Global Competition and Brexit
Online Appendix

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A List of Low-Income Countries

Table A1 reports the list of 52 low-income countries identified by Bernard et al. (2006), using as a criterion a level of GDP per-capita below 5% of the U.S. figure.

Table A1: Low-income countries

Afghanistan	Ethiopia	Moldova
Albania	Gambia	Mozambique
Angola	Georgia	Nepal
Armenia	Ghana	Niger
Azerbaijan	Guinea	Pakistan
Bangladesh	Guinea Bissau	Rwanda
Benin	Guyana	Samoa
Bhutan	Haiti	Sao Tome
Burkina Faso	India	Sierra Leone
Burundi	Kenya	Somalia
Cambodia	Lao PDR	Sri Lanka
Central African Rep	Lesotho	St. Vincent
Chad	Madagascar	Sudan
China	Malawi	Togo
Comoros	Maldives	Uganda
Congo	Mali	Vietnam
Equatorial Guinea	Mauritania	Yemen
Eritrea		

B NACE Subsections

Table A2: Nace Revision 1.1 manufacturing subsections

DA	Manufacture of food products, beverages and tobacco
DB	Manufacture of textiles and textile products
DC	Manufacture of leather and leather products
DD	Manufacture of wood and wood products
DE	Manufacture of pulp, paper and paper products; publishing and printing
DF	Manufacture of coke, refined petroleum products and nuclear fuel
DG	Manufacture of chemicals, chemical products and man-made fibres
DH	Manufacture of rubber and plastic products
DI	Manufacture of other non-metallic mineral products
DJ	Manufacture of basic metals and fabricated metal products
DK	Manufacture of machinery and equipment n.e.c.
DL	Manufacture of electrical and optical equipment
DM	Manufacture of transport equipment
DN	Manufacturing n.e.c.

C Robustness Checks Controlling for Regional Characteristics

In this Section, we augment the specification of column 4 in Table 1 with a large number of additional controls. Tables A3 to A5 report, respectively, results controlling for: additional immigration measures; political and social factors; and economic factors. As discussed in the paper, the inclusion of these variables is motivated by the correlational evidence presented in other contributions, and most comprehensively in Becker et al. (2016). Many of the controls we include are plausibly post-treatment, hence we do not consider these models as yielding the most accurate estimate of the effect of the import shock.[21] Nonetheless, the robustness of our main result under several different specifications can assuage doubts about the importance of Chinese competition as a determinant of Brexit.

Table A3 contains results from regressions in which additional measures of immigration are included. We start in column (7) by including the variable *Temporary*, i.e. the inflow of temporary immigrant workers disaggregated at the NUTS-3 level, sourced from ONS. The anti-immigration backlash could be in fact driven more by competition with seasonal workers rather than with settled immigrants, as captured by our main immigration variables. While temporary immigrants are not significantly associated with Brexit vote, the coefficient on the import shock is still positive and statistically significant, and its magnitude is slightly larger than in column 4 of Table 1, probably due to the loss of the 23 observations for Scotland.[22]

[21]See Samii (2016) for a discussion of post-treatment bias and over-conditioning in political science research, and Angrist and Pischke (2008) for a discussion of "bad controls".

[22]We also test the robustness of our finding regarding the import shock including a measure of the acceleration in the inflow of immigrants between 2005 and 2015, in line with the explanation proposed by Langella and Manning (2016). The acceleration is defined as

