Voting for Populism in Europe: Globalization, Technological Change, and the Extreme Right

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Abstract

What are the political consequences of economic globalization? Since the 1990s, scholars of European party politics have noted the rise of extremist parties, especially right-wing populist ones, and the decline of mainstream left and right parties. This paper focuses on the association between globalization in terms of trade, capital and labor flows, technological change, and popular support for extreme right parties. I examine these relations at the regional and individual level in 15 advanced industrial democracies in Western Europe from 1990-2018. Globalization, especially in the form of trade, is associated with growing vote shares for extreme right parties. Technological change in the form of automation increases support for extreme right parties. The financial crisis enhanced support for populist right parties and strengthened the negative relationship between trade shocks and declining support for mainstream left parties. And the use of social welfare compensation seems unable to dampen these political trends.

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1 Introduction

What are the political consequences of economic globalization? Has globalization — that is, the increasing flows of goods, services, people and capital across borders — affected democracies? A long literature has noted that global capitalism and democracy may create stresses for each other (Marx (2012), Polanyi (1957), Piketty (2014)). Capitalism is a dynamic system with large distributive effects that can cause "creative destruction" (Schumpeter 1942). Its dynamism and its distributive consequences can pose threats to democracy. Declines in people's economic situations and rising inequality can shake support for democracy. Progressive tax systems, social welfare policies, and restrictions on international economic flows were used to help democracy accommodate capitalism, as theories of "embedded liberalism" noted (Ruggie 1982). In this time of very open global markets, concern exists that tax systems are no longer able to be progressive and that social welfare policies are increasingly unable to meet demand. If these mechanisms no longer work, will globalization erode support for democracy and promote political parties that challenge it?

Since the 1990s, scholars of European party politics have noted the rise of extremist parties, especially right-wing ones (Betz 1994; Golder 2016; Kitschelt 1996; Kriesi 2010; Mayer 2013; Mudde 2007). Norris and Inglehart (2019) note that populist parties have entered into government coalitions in 11 Western democracies, increased their average vote share in national and European elections from 5% to 13%, and seen their average seat share rise from 4% to 13%. Furthermore, scholars have noticed that traditional centrist parties of the left and right are losing support. Figure 3 shows the changing vote shares of the four main party families over time. Among the 15 West European countries[1] in the sample, right populist parties scored on average 5% in the early 1970s, barely rising to to 5.5% in 1990, but then doubling to 10% in 2008, finally growing further to 17% after 2018. If extreme right parties promote more authoritarian politics, their rise may signal trouble for democracy. Much debate exists over what is causing the rise of the far right parties and the decline of centrists ones. What role does globalization play?

This paper focuses on the relationship between globalization in terms of trade, capital and labor flows, and popular support for extreme right parties. I also examine how technological change is affecting such support. The introduction of new technologies is part of globalization and has been accelerated by it. I also ask whether social welfare programs can mitigate the effects of globalization, as others have argued. I ask three main questions. Is globalization undermining traditional demo-

[1] Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, and the United Kingdom.

cratic party systems? Is technological change associated with support for more extreme political parties? Can social welfare spending temper the impact of technology and globalization? I examine these questions at the regional level in 15 advanced industrial democracies in Western Europe over the nearly thirty year period from 1990 to 2018, as well as at the individual level using the European Social Surveys.

Unlike previous research, this paper looks at all the main elements of globalization and asks what impact each one has. I examine trade, foreign investment, and migration, while most research looks only at one of these three, usually trade. Furthermore, I combine this analysis with an exploration of technological change and how it is affecting voting. I focus on different elements of technological change: the introduction of automation via robots and the extent of routine task intensity of jobs. Furthermore, I examine the interaction of trade with the global financial crisis beginning in 2008. The paper examines these relations at two levels: the regional and the individual, allowing a closer look at the microlevel foundations of these impacts. Previous research has tended to stop before the financial crisis (Autor, Dorn, Hanson, & Majlesi forthcoming; Colantone & Stanig 2018a, 2018b) and has not covered all of these aspects of globalization, nor has it included a focus on technological change.

I find that the traditional party systems in many European countries seem to be under pressure, especially after the financial crisis. Center left parties are losing votes, and extreme right parties are gaining votes. Trade is most associated with this; import shocks—from China and other low-wage countries—are related to increasing extreme right party votes within regions, and after the financial crisis began in 2008 these shocks also reduce center left party votes. Foreign investment and surprisingly migration have had limited impact on party fortunes. Finally, technological change in the form of automation is having an impact. Regions with more robots or those most susceptible to automation are seeing increased votes for extreme right parties. Globalization, especially trade, is associated with declines for mainstream left parties and growing vote shares for extreme right ones. These effects accelerated with the financial crisis. Trade and technological change, which are related, are most salient among globalization forces in (re)shaping political support for European parties.

2 Previous Research

2.1 Changes in Party Systems and Globalization

How might globalization be related to changes in party politics? Two strands of the research on party politics in Western Europe note how globalization might be transforming them. Kriesi et al. (2006)

and Kriesi (2010, 2014) argue that support for the extreme right and populism arise in part from a new cleavage caused by globalization. The "new right-populist parties which, for more than 20 years now have spearheaded the nationalist reaction to economic (neoliberal reform of the economy including delocalisation, liberalisation of financial markets, and privatisation), cultural (immigration), and political (European integration, internationalisation of politics) processes of denationalisation ... articulate a new structural conflict that opposes globalisation 'losers' to globalisation 'winners."(Kriesi 2014, p. 369).

Kriesi et al. (2006, p. 922) further note that the "losers of the globalization process to seek to protect themselves through protectionist measures and through an emphasis on the maintenance of national boundaries and independence. Winners, by contrast, who benefit from the increased competition, support the opening up of the national boundaries and the process of international integration." Parties have begun aligning across this new cleavage to compete for votes. In most countries, parties of the extreme right have been able to formulate a highly attractive ideological package for the 'losers' of economic transformations and cultural diversity (Decker 2004). Moreover, these losers are powerful politically since they do not have exit options and thus must stay and fight.

Hooghe and Marks (2018) argue that a new transnational cleavage is transforming European political systems. They document the emergence of a transnational cleavage and claim this is a political reaction against European integration and immigration. They view this change as epochal, arguing that it constitutes a decisive realignment of European party systems. This transnational cleavage in Europe pits the extreme right against those parties supporting the EU and globalization, which is seen as being supported by the EU. For instance, in France, the best predictor in 2012 for votes for the National Front was having negative feelings about the EU. Europeanization and globalization of which it is a part thus generate forces that engender support for the extreme right.

This new globalization cleavage is reshaping European party systems and thus their politics. Support for the left is draining as working class voters, especially older men, shift to the extreme right. This growing influence of the extreme right has had effects on the entire system Wagner and Meyer (2017).

2.2 Cultural Backlash and Globalization

Cultural factors may explain the rise of the extreme right, but these are also related to globalization. Bornschier (2010, p. 3) claims the rise of populism and the radical right are due to a new cultural cleavage between those with traditional values against those holding new multicultural ones. These values of cosmopolitanism and multiculturalism are, however, related to the economic transformations identified by Kriesi (2010) as deriving from globalization. Winners and losers from globalization seem to overlap with those in the new cultural cleavage. Norris and Inglehart (2019) try to separate out the two sets of causes, arguing for the primacy of the cultural. However, they point out that authoritarian and populist values are most widespread among the "losers" from globalization and that the societal changes responsible for the shift in values are related to fundamental economic changes produced by globalization. Gidron and Hall (2017a, 2017b) argue that the combination of economic change wrought by globalization and changes in society have generated growing support for the populist extreme right. The social status of white, working class men has declined due in part to globalization, which has eroded trust in politics and fostered social disintegration, raising support for populism.

Other argue that economic forces have produced the cultural reaction. Carreras, Irepoglu Carreras, and Bowler (2019) find that cultural grievances mediate the effect of long-term economic decline on support for Brexit. Ballard-Rosa, Malik, Rickard, and Scheve (2019) show that negative economic shocks cause the adoption of authoritarian values through a frustration-aggression mechanism, which increases support for extreme right parties. Algan, Guriev, Papaioannou, and Passari (2017) find that increases in regional unemployment lead to a drop in trust toward the national parliaments. Guiso, Herrera, Morelli, and Sonno (2018) find strong negative association between individual economic insecurity generated by unemployment, falling income, and higher exposure to globalization and trust in political institutions, similar to Dustmann et al. (2017)'s findings.

For many scholars, the economic and cultural elements of the globalization cleavage are tightly interlinked. This paper does not try to examine the linkage nor explore the cultural aspects of support for the extreme right. These elements are important, and economic factors may work through the individual psychological factors cited by others: globalization can generate rising insecurity and status anxiety, declining trust, and increasing authoritarianism in individuals. Here the focus is on the economic sources of backlash against traditional parties and the rise in support for extreme right-wing ones.

2.3 Economic Sources of Support for the Extreme Right

What is the causal story linking globalization to the extreme right in Western European democracies? Globalization has produced uneven effects. Some people have benefited economically, and the regions where they are concentrated are vibrant and well-integrated into the global economy; other people have lost jobs and had their wages shrink while the regions they are concentrated in suffer from long-term decline (Martin & Sunley 2015; McCann 2016). The former group are the winners from globalization, while the latter are the losers of globalization (Hobolt & Tilley 2016). These economic effects could have forceful political ramifications.

Economists have begun to research the political consequences of globalization, finding strong effects for trade, especially imports from developing countries like China. The losers from trade face significant adjustment costs in terms of job displacement and reduced earnings (Acemoglu, Autor, Dorn, Hanson, & Price 2016; Autor et al. forthcoming; Autor, Dorn, & Hanson 2013; Dauth, Findeisen, & Suedekum 2014), as well as health problems (Colantone, Crino, & Ogliari 2019; Hummels, Munch, & Xiang 2016; Lang, McManus, & Schaur 2019; Pierce & Schott 2020). Rodrik (2011, p. 60) points out that the amount of redistribution from trade is usually many times larger than the actual gains from trade. Autor et al. (2013) and Autor et al. (forthcoming) show that American districts most affected by import surges from China removed moderate members of Congress and voted in more extreme ones, especially on the right. Colantone and Stanig (2018b) show that increased trade, especially Chinese imports, led voters to shift right, to increase support for nationalist and extreme right parties in 15 West European countries from 1988-2007. Colantone and Stanig (2018a) show that support for the "Leave" option in the UK was stronger in areas hit hardest by trade. Dippel, Gold, and Heblich (2016) demonstrate that German voters in areas most exposed to increases in trade increased their support for extreme right parties the most. Barone and Kreuter (2019) show similar patterns for Italy looking at 8,000 municipalities from 1992 to 2013. Malgouyres (2017) studied 3,500 French cantons from 1995 to 2012 and finds similar outcomes from increased trade.[2] These costs and the rising insecurity associated with globalization may create strong demands for assistance from the state (Cusack, Iversen, & Rehm 2006; Margalit 2013; Rehm 2009; Walter 2010). When these demands are not met, disappointed voters may become attracted to more extreme parties and their protectionist and nationalist programs.

3 How Globalization Affects Vote Choice: Hypotheses

This paper advances the burgeoning literature on globalization and political change by examining a longer time period than most papers (1990-2018), looking at all three major sources of globalization pressures (trade, capital and labor flows), including a focus on the 2008 global financial crisis and its effects, exploring the impact of technological change from several different angles, and finally beginning an examination of the effects of social welfare policies on reducing growth of support for the extreme right in the face of globalization. I set forth the logic of each element of this argument

[2]Other research confirms the impact of globalization but finds more nuanced patterns; see Moriconi, Peri, and Turati (2018) and Burgoon, van Noort, Rooduijn, and Underhill (2018), for example.

and develop four major testable hypotheses below.

3.1 Globalization and Political Change

For globalization to have political effects on vote choice, two processes have to occur. First, individuals must experience losses and/or increased insecurity due to globalization, either perceived or actual. Second, to change their vote choice, this dissatisfaction from economic pressures must be better addressed by a party other than their usual one. We can capture two parts of this process in the data: globalization pressures on a region a person lives in and their vote choice later. In between lies the process by which this occurs and it is much harder to analyze. Many recent studies, including this one, use micro-level data matching geographic data on imports to political constituencies and then link this to individual public opinion or local voting data. They are thus better able to pinpoint the causal nature of the link between trade and political action.

As for the causal mechanism, the main sources identified in the literature have been cultural and economic. The focus here is on the economic side and how growing globalization has had distributive consequences within countries that have generated losses for parts of the population. Almost all the negative effects of trade, FDI, and migration and recent technological change seem to have fallen on similar types of individuals, mainly lower and middle skill ones, often in less urban areas. Economic theories, like Heckscher-Ohlin trade models and even more recent new, new trade theories, have long noted these distributive effects for relatively wealthy countries. The China (and generally low wage countries') import shock is associated with declines in wages especially for lower skilled workers, reduced employment in the most affected sectors, and rising inequality within countries overall. Individuals and those within regions experiencing such shocks are likely to develop a sense of insecurity as these negative events occur. Automation usually targets jobs that are more easily routinized and these often employ low skill workers (Grigoli, Koczan, & Topalova 2020). Inward foreign direct investment can be a boon bringing jobs, but it can also result in buyouts of local firms and reduced employment as the enterprise rationalizes and/or automates. The labor market effects of migration are debated, but there is some evidence that they also affect mostly low wage sectors and reduce employment and compensation.

These negative economic outcomes and the insecurity they can generate in regions experiencing them produce political grievances. Often these grievances are not addressed by mainstream parties and governments because they support globalization. In the past low skilled individuals faced with economic dislocation would turn to left parties, like Social Democratic ones (Benedetto, Hix, & Mastrorocco 2020), and extreme left ones who promised compensation for such economic shocks.

The puzzle now is why have voters who are hurt by globalization (or live in regions hurt by it) turned to the right, and not to the left. One reason is that extreme right parties responded more strongly to the economic shocks by making their rhetoric more anti-globalization and anti-elite and they combined this with strong support for traditional cultural values (Guiso et al. 2018). The extreme right in European countries has led the way in condemning the EU, trade, and automation, but the extreme left has also voiced opposition to these trends. But the combination of anti-globalization rhetoric and support for traditional values seems to appeal more strongly to those 'left behind" by globalization.

Recent papers, including one in this volume, trace out different psychological mechanisms that these economic grievances produce, which then lead to changes in political behavior. Ballard-Rosa et al. (2019) in this volume argue that economic grievances related to globalization and technological change lead negatively affected individuals to adopt more authoritarian stances. These preferences make them more interested in and susceptible to appeals from the extreme right, as these parties often promote more authoritarian stances (Norris & Inglehart 2019). Other research points to different causal pathways. Economic grievances can threaten individual's social status and set in motion greater support for parties that claim to elevate these groups' statuses (Gidron & Hall 2017a). Another line of research points to rising insecurity of individuals as they face rapid and large economic shifts. Such rising insecurity may set off growing distrust of existing political institutions and elites, making space for more support for extreme right parties and their anti-elite narratives (Algan et al. 2017). There are thus multiple psychological pathways that deep economic shocks can trigger that lead to rising support for extreme right parties. This project doesn't look at these psychological mechanisms; it first tries to ascertain if globalization and technological change are connected to political change. It seeks to show which specific elements of globalization and technological change are most strongly associated with these political changes. I expect that support for the extreme right should rise as voters' economic situation deteriorates and they become disenchanted with the traditional parties and more attracted by the extreme right.

