our analysis draws on data from several sources. We use the 2016 Business Structure Database (BSD) to measure the industrial composition of each local labour market. The BSD is an administrative dataset covering the employment, turnover and industry of all 'local units' (plants and offices) for UK firms whose turnover exceeds the threshold for VAT payments (£85,000 in 2016/17).

In 2004 the BSD was estimated to account for almost 99% of economic activity in the UK. Local labour markets are defined using the 228 Travel to Work Areas (TTWAs); geographical units analogous to American Commuting Zones. The boundaries of TTWAs are delineated by the Office for National Statistics (ONS) such that (in normal cases) i) at least 75% of workers in the TTWA also reside in that TTWA, and ii) at least 75% of those residing in the TTWA also reside in that TTWA.[1] Over time, the number of TTWAs has tended to fall as commuting distances have risen.

We take data on individual workers from the 2016 Annual Survey of Hours and Earnings (ASHE). ASHE is a 1% sample of employees aged 16 or older in Great Britain (the UK, excluding Northern Ireland), who earn above the lower earnings limit of the UK national insurance system (£112 per week in 2016/17).

We take information from the 2019 Quarterly Labour Force Survey (QLFS) to look at the characteristics of workers in different occupation groups. The QLFS is a nationally representative survey of UK households, interviewing all members aged 16 and over.

Information on industry exports and inputs comes from two sources. The first is the ONS Input-Output (IO) tables. These describe the sale and purchase relationships between industries, including the proportion of output each industry exports to the EU and their use of imported inputs. We use these tables to examine the effect of trade barriers on 102 different industries. The national IO tables do not record the source of imported inputs. In order to understand the degree to which industries specifically make use of EU inputs, we supplement the information contained in the IO tables with data from the 2014 World Input-Output Database (WIOD, see Timmer et al. (2015); Timmer et al. (2016) for detailed descriptions). This database was specifically developed for the purpose of analysing the sources of and uses of industries' inputs and output. We use the WIOD tables to separate out imported inputs by industry according to their country of origin. The industry headings in the WIOD tables are somewhat broader than those in the national input-output tables

[1] Areas must also have a minimum size of 3,500 economically active residents. Thresholds below 75% are sometimes accepted as part of a trade-off between ensuring areas have sufficient workforce size and defining self-contained areas.

(with 56 industries rather than 102), we assume that the split of intermediate inputs into imports from the EU and non-EU countries is the same for all industries covered by a given WIOD heading.

2. Data used in the construction of the left-behind index

Employment: Employment is taken from ONS Annual Population Survey and downloaded from the NOMIS website. Average of year to end of March, June, September and December 2019 16-64 employment rates, giving an average employment for 2019 before the Covid-19 crisis.

Formal education: Formal education is taken from ONS Annual Population Survey and downloaded from the NOMIS website. Jan – Dec 2019, percentage of the 16-64 population with NVQ4+ qualifications.

Pay: Annual Survey of Hours and Earnings, Office for National Statistics (2019a), Median weekly pay, gross, for all employee jobs. In 14 TTWAs, mostly in Scotland, pay data was missing at the median since this could be disclosive. However mean values were still reported, and so median values were imputed from these mean values and the country average of a TTWA.

Incapacity benefits: This data is from the Department for Work and Pensions and was downloaded from Stat-Xplore. Recipients of incapacity benefits as a proportion of the 2019 16-64 population in February 2020. Incapacity benefit claimants are those on either ESA (employment support allowance) or its universal credit (UC) equivalent. The UC equivalent of ESA is having the Limited Capacity for Work Entitlement (LCW or LCWRA). The UC LCW/LCWRA claimant total for February 2020 is added to the ESA recipient count for the 3 months to February 2020.