Table A3: Regional-level robustness - immigration

	(7)	(8)	(9)	(10)	(11)
VARIABLES	Leave Share	Leave Share	Leave Share	Leave Share	Leave Share
Import Shock	15.985***	9.391**	14.920**	15.643***	10.216**
	[4.520]	[3.858]	[6.061]	[5.704]	[4.263]
Immigrant Share	-0.453**	-0.328**	-0.282**	-0.48	-0.045
	[0.189]	[0.130]	[0.123]	[0.320]	[0.203]
Immigrant Arrivals	-0.224	-1.141	-1.434*	-2.702	2.050*
	[0.796]	[0.822]	[0.751]	[1.914]	[1.039]
Temporary Immigrants	0.114				
	[1.393]				
EU Accession Immigrants (2001)		-12.045**	-10.301	4.388	-4.115
		[5.824]	[8.104]	[10.819]	[6.365]
EU Accession Immigrants Growth (2001-2011)		1.527***	2.431*	3.271**	-0.341
		[0.549]	[1.286]	[1.546]	[0.790]
EU Accession Immigrants * Import Shock			-15.685	-70.423	
			[34.567]	[49.979]	
EU Accession Immigrants Growth * Import Shock			-1.831	-4.874	
			[3.745]	[4.323]	
Immigrant Share * Import Shock				0.497	
				[0.807]	
Immigrant Arrivals * Import Shock				5.239	
				[5.953]	
EU 15 Immigrants (2001)					-1.416
					[1.877]
EU 15 Immigrants Growth (2001-2011)					-3.742***
					[1.014]
Other Immigrants (2001)					-0.807*
					[0.401]
Other Immigrants Growth (2001-2011)					-0.003
					[0.023]
NUTS-1 Fixed effects	Y	Y	Y	Y	Y
Observations	144	167	167	167	167
R-squared	0.58	0.68	0.68	0.68	0.74
Model	Linear	Linear	Linear	Linear	Linear

Standard errors clustered by NUTS-2 area in all columns.
*** p<0.01, ** p<0.05, * p<0.1

Table A4: Regional-level robustness - political and social factors

	(12)	(13)	(14)	(15)	(16)	(17)
VARIABLES	Leave Share	Leave Share	Leave Share	Leave Share	Leave Share	Leave Share
Import Shock	4.551**	14.889***	9.460**	10.592**	9.849**	9.630**
	[2.166]	[5.245]	[4.084]	[4.075]	[3.913]	[4.193]
Immigrant Share	-0.148	-0.024	-0.592***	-0.617***	-0.601***	-0.592***
	[0.096]	[0.308]	[0.178]	[0.183]	[0.179]	[0.179]
Immigrant Arrivals	0.573	0.795	-0.083	0.025	-0.053	-0.077
	[0.426]	[1.573]	[0.777]	[0.809]	[0.778]	[0.780]
BNP Vote Share	4.153***					
	[0.675]					
UKIP Vote Share	0.820***					
	[0.072]					
Lib-Dem Vote Share	-0.016					
	[0.110]					
Labour Vote Share	0.004					
	[0.061]					
Green Vote Share	-0.677***					
	[0.148]					
Conservative Vote Share	-0.067					
	[0.072]					
Share High Skilled		-1.003***				
		[0.162]				
Share Above 60		1.009***				
		[0.343]				
Share Above 60 Growth		0.331**				
		[0.161]				
Share Home Owners		0.28				
		[0.166]				
Share Home Owners Growth		-1.081***				
		[0.318]				
Share Council Rented		0.446**				
		[0.201]				
Share Council Rented Growth		0.025				
		[0.018]				
Share Commuters to London		0.254**				
		[0.101]				
Fiscal Cuts			0.022***	0.014	0.021***	0.022***
			[0.006]	[0.013]	[0.006]	[0.006]
Cancer Treated in 62 days			-0.591	-0.503	0.271	-0.594
			[0.596]	[0.616]	[1.157]	[0.596]
Public Employment Growth			0.813	0.910*	0.802	0.97
			[0.519]	[0.536]	[0.541]	[1.190]
Fiscal Cuts * Import Shock				0.028		
				[0.031]		
Cancer Treated in 62 days * Import Shock					-3.512	
					[3.449]	
Public Employment Growth * Import Shock						-0.531
						[2.853]
NUTS-1 Fixed effects	Y	N	Y	Y	Y	Y
Observations	167	139	167	167	167	167
R-squared	0.93	0.52	0.70	0.70	0.70	0.70
Model	Linear	Linear	Linear	Linear	Linear	Linear