Hypothesis 1 *Regions and individuals in regions more affected by economic globalization will be more likely to vote for extreme right parties and less likely to support traditional centrist ones.*

This is the main hypothesis, but there are three more specific hypotheses subsumed in it. First, international trade shocks, especially from Chinese imports and low wage country imports, should be most associated with rising political support for the extreme right. Trade is the biggest and most salient element of globalization for this 30 year period. Its distributive impact has been the largest and clearest to identify. FDI may also bring shocks as domestic firms are bought out by foreign companies and retooled. But FDI may also create greenfield establishments and new jobs. Its overall effects are much more mixed than trade. Labor flows, however, may be a big factor in increasing insecurity and grievance. Rapid and large surges of migrants may destabilize regions and foster anti-foreign sentiment that benefits the extreme right. While migration may not have clear distributive effects, the visibility of migrants may trigger political reactions. Throughout most of this period, migrants shocks have been limited in time and magnitude compared to trade ones, however.

3.2 The Global Financial Crisis and Political Change

The globalization shocks beginning in the late 1990s were later accompanied by the global financial crisis beginning in 2008. It is important to explore the effects of this on voters and the rise of the extreme right. One recent survey of the impact of economic shocks on political outcomes has noted that the effects can be indeterminate (Margalit 2019, p. 15). However, Funke, Schularick, and Trebesch (2016, p. 245) demonstrate that "financial crises put a strain on modern democracies. The typical political reaction is as follows: votes for far-right parties increase strongly, government majorities shrink, the fractionalization of parliaments rises and the overall number of parties represented in parliament jumps. These developments likely hinder crisis resolution and contribute to political gridlock." Guiso, Herrera, Morelli, and Sonno (2019) show that both the globalization shock and the financial crisis boosted support for populist parties more in Eurozone than in non-Eurozone countries. It is important to note that the global financial crisis hit soon after the globalization shocks accelerated. China entered the WTO after 2001 and the East European countries fully entered the EU after 2004. I also explore whether the financial crisis beginning in 2008 exacerbated the political effects of globalization. Were voters pushed to the right even more by globalization once the crisis hit?

Hypothesis 2 *Regions and individuals in regions more affected by economic globalization will be even more likely to vote for extreme right parties and less likely to support traditional centrist ones after the financial crisis hit.*

3.3 Technological Innovation and Political Change

Another factor related to globalization is technological change. Boix (2019) argues that capitalism and democracy seemed compatible in the period from 1940-1990 because technological change was complementary to labor. But in the current period technological change is substituting for labor and creating the same tensions between capitalism and democracy as in the late 19th century.

Skill-biased technological change and rising inequality due to it are generating intense pressures on democracies. Such technological change is aided by globalization but can also occur without these flows.[3] Economists estimate that around 30% of technological change comes from international sources (Keller 2002). Moreover, the recent China import surge has been shown to induce technological change at a high rate (Bloom, Draca, & Van Reenen 2016).

The loss of jobs and downward wage pressures caused by automation may intensify the distributive consequences of globalization. Anelli, Colantone, and Stanig (2019) show that higher exposure to robot adoption in Western Europe increases support for extreme right parties, both at the regional and at the individual level.[4] In addition to the introduction of robots into the production process, economists have identified certain jobs as being more susceptible to automation than others. Routine task intensity (RTI) is one measure of this; the more routine a task, the easier it is to program a robot to do this job.

Routine occupations are mostly middle-skill and middle-wage jobs in both blue-collar (i.e, manufacturing) and white-collar (i.e., administrative) sectors (Autor, Levy, & Murnane 2003). Routine workers are a large and electorally relevant group who traditionally participate in politics. I look also at the role of robots and RTI in industrial production in inducing right-wing support.

Hypothesis 3 *Regions and individuals in regions more affected by technological change that might take their jobs (i.e., automation or outsourcing) are more likely to vote for the extreme right and less likely to vote for traditional centrist parties.*

3.4 Social Welfare and Political Change in a Globalized World

For a long time, scholars assumed that voters faced by the vicissitudes of openness to the global economy would demand compensation in exchange for such openness, the so called "embedded liberalism" bargain (Ruggie 1982). Government compensation is defined as public programs that transfer resources to those facing income shocks or economic vulnerability. Compensation via redistribution was the program of the left and seemed to attract working class voters and damp preferences for extremism (see Burgoon 2009; Garrett 1998). A key puzzle now is why working class voters when they are hurt by globalization and/or technological change choose right-wing parties instead of their more "natural" attachments to the left, who tend to support social welfare programs more (Evans 2000).

[3] Economics literature points to a strong relationship between trade, FDI and technology adoption, (Keller 2002, 2004; Maskus 2014; Saggi, Maskus, & Hoekman 2004)

[4] Some (Kurer & Gallego 2019) and Gallego, Kurer, and Schöll (2019) argue that new technology, however, can create winners who benefit from its introduction and become political forces in its favor.

Some scholars increasingly question whether such compensation is still appealing and effective. Gidron and Hall (2017a) maintain that people whose social status has fallen and who feel left behind by globalization because they are its unacknowledged "losers" prefer recognition over redistribution. Gingrich (2019) also casts doubt on the ability of welfare programs to compensate voters these days. Milner (2018) shows that welfare compensation no longer seems to condition the effects of globalization. In this volume, however, Kim and Pelc (forthcoming) show that trade adjustment assistance in the US can help create support for traditional parties and especially parties of the left. The questions now are whether compensation at a level necessary to support the losers from globalization is possible, and whether it still appeals to voters.

Hypothesis 4 *Individuals who benefit more from social welfare policies will be less likely to vote for extreme right parties even when they are more exposed to globalization.*

I test these four hypotheses about globalization, its interaction with the financial crisis, technological change, and social welfare spending in the sections below.

4 Regional Level Empirical Analysis

4.1 Measuring Globalization: the Independent Variables

Globalization in terms of trade, capital and labor flows has grown greatly in the past 50 years. Figure 1 depicts these trends at the national level, showing that trade flows, FDI inflows, and international migration accelerate in the 1990s. However, after the 2008 great recession, both growth in trade flows and FDI inflows drop considerably. Trade is by far the biggest source of globalization flows. Figure 1 depicts the rise in trade openness at the national-level, measured as the share of exports and imports in real GDP at current PPP and drawn from the World Bank (2020), from an average of 50% in 1970 to 99% in 2018. The biggest component of this change has been Chinese trade. In 1980 China accounted for under 1% of the imports coming into the US and EU, whereas by 2007 it accounted for around 12% (Van Reenen 2011). For the 15 countries in my sample, imports from China accounted for 0.2% of total imports in 1980, 6.5% in 2007, and around 8% in 2017. These measures show what has happened at the national level. Numerous studies use the China import shock associated with its export surge after China's accession to the WTO in 2001 as a measure of the trade shock that the advanced industrial countries experienced in the 2000s (Autor et al. forthcoming, 2013). But more interesting is the regional one, where the differences have been large.

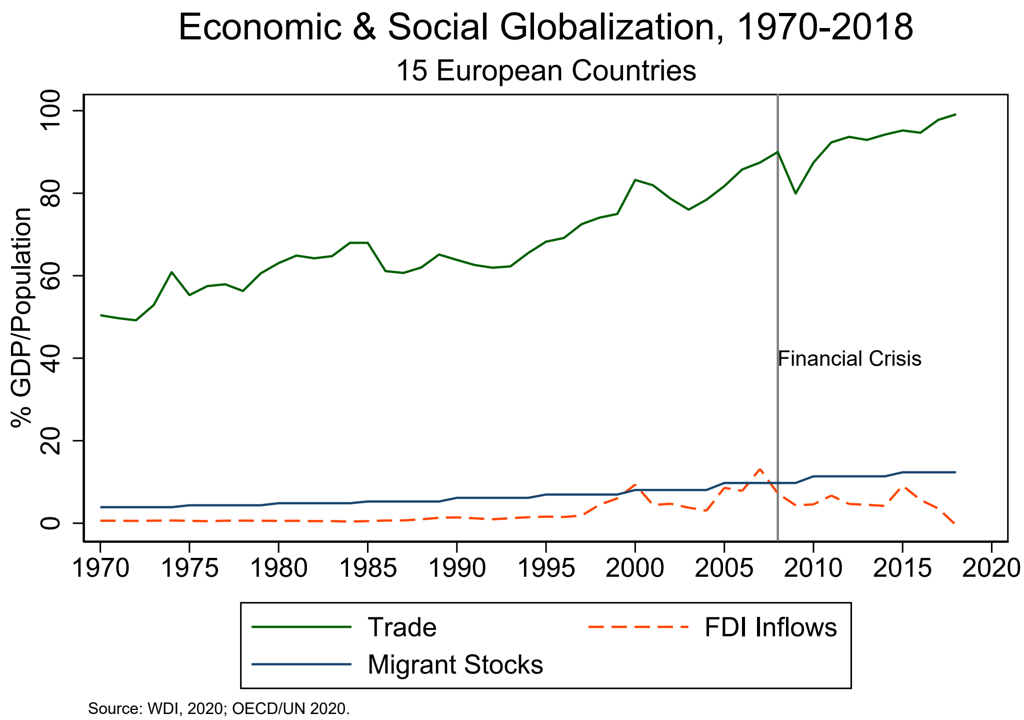

Figure 1: Economic and Social Globalization Measures. Trade flows as a share of GDP, FDI inflows as a share of GDP, and immigrants as a percentage of the total population for 15 European countries.

I explore as many sources of globalization pressure as possible. Beside the three flows that globalization refers to most often, that is, trade, foreign investment, and migration, I also focus on technological changes that might be associated with globalization: automation in the form of robots, routine task intensity of jobs (RTI), and the potential for offshoring of jobs. For the first two, I develop a measure at the regional level because these vary greatly within countries. For offshoring I have individual level data. I create a measure of the shock from change in these factors over a three year period, prior to the next election.

Following the existing literature, I mapped labor and demographic measures to election results and public opinion surveys at 2016 NUTS-1/2 level for all countries, adjusting for regional consistency over time. I constructed regional labor exposure measures to manufacturing imports from China and from low wage countries, inward foreign direct investment, migrants, robots, and RTI. My calculations weight three-year changes in imports, FDI, migrant stock, and the operational stock of robots by regional and national labor shares in 1992. In addition, I adapt Das and Hilgenstock (2018) in constructing a weighted routine task intensity index at the regional level by leveraging Eurostat's Labor Force Survey. Finally, I followed Anelli et al. (2019) in creating an automation exposure measure by using the operational stock of robots in manufacturing from data by the International Federation of Robotics. Full variable definitions and calculations are described in Appendix A.

I follow Autor et al. (2013), Colantone and Stanig (2018b), and others in defining the globalization shocks as:

$$Globalization\ Shock_{crt} = \sum_j \frac{L_{rj(1992)}}{L_{r(1992)}} \times \frac{\Delta M_{cjt}}{L_{cj(1992)}}$$

where $\frac{L_{rj(1992)}}{L_{r(1992)}}$ is the share of total workers of region r in country c employed in industry j. ΔM_{cjt} is the change in imports, foreign direct inflows, or the operational stock of robots in industry j (manufacturing) in country c between year t and $t-3$, normalized by the number of workers in manufacturing in that country in 1992. I use a three-year difference to match the average time between elections (3.8 years). Similarly, I calculated the immigration globalization shock as the change in resident foreign nationals by NUTS 1/2 region normalized by the total regional population in 1992.

Figure 2 shows the evolution of import competition from China and low-wage countries. An important point is that only around 2000 do these trade shocks begin to appear. They slow or decline after the 2008 financial crisis. The high point of the trade shock then was the beginning of the financial crisis.

Obtaining historical time-series data at the regional level is difficult and approximately 24% of all variables (including auxiliary variables) have missing data. To mitigate concerns over how missingness can bias the estimates if observations are not missing completely at random, I use multiple imputation to create 30 datasets, which is roughly equal to the average missingness rate of all variables in the imputation model, detailed further in Appendix B.

These regional measures are the main independent variables. Interestingly, the different measures of globalization are not highly correlated with one another at the regional level as shown in Appendix A4. While the two different trade measures are correlated as expected, the relationships between trade, capital flows, and migration are not strong. I use all three forms of globalization in the data analysis, in part to show which seems to have the strongest effects.

The regional measures have large standard deviations, especially within countries, suggesting very different experiences for local districts within countries. Different regions are experiencing different levels and types of globalization shocks. On the extreme end, Limburg in the Netherlands has been one of the regions hardest hit by the China shock, but much less by immigration. It is also the home

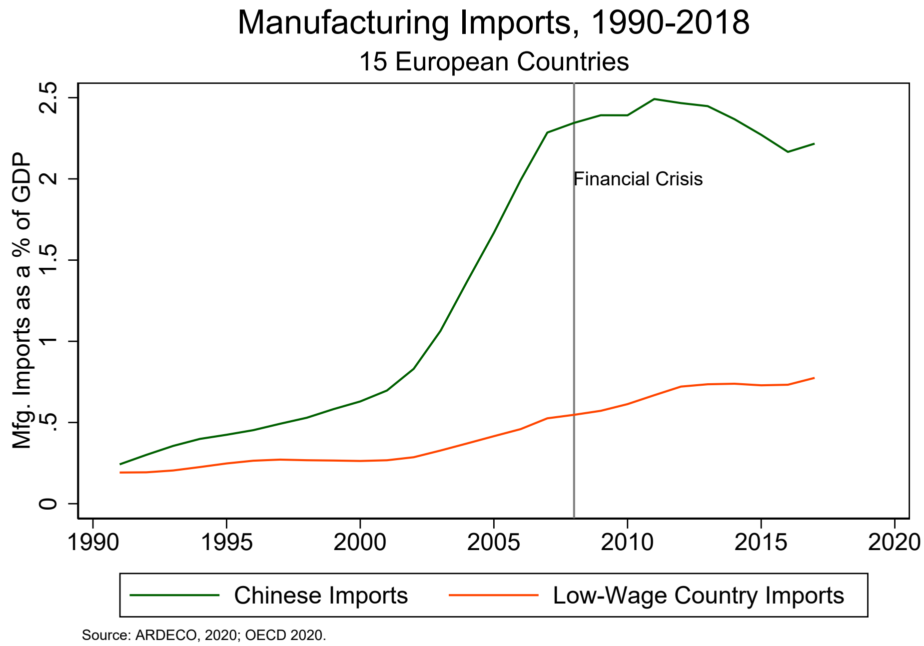

Figure 2: Imports from China and Low-Wage Countries. Three year moving average of manufacturing imports from China and Low-Wage Countries as a percent of GDP (constant 2015 Euros).

to Geert Wilders, the leader of the extreme right Dutch Party for Freedom (PVV). Limburg is a stronghold for Wilders' populist party, which is anti-immigrant, anti-EU, and anti-establishment. In 2017, the PVV polled about 16 per cent of the vote nationally, but for Limburg it was 28 percent, the highest of any Dutch region (Robinson 2017). In contrast, the China Shock in Groningen in the northeast Netherlands was about 1/3 lower than Limburg and saw a much smaller increase in support for the PVV and other far right parties.