3. Data used in the Covid-19 impact index

Furlough rates: Furlough rates are from see HM Revenue and Customs (2021), Table 11. Proportion of those eligible for furlough furloughed in each local authority calculated from an average of numbers furloughed in November and December 2020 and total employments eligible for furlough. TTWA averages of numbers furloughed and eligible are constructed using an LA-TTWA lookup based on population weights aggregated from the MSOA level. For example, if 50% of an a TTWA's population reside in LA x, 30% in LA y and 20% in LA z, and subscript r denotes the furlough rate in that LA, the furlough rate of the TTWA would be calculated as $0.5x_r + 0.3y_r + 0.2z_r$. The averaging across November/December is then applied on a TTWA level.

Changes in unemployment: This data is from the Department for Work and Pensions and was downloaded from Stat-Xplore. The measured used is the Alternative Claimant Count (I).[2] Claimant count numbers for each MSOA are obtained. These are aggregated up to the TTWA level using an MSOA-TTWA lookup. Monthly figures for December 2019 to February 2020 and September 2020 to November 2020 are averaged to give pre-crisis and during-crisis numbers. These are divided by the

[2] The alternative claimant count is an experimental statistic produced by the Department for Work and Pensions. Standard claimant count figures are no longer reliable due to the uneven rollout of universal credit (UC). The alternative claimant count models what the claimant count would be if UC were present everywhere. Details of the methodology can be found at Department for Work & Pensions (2020).

TTWA 16-64 population to give a claimant count rate, and then the pre-crisis rate is subtracted from the during-crisis rate to give a change in unemployment.

Changes in job vacancy postings: Job vacancy statistics are from the Institute for Employment Studies (IES) Monthly vacancy analysis (see Papoutsaki and Wilson (2020a), (2020b) and (2020c)). The IES used real time data from job advertisement aggregator Adzuna to construct regular analysis of job vacancies over the pandemic, and in later months this was done on a local authority level. These have been validated against ONS analysis of the same data from which data on a regional level was produced.[3] We take the year on year change in job vacancy figures for weeks ending 9th August, 13th September and 11th October 2020 from Papoutsaki and Wilson (2020a), (2020b) and (2020c) respectively. We average these to get an average change in job vacancies year on year over these weeks by local authority. This are then transformed to TTWA figures using the LA to TTWA lookup method outlined above for furlough rates. Finally, the bottom 1% of areas, which saw the least decline in vacancies, are winsorised to remove extreme outliers that saw a more than 200% increase in job vacancies.

Employment in sectors closed in lockdown: Sectoral employment is taken from the ONS Business Register and Employment Survey (BRES) and downloaded from the NOMIS website. Counts of employees in the sectors identified as being shut during lockdowns in Joyce and Xu (2020) by 4-digit SIC codes are obtained for each TTWA and given as a proportion of all employees in each TTWA. Although compiled during the first lockdown, the sectors shut during the second and third national lockdowns are very similar and this list represents sectors especially vulnerable to lockdowns and social distancing requirements, and so capture the vulnerability of the workforce to these measures.

It should be noted that for 2 of these 4 measures, furlough and job vacancies, TTWA figures are constructed from constituent LA parts. In some rare cases, specifically with the unitary authority of Cornwall, and the large, mostly rural Scottish LAs of Dumfries and Galloway, Argyll and Bute, Scottish Borders and Highland, several TTWAs are contained entirely within a single LA, in which case these TTWAs will have identical values for these measures.

B. Sensitivity analyses

In this Appendix, we examine the sensitivity of our results to making different assumptions about the nature of non-tariff barriers, consumer preferences and firm technology and putting workers into larger occupation groups.