Standard errors clustered by NUTS-2 area in all columns.
*** p<0.01, ** p<0.05, * p<0.1

Table A5: Regional-level robustness - economic factors

	(18)	(19)	(20)	(21)	(22)
VARIABLES	Leave Share	Leave Share	Leave Share	Leave Share	Leave Share
Import Shock	13.275**	9.765**	10.848***	8.900**	7.997*
	[5.244]	[4.125]	[3.869]	[3.332]	[4.011]
Immigrant Share	-0.529**	-0.462***	-0.585**	-0.360**	-0.529***
	[0.196]	[0.163]	[0.221]	[0.160]	[0.147]
Immigrant Arrivals	0.025	-0.102	-0.028	-0.715	0.309
	[0.780]	[0.713]	[0.965]	[0.696]	[0.652]
Agriculture	0.605				
	[0.603]				
Agriculture * Import Shock	-2.369**				
	[1.072]				
EU Economic Dependence		0.683*			
		[0.384]			
Unemployment			1.017**		
			[0.400]		
Median Wage				-3.014***	
				[0.480]	
Median Wage Growth				-0.123	
				[0.098]	
Change in Relative Income vs. Median Region					-0.225***
					[0.059]
NUTS-1 Fixed effects	Y	Y	Y	Y	Y
Observations	158	167	166	167	167
R-squared	0.66	0.66	0.67	0.72	0.69
Model	Linear	Linear	Linear	Linear	Linear

Standard errors clustered by NUTS-2 area in all columns.
*** p<0.01, ** p<0.05, * p<0.1

In the following columns, we add immigration variables disaggregated by country of origin, using U.K. Census data. In particular, in column 8 we single out immigrants from countries that have entered the European Union after 2004 (*EU Accession Immigrants*). Following Becker et al. (2016), we control both for the stock of immigrants in 2001 as a share of the resident population, and for their growth rate between 2001 and 2011. In column 9 we also interact these variables with the import shock. These results are discussed in the paper (columns 1 and 2 of Table 2). In model 10 we add interactions between the import shock and the overall measures of immigration. The estimates indicate that regions experiencing faster growth in EU accession immigrants were more supportive of Leave. None of the interactions are close to statistical significance, pointing to the absence of any evidence in favor of heterogeneity in the effect of the import shock as a function of actual immigration. Finally, in column 11 we report estimates of a specification that includes all the disaggregated measures of immigration by country of origin, but without interactions with the import shock. In particular, besides EU accession immigrants, we also control for immigrants from EU 15 countries, as well as immigrants from the rest of the world. This

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$A = \frac{Arrivals_{2015}}{Arrivals_{2005}}$. The magnitude and statistical significance of the import shock coefficient are unaffected. At the same time, the acceleration does have a positive and statistically significant association with Leave vote share. To understand this further, we estimate the model in log scale, including separately both the (log) arrivals in 2005 and the (log) arrivals in 2015. This is equivalent to estimating a model with the log acceleration, as $\log A = \log \frac{Arrivals_{2015}}{Arrivals_{2005}} = \log Arrivals_{2015} - \log Arrivals_{2005}$. It emerges that the relationship between acceleration and Leave share is driven only by the denominator (i.e., arrivals of foreign workers in 2005). In other words, the association between acceleration in arrivals and Leave share seems to be a manifestation of the lower popularity of Leave in areas with more non-U.K. born residents, i.e., those in which past arrivals were higher.

leads to a loss of significance for growth in immigration from EU accession countries.