A number of research papers note that regional measures of economic trends are more useful to understand the politics and economics of globalization. Trade exerts a stronger effect on regional, rather than national, labor markets because of the spatially concentrated nature of industrial activities, the inflexible nature of wages in the manufacturing sector, and the lower levels of inter-regional migration (e.g., Rusticelli, Haugh, Arquie, & Demmou 2018). Hence, regions that suffer a decline in their manufacturing employment rate greater than the national average also experience a larger decline in their total employment because inter-industry regional reallocation is slow and costly. In other words, globalization shocks are more pronounced and more persistent in regions than nationally, hence the initial focus on regions.

4.2 Instrumenting for the Import Shocks: US Import Data

A concern might be that import shocks and globalization itself are endogenous to policy choices by different governments, which depend on prior vote shares. To deal with this, I follow Autor et al. (2013) and Colantone and Stanig (2018b) in using an instrumental variable composed of US imports for the import trade shock in the EU countries. To separate out the potential causal effect of these import shocks, I control for endogeneity arising from factors such as demand shocks or domestic political elements that are correlated with such changes in imports. The instrument estimates changes in import shocks arising from exogenous factors, such as supply conditions in China and Low-Wage countries. The instrument is defined as:

$$Instrument\ for\ Shock_{crtp} = \sum_j \frac{L_{rj(1992)}}{L_{r(1992)}} \times \frac{\Delta M_{USjtp}}{L_{cj(1992)}}$$

where $\frac{L_{rj(1992)}}{L_{r(1992)}}$ is the share of total workers of region r in country c employed in industry j (manufacturing). ΔM_{USjtp} is the change in imports in manufacturing (j) between the United States and trading partner p (China or Low-Wage countries) between year t and $t-3$, normalized by the number of workers in manufacturing in country c in 1992. The validity of the instruments is shown in my results discussion and Appendix C.

Given this, my regression estimates are determined using the following equation for my Ordinary Least Squares (OLS) models:

$$Vote\ Share\ _{rtf} = \alpha_{rt} + \beta^1 Imports\ Shock_{crp,t-1} + \beta^2 Post.Crisis + \beta^3 \Gamma_{r,t-1} + \epsilon$$

where α_{rt} are country-year (effectively election-year) fixed effects, $\Gamma_{r,t-1}$ is a vector of the *Globalization Shock* variables (lagged one year), and ϵ is an error term. Implementing the instrumental variable, I then fit the models to the following Two-Stage Least Squares (2SLS) reduced form equation:

$$Imports\ Shock_{crp,t-1} = \alpha_{rt} + \gamma^1 Instrument\ for\ Shock_{crp,t-1} + \gamma^2 Post.Crisis + \gamma^3 \Gamma_{r,t-1} + \eta$$

4.3 Party Electoral Support by Region: the Dependent Variable

Our main dependent variable is party support by region for 15 advanced industrial democracies from 1990 to 2018. To understand how the party systems were affected by globalization, I coded parties as one of four types: extreme right, center right, center left, and extreme left. Scholars have used various classification schemes to group party by policy preferences either through scoring parties along a left-right dimension (Benoit & Laver 2007; Castles & Mair 1984; Huber & Inglehart 1995), broad classification groups (e.g., Christian-Democratic, Socialist) (Hix 2003), or various policy dimensions scored by either area experts (Hooghe & Marks 2018; Kriesi et al. 2006; Marks, Attewall, Rovny, & Hooghe 2017) or found in political party manifestos (Benoit & Laver 2007). In the populism-specific literature, researchers have devised a further set of classifications but many only investigate one particular party family (e.g., extreme right parties) or a brief time-period. Classifying extreme parties is further complicated since many extreme parties fail to meet minimum thresholds for inclusion in party manifesto collections and expert surveys.

To gain broader coverage of mainstream and extreme parties since the 1970s, I looked at existing classifications of parties in 35 seminal and recent works on mainstream or extreme parties in international and comparative political economy as summarized in Table A6. Among these 35 studies, 17 of them created original classifications of mainstream and extreme parties based on a party's nationalist or cosmopolitan stances, liberal-authoritarian dimensions, economic conservatism, and left-right positioning, shown in Table A6. My goal was to create a comprehensive view of extreme parties over time that did not rely on a single pre-existing study or dataset. I classified parties as 1) right populist, 2) center or mainstream right, 3) center or mainstream left, and 4) left populist if any of these existing studies referenced the party as such. Since many extreme parties capture a very small fraction of the vote, especially during the 1980s and 1990s, I did not want to artificially exclude them from the analysis. This would be problematic if I relied solely upon the Comparative Manifesto Project or Chapel-Hill Expert Survey where many extreme parties failed to meet minimum thresholds for inclusion.

First, I look at aggregate vote shares by party family at the regional level. I matched individual electoral constituencies from the Constituency-Level Elections Archive (CLEA) to a consistent set of regions using 2016 NUTS divisions (Appendix A5 for further description). I then aggregated vote share by party family up to the regional level.

Figure 3 depicts how the national average of this measure for extreme right-wing parties has changed over time. Votes for the extreme right and left have risen, while those for the mainstream

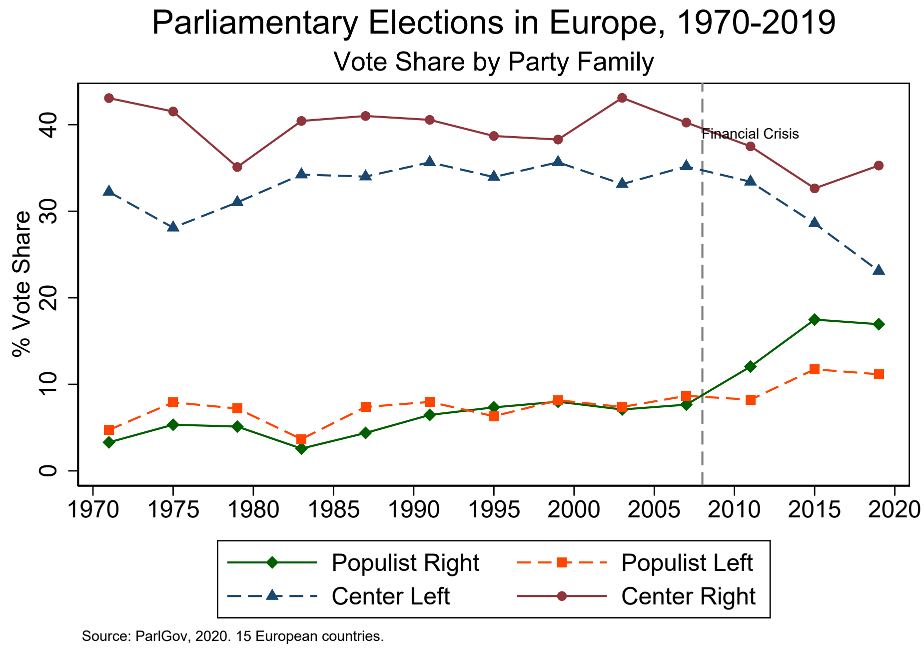

Figure 3: Vote Share by Party Family (four-year averages). The simple mean of vote share by party family from 1970-2019 across 15 European countries. Classification of parties is described in Section 4.3 and voting data was drawn from the ParlGov database (Döring & Manow 2016). 4-year averages were constructed to smooth the overall distribution.

right and left have fallen, especially for the left. But within regions such party support has varied a lot.

4.4 Regional Level Methods

In the first set of analyses, I investigate the relationship between globalization and party electoral outcomes in Europe from 1990-2018. I calculate regional exposure to Chinese imports in line with Autor et al. (2013) and Colantone and Stanig (2018b) as in section 4, albeit with a coarser measure of employment using total industrial employment rather than manufacturing employment at the subsector level. In addition to trade, I directly compare regional exposure to imports with exposure to two other globalization flows: FDI inflows and migration. I also look at the impact of technological change via measures of robots introduced or routine task intensity industries. And I add a variable for the global financial crisis since its effect in Europe was strong and extended. While other studies have investigated some of these measures in isolation (e.g., Anelli et al. 2019), none seems to directly compare globalization shocks with one another, nor examine technological pressures, nor look at the interaction with the financial crisis. In addition to the extreme right, I also look at how globalization has affected support for center left and right parties as well as more extreme left parties.

To examine the structural pressures of globalization on electoral outcomes, I specify linear models with election (i.e., country-year) fixed effects and robust standard errors clustered at the regional level to account for any non-interdependence within regions. I look at voting behavior at the regional rather than constituency level, because the globalization shocks are measured regionally which is larger than individual constituencies. I also use a three-year difference in real imports to directly proxy globalization's pressures between elections (the average time between elections is 3.8 years). The dependent variable is vote share by party family (populist right, populist left, center left, and center right) at the regional level of the total votes for each country election-year.

Making inferences about individual behavior from such aggregated data runs into the problem of ecological inference. The regional data is the lowest level I can obtain for the globalization variables, however. I supplement this regional level analysis with individual level below. But again it is constrained by the fact that the globalization variables are all measured at the regional level. To the extent the two sets of analyses produce similar results, we should have more confidence in the findings.

4.5 Regional Level Results

How does globalization impact voting behavior? In tables 1 and 2, I investigate Hypothesis 1 that regions more affected by economic globalization will be more likely to vote for extreme right parties and less likely to support traditional centrist ones. The top panel of table 1 finds a strong correlation between populist right voting and import competition from China. The magnitude of trade's effects is also sizable; a one standard deviation increase in import exposure (approximately 245 Euros per worker) approximates a 1.11% increase in populist right voting. Trade's impact on voting for other party types is less straightforward, however. I find similar results for the Low-wage country import shock variable as shown in Appendix E. The other globalization measures focusing on FDI and migration seem to have little association; rather, it is trade that matters most.

I next probe the effects of the financial crisis. I find the crisis had a large effect on voting behavior, with post-crisis elections associated with increased votes for both right and left populist parties and lower vote shares for traditional centrist parties. While the effects are sizable, I also investigate whether trade moderates these effects and include an interaction term between the trade and post-crisis elections in models 5-8. Consistent with Hypothesis 2, I find a significant negative interaction for centrist left parties. For ease of interpretation, figure 4 examines the marginal effect of the financial crisis as regional exposure to trade varies. Right populist parties saw sizable gains in vote shares following the post-crisis period and in regions where their exposure to imports from

China rose, but the interaction between them is insignificant. For left populist parties, the China trade shock has a moderating effect on the increase in vote shares seen following the financial crisis. For mainstream left parties, the aftermath of the financial crisis magnifies the negative effect of the trade shock, eroding their electoral support significantly. In particular, high import-competition in the wake of the crisis exacerbates the decline of support for center left parties by double-digit percentage points, as shown in figure 4.

Turning to Hypothesis 3, I find a positive relationship between robot exposure and extreme right party voting (a one standard deviation increase is associated a 0.7 percentage point increase in vote share). The pressures of automation as proxied by the routine task intensity index also are a strong predictor of voting for populist right parties (also about a 0.85 percentage point increase in vote share). Conversely, a one standard deviation increase in the routine task intensity index is associated with a nearly 1 percentage point decrease in support for left populist parties. Technological change also seems to have strong connection to the growth of extreme right support over time.

As discussed in 4.2, I implement a 2SLS analysis to account for endogeneity in the import shock variable. Table 1 reflects positive coefficients with greater magnitude and statistical significance than the OLS analysis for all models with reference to right populist voting. This suggests that unobserved determinants may be correlated with variations in manufacturing imports from China but may have a dampening effect on voting decisions for right populist parties. To ensure that the instrument is not weak and correctly specified, I subjected it to multiple robustness checks, detailed in Appendix C. The 2SLS results estimate that a one standard deviation increase in the China Shock variable leads to a 2.18 percentage point increase in right populist voting. This result is largely consistent across models, even controlling for other globalization and technology-related factors. This result provides more evidence that trade pressures have played a substantial role in increasing support for the extreme right, as Hypothesis 1 implies.

Table 1: Regional Voting (1990-2018)
(Populist Parties)

Right Populist	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
China Shock	2.451**	4.803***	2.269**	4.303***	2.225*	4.264**	2.041	3.767**
	(1.014)	(1.543)	(0.961)	(1.545)	(1.279)	(1.905)	(1.236)	(1.893)
FDI Shock	-0.118	-0.334	-0.229	-0.407	-0.180	-0.487	-0.290	-0.559
	(1.811)	(1.754)	(1.781)	(1.734)	(1.828)	(1.794)	(1.803)	(1.775)
Immigration Shock			-19.300	-20.519			-19.494	-21.047
			(14.592)	(14.072)			(14.602)	(14.050)
Post-Crisis	20.692***	21.358***	22.849***	23.276***	20.600***	21.136***	22.750***	23.037***
	(2.614)	(2.608)	(2.727)	(2.656)	(2.624)	(2.634)	(2.730)	(2.688)
Post-Crisis × China Shock					0.763	1.991	0.769	1.989
					(1.566)	(2.912)	(1.544)	(2.793)
Robot Shock	3.577**	2.796	2.110	1.559	3.552**	2.717	2.091	1.497
	(1.709)	(1.802)	(1.589)	(1.644)	(1.700)	(1.798)	(1.586)	(1.643)
RTI Region			7.072**	6.585**			7.050**	6.517**
			(2.870)	(2.790)			(2.865)	(2.789)
Constant	-0.437		-0.730		-0.356		-0.645	
	(1.173)		(1.161)		(1.180)		(1.172)	
N	1150	1150	1150	1150	1150	1150	1150	1150
Estimator	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
First Stage Results								
US-China Instrument		0.022***		0.022***		0.021***		0.021***
		(0.002)		(0.002)		(0.003)		(0.003)
Post-Crisis × US China Inst.						0.006*		0.006*
						(0.004)		(0.004)
Kleibergen-Paap rk Wald F-statistic		139.84		138.00		54.07		54.22
Anderson-Rubin Confidence Interval		[2.76, 7.68]		[2.39, 7.57]				

Left Populist	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
China Shock	-0.084	-0.695	0.239	-0.211	0.403	-0.182	0.668	0.298
	(0.641)	(1.760)	(0.621)	(1.750)	(0.786)	(1.864)	(0.774)	(1.826)
FDI Shock	-0.824	-0.769	-0.704	-0.665	-0.703	-0.623	-0.599	-0.522
	(2.120)	(2.073)	(2.126)	(2.081)	(2.115)	(2.050)	(2.126)	(2.063)
Immigration Shock			-7.943	-7.688			-7.585	-7.199
			(10.519)	(10.194)			(10.518)	(10.174)
Post-Crisis	10.291***	10.124***	7.933***	7.843***	10.482***	10.335***	8.111***	8.068***
	(1.910)	(1.844)	(2.159)	(2.048)	(1.910)	(1.840)	(2.154)	(2.041)
Post-Crisis × China Shock					-1.595	-1.861	-1.408	-1.852
					(0.980)	(1.663)	(0.963)	(1.583)
Robot Shock	-1.564	-1.354	0.256	0.386	-1.515	-1.276	0.292	0.449
	(1.890)	(1.855)	(1.931)	(1.879)	(1.882)	(1.845)	(1.924)	(1.872)
RTI Region			-7.927**	-7.825**			-7.896**	-7.764**
			(3.515)	(3.417)			(3.516)	(3.416)
Constant	1.842*		2.427**		1.672		2.271*	
	(1.071)		(1.162)		(1.079)		(1.172)	
N	1150	1150	1150	1150	1150	1150	1150	1150
Estimator	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
First Stage Results								
US-China Instrument		0.022***		0.022***		0.021***		0.021***
		(0.002)		(0.002)		(0.003)		(0.003)
Post-Crisis × US China Inst.						0.006*		0.006*
						(0.004)		(0.004)
Kleibergen-Paap rk Wald F-statistic		139.84		138.00		54.07		54.22
Anderson-Rubin Confidence Interval		[-4.21, 2.82]		[-3.64, 3.58]				

Notes: * p<.1, ** p<.05, *** p<.01. OLS and 2SLS estimates with country-year (i.e., election) fixed effects and robust standard errors clustered over 164 European regions (NUTS-1/2) in parentheses. The dependent variable is vote share for each party family as a percentage of the total regional vote.