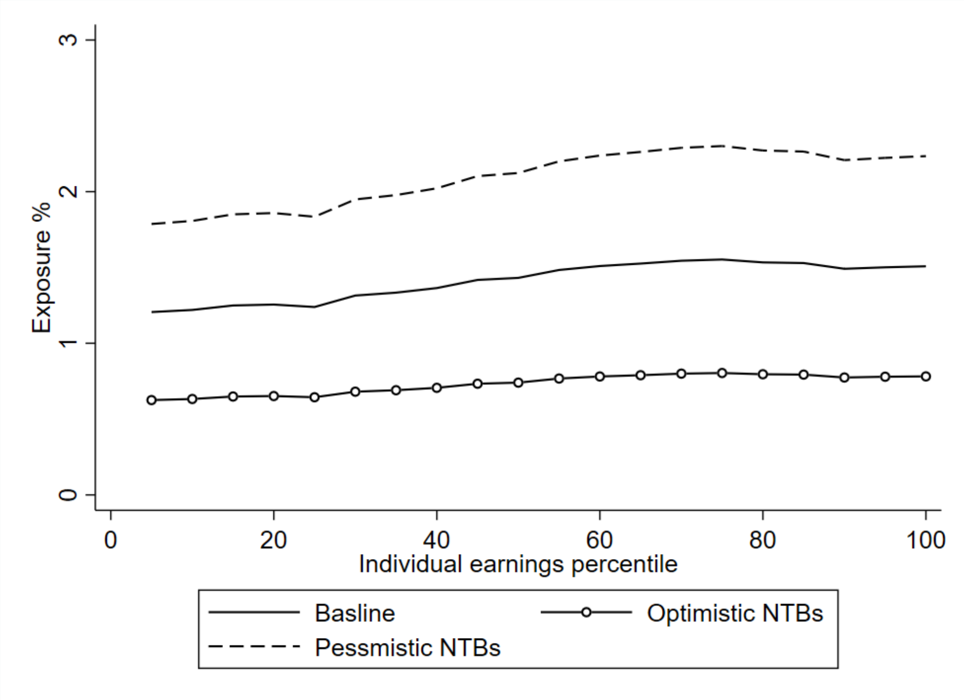
Non-tariff barriers

There is considerable uncertainty about the nature and scale of non-tariff barriers to trade under the TCA. Here we consider how our results are affected by changes in the level of NTBs. In a 'pessimistic' scenario, we assume NTBs are 50% higher than they are under our baseline scenario. In an optimistic scenario, we assume they are 50% smaller. Figure B.1 shows how the distribution in impacts across

[3] See Office for National Statistics (2020).

earnings is affected. Different assumptions on NTBs lead to different levels of exposure, but the pattern of relative exposure across earnings groups is similar.

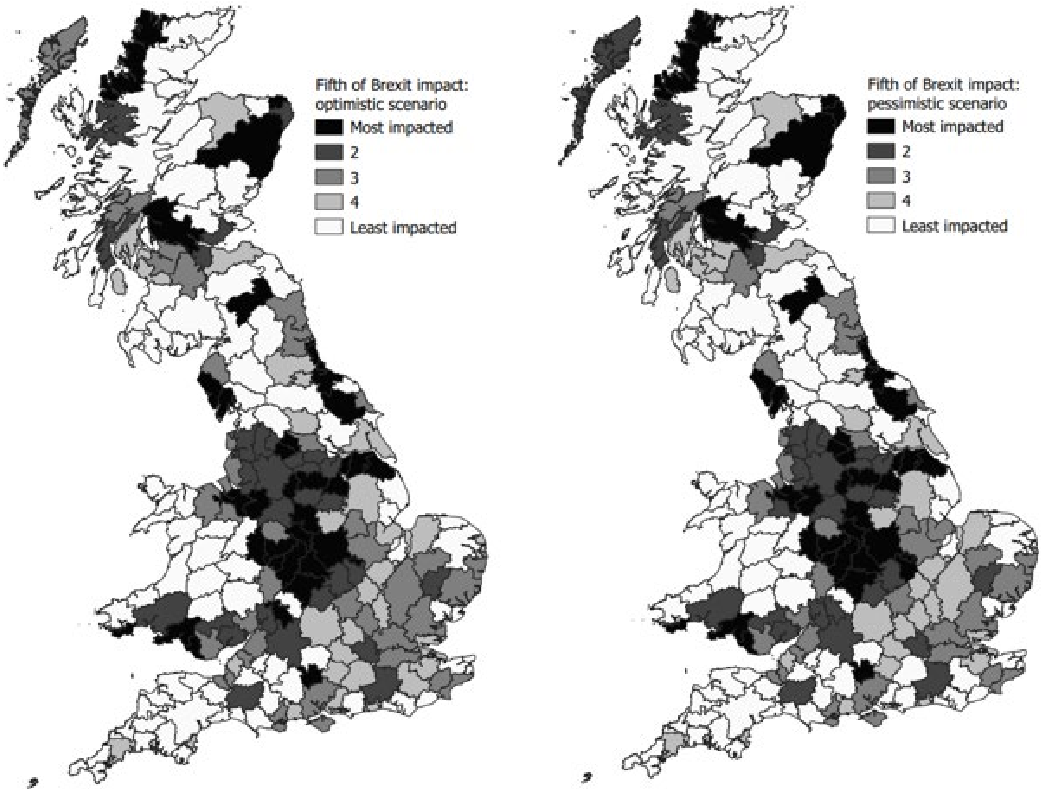
Figure B.1: Measures of response-inclusive exposure over the earnings distribution: different assumptions on non-tariff barriers