To sum up, in all the specifications the coefficient on the import shock is positive and statistically significant, and approximately of the same magnitude as compared to the baseline estimate of column 4 in Table 1. There is some evidence that the composition of the pool of immigrants mattered, pointing to higher Leave support in areas that experienced faster growth in immigration from EU accession countries. Conversely, we find no evidence of an interactive effect between immigration and the trade shock. In any case, in light of the importance that immigration had in the referendum campaign, we further explore the interplay between Chinese imports and attitudes about immigration in the individual-level analysis.

In Table A4, we check the robustness of the import shock result to the inclusion of political and social variables. In the first column we include regional-level vote shares for several parties in the latest European Parliament election of 2014. These are meant to control for differences in political preferences across regions, especially in virtue of the system of proportional representation that applies to these elections. Three of the coefficients on vote shares are statistically distinguishable from zero: those on BNP, UKIP, and Green Party. Their signs are intuitive, as higher support for Leave is observed in areas where more people voted for BNP and UKIP, whereas a higher Green Party share is associated to lower backing for Leave. The coefficients on the major parties outside of Scotland –i.e., Labour, Conservative, and Liberal Democrats– are negligibly small in substantive terms and not statistically significant. This might be due to the bluntness of the measures, i.e. vote shares aggregated by NUTS-3 regions, and does not exclude potential differences in the treatment effect across supporters of different parties. For this reason, we also investigate the interaction between partisanship and the import shock in the individual-level analysis.

Once we account for the party share variables, the estimate of the effect of the import shock is reduced in magnitude, but it is still positive and statistically significant, with a t-ratio above 2.1. Party shares are anyway arguably post-treatment with respect to the trade shock. Hence, by including them in the regression, we are effectively blocking one of the channels that might link the import shock to Leave vote: support for anti-establishment and, importantly, also vocal anti-EU parties like the UKIP. The fact that we still find a positive and significant coefficient for the import shock, albeit reduced, further corroborates the robustness of our main finding.

In column 13 of Table A4 we control for the socio-economic composition of the population in each region. First, since skill-biased technical change in the recent past might have led regions with a less educated workforce to be left behind, we include the variable *Share High Skilled*, i.e. the share of the population with a higher education degree in the oldest available year (2000). Higher education is defined as levels 5 to 8 of the International Standard Classification of Education (ISCED), which cover from short-cycle tertiary education up to doctoral degree or equivalent. Data are drawn from Eurostat and are only available at the NUTS-2 level of regional disaggregation. For this reason, we do not include NUTS-1 fixed effects in column 13, as there would not be enough variation left for identification. Besides controlling for the high-skilled share, we also include: the share of the population older than 60 (*Share Above 60*); the share of the population living in an owned home, possibly with a mortgage (*Share Home Owners*); and the share of the population residing in public housing (*Share Council Rented*). These variables are sourced from the U.K. Census, and are aggregated at the NUTS-3 level. For all of them, following Becker et al. (2016), we include both the level in 2001 and the growth rate between 2001 and 2011. We also control for the share of residents in the working age that commute to Inner London for work (*Share Commuters to London*), obtained from the U.K. Census. We lose 28 observations due to education data availability (7 from North West England, and 21 from Greater London). Despite the smaller dataset, the coefficient on the import shock is positive, close to the baseline estimate, and statistically significant. At the same time, skills seem to be a strong predictor of the Brexit vote, in the expected direction. Indeed, if we compare two areas located in NUTS-2 regions that differ by one standard deviation in higher education levels, the area in the more skilled region is expected to support the Leave option by almost five percentage points less than the area in the less skilled region, *ceteris paribus*. In addition, there is a positive and statistically significant association between support for Leave and, respectively, an aging population and the share of population living in public housing in 2001 (but not its growth rate). On the other hand, areas with a stronger growth in home ownership tend to be less supportive of Leave, possibly capturing the effect of a dynamic real estate market at the regional level. Finally, all else equal, a larger share of commuters to London is associated with more support for Leave.