Table 2: Regional Voting (1990-2018)
(Centrist Parties)

Center Left	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
China Shock	-1.243	0.144	-1.140	0.434	0.851	1.941	0.948	2.222
	(1.787)	(3.289)	(1.774)	(3.371)	(2.006)	(3.610)	(2.005)	(3.673)
FDI Shock	1.050	0.925	1.094	0.959	1.577	1.445	1.618	1.474
	(2.982)	(2.886)	(2.996)	(2.896)	(2.998)	(2.892)	(3.017)	(2.909)
Immigration Shock			8.299	7.393			10.003	9.125
			(29.315)	(28.038)			(28.950)	(27.645)
Post-Crisis	-8.684*	-8.312*	-9.738**	-9.434**	-7.861*	-7.585*	-8.863**	-8.646**
	(4.426)	(4.295)	(4.495)	(4.276)	(4.428)	(4.334)	(4.483)	(4.293)
Post-Crisis × China Shock					-6.851**	-6.520*	-6.869**	-6.518*
					(2.895)	(3.638)	(2.902)	(3.625)
Robot Shock	-3.558	-4.032	-2.839	-3.275	-3.344	-3.769	-2.675	-3.074
	(3.824)	(3.700)	(3.946)	(3.752)	(3.745)	(3.600)	(3.870)	(3.666)
RTI Region			-3.491	-3.890			-3.306	-3.661
			(6.166)	(6.096)			(6.150)	(6.069)
Constant	35.440***		35.587***		34.711***		34.832***	
	(4.402)		(4.389)		(4.384)		(4.370)	
N	1150	1150	1150	1150	1150	1150	1150	1150
Estimator	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
First Stage Results								
US-China Instrument		0.022***		0.022***		0.021***		0.021***
		(0.002)		(0.002)		(0.003)		(0.003)
Post-Crisis × US China Inst.						0.006*		0.006*
						(0.004)		(0.004)
Kleibergen-Paap rk Wald F-statistic		139.84		138.00		54.07		54.22
Anderson-Rubin Confidence Interval		[-5.60, 6.77]		[-4.99, 8.06]				

Center Right	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
China Shock	-1.161	1.791	-1.196	1.832	-0.508	2.553	-0.532	2.590
	(1.945)	(3.749)	(1.954)	(3.828)	(2.160)	(4.229)	(2.172)	(4.320)
FDI Shock	-1.369	-1.662	-1.347	-1.632	-1.198	-1.443	-1.172	-1.415
	(3.269)	(3.211)	(3.283)	(3.217)	(3.328)	(3.227)	(3.344)	(3.235)
Immigration Shock			5.458	3.564			5.991	4.297
			(21.430)	(20.830)			(21.529)	(20.916)
Post-Crisis	-16.787***	-15.936***	-16.782***	-16.144***	-16.530***	-15.623***	-16.504***	-15.808***
	(4.479)	(4.315)	(4.853)	(4.597)	(4.473)	(4.347)	(4.829)	(4.590)
Post-Crisis × China Shock					-2.173	-2.794	-2.223	-2.794
					(3.459)	(4.777)	(3.470)	(4.780)
Robot Shock	-5.583	-6.563	-5.629	-6.447	-5.507	-6.447	-5.567	-6.356
	(4.761)	(4.598)	(4.728)	(4.502)	(4.710)	(4.503)	(4.681)	(4.425)
RTI Region			0.111	-0.652			0.167	-0.564
			(7.487)	(7.301)			(7.472)	(7.270)
Constant	39.759***		39.724***		39.532***		39.484***	
	(4.123)		(4.133)		(4.089)		(4.097)	
N	1150	1150	1150	1150	1150	1150	1150	1150
Estimator	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
First Stage Results								
US-China Instrument		0.022***		0.022***		0.021***		0.021***
		(0.002)		(0.002)		(0.003)		(0.003)
Post-Crisis × US China Inst.						0.006*		0.006*
						(0.004)		(0.004)
Kleibergen-Paap rk Wald F-statistic		139.84		138.00		54.07		54.22
Anderson-Rubin Confidence Interval		[-4.53, 9.06]		[-4.91, 9.75]				

Notes: * $p<.1$, ** $p<.05$, *** $p<.01$.

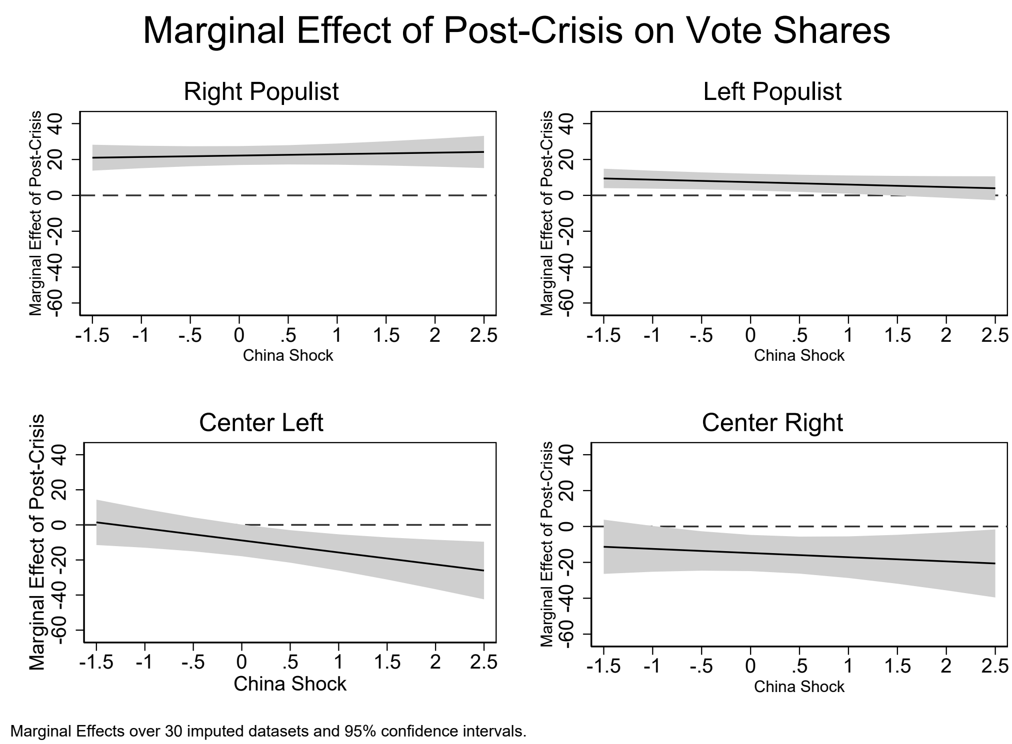

Figure 4: Marginal Effects: Vote Shares

5 Individual Level Empirical Analysis

5.1 Individual Level Methods

The analysis above focuses on regions and how globalization has affected overall changes in party support during this thirty year period. To understand the interaction between globalization and individual voting behavior, I leverage the European Social Survey for the same 15 countries and focus on individual-level data. This multinational survey is administered approximately every two years starting in 2002. Based on ESS vote choice question responses, I created separate indicators for each party family by individual vote choice, detailed in Appendix F.

I placed individuals in their respective NUTS-1/2 regions using regional identifiers within the ESS and matched respondents to the globalization measures by merging on election year. I use the same globalization measures from the regional level models above with the aforementioned multiple imputed datasets. The dependent variable is a quinary categorically distributed set of outcomes (i.e., vote choice for a party family). I estimate multinomial logistic models across the five party families (including Other parties) with robust standard errors clustered by region and country-year (i.e., election) fixed effects. I include a battery of individual-level controls that are known to affect partisanship, including gender, age, union membership, education, religiosity, and urban/rural location. To understand the effects of automation and global production on vote choice in Hypothesis 3, I create measures of an individual's "routine task intensity" (RTI) and "offshoring" based on ISCO-88 occupation classifications to match the individual's job classification. I include a measure of whether the individual relies on unemployment benefits as their main source of income. And I interact this with the import shock variable as a test of Hypothesis 4.

5.2 Individual Level Results

Table 3 presents multinomial logistic estimates of globalization's effects on individual vote choice. The findings suggest that individuals in regions hardest hit by imports are more likely to vote for a populist right party. The results are robust across reference categories and to using OLS as shown in Appendix F. This finding supports Hypothesis 1, with effect sizes similar to those found in the regional models. Given a one standard deviation increase in the China Shock variable, the relative risk of voting for a right populist party would be around 28% more likely than voting for an "Other" classified party. These results hold for the low-wage import shock as well, as shown in Appendix H.

Similar to the region-level estimates, individual workers at risk of automation as measured by their RTI are more likely to support right populist parties, which is consistent with Hypothesis 3.

However, the introduction of robots has more complicated effects on individuals in that region. It seems to reduce support for the extreme left. On the other hand, offshoring does not have the expected effects. It decreases support for the extreme right and weakly increases it for mainstream left parties. These results may be due to the differential impacts that automation and offshoring are having on parts of the electorate. The negative coefficient on offshoring for populist right voting is puzzling, but Rommel and Walter (2018) find a differential effect between skill and offshoring: higher skilled workers at risk of offshoring prefer center-right parties while lower-skill workers at risk prefer left parties. Offshoring and automation seem to be different processes. Some data suggest that offshoring is affecting higher skill jobs more and automation (measured through RTI) is affecting the middle of the skill spectrum most.

The financial crisis encourages voting for the right and extreme left, but reduces support for the center left. The interaction with trade shocks is not significant for any party apart from populist left, as in Appendix G, providing no support for Hypothesis 2. The crisis has a less consistent role at the individual level. The other individual-level covariates align with expectations: males and respondents with a lower education level prefer populist right parties, while urban residents and union members support left parties, and those relying on unemployment benefits favor more extreme left parties.

Does social welfare in the form of unemployment benefits moderate support for the extreme right? While individuals receiving unemployment benefits appear to have a strong preference for left populist parties and less support for traditional parties, there is evidence that those receiving unemployment benefits tend to gravitate toward the extreme right as import-competition increases (see column 4 in Table 3 and figure 5). While extreme right parties have historically been viewed as anti-welfare, recent research demonstrates that there has been a shift among the populist right toward more generous welfare policies, albeit only for core supporters (Afonso & Rennwald 2018). Receiving unemployment benefits, however, means that the individual has been adversely affected in the job market and hence may be one of the "losers" from globalization, which may also explain their antipathy to the mainstream right and left parties. In any case, there is little evidence that social welfare spending of this type moderates the political effects of trade exposure, providing no support for Hypothesis 4.

Table 3: ESS Individual Data: Unemployment Benefits, 2002-2016

	(1) Pop Left b/se	(2) Main Left b/se	(3) Main Right b/se	(4) Pop Right b/se
Globalization Variables				
China Shock	-0.055	-0.034	-0.031	0.512**
	(0.204)	(0.160)	(0.185)	(0.248)
FDI Shock	0.134	0.042	-0.037	0.151
	(0.741)	(0.361)	(0.212)	(0.573)
Immigration Shock	1.006	1.119	4.794	-0.951
	(3.483)	(2.924)	(4.005)	(6.139)
Unemp. Ben.	0.420***	-0.136	-0.363***	0.003
	(0.117)	(0.085)	(0.080)	(0.159)
Unemp. Ben $\times$ China Shock	0.120	0.151	0.062	0.551***
	(0.193)	(0.123)	(0.088)	(0.201)
Post-Crisis	3.171***	-0.409*	0.546**	3.556***
	(0.805)	(0.209)	(0.266)	(1.034)
Robots Shock	-2.305***	-0.536	-0.496	-0.682
	(0.668)	(0.355)	(0.434)	(0.513)
Individual Variables				
RTI	-0.002	0.007	0.007	0.087***
	(0.018)	(0.015)	(0.014)	(0.025)
Offshore	-0.010	0.039*	0.019	-0.081***
	(0.028)	(0.020)	(0.017)	(0.028)
Male	0.034	0.070***	0.292***	0.478***
	(0.044)	(0.025)	(0.033)	(0.041)
Age	0.004	0.002	0.004	0.001
	(0.007)	(0.004)	(0.004)	(0.009)
Age^2	-0.000	0.000	0.000**	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Education	-0.008	-0.036***	-0.004	-0.095***
	(0.006)	(0.006)	(0.006)	(0.010)
Urban	0.172**	0.214***	-0.106***	-0.017
	(0.073)	(0.037)	(0.030)	(0.069)
Union	0.705***	0.297***	-0.273***	0.003
	(0.052)	(0.033)	(0.028)	(0.054)
Religiosity	-0.157***	-0.026***	0.079***	-0.025**
	(0.016)	(0.007)	(0.007)	(0.012)
Constant	-3.150***	0.557***	-0.757***	-3.085***
	(0.743)	(0.195)	(0.191)	(1.018)
N	141505	141505	141505	141505

Notes: Multinomial logistic regression estimates with country-year fixed effects and robust standard errors clustered by region in parentheses for elections from 2002-2016. The dependent variables are individual vote choice by party family spanning from populist left $\rightarrow$ populist right (reference category=Other). The globalization variables are lagged one year prior to the election. * p<.1, ** p<.05, *** p<.01.

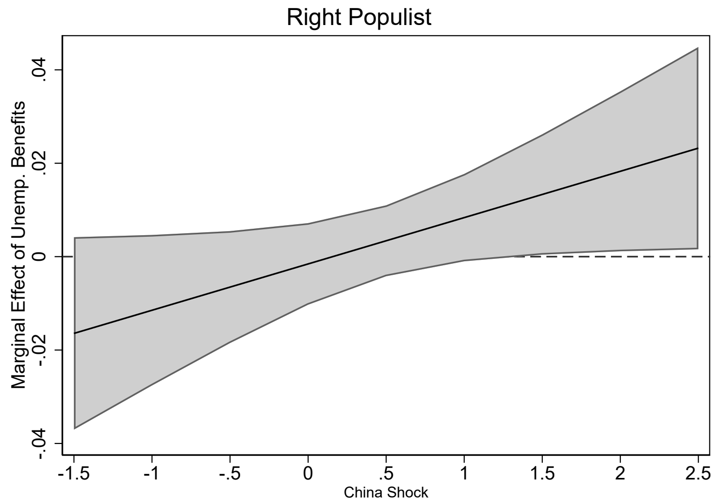

Figure 5: Marginal Effects of Unemployment Benefits on Vote Choice: Voting for the extreme right becomes more likely as imports rise in their region when the person receives unemployment benefits. Results from column 1 in OLS models in Appendix A13.