Note: Authors' calculations from Annual Survey of Hours and Earnings and Business Structure Database. Responsive-inclusive exposure is the predicted real wage fall from the model outlined in Section II. It varies by workers' region and across nine occupation groups. In the pessimistic scenario, we assume NTBs are 50% higher than they are under our baseline scenario. In the optimistic scenario, we assume they are 50% smaller. We smooth by plotting average exposure within five percentile bands.

Figure B.2 shows how exposure across areas varies in our optimistic and pessimistic scenarios for NTBs. Relative Impacts across areas are very similar in the two scenarios.

Figure B.2: Measures of response-inclusive exposure across travel to work areas: optimistic and pessimistic assumptions on non-tariff barriers

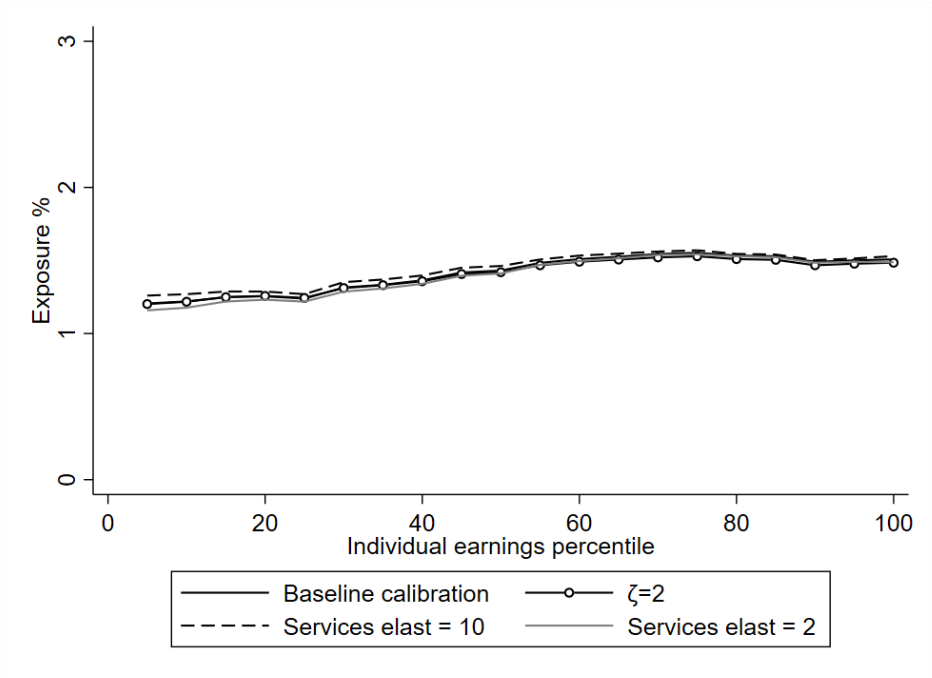


Note: Authors' calculations from Annual Survey of Hours and Earnings and Business Structure Database. Responsive-inclusive exposure is the predicted real wage fall from the model outlined in Section II averaged across workers within in each TTWA. In the pessimistic scenario, we assume NTBs are 50% higher than they are under our baseline scenario. In the optimistic scenario, we assume they are 50% smaller.