In models 14-17 we include measures of fiscal cuts and underprovision of public services at the regional level, and we explore how they might compound with the globalization shock in affecting the referendum outcome. Specifically, we focus on three variables: *Fiscal Cuts*, *Cancer Treated in 62 Days*, and *Public Employment Growth*. These variables are presented in the paper, and the results of models 14-15 are also discussed in the manuscript (columns 3 and 4 of Table 2). In column 16, we include the interaction between the import shock and the proxy for the quality of NHS services (*Cancer Treated in 62 Days*). This interaction is not statistically significant at conventional levels but, as for the case of fiscal cuts in model 15, it provides (very mild) evidence that the import shock had a stronger impact on the Leave vote share in areas with less efficient public services. Finally, in the last column of Table A4 we include the interaction between the import shock and public employment growth. Also in this case, the interaction is not statistically significant but points to a possible (yet very imprecisely estimated) interactive effect, slightly muting the main effect of the import shock in areas where public employment grew more (or better, decreased less).

Table A5 probes the robustness of our result regarding the import shock to the inclusion of additional economic characteristics of NUTS-3 regions. In the first column we include the variable *Agriculture*, i.e., the share of agriculture in regional GDP, and its interaction with the import shock. The agricultural share of GDP is obtained from Eurostat, and is averaged over the period 2004-2013. Regardless of the import shock, more agricultural areas are somewhat more in favor of Leave, albeit not statistically significantly so. Importantly for our argument, the vote share for Brexit is less sensitive to the import shock in more agricultural areas. In fact, in regions above the 90th percentile of importance of agriculture in GDP, the effect of the import shock is no longer statistically distinguishable from zero. This further reassures us that our measure of the Chinese import shock is picking up the actual effect of import competition, which strongly affects areas that are traditionally specialized in manufacturing, and from which more agricultural regions are to some extent sheltered.

In the second column, we include an index of *EU Economic Dependence*. This robustness check is discussed in the paper (column 5 of Table 2). In the third column, we include in the specification the unemployment rate at the NUTS-3 level (*Unemployment*), measured in the most recent year prior to the referendum (2015). Data are from the Office for National Statistics. As expected, a higher unemployment rate is significantly associated with higher support for Leave. Yet, its inclusion does not eliminate the effect of the import shock, which remains close to the baseline estimate. The unemployment rate in a region is clearly post-treatment with respect to the import shock. However, its inclusion shows that globalization, with the ensuing decline of manufacturing, is a long-term structural process whose effects work beyond an increase in the unemployment rate, that could also be largely reflecting a temporary economic downturn. Overall, our evidence suggests that globalization drove support for the Leave option through a broader type of impact, possibly involving increasing uncertainty, reduced income, and even higher mental distress on top of unemployment, as found in a recent study on the U.K. by Colantone et al. (2015).

In the fourth column, we include two measures that capture another channel through which the import shock might be operating: *Median Wage* and *Median Wage Growth*. Specifically, we include the median (gross) wage level for the year 2005, and its change between 2005 and 2015. These variables are based on data from the Annual Survey of Hours and Earnings of the ONS, averaged at the NUTS-3 level. While there is no statistically significant evidence that growth in the median wage in the past decade is, all else equal, associated with a lower Leave vote share, the coefficient on median wage in 2005 is negative and highly statistically significant. That is, regions with higher hourly pay were less in favor of Leave. To put this result in context, a one-standard-deviation difference in median hourly pay in 2005 is associated with lower support for Leave by about 5 percentage points. In particular, if we compare Greater Manchester South West (UKD34), which had a median hourly wage of 9.60 GBP, and Blackburn with Darwen (UKD41, in Lancashire), at 8 GBP, they are expected to differ by 4.8 percentage points in their support for Leave. In fact, Leave shares differed by around 7 percentage points between these two areas. The coefficient on the import shock is still positive and significant, although slightly reduced in magnitude as compared to the baseline estimate. This is in line with lower wages being a possible channel for the effect of the trade shock on voting.