6 Discussion

As other studies, this paper shows that globalization, in the form of trade mainly, has had strong effects on party systems in Western Europe. Import shocks, especially from China and low wage countries in general, have been linked to increases in support for extreme right parties. Technological change also matters. Regions more affected by automation or voters in jobs susceptible to it are associated with more support for the extreme right. Social welfare spending, at least in the form of unemployment benefits, is not associated with reduced support for the extreme right when regions face strong low-wage import shocks. Trade and technological change, which may be related to it, are the primary globalization influences on changing party outcomes in Western Europe.

These results are robust to various modifications as outlined in the appendix. First, it is possible that the relationships between the dependent variables may make the error terms correlated across each of the individual models thus biasing the results. Through a series of seemingly unrelated regressions (SUR) as shown in Appendix D, I demonstrate that any possible correlation across models does not change the main findings. For the individual data, the results are not sensitive to estimating the models as either individual logits or OLS. In addition, I show in Appendix E that the findings are not driven exclusively by Chinese imports but imports from "low-wage" countries more generally. In many cases, the correlation between vote share and imports are even more pronounced when I estimate the trade shock from 50 of the lowest wage countries (excluding China), rather than only China. Third, the trade shock results are not sensitive to variable and observation inclusion such as dropping all 15 countries individually. Appendix J presents models similar to those in Tables 1- 2 using the unimputed data. They show similar results but are limited to only about half the number of observations as in the imputed results. Moreover, they are unstable for some variables as the sample changes with the listwise deletion of cases as new variables are added.

The analysis attempts to show causal effects. I use the regional level to dig deeper into the impact of trade and other globalization flows as they tend to affect regions differentially and pooling nationally obscures this. The use of country-year (i.e., election) fixed effects also helps identify the impact since the variation detected is that across regions in the same country in the same election. The use of an instrumental variable also reduces endogeneity concerns. The individual data is even more precise in that it holds constant individual-level characteristics that are known to affect vote choice. It also uses country-year fixed effects to pin down variation among individuals in a region within a country in a year. Clustering the standard errors on the region implies a more conservative estimate. The goal is to rule out as many potential confounders as possible. The exact causal mechanism is not identified. But job insecurity, lack of wage growth, and rising inequality are all main suspects that are associated with the explosion of trade flows from low wage countries. These economic concerns often spark more psychological factors, such as increased tolerance of authoritarianism and distrust for existing institutions, that make the programs of extreme right parties more appealing to affected voters. My analysis suggests that trade and technological change are of central importance in initiating this causal process.

7 Conclusion

Globalization appears to be associated with the decline of traditional parties and the rise of extreme right ones. I show that at the regional level trade shocks from China and low-wage countries have a strong positive relationship to support for extreme right parties. FDI inflows and immigration flows show no consistent effects on any party. This result seems surprising given all the concerns over migration in Europe lately. At the individual level, I find similar results. The financial crisis exacerbated these trends. The trade shock after the crisis hit dampened support for left parties, mainstream or populist. In addition, people in regions with jobs very susceptible to automation (those subject to the robot shock or with high RTI) are more likely to vote extreme right. The role of social compensation is also more complicated than "embedded liberalism" may suggest. It did not reduce support for the extreme right when those individuals were exposed to the trade shocks.

In sum, among the globalization factors, trade seems to have the most consistent and important effects on support for parties. Years ago Rogowski (1989) pointed out how opening up to trade could over the long term have dramatic effects on domestic politics within countries. Trade would create new winners and losers domestically, and the cleavage between these groups would shape politics within countries. In line with this, some analysts today posit that globalization is creating a new cleavage that will reorganize party systems in established democracies. Rogowski seemed to predict the ultimate political victory of the economic winners from trade as they grew stronger. But what we see today is the growing influence of the economic losers from trade who are forming opposition to globalization in all its forms via support for extreme right populist parties. Should the rise of populist parties cause worry? Perhaps they are just representing the preferences of intense minorities and hence are helping democracy. But as Levitsky and Ziblatt (2018, p. 22) warn, "What kinds of candidates tend to test positive on a litmus test for authoritarianism? Very often, populist outsiders do. ... When populists win elections, they often assault democratic institutions." In this view, extreme right populist parties are a cause for concern for democracy.

Finally, technological change, as evidenced through robots and RTI, is also important. Globalization propels technological change. And both processes seem to independently bolster support for extreme right parties and undermine support for mainstream ones. The rise of these parties also seems to have pulled the entire political spectrum in a more conservative and protectionist direction. Globalization has already slowed down and now the question is whether governments will adopt policies to slow or reverse it and whether they will also target technological change. The political contest for the future of globalization is under way, and which groups will dominate is unclear today.

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Supplemental Appendix

Contents

A Regional Variables

European Union countries follow the "Nomenclature of Territorial Units for Statistics" (NUTS) for subdividing administrative regions based on population ranges: NUTS-0 (national), NUTS-1 (larger macro regions with populations between 3 and 7 million people), NUTS-2 (smaller regions between 800,000 and 3 million), NUTS-3 (smallest regions with more than 150,000 people), and local administrative units (LAUs) below them.

A.1 Labor Data

I obtained local labor data at the NUTS-1/2 levels from the European Commission's Knowledge for Policy `ARDECO`[1] database with coverage at the broad industry level (NACE rev 2) from 1980-2018. Employment data is based on persons who are either employees or self-employed in that industry. The database defines regional employment as place of work rather than place of residence. I weight globalization measures by 1992 employment shares in order to proxy for the relative pressures of import competition and automation from this baseline.

A.2 Globalization Data

Imports data

I leverage the OECD's `STructural ANalysis (STAN) Database` for bilateral, industry-specific Imports data in current U.S. dollars[2]. I deflated and converted to constant 2015 Euros using exchange rates given by the Federal Reserve Bank of St. Louis' `FRED` database[3].

FDI Inflows Data

I assign industry classifications for net foreign direct investment inflows from the OECD's `FDI Flows by Industry`[4] database. The OECD classifies inflows by broad sector, primary (`AB/100`), Manufacturing (`C/3995`) and Services (`G/5095`), and subsector, but the degree of missingness at the subsector level is severe. I deflate and convert to constant 2015 Euros.

Immigration Data

I obtained data on resident foreign nationals from the relevant country's statistics office, and supplemented with OECD and EULFS estimates for years in which data were unavailable, as shown in Table A1 for each region-year.

For region-years not available from the national statistics offices, I gathered regional immigration data (estimated population share for the population above age 15) from Eurostat for the years 1999-2019 for France, Greece, and Portugal and used that proportion to proxy for immigrant population in each region. I further obtained detailed migration data from the `European Union Labor Force Survey (EULFS)` from 1983 to 2017. The EULFS is conducted annually for 28 European Union countries and three EFTA members and is representative for the population older than 15 years old. Regional identifiers, however, only appear in the data starting in 1993 for most countries and migration data becomes available at the regional level from 1995.

[1] https://ec.europa.eu/knowledge4policy/territorial/ardeco-database_en
[2] https://stats.oecd.org/index.aspx?queryid=64755#
[3] https://fred.stlouisfed.org/series/USAGDPDEFQISMEI
[4] https://stats.oecd.org/Index.aspx?DataSetCode=FDI_POS_CTRY

Table A1: Migration Data Sources

Country	Source	Years
Austria	Bundesanstalt Statistik Österreich	1987-2020
Belgium	Statbel	1992-2020
Denmark	StatBank Denmark	1987-2006, 2008-2020
	EULFS	2007
Finland	Tilastokeskus	1990-2019
France	Eurostat	1999-2019
	EULFS	1995-1998
Germany	Statistisches Bundesamt	1987-2019
		(1991-2019 for former DDR)
Greece	Eurostat	1999-2019
	EULFS	1995-1998
Ireland	EULFS	1998-2017
Italy	Istituto Nazionale di Statistica	1992-2018
Netherlands	Centraal Bureau voor de Statistiek	1995-2019
Norway	Statistisk sentralbyra	1987-2019
Portugal	Eurostat	1999-2019
	EULFS	1995-1998
Portugal (PT15, PT2, & PT3)	Instituto Nacional de Estatística	1990-1996
Spain	Instituto Nacional de Estadística	1998-2019
	EULFS	1995-1997
Sweden	Statistiska centralbyran	1987-2019
United Kingdom	Office for National Statistics	2000-2018
	EULFS	1995-1999

Robots Data

The pressures of automation are proxied using the Operational Stock of Robots in manufacturing by country from the `International Federation of Robotics`.[5]. Data is available starting in 1993, but temporal coverage depends on individual countries (Austria in 2003, Belgium in 2004, Denmark in 1996, Greece in 2006, Netherlands in 2004, and Portugal in 2004). To calculate the automation shock, I use the three-year difference in the operational stock weighted by labor shares in industry.

RTI and Offshoring

I merged the occupational status of individuals in Eurostat's micro-level Labor Force Survey (EU-LFS) with RTI and Offshoring scores. In order to harmonize occupation groups, I used Harry Ganzeboom's[6] cross-walks to convert ISCO-08 codes to ISCO-88 codes. A full correspondence was not available due to occupation classifiers being recorded at only the three-digit level in the EULFS. In instances of multiple matches, I used Julie Falcon's "Social Position" `R` package[7] to conduct the three-digit crosswalk.

RTI and Offshoring scores were derived using standard classification schemes as defined in the variable descriptions below.

[5] https://ifr.org/.

[6] http://www.harryganzeboom.nl/isco08/index.htm

[7] https://cran.r-project.org/web/packages/SocialPosition/index.html.

Table A2: NUTS Statistical Regions and Administrative Equivalents

Country	Level	Equivalent	Num. of Regions	Pop Avg
Austria	NUTS-1	Gruppen von Bundesländern	3	2,940,756
Belgium	NUTS-2	Provinces	11	1,036,235
Denmark	NUTS-2	Regioner	3	1,927,063
Finland	NUTS-2	Suuralueet / Storomraaden	4	1,378,283
France	NUTS-2	Régions and DOM	27	2,478,479
Germany	NUTS-1	Länder	16	5,174,522
Greece	NUTS-2	Periferies - Regions	13	826,243
Ireland	NUTS-2	Regions	2	2,415,196
Italy	NUTS-2	Regioni	20	3,024,199
Netherlands	NUTS-2	Provincies	12	1,431,757
Norway	NUTS-2	Landsdeler	7	745,088
Portugal	NUTS-2	Regiões	7	1,470,147
Spain	NUTS-2	Comunidades y ciudades Autonomas	19	2,455,708
Sweden	NUTS-2	Riksomraden	8	1,265,030
United Kingdom	NUTS-1	Government Office Regions; Country	12	5,522,798

Notes: 2016 NUTS statistical regions and their national administrative equivalents. Average population of all regions within a country are reported in the last column with 2018 population totals drawn from Eurostat. The number of regions and population average are drawn from the regions used for this analysis, thus there are fewer regions listed than there are in the NUTS-2 classification. For some regions, differences across datasets prevented a direct relationship between current and past regional boundaries requiring me to revert current NUTS-2 regions to older, larger regions or join two regions together: 1. FI1C (Etelä-Suomi (NUTS2010/2013/2016) + FI1B (Helsinki-Uusimaa) = FI18 (Etelä-Suomi (pre-NUTS2010)) to correspond with the Eurostat Labor Force Survey; 2. (DK04 (Midtjylland) + DK05 (Nordjylland)) to correspond with Midtjylland-Nordjylland and Jylland Danish election constituencies; 3. (DK02 (Hovedstaden) + DK03 (Sjælland)) to correspond with Sjælland-Syddanmark Danish election constituencies; 4. IE04 (Northern and Western) + IE063 (Midland) = IE01 (Border, Midland, and Western, NUTS 2013 classification) to correspond with Eurostat Labor Force Survey; 5. IE05 (Southern) + IE061 (Dublin) + IE062 (Mid-East) = IE02 (Southern and Eastern, NUTS 2013 classification) to correspond with Eurostat Labor Force Survey; and 6. ITH1 (Trento)+ITH2 (Bolzano/Bolzen) = ITH1 (Trentino-Alto Adige) to harmonize across data sources. This required building a correspondence table to track changes to administrative regions from 1980 to present. Numerous regions were split, merged, or discontinued when administrative redistricting occurred. NUTS codes were revised in 1995, 1999, 2003, 2006, 2010, 2013, and 2016. See https://ec.europa.eu/eurostat/web/nuts/history. I used the 2016 NUTS classification scheme as the reference year. Regional classifiers were only available at the NUTS-1 level for Austria, Germany, and the United Kingdom in the micro-level European Union Labor Force Surveys, requiring us to harmonize measures to the NUTS-1 level for these countries.

A.3 Regional Variable Descriptions

- **Vote Share by Party Family** Vote Share by party family at the regional level. Party vote share was first aggregated by family at the consistuency level and then aggregated up to the regional level. On average, there are 39 constituencies per region with large variation between countries (e.g., an average of two per NUTS-2 regions in Norway versus an average of 61 constituencies per NUTS-1 region in the United Kingdom). *Source: Constituency-Level Elections Archive (CLEA), 2018.*[8]

- **Labor Share** The percentage of labor by broad sector using NACE Rev. 2 sectoral definitions over total employment in the region population (Agriculture, Forestry and Fishing, Industry (excluding Construction), Construction, Wholesale, Retail, Transport,, Accommodation & Food Services, Information and Communication, Financial & Business Services, Non-market Services), Coverage: 1980-2015. *Source: European Commission's Knowledge for Policy ARDECO database, 2020.*

- **Chinese Imports** Three-year change in real manufacturing imports from China at the country-level. Coverage: 1990-2018. *Source: OECD STAN, 2019*

- **Low-Wage Imports** Three-year change in real imports by broad sector (agriculture, minning, and manufacturing) from "low-wage" countries the country-level by sector. Low-wage countries defined using Bernard et al (1986)'s classification of GDP per capita below 5% of U.S. Relevant countries: 1. Afghanistan 2. Ethiopia 3. Moldova 4. Albania 5. The Gambia 6. Georgia 7. Nepal 8. Armenia 9. Ghana 10. Niger 11. Azerbaijan 12. Guinea 13. Pakistan 14. Bangladesh 15. Rwanda 16. Guyana 17. Samoa 18. Bhutan 19. Haiti 20. São Tomé and Príncipe 21. Burkina Faso 22. India 23. Sierra Leone 24. Burundi 25. Kenya 26. Somalia 27. Cambodia 28. Lao PDR 29. Sri Lanka 30. Central African Rep. 31. Lesotho 32. St. Vincent 33. Chad 34. Madagascar 35. Sudan 36. Malawi 37. Togo 38. Comoros 39. Maldives 40. Uganda 41. Congo 42. Vietnam 43. Equatorial Guinea 44. Mauritania 45. Yemen 46. Eritrea 47. Vietnam 48. Yemen Arab Rep. 49. Yemen People's Republic 50. Guinea-Bissau
  Coverage: 1990-2018. *Source: OECD STAN, 2019.*

- **FDI Inflows** Three-year change in real FDI inflows by broad sector (Agriculture and Industry) harmonized between BDM3 and BDM4 definitions. Coverage: 1985-2018. *Source: OECD STAN, 2013/2018.*

- **Immigration Shock** Three year difference in the population of foreign nationals over the total population at the regional level in base year 1992. Coverage: 1987-2019. *Source: National Statistical Offices (see Table A1), European Union Labor Force Microlevel Data, 1983-2017, Eurostat.* I calculated the immigration globalization shock as:

$$Immigration\ Shock_{crt} = \frac{\Delta Imm_{rt}}{P_{r(1992)}}$$

  where ΔImm_{rt} is the change in the stock of foreign nationals in region r between year $t-1$ and $t-4$ normalized by $P_{r(1992)}$, the total population in NUTS-2 region r in 1992.