Modelling assumptions

Figure B.3 shows that our results for exposure over the earnings distribution are not greatly affected by i) assuming an elasticity of substitution across factor inputs of two instead of one ii) assuming an elasticity of substitution of five for all goods iii) assuming different elasticities of demand for service industries.

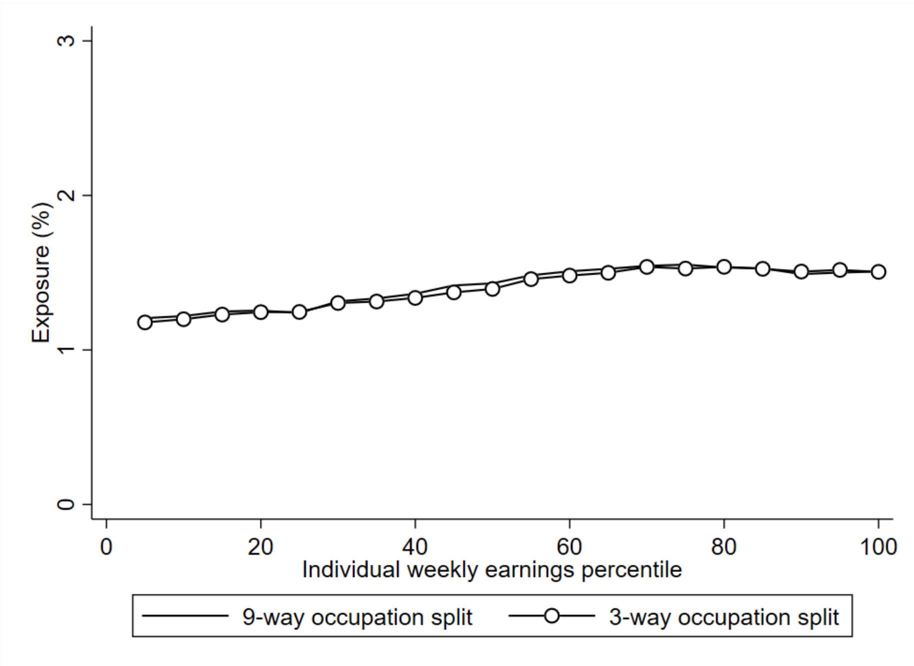
Figure B.3: Measures of response-inclusive exposure over the earnings distribution: different modelling assumptions



Note: Authors' calculations from Annual Survey of Hours and Earnings and Business Structure Database. Responsive-inclusive exposure is the predicted real wage fall from the model outlined in Section II. It varies by workers' region and across nine occupation groups. We smooth by plotting average exposure within five percentile bands.

To examine how our results might change if we allowed for a greater degree cross-occupation mobility, we split workers into three groups in which job moves appear relatively more likely, and in which educational and earnings requirements appear similar. We define these groups as "white-collar" (occupation groups 1-3), "blue-collar" (occupation groups 5 and 8) and "low-skilled" workers (occupation groups 4, 6 and 7). Figure B.4 shows that our this has very little impact on our assessment on the distribution of impacts over the earnings distribution.

Figure B.4: Measures of response-inclusive exposure over the earnings distribution: 3-way vs 9-way occupation split



Note: Authors' calculations from Annual Survey of Hours and Earnings and Business Structure Database. Responsive-inclusive exposure is the predicted real wage fall from the model outlined in Section II. The figure shows exposure predicted by our model across percentiles of the individual earnings distribution when we use a three-way (as opposed to nine-way) occupations split alongside results from our baseline model. We smooth by plotting average exposure within five percentile bands.

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