Finally, in the fifth column we include one further variable that captures the most comprehensive channel through which globalization might induce spatial variation in voting behavior: an increase in inequality across regions, through the creation of geographically concentrated "winners" and "losers". In particular, for each NUTS-3 region we compute the *Change in Relative Income* (CRI) between 1997 (the earliest year for which we have data) and 2015. This regression is also presented and discussed in the paper (column 6 of Table 2). The estimated coefficient on CRI is negative and significant, pointing to higher support for Leave in areas that are falling behind in relative terms. Nevertheless, the coefficient on the import shock is still positive and, albeit smaller, in the same order of magnitude of the baseline estimate (around 8 vs. 12 in the main specification of Table 1). The effect of imports is less precisely estimated, hence the p-value falls just above conventional levels of statistical significance (being equal to 0.053).[23]

[23] We also calculate analogous measures of CRI based on the mean and maximum values of regional GVA per capita, rather than the median. The results obtained with these measures are unsurprisingly similar to the ones reported in Table A5, and are available upon request.

D Additional Results

In Table A6 we show that our main regional-level result is robust to the exclusion of specific NUTS-1 regions. In particular, if we omit Scotland and Greater London, two potentially outlying regions, the coefficient on the import shock is 14.3 (t=2.99). If we omit these two NUTS-1 macro-regions and, iteratively, also one additional NUTS-1 region, the coefficient on the import shock varies from a minimum of 12.8 (t=2.48) to a maximum of 16.7 (t=3.05). The smallest t-ratio we estimate is 2.43. A hierarchical varying-slope varying-intercept model, where the slope and the intercept are allowed to vary by NUTS-1, yields a coefficient for the mean of the slopes of 13.6 (t=3.04) and a standard deviation for the varying component of the slope of 2.05, which points to a modest degree of variation of the slope across NUTS-1 macro-regions.

Table A6: Regional-level results - robustness

	Coeff.	Std. Err.	Obs.	R-sq.
1) Excluding London (UKI) and Scotland (UKM)	14.334***	[4.792]	123	0.3
Excluding also:				
2) North East (UKC)	14.942***	[4.899]	116	0.3
3) North West (UKD)	12.891**	[5.041]	103	0.3
4) Yorkshire and the Humber (UKE)	13.274**	[4.795]	112	0.3
5) East Midlands (UKF)	16.740***	[5.487]	112	0.3
6) West Midlands (UKG)	12.748**	[5.144]	109	0.3
7) East of England (UKH)	15.474***	[4.874]	107	0.4
8) South East (UKJ)	13.632**	[5.056]	103	0.3
9) South West (UKK)	14.476***	[4.923]	111	0.3
10) Wales (UKL)	14.199**	[5.851]	111	0.3

In all rows the specification is the same as in column 4 of Table 1.
Standard errors clustered by NUTS-2 area.
*** p<0.01, ** p<0.05, * p<0.1

In Tables A7 and A8 we replicate the individual-level regressions using BES data from Wave 9. These include information on self-reported vote.