- **Robot Shock** Three-year change in the operational stock of robots in Manufacturing normalized by labor shares in industry. 1993-2018. *Source: International Federation of Robotics, 2020.*

[8] http://www.electiondataarchive.org/index.html

- **Regional RTI** I weight routine task intensity scores for occupational shares at the regional level from the EULFS. RTI scores were assigned at the three-digit ISCO-88 level following Goos et al. (2014); Thewissen and Rueda (2019), and updated by Mahutga, Curran, and Roberts (2018). I adapt Das and Hilgenstock (2018, p. 13) country-level exposure to routinization weights to the regional level. Specifically,

$$RTI_{jt} = \sum_{ljt} \times RTI_l$$

where occupation l's share of total employment in region j at t. *Source: European Union Labor Force Microlevel Data, 1993-2017.*

- **Regional Offshoring Potential** I weight offshoring potential scores for occupational shares at the regional level from the EULFS. Offshoring index scores from Blinder and Krueger (2013) were assigned using Rommel and Walter (2018); Thewissen and Rueda (2019)'s coding protocol. I adapt Das and Hilgenstock (2018, p. 13) country-level exposure to routinization/off-shoring weights to the regional level. Specifically,

$$\mathit{Offshore}_{jt} = \sum_{ljt} \times \mathit{Offshore}_l$$

where occupation l's share of total employment in region j at t. *Source: European Union Labor Force Microlevel Data, 1993-2017.*

Table A3: Summary Statistics (MI Data)

Variable	Mean	SD	min	max	N
China Shock	0.237	0.453	-2.813	3.136	1150
Low-Wage Imp Shock	0.064	0.101	-0.232	0.797	1150
FDI Shock	-0.020	0.221	-2.669	0.744	1150
Robots Shock	0.171	0.202	-0.372	1.103	1150
RTI Region	0.013	0.121	-0.508	0.485	1150
Immigration Shock	0.006	0.018	-0.143	0.240	1150
30 Multiple Imputed Datasets					

Table A4: MI estimate of correlations

	China Shock	Low-Wage Shock	FDI Shock	Robots Shock	RTI Region	Imm. Shock
China Shock	1.000					
Low-Wage Imp Shock	0.509	1.000				
FDI Shock	0.126	-0.098	1.000			
Robots Shock	0.114	0.210	-0.119	1.000		
RTI Region	0.024	-0.086	0.045	0.207	1.000	
Immigration Shock	0.048	0.018	-0.043	0.089	-0.089	1.000

Correlation between the China Shock and Low-Wage Shock was anticipated. There exists a minor level of correlation between some variables (e.g., Robots Shock and RTI Region). In an effort to ensure that the models used were foundationally sound, I conducted Variance Inflation Factor (VIF) tests to test for multicollinearity. The mean VIF across all model setups and variable combinations was slightly above 1, well below the generally accepted level of 10 to warrant further investigation into multicollinearity using Stata's *MIVIF* package developed by Klein (2013).

A.4 Elections and Voting Data

I obtained election results from national parliamentary elections at the constituency level from the University of Michigan's Constituency-Level Elections Archive (CLEA) (Kollman, Hicken, Caramani, Backer, & Lublin 2019). On average, parliamentary elections occurred every 3.8 years in the 15 countries (see table A5). In the two instances where there were multiple elections in one year, I used the first election (Greece, (May 2012) and Greece (January 2015). CLEA reports election results by candidate and party for each constituency. In order to match constituencies to administrative regions, I created a series of correspondence tables to first match constituencies to NUTS regions and then standardize codes to 2013 regional divisions. I then aggregated party vote shares up to the regional level for each election. A full list of parties and their classifications is available from the author upon request.

Table A5: European Elections, 1990-2018

Country	**Election 1**	**Election 2**	**Election 3**	**Election 4**	**Election 5**	**Election 6**	**Election 7**	**Election 8**
Austria	1994	1995	1999	2002	2006	2008	2013	
Belgium	1991	1995	1999	2003	2007	2010	2014	
Denmark	1994	1998	2001	2005	2007	2011	2015	
Finland	1991	1995	1999	2003	2007	2011	2015	
France	1993	1997	2002	2007	2012	2017		
Germany	1994	1998	2002	2005	2009	2013		
Greece	1993	1996	2000	2004	2007	2009	2012	2015
Ireland	1992	1997	2002	2007	2011	2016		
Italy	1992	1994	1996	2001	2006	2008	2013	2018
Netherlands	1994	1998	2002	2003	2006	2010	2012	2017
Norway	1993	1997	2001	2005	2009	2013	2017	
Portugal	1991	1995	1999	2002	2005	2009	2011	2015
Spain	1993	1996	2000	2004	2008	2011	2015	2016
Sweden	1991	1994	1998	2002	2006	2010	2014	
United Kingdom	1992	1997	2001	2005	2010	2015	2017	

A.5 Political Parties Classifications

I classified parties based on a survey of 35 leading articles and books on populism in comparative and international political economy. From these 35 articles, I found that 17 studies used original classifications of political parties. I classified parties as 1) right populist, 2) center or mainstream right, 3) center or mainstream left, and 4) left populist if any of these existing studies referenced the party into any of those categories. Since many extreme parties persistently captured a fraction of

Table A6: Party Classifications in the Existing Literature

Study	Cntries	Centrist	M. Left	M. Right	Populist	Far Right	Far Left	SYear	EYear
Wagner and Meyer (2017)	17		✓	✓		✓		1980	2015
Hernandez and Kriesti (2016)	20	✓				✓		2008	2014
Hix (2003)	15		✓	✓				1960	1998
Ivarsflaten (2008)	7		✓	✓		✓		2002	2002
Rovny (2013)	13		✓	✓		✓		1999	2006
Pontusson and Rueda (2017)	17		✓	✓				1975	2000
Mudde (2007)	37					✓		1980	2005
van Kessel (2015)	31				✓			2000	2013
March (2011)	26						✓	1990	2010
Arzheimer (2009)	18					✓		1980	2002
Marks, Attewall, Rovny, and Hooghe (2017)	23					✓		2002	2004
Funke, Schularick, and Trebesch (2016)	20					✓	✓	1870	2014
Rooduijn and Burgoon (2017)	23					✓	✓	2002	2014
Rodrik (2018)	19					✓	✓	1963	2015
Golder (2003)	19				✓	✓		1970	2000
Gidron and Hall (2017)	15					✓		2009	2009
Algan, Guriev, Papaioannou, and Passari (2017)	26				✓	✓	✓	2000	2017

An ✓indicates whether the article or book classified parties as only "Centrist" (i.e., no left/right distinction) ("Centrist"), Mainstream Left ("M Left"), Mainstream Right ("M Right"), only "Populist" (i.e., no left/right distinction) , "Far Right", or "Far Left". Cntries == Number of countries, SYear == First Year in Study, EYear == Last Year in Study. All of the above used time *invariant* party classifications with the exception of Mudde (2007).

the total vote, especially during the 1980s and 1990s, I did not want to artificially exclude them from the analysis. This would be problematic if I relied solely upon the Comparative Manifesto Project (CMP) or Chapel-Hill Expert Survey (CHES) where many extreme parties failed to meet minimum thresholds for inclusion. Among the 15 European countries investigated in this paper, 343 distinct political parties in CLEA's dataset were referenced in the existing literature as either extreme right (115), extreme left (79), center left (20), and center right (34). To be sure, the classification cannot distinguish degrees of extremism or particular policy stances *within* extreme parties (e.g., UKIP versus the British National Party) as would be possible using a Center of Gravity (CoG) approach with party manifestos.

B Multiple Imputation Setup

Obtaining historical time-series data at the regional level is difficult and approximately 24% of all variables (including auxiliary variables) have missing data. To mitigate concerns over how missingness can bias the estimates if observations are not missing completely at random, I use multiple imputation to create 30 datasets, which is roughly equal to the average missingness rate of all variables in the imputation model.[9] I use Rubin's rules to average coefficient estimates and standard errors across the 30 imputed datasets. The regression analyses with imputed data were also run on the unimputed data. The results in Appendix J suggest that the models used here are applicable, as the results are similar. Variations in missingness across variables, however, causes instability in comparing models. To avoid potential biases from fitting the models solely to complete cases I thus utilize the alternative to listwise deletion of multiple imputation at the recommendation of Allison (2002). For the imputation method, I utilized the Amelia II R package (Honaker, King, & Blackwell 2011), which utilizes a hybrid Expectation-Maximization algorithm with bootstrapping. Amelia II contains features specific for imputation of time-series data, and the imputed data is easily transferable between other statistical software, such as Stata.

[9]I follow Lall (2016, p. 426) in setting the number of imputations using the average missingness of all rows, including a "sequence of third-order time polynominals. . . to smooth temporal variation within cross-section units" and "a ridge prior of 1% of the number of observations" in the dataset to alleviate computational issues.

C Instrumental Variable and Two Stage Least Squares Analysis

A concern might be that import shocks and globalization itself are endogenous to policy choices by different governments, which depend on prior vote shares. In order to deal with this, I follow Autor, Dorn, and Hanson (2013) and Colantone and Stanig (2018) in using an instrumental variable composed of US import shares for the import trade shock in the EU countries. In an attempt to separate out the potential causal effect of these import shocks, I control for endogeneity arising from factors such as demand shocks or domestic political factors in the EU that are correlated with such changes in imports. With that, the instrument estimates changes in import shocks arising from exogenous factors, such as supply conditions in China and Low-Wage countries. The instrument is defined as follows:

$$\textit{Instrument for Shock}_{crtp} = \sum_j \frac{L_{rj(1992)}}{L_{r(1992)}} \times \frac{\Delta M_{USjtp}}{L_{cj(1992)}}$$

where $\frac{L_{rj(1992)}}{L_{r(1992)}}$ is the share of total workers of region r in country c employed in industry j . ΔM_{USjtp} is the change in imports in industry j (manufacturing) between the United States and trading partner p (China or Low-Wage countries) between year t and $t-3$, normalized by the number of workers in manufacturing in country c in 1992. The structure of the instrumental variable approach is given graphically below:

$$\begin{tikzcd}
\textit{Instrument for Shock}_{crtp} \arrow[r] & \textit{Imports Shock}_{crtp} \arrow[r] & \textit{Vote Share}_{rtf} \\
& \textit{Unobserved Determinants} \arrow[u] \arrow[ur] &
\end{tikzcd}$$

where $Vote\ Share_{rtf}$ is the dependent variable of vote share (by party family f) in NUTS region r at time t and *Imports Shock*$_{ctrp}$ is the *Globalization Shock* variable as defined above with ΔM being the change in manufacturing imports. This instrument *Instrument for Shock*$_{crtp}$ is correlated with the endogenous regressor *Imports Shock*$_{ctrp}$, uncorrelated with unobserved determinants, and has no direct effect on the dependent variable of the analysis. The validity of the instruments is shown below.

Given this, the regression estimates are determined using the following equation for my Ordinary Least Squares (OLS) models:

$$\textit{Vote Share}_{\ rtf} = \alpha_{rt} + \beta^1 Imports\ Shock_{crp,t-1} + \beta^2 Post.Crisis + \beta^3 \Gamma_{r,t-1} + \epsilon$$

where α_{rt} are country-year (effectively election-year) fixed effects, $\Gamma_{r,t-1}$ is a vector of the Globalization Shock variables discussed above (lagged one year), and ϵ is an error term. Implementing the instrumental variable, I then fit the models to the following Two-Stage Least Squares (2SLS) reduced form equation:

$$\textit{Imports Shock}_{crp,t-1} = \alpha_{rt} + \gamma^1 Instrument\ for\ Shock_{crp,t-1} + \gamma^2 Post.Crisis + \gamma^3 \Gamma_{r,t-1} + \eta$$

Using regional level data, election-year fixed effects, and an instrument increases confidence that the estimates I find are causal.

Table 1 and Appendix E reflect positive coefficients with greater magnitude and statistical significance than the OLS analysis for all models with reference to right populist voting. This suggests that the aforementioned unobserved determinants shown in the DAG may be correlated with variations in manufacturing imports from China but may have a dampening effect on voting decisions for right populist parties. To ensure that the instrument is not weak and correctly specified, I have subjected the instrument to multiple robustness checks. Across all models, the first stage results coefficient on the instrument is positive and statistically significant, satisfying the first assumption of a consistent instrumental variable $[Cov(Instrument, Endogenous\ Regressor) > 0]$. To test for weak instruments, I report the Kleibergen-Paap rk Wald F-statistic[10]. As this is a 2SLS analysis with one endogenous regressor, the Kleibergen-Paap rk Wald F-statistic is equivalent to the effective first-stage F-statistic suggested by Olea and Pflueger (2013). The F-statistics shown are the mean F-statistic of the 30 multiple imputation regression analyses (for each imputed data set), and are above 130 for models without an interaction variable, and above 50 for models including an interaction variable. Given that the generally accepted threshold for defining a weak instrument is an F-statistic value of 10, this suggests that the instrument is not weak. Further, as recommended by Andrews, Stock, and Sun (2019), I report the identification-robust Anderson-Rubin Confidence Intervals for cases in which there is a single endogenous regressor and single instrument (i.e. models without the interaction variable, in this case). Using an inverted Anderson-Rubin Confidence Interval Set as done by Mikusheva and Poi (2001)[11], I test for the minimum level of explanatory information provide by the instrument. If the instrument were weak, this would result in an unbounded or empty set. In my analyses, there exists a bounded-finite inverted Anderson-Rubin Confidence Interval for each of the models. These values are the mean inverted Anderson Rubin Confidence Interval for each of the multiply imputed data set regressions, and the interval is finite in each set. Between the positive and significant first-stage coefficient, Kleibergen-Paap rk Wald F-statistic greater than 10, and finite inverted Anderson-Rubin Confidence Interval across all models and imputations, this is a strong suggestion that I do, in fact, have a valid, consistent, and strong instrument. To allay concerns regarding the finite sample bias of 2SLS in models where imputation is used, I incorporate the instrument into the imputation model (McDonough & Millimet 2017).

D Regional Votes Share Models, Seemingly Unrelated Regressions

In this section, I estimate a series of seemingly unrelated regressions (SUR) for the aggregate vote share models, because the errors may correlated across the each of the individual models. I find that all of the main findings are robust to use of SUR and possible correlation across models does not affect the correlational claims.

[10] Calculated using the *IVREG2* Stata package from Baum, Schaffer, and Stillman (2015)

[11] Calculated using the *twostepweakiv* package in Stata developed by Sun (2018)

Table A7: SUREG: Vote Share, 1990-2018

	Right Pop b/se	Center Right b/se	Center Left b/se	Left Pop b/se	Other b/se
Panel A					
China Shock	2.451**	-1.161	-1.243	-0.084	2.941
	(0.979)	(1.870)	(1.724)	(0.618)	(2.281)
FDI Shock	-0.118	-1.369	1.050	-0.824	0.168
	(1.757)	(3.166)	(2.902)	(2.073)	(2.999)
Post-Crisis	20.692***	-16.787***	-8.684**	10.291***	-4.380
	(2.489)	(4.262)	(4.212)	(1.818)	(5.298)
Robot Shock	3.577**	-5.583	-3.558	-1.564	9.432
	(1.645)	(4.555)	(3.671)	(1.812)	(6.359)
Constant	-0.437	39.759***	35.440***	1.842*	21.737***
	(1.120)	(3.924)	(4.189)	(1.020)	(4.575)
Panel B					
China Shock	2.195**	-1.175	-1.109	0.208	3.205
	(0.931)	(1.873)	(1.717)	(0.595)	(2.297)
FDI Shock	-0.224	-1.345	1.090	-0.703	0.288
	(1.733)	(3.187)	(2.912)	(2.086)	(3.045)
Post-Crisis	22.789***	-16.762***	-9.714**	7.913***	-6.511
	(2.631)	(4.615)	(4.273)	(2.043)	(5.845)
Robot Shock	2.008	-5.600	-2.792	0.214	11.035*
	(1.539)	(4.513)	(3.799)	(1.851)	(6.552)
RTI Region	7.030**	0.121	-3.478	-7.935**	-7.144
	(2.782)	(7.139)	(5.899)	(3.348)	(9.660)
Constant	-0.887	39.765***	35.654***	2.359**	22.195***
	(1.086)	(3.938)	(4.154)	(1.110)	(4.588)
Panel C					
China Shock	2.269**	-1.196	-1.140	0.239	3.339
	(0.928)	(1.877)	(1.710)	(0.599)	(2.321)
FDI Shock	-0.229	-1.347	1.094	-0.704	0.281
	(1.726)	(3.177)	(2.914)	(2.080)	(3.070)
Immigration Shock	-19.300	5.458	8.299	-7.943	-35.360
	(13.939)	(20.523)	(27.917)	(10.079)	(38.834)
Post-Crisis	22.849***	-16.782***	-9.738**	7.933***	-6.389
	(2.594)	(4.617)	(4.277)	(2.056)	(5.882)
Robot Shock	2.110	-5.629	-2.839	0.256	11.223*
	(1.532)	(4.520)	(3.792)	(1.855)	(6.569)
RTI Region	7.072**	0.111	-3.491	-7.927**	-7.078
	(2.745)	(7.145)	(5.892)	(3.356)	(9.665)
Constant	-0.730	39.724***	35.587***	2.427**	22.467***
	(1.107)	(3.930)	(4.173)	(1.108)	(4.591)
N	1150				

Notes: * p<.1, ** p<.05, *** p<.01. SUREG estimates with country-year (i.e., election) fixed effects and robust standard errors clustered over 164 European regions (NUTS-1/2) in parentheses. The dependent variable is vote share by party family as a percentage of the total regional vote. Globalization shocks are three-year differences in total imports, inward FDI flows in manufacturing, and the stock of robots in manufacturing, all weighted by labor shares in industry, regional-level exposure to routinization, and the portion of migrants over the region's total population.

Table A8: SUREG: Vote Share w/ Interactions, 1990-2018

	Right Pop	Center Right	Center Left	Left Pop	Other
Panel A					
China Shock	2.225*	-0.508	0.851	0.403	1.089
	(1.238)	(2.087)	(1.947)	(0.759)	(2.422)
FDI Shock	-0.180	-1.198	1.577	-0.703	-0.297
	(1.772)	(3.222)	(2.914)	(2.068)	(2.945)
Post-Crisis	20.600***	-16.530***	-7.861*	10.482***	-5.103
	(2.497)	(4.256)	(4.212)	(1.817)	(5.250)
Post-Crisis × China Shock	0.763	-2.173	-6.851**	-1.595*	6.073
	(1.509)	(3.313)	(2.777)	(0.940)	(4.283)
Robot Shock	3.552**	-5.507	-3.344	-1.515	9.236
	(1.636)	(4.504)	(3.595)	(1.803)	(6.267)
Constant	-0.356	39.532***	34.711***	1.672	22.378***
	(1.127)	(3.891)	(4.171)	(1.027)	(4.473)
Panel B					
China Shock	2.007*	-0.523	0.964	0.654	1.319
	(1.197)	(2.101)	(1.945)	(0.751)	(2.456)
FDI Shock	-0.276	-1.174	1.609	-0.593	-0.184
	(1.752)	(3.245)	(2.929)	(2.085)	(2.985)
Post-Crisis	22.707***	-16.488***	-8.841**	8.099***	-7.297
	(2.634)	(4.592)	(4.259)	(2.038)	(5.744)
Post-Crisis × China Shock	0.635	-2.181	-6.799**	-1.460	6.208
	(1.472)	(3.303)	(2.768)	(0.927)	(4.216)
Robot Shock	1.991	-5.536	-2.620	0.253	10.870*
	(1.536)	(4.467)	(3.728)	(1.843)	(6.472)
RTI Region	7.011**	0.177	-3.290	-7.903**	-7.307
	(2.776)	(7.120)	(5.883)	(3.348)	(9.609)
Constant	-0.818	39.533***	34.918***	2.201**	22.859***
	(1.095)	(3.902)	(4.135)	(1.119)	(4.468)
Panel C					
China Shock	2.041*	-0.532	0.948	0.668	1.377
	(1.195)	(2.098)	(1.945)	(0.748)	(2.476)
FDI Shock	-0.290	-1.172	1.618	-0.599	-0.212
	(1.746)	(3.236)	(2.931)	(2.079)	(3.007)
Immigration Shock	-19.494	5.991	10.003	-7.585	-36.981
	(13.942)	(20.609)	(27.555)	(10.074)	(39.142)
Post-Crisis	22.750***	-16.504***	-8.863**	8.111***	-7.202
	(2.597)	(4.593)	(4.264)	(2.050)	(5.780)
Post-Crisis × China Shock	0.769	-2.223	-6.869**	-1.408	6.469
	(1.485)	(3.321)	(2.781)	(0.926)	(4.247)
Robot Shock	2.091	-5.567	-2.675	0.292	11.061*
	(1.529)	(4.474)	(3.720)	(1.848)	(6.487)
RTI Region	7.050**	0.167	-3.306	-7.896**	-7.244
	(2.739)	(7.128)	(5.876)	(3.355)	(9.615)
Constant	-0.645	39.484***	34.832***	2.271**	23.171***
	(1.117)	(3.895)	(4.154)	(1.118)	(4.469)
N	1150				

Notes: * p<.1, ** p<.05, *** p<.01. SUREG estimates with country-year (i.e., election) fixed effects and robust standard errors clustered over 164 European regions (NUTS-1/2) in parentheses. The dependent variable is vote share by party family as a percentage of the total regional vote. Globalization shocks are three-year differences in total imports, inward FDI flows in manufacturing, and the stock of robots in manufacturing, all weighted by labor shares in industry, regional-level exposure to routinization, and the portion of migrants over the region's total population.

Table A9: SUREG: Vote Share, 1990-2018
Low-Wage Imports

	Right Pop	Center Right	Center Left	Left Pop	Other
	b/se	b/se	b/se	b/se	b/se
Panel A					
Low-Wage Imp Shock	15.968***	-18.912**	-6.611	3.766	16.985
	(4.337)	(8.816)	(7.399)	(3.347)	(10.815)
FDI Shock	0.503	-1.957	0.794	-0.736	0.855
	(1.779)	(3.142)	(2.904)	(2.061)	(3.042)
Post-Crisis	18.963***	-15.176***	-7.916*	10.057***	-6.344
	(2.390)	(4.439)	(4.238)	(1.918)	(5.462)
Robot Shock	2.441	-3.649	-3.149	-2.056	8.336
	(1.688)	(4.349)	(3.571)	(1.929)	(6.218)
Constant	0.169	39.451***	35.141***	1.821*	22.500***
	(1.200)	(3.913)	(4.151)	(1.022)	(4.476)
Panel B					
Low-Wage Imp Shock	15.418***	-18.975**	-6.303	4.404	17.527
	(4.245)	(8.739)	(7.328)	(3.261)	(10.717)
FDI Shock	0.358	-1.941	0.855	-0.574	1.006
	(1.740)	(3.162)	(2.915)	(2.072)	(3.090)
Post-Crisis	21.200***	-15.063***	-9.033**	7.531***	-8.492
	(2.497)	(4.754)	(4.278)	(2.114)	(5.955)
Robot Shock	0.833	-3.722	-2.355	-0.242	9.889
	(1.590)	(4.332)	(3.715)	(1.989)	(6.481)
RTI Region	7.124**	0.372	-3.567	-8.010**	-6.843
	(2.810)	(7.042)	(5.864)	(3.327)	(9.543)
Constant	-0.358	39.433***	35.399***	2.421**	23.005***
	(1.144)	(3.928)	(4.109)	(1.114)	(4.489)
Panel C					
Low-Wage Imp Shock	15.344***	-18.971**	-6.278	4.382	17.388
	(4.260)	(8.736)	(7.346)	(3.251)	(10.757)
FDI Shock	0.358	-1.945	0.856	-0.573	1.006
	(1.734)	(3.156)	(2.917)	(2.066)	(3.115)
Immigration Shock	-17.411	4.054	7.386	-7.638	-32.712
	(14.123)	(20.614)	(28.168)	(10.010)	(38.443)
Post-Crisis	21.243***	-15.074***	-9.050**	7.545***	-8.393
	(2.466)	(4.757)	(4.284)	(2.125)	(5.995)
Robot Shock	0.953	-3.749	-2.408	-0.191	10.114
	(1.583)	(4.342)	(3.711)	(1.995)	(6.508)
RTI Region	7.179***	0.364	-3.585	-7.994**	-6.750
	(2.777)	(7.043)	(5.855)	(3.336)	(9.547)
Constant	-0.198	39.398***	35.332***	2.494**	23.286***
	(1.168)	(3.924)	(4.129)	(1.113)	(4.502)
N	1150				

Notes: * p<.1, ** p<.05, *** p<.01. SUREG estimates with country-year (i.e., election) fixed effects and robust standard errors clustered over 164 European regions (NUTS-1/2) in parentheses. The dependent variable is vote share by party family as a percentage of the total regional vote. Globalization shocks are three-year differences in total imports, inward FDI flows in manufacturing, and the stock of robots in manufacturing, all weighted by labor shares in industry, regional-level exposure to routinization, and the portion of migrants over the region's total population.

Table A10: SUREG: Vote Share w/ Interactions, 1990-2018

	Right Pop	Center Right	Center Left	Left Pop	Other
Panel A					
Low-Wage Imp Shock	13.504**	-15.154*	0.073	2.035	6.633
	(6.027)	(8.800)	(8.212)	(3.440)	(9.920)
FDI Shock	0.602	-2.099	0.532	-0.671	1.258
	(1.787)	(3.166)	(2.944)	(2.060)	(3.128)
Post-Crisis	18.510***	-14.482***	-6.710	9.741***	-8.216
	(2.370)	(4.563)	(4.314)	(2.015)	(5.757)
Post-Crisis × Low-Wage Imp Shock	7.085	-10.600	-18.977*	4.857	29.287
	(8.754)	(15.384)	(11.418)	(6.109)	(20.008)
Robot Shock	2.364	-3.537	-2.948	-2.110	8.033
	(1.681)	(4.272)	(3.499)	(1.936)	(6.124)
Constant	0.252	39.307***	34.922***	1.886*	22.853***
	(1.163)	(3.860)	(4.118)	(1.018)	(4.388)
Panel B					
Low-Wage Imp Shock	13.279**	-15.190*	0.223	2.318	6.876
	(5.906)	(8.742)	(8.170)	(3.345)	(9.860)
FDI Shock	0.448	-2.087	0.592	-0.494	1.429
	(1.744)	(3.186)	(2.954)	(2.073)	(3.177)
Post-Crisis	20.780***	-14.323***	-7.779*	7.128***	-10.540*
	(2.496)	(4.861)	(4.327)	(2.179)	(6.051)
Post-Crisis × Low-Wage Imp Shock	6.174	-10.699	-18.569	5.879	30.203
	(8.525)	(15.356)	(11.335)	(5.947)	(19.708)
Robot Shock	0.782	-3.639	-2.212	-0.289	9.661
	(1.582)	(4.273)	(3.654)	(1.998)	(6.420)
RTI Region	7.048**	0.501	-3.329	-8.084**	-7.218
	(2.810)	(7.039)	(5.854)	(3.316)	(9.460)
Constant	-0.279	39.278***	35.166***	2.503**	23.397***
	(1.117)	(3.874)	(4.074)	(1.101)	(4.380)
Panel C					
Low-Wage Imp Shock	13.346**	-15.218*	0.190	2.359	6.992
	(5.910)	(8.732)	(8.154)	(3.339)	(9.965)
FDI Shock	0.442	-2.089	0.595	-0.495	1.420
	(1.737)	(3.180)	(2.956)	(2.067)	(3.200)
Immigration Shock	-17.126	3.528	6.485	-7.356	-31.307
	(14.082)	(20.546)	(28.393)	(9.980)	(38.404)
Post-Crisis	20.850***	-14.339***	-7.804*	7.153***	-10.397*
	(2.467)	(4.859)	(4.334)	(2.188)	(6.071)
Post-Crisis × Low-Wage Imp Shock	5.772	-10.611	-18.408	5.703	29.490
	(8.466)	(15.294)	(11.394)	(5.937)	(19.722)
Robot Shock	0.904	-3.663	-2.261	-0.238	9.883
	(1.574)	(4.280)	(3.650)	(2.005)	(6.447)
RTI Region	7.107**	0.493	-3.347	-8.066**	-7.120
	(2.777)	(7.038)	(5.846)	(3.323)	(9.459)
Constant	-0.128	39.250***	35.109***	2.571**	23.656***
	(1.143)	(3.872)	(4.092)	(1.100)	(4.391)
N	1150				

Notes: * p<.1, ** p<.05, *** p<.01. SUREG estimates with country-year (i.e., election) fixed effects and robust standard errors clustered over 164 European regions (NUTS-1/2) in parentheses. The dependent variable is vote share by party family as a percentage of the total regional vote. Globalization shocks are three-year differences in total imports, inward FDI flows in manufacturing, and the stock of robots in manufacturing, all weighted by labor shares in industry, regional-level exposure to routinization, and the portion of migrants over the region's total population.

E Regional Vote Share Models, Low-Wage Imports

Tables A11-A12 report OLS estimates with alternative import shocks from 50 low- and mid-wage countries as defined as 5% of GDP per capita below the U.S.. I find similar results as using the China shock measure alone and the interactions between the import shock and financial crisis remain statistically significant. In the right populist models, the coefficient on the import shock remains statistically significant. As with the China imports models, the trade shock results are not sensitive to variable and observation inclusion such as dropping all 15 countries individually. These analyses can be supplied upon request.