Table A7: Individual-level results - BES Wave 9

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Leave	Leave	Leave	Leave	Leave	Leave
Import Shock	0.244**	0.095**	0.228**	0.234**	0.092**	0.213**
	[0.100]	[0.038]	[0.107]	[0.103]	[0.039]	[0.109]
Immigrant Share				-0.010*	-0.003	-0.010*
				[0.006]	[0.002]	[0.006]
Immigrant Arrivals				0.011	0.003	0.01
				[0.029]	[0.011]	[0.029]
Age	0.011***	0.004***	0.011***	0.011***	0.004***	0.011***
	[0.001]	[0.000]	[0.001]	[0.001]	[0.000]	[0.001]
Gender	-0.011	-0.005	-0.011	-0.013	-0.005	-0.013
	[0.024]	[0.009]	[0.024]	[0.024]	[0.009]	[0.024]
ED1	-0.159**	-0.055**	-0.159**	-0.160**	-0.055**	-0.160**
	[0.070]	[0.025]	[0.070]	[0.070]	[0.025]	[0.070]
ED2	-0.138***	-0.048***	-0.138***	-0.141***	-0.049***	-0.141***
	[0.046]	[0.016]	[0.046]	[0.046]	[0.016]	[0.046]
ED3	-0.458***	-0.173***	-0.459***	-0.464***	-0.174***	-0.464***
	[0.050]	[0.018]	[0.050]	[0.050]	[0.018]	[0.050]
ED4	-0.737***	-0.277***	-0.737***	-0.738***	-0.277***	-0.739***
	[0.050]	[0.018]	[0.050]	[0.051]	[0.018]	[0.051]
ED5	-1.030***	-0.375***	-1.030***	-1.029***	-0.375***	-1.029***
	[0.059]	[0.020]	[0.059]	[0.059]	[0.020]	[0.059]
NUTS-1 Fixed effects	Y	Y	Y	Y	Y	Y
NUTS-3 Random intercepts	N	Y	N	N	Y	N
Observations	15,923	15,923	15,923	15,923	15,923	15,923
Kleibergen-Paap F statistic			798.9			815.4
Number of groups		167			167	
Model	Probit	Linear Hierarchical	IV Probit	Probit	Linear Hierarchical	IV Probit

Standard errors clustered by NUTS-3 area in all columns except 2 and 5.
*** p<0.01, ** p<0.05, * p<0.1

Table A8: Individual-level results with interactions - BES Wave 9

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Leave	Leave	Leave	Leave	Leave	Leave
Import Shock	0.362***	0.215**	0.226**	0.257**	0.235**	0.252**
	[0.123]	[0.098]	[0.106]	[0.121]	[0.104]	[0.113]
Retired	0.104					
	[0.083]					
Retired * Import Shock	-0.603***					
	[0.220]					
Student		-0.514**				
		[0.201]				
Student * Import Shock		0.139				
		[0.587]				
Unemployed			0.029			
			[0.198]			
Unemployed * Import Shock			0.165			
			[0.538]			
Manual				0.195*		
				[0.111]		
Manual * Import Shock				0.113		
				[0.305]		
Self-employed					0.042	
					[0.103]	
Self-employed * Import Shock					0.017	
					[0.307]	
Service						0.108
						[0.117]
Service * Import Shock						-0.142
						[0.304]
Immigrant Share	-0.010*	-0.009	-0.010*	-0.016***	-0.010*	-0.010*
	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]
Immigrant Arrivals	0.013	0.008	0.01	0.049	0.011	0.011
	[0.030]	[0.031]	[0.029]	[0.032]	[0.029]	[0.030]
Individual Controls	Y	Y	Y	Y	Y	Y
NUTS-1 Fixed effects	Y	Y	Y	Y	Y	Y
Observations	15,923	15,923	15,923	12,579	15,923	15,923
Model	Probit	Probit	Probit	Probit	Probit	Probit

Standard errors clustered by NUTS-3 area.
*** p<0.01, ** p<0.05, * p<0.1

E Attitudes about Immigration

In the analysis of attitudes about immigration, in Section 5.3 of the paper, the reference survey questions are: (1) "Do you think that immigration is good or bad for Britain's economy?" (*Immig Econ*); (2) "And do you think that immigration undermines or enriches Britain's cultural life" (*Immig Cultural*); (3) "Do you think that the level of immigration is getting higher, getting lower or staying about the same?" (*Immig Change*); (4) "Some people think that the U.K. should allow many more immigrants to come to the U.K. to live and others think that the U.K. should allow many fewer immigrants. Where would you place yourself and the parties on this scale?" (*Immig Policy*). The survey questions are answered, respectively, on a 7-point scale for the first two, a 5-point scale for Immig Change, and an 11-point scale for Policy.

F Reconciling Regional and Individual Analysis

As discussed in the paper, the regional-level results of Table 1 are consistent with the individual-level outcomes of Table 3, except for the findings on the share of immigrants in the population. Indeed, in the regional analysis we obtain a negative and significant coefficient on this variable, which is instead not significant in the individual-level analysis. It is important to assess the possible reasons for such a discrepancy.

In general, there are two possible explanations for differences in results on contextual variables between aggregate and individual analysis. On the one hand, differences in the socio-demographic composition of regions could be correlated with regional-level explanatory variables. As a result, when controlling for socio-demographic characteristics, at the individual level, results on the regional-level explanatory variables could change as compared to the regional analyis. On the other hand, such differences in results could also stem from a suboptimal representativeness of the survey sample across regions.

In order to investigate which of these two explanations applies to our case, in Table A9 we replicate all the individual-level regressions of Table 3, but excluding the individual controls: age, gender, and education dummies. The results are very reassuring on the representativeness of our sample of individuals. In fact, the coefficients on the import shock –e.g., around 0.14 in the linear model of column 5– are very close in substantive terms to the ones obtained at the regional level in Table 1, around 12. One should of course take into account that the dependent variable in the regional analysis is the Leave vote share, on a scale between 0 and 100. Therefore, a coefficient of 12 in those regressions is equivalent to a coefficient of 0.12 if one rescales the vote share on a 0-1 scale, thus making it immediately comparable to the individual probability of voting Leave.

Interestingly, when omitting the individual controls, in Table A9, we retrieve again a negative and significant coefficient for the share of immigrants in the population, as in the regional analysis. This suggests that the differences between Table 1 and Table 3 are driven by a correlation between the socio-demographic composition of the population and the incidence of immigration across regions. Specifically, the evidence is consistent with relatively more immigrants settling in regions characterized by a younger and more educated population (e.g., London). Indeed, younger and more educated people are less likely to vote Leave. In turn, when age and education are controlled for at the individual level, in Table 3, the share of immigrants is not found to be statistically significant. Conversely, if one omits the individual controls from the individual-level regressions, as we do in Table A9, the share of immigrants emerges again as a significant correlate of the probability of voting Leave. Also in this case, the substantive magnitude of the coefficient is very close to the one obtained in the regional analysis. For instance, in the linear probability model of column 5 in Table A9, the coefficient on the share of immigrants is -0.004. This is very similar to the coefficient of around -0.5 obtained across specifications in Table 1, considering the different scale of the dependent variable.

Overall, this evidence suggests that immigration is endogenous to the socio-demographic characteristics of regions. This is a well-known result in the literature on immigration, where recent work is exploiting policy changes that induce exogenous variation in the presence of immigrants across regions, in order to identify causal effects of immigration on voting (e.g. Dustmann et al., 2016).

Table A9: Individual-level results: excluding individual controls

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Leave	Leave	Leave	Leave	Leave	Leave
Import Shock	0.411***	0.152***	0.389***	0.374***	0.144***	0.348***
	[0.134]	[0.053]	[0.131]	[0.116]	[0.049]	[0.114]
Immigrant Share				-0.013**	-0.004*	-0.013**
				[0.005]	[0.002]	[0.005]
Immigrant Arrivals				-0.003	-0.002	-0.004
				[0.026]	[0.010]	[0.027]
NUTS-1 Fixed effects	Y	Y	Y	Y	Y	Y
NUTS-3 Random intercepts	N	Y	N	N	Y	N
Observations	16,331	16,331	16,331	16,331	16,331	16,331
Kleibergen-Paap F statistic			788.6			791.2
Number of groups		167			167	
Model	Probit	Linear Hierarchical	IV Probit	Probit	Linear Hierarchical	IV Probit

Standard errors clustered by NUTS-3 area in all columns except 2 and 5.
*** p<0.01, ** p<0.05, * p<0.1