Table A11: Regional Voting (1990-2018) (Low-Wage Imports) Populist Parties

Right Populist	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
Low-Wage Imp Shock	15.968***	37.922***	15.344***	34.539***	13.504**	31.995*	13.346**	28.976*
	(4.494)	(11.462)	(4.416)	(11.420)	(6.246)	(16.376)	(6.129)	(16.255)
FDI Shock	0.503	1.063	0.358	0.854	0.602	1.205	0.442	0.994
	(1.832)	(1.883)	(1.788)	(1.821)	(1.841)	(1.916)	(1.791)	(1.849)
Immigration Shock			-17.411	-16.620			-17.126	-16.128
			(14.790)	(14.542)			(14.757)	(14.464)
Post-Crisis	18.963***	17.589***	21.243***	19.868***	18.510***	16.976***	20.850***	19.264***
	(2.508)	(2.504)	(2.590)	(2.569)	(2.489)	(2.685)	(2.593)	(2.811)
Post-Crisis × Low-Wage Imp Shock					7.085	12.060	5.772	11.450
					(9.147)	(19.812)	(8.853)	(19.760)
Robot Shock	2.441	-0.251	0.953	-1.273	2.364	-0.187	0.904	-1.213
	(1.748)	(2.315)	(1.636)	(2.169)	(1.742)	(2.319)	(1.627)	(2.190)
RTI Region			7.179**	6.602**			7.107**	6.541**
			(2.903)	(2.912)			(2.905)	(2.922)
Constant	0.169		-0.198		0.252		-0.128	
	(1.251)		(1.219)		(1.215)		(1.195)	
N	1150	1150	1150	1150	1150	1150	1150	1150
Estimator	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
First Stage Results								
US-Low Wage Instrument		0.018***		0.018***		0.018***		0.018***
		(0.003)		(0.003)		(0.005)		(0.005)
Post-Crisis × US Low-Wage Inst.						-0.000		-0.000
						(0.005)		(0.005)
Kleibergen-Paap rk Wald F-statistic		38.42		37.30		11.12		11.16
Anderson-Rubin Confidence Interval		[21.05, 60.51]		[17.54, 57.02]				
Left Populist	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
Low-Wage Imp Shock	3.766	-4.339	4.382	-1.450	2.035	0.045	2.359	2.944
	(3.470)	(12.436)	(3.377)	(12.260)	(3.522)	(14.624)	(3.427)	(14.258)
FDI Shock	-0.736	-0.950	-0.573	-0.729	-0.671	-1.026	-0.495	-0.811
	(2.107)	(2.119)	(2.112)	(2.118)	(2.107)	(2.133)	(2.113)	(2.131)
Immigration Shock			-7.638	-7.834			-7.356	-8.198
			(10.443)	(10.006)			(10.417)	(10.129)
Post-Crisis	10.057***	10.591***	7.545***	7.992***	9.741***	11.044***	7.153***	8.479***
	(2.014)	(2.049)	(2.231)	(2.319)	(2.117)	(2.067)	(2.300)	(2.303)
Post-Crisis × Low-Wage Imp Shock					4.857	-8.479	5.703	-8.613
					(6.382)	(12.678)	(6.206)	(12.325)
Robot Shock	-2.056	-1.051	-0.191	0.497	-2.110	-1.126	-0.238	0.419
	(2.011)	(2.248)	(2.076)	(2.255)	(2.019)	(2.278)	(2.087)	(2.281)
RTI Region			-7.994**	-7.823**			-8.066**	-7.755**
			(3.493)	(3.408)			(3.482)	(3.394)
Constant	1.821*		2.494**		1.886*		2.571**	
	(1.073)		(1.166)		(1.070)		(1.154)	
N	1150	1150	1150	1150	1150	1150	1150	1150
Estimator	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
First Stage Results								
US-Low Wage Instrument		0.018***		0.018***		0.018***		0.018***
		(0.003)		(0.003)		(0.005)		(0.005)
Post-Crisis × US Low-Wage Inst.						-0.000		-0.000
						(0.005)		(0.005)
Kleibergen-Paap rk Wald F-statistic		38.42		37.30		11.12		11.16
Anderson-Rubin Confidence Interval		[-29.27, 17.96]		[-25.77, 20.59]				

Notes: * p<.1, ** p<.05, *** p<.01. OLS and 2SLS estimates with country-year (i.e., election) fixed effects and robust standard errors clustered over 164 European regions (NUTS-1/2) in parentheses. The dependent variable is vote share as a percentage of the total vote.

Table A12: Regional Voting (1990-2018) (Low-Wage Imports) Centrist Parties

Center Left	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
Low-Wage Imp Shock	-6.611	-3.727	-6.278	-1.801	0.073	13.510	0.190	15.129
	(7.671)	(21.592)	(7.624)	(22.136)	(8.437)	(28.475)	(8.383)	(28.833)
FDI Shock	0.794	0.862	0.856	0.966	0.532	0.561	0.595	0.657
	(2.983)	(2.996)	(2.998)	(3.017)	(3.025)	(3.032)	(3.038)	(3.047)
Immigration Shock			7.386	7.493			6.485	6.083
			(29.583)	(28.039)			(29.837)	(28.312)
Post-Crisis	-7.916*	-8.122*	-9.050**	-9.403**	-6.710	-6.362	-7.804*	-7.565
	(4.453)	(4.392)	(4.503)	(4.616)	(4.535)	(4.525)	(4.558)	(4.640)
Post-Crisis × Low-Wage Imp Shock					-18.977	-33.357	-18.408	-33.095
					(11.877)	(24.290)	(11.864)	(24.285)
Robot Shock	-3.149	-3.500	-2.408	-2.918	-2.948	-3.838	-2.261	-3.278
	(3.713)	(3.923)	(3.854)	(3.853)	(3.640)	(4.061)	(3.792)	(3.989)
RTI Region			-3.585	-3.744			-3.347	-3.494
			(6.127)	(6.038)			(6.120)	(6.038)
Constant	35.141***		35.332***		34.922***		35.109***	
	(4.362)		(4.343)		(4.329)		(4.306)	
N	1150	1150	1150	1150	1150	1150	1150	1150
Estimator	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
First Stage Results								
US-Low Wage Instrument		0.018***		0.018***		0.018***		0.018***
		(0.003)		(0.003)		(0.005)		(0.005)
Post-Crisis × US Low-Wage Inst.						-0.000		-0.000
						(0.005)		(0.005)
Kleibergen-Paap rk Wald F-statistic		38.42		37.30		11.12		11.16
Anderson-Rubin Confidence Interval		[-44.12, 36.28]		[-43.24, 39.98]				
Center Right	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
Low-Wage Imp Shock	-18.912**	9.482	-18.971**	9.886	-15.154*	12.571	-15.218*	12.915
	(9.184)	(25.773)	(9.109)	(26.140)	(9.080)	(34.696)	(9.019)	(35.155)
FDI Shock	-1.957	-1.233	-1.945	-1.193	-2.099	-1.295	-2.089	-1.256
	(3.248)	(3.341)	(3.264)	(3.369)	(3.276)	(3.392)	(3.293)	(3.420)
Immigration Shock			4.054	5.116			3.528	4.926
			(21.509)	(20.391)			(21.450)	(20.520)
Post-Crisis	-15.176***	-17.031***	-15.074***	-17.245***	-14.482***	-16.757***	-14.339***	-16.961***
	(4.661)	(4.481)	(4.995)	(5.011)	(4.796)	(4.615)	(5.107)	(5.011)
Post-Crisis × Low-Wage Imp Shock					-10.600	-5.410	-10.611	-5.331
					(16.092)	(32.778)	(16.012)	(32.891)
Robot Shock	-3.649	-7.156	-3.749	-7.108	-3.537	-7.311	-3.663	-7.264
	(4.540)	(4.600)	(4.534)	(4.446)	(4.460)	(4.775)	(4.470)	(4.638)
RTI Region			0.364	-0.554			0.493	-0.522
			(7.381)	(7.272)			(7.378)	(7.270)
Constant	39.451***		39.398***		39.307***		39.250***	
	(4.108)		(4.122)		(4.056)		(4.071)	
N	1150	1150	1150	1150	1150	1150	1150	1150
Estimator	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
First Stage Results								
US-Low Wage Instrument		0.018***		0.018***		0.018***		0.018***
		(0.003)		(0.003)		(0.005)		(0.005)
Post-Crisis × US Low-Wage Inst.						-0.000		-0.000
						(0.005)		(0.005)
Kleibergen-Paap rk Wald F-statistic		38.42		37.30		11.12		11.16
Anderson-Rubin Confidence Interval		[-30.83, 63.86]		[-30.95, 65.00]				

Notes: * p<.1, ** p<.05, *** p<.01. OLS and 2SLS estimates with country-year (i.e., election) fixed effects and robust standard errors clustered over 164 European regions (NUTS-1/2) in parentheses. The dependent variable is vote share as a percentage of the total vote.

F European Social Survey Data

To evaluate individual voting behavior, I rely on eight rounds of the `European Social Survey (ESS)`. The ESS is a biannual survey of 36 countries from 2002 to 2016. Approximately 2,00 people are surveyed in each country every wave and it is representative of the population older than 18 years old. I relied on two questions to obtain retrospective vote choice ("vote" and 'prtvt"). First respondents were asked, "Some people don't vote nowadays for one reason for one reason or another. Did you vote in the last (country) national election in (month/year)?" If an individual answered in the affirmative, they were asked "Which party did you vote for in that election?". I then constructed binary variables for each party family with a 1 indicating a party within that classification and zero if not.

I placed individuals in the same NUTS-1/2 regions as the district-level voting models using regional identifiers within the ESS and matched respondents to the globalization measures by merging on election year. For France, continuous data was not available across NUTS 2 changes over time, so the French data have been harmonized to the 2013 NUTS 1 classification. I use the same globalization measures from the regional level models above with multiple imputation of them to deal with missingness. The dependent variable is a quinary categorically distributed set of outcomes (i.e., vote choice for a party family). The party families are sorted into five categories: Populist Left, Main Left, Main Right, Populist Right, and Other. The multinomial logit models given in this Appendix F reflect the reference categories of Other (which includes mainstream center parties, such as Le Republic En Marche, Liberales Forum, and Democraten 66) and Main Right.

F.1 Individual Variable Descriptions

- **Vote Choice** Dummy from ESS items "vote" and 'prtvt". "Some people don't vote nowadays for one reason for one reason or another. Did you vote in the last (country) national election in (month/year)?...Which party did you vote for in that election?". A one indicates vote choice for that party family and zero otherwise.

- **Age** Age in years.

- **Education** Education in years.

- **Urban**. Dummy indicating whether respondent reported living in an urban area. ESS item (domicil): "Which phrase on this card best describes the area where you live? (a big city, suburbs or outskirts of big city, town or small city, country village, farm or home in countrysid).? The dummy definition is adopted from Kitschelt and Rehm (2014); Rommel and Walter (2018); Thewissen and Rueda (2019) by collapsing big city-town, suburbs, town or small city, as urban==1, and country village and farm/countryside as urban==0. The original categories are retained in the dataset in categorical variable citysize (not currently used in the models).

- **Male**. Gender. Male Dummy.

- **Union Mem**. Dummy indicating whether the respondent is a member of trade union or similar organization. ESS item (mbtru): "Are you or have you ever been a member of a trade union or similar organisation? IF YES, is that currently or previously? (1 yes currently, 2 previously, 3 no)." Dummy for union collapses 1 and 2 (currently or previously union member) into one category (union==1).

- **Religiosity**. Categorical measure of self-reported level of religiosity. ESS item (rlgdgr): "Regardless of whether you belong to a particular religion, how religious would you say you are? (10-point scale, 0 not at all religious, through 10 extremely religious)'.

- **Unemp Benefits**. Dummy indicating whether respondent? self-reported main source of income is unemployment benefits. ESS item (hincsrc): "Please consider the income of all household members and any income which may be received by the household as a whole. What is the main source of income in your household? (wages or salaries, self-employment or farming, pensions, unemployment benefits, any other social benefits, investments and savings, other sources)."

- **Routine Task Intensity (RTI)**. I calculate the RTI from the ESS occupational identifier at the four-digit ISCO-88 level for 2002-2010 and ISCO-08 for 2012-2016. I update the recode for the 2012-2016 waves into ISCO-88 definitions using the International Labour Organization (ILO) four-digit correspondence and use this occupational identifier to link individuals to the RTI index from Goos et al. (2014); Mahutga et al. (2018); Thewissen and Rueda (2019).

- **Offshoring Potential**. In a similar manner to RTI, I assign Blinder's offshoring index measures to standardized occupation classes using concordance tables constructed by Rommel and Walter (2018); Thewissen and Rueda (2019) and updated by Mahutga et al. (2018).

F.2 Individual-Level Multinomial Logit Models

Table A13: ESS Individual Data: Unemployment Benefits, 2002-2016

	(1) Other b/se	(2) Pop Left b/se	(3) Main Left b/se	(4) Pop Right b/se	(5) Pop Right b/se
Globalization Variables					
ChinaShock	0.031	-0.025	-0.003	0.543**	0.558**
	(0.185)	(0.183)	(0.160)	(0.270)	(0.245)
FDI Shock	0.037	0.171	0.079	0.188	0.137
	(0.212)	(0.742)	(0.375)	(0.551)	(0.571)
Immigration Shock	-4.794	-3.788	-3.675	-5.745	-3.213
	(4.005)	(4.125)	(2.730)	(6.751)	(6.312)
Unemp. Ben.	0.363***	0.783***	0.227***	0.366**	0.115
	(0.080)	(0.111)	(0.080)	(0.163)	(0.156)
Unemp. Ben $\times$ China Shock	-0.062	0.059	0.089	0.490**	0.505***
	(0.088)	(0.162)	(0.094)	(0.194)	(0.188)
Post-Crisis	-0.546**	2.625***	-0.956***	3.009***	3.364***
	(0.266)	(0.805)	(0.179)	(1.082)	(1.051)
Robots Shock	0.496	-1.809**	-0.040	-0.186	-0.299
	(0.434)	(0.789)	(0.309)	(0.490)	(0.433)
Individual Variables					
RTI	-0.007	-0.009	-0.001	0.080***	0.084***
	(0.014)	(0.020)	(0.016)	(0.023)	(0.023)
Offshore	-0.019	-0.029	0.020	-0.100***	-0.099***
	(0.017)	(0.030)	(0.019)	(0.027)	(0.024)
Male	-0.292***	-0.258***	-0.222***	0.186***	0.367***
	(0.033)	(0.043)	(0.027)	(0.037)	(0.034)
Age	-0.004	-0.000	-0.003	-0.003	0.001
	(0.004)	(0.007)	(0.004)	(0.009)	(0.009)
Age^2	-0.000**	-0.000	-0.000	-0.000**	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Education	0.004	-0.004	-0.032***	-0.091***	-0.083***
	(0.006)	(0.008)	(0.006)	(0.010)	(0.009)
Urban	0.106***	0.278***	0.320***	0.089	-0.055
	(0.030)	(0.076)	(0.044)	(0.076)	(0.071)
Union	0.273***	0.978***	0.570***	0.276***	-0.038
	(0.028)	(0.053)	(0.033)	(0.056)	(0.052)
Religiosity	-0.079***	-0.236***	-0.105***	-0.104***	-0.035***
	(0.007)	(0.017)	(0.010)	(0.012)	(0.012)
Constant	0.757***	-2.394***	1.313***	-2.328**	-4.241***
	(0.191)	(0.767)	(0.233)	(1.075)	(1.045)
N	141505	141505	141505	141505	141505

Notes: Multinomial logistic regression estimates with country-year fixed effects and robust standard errors clustered by region in parentheses for elections from 2002-2016. The dependent variables are individual vote choice by party family spanning from populist left → populist right (reference category=Main Right). Reference category Other is in the main text. The globalization variables are lagged one year prior to the election. Column five reflects logistic regression in which party families are designated right populist or not right populist (reference category= not right populist). * p<.1, ** p<.05, *** p<.01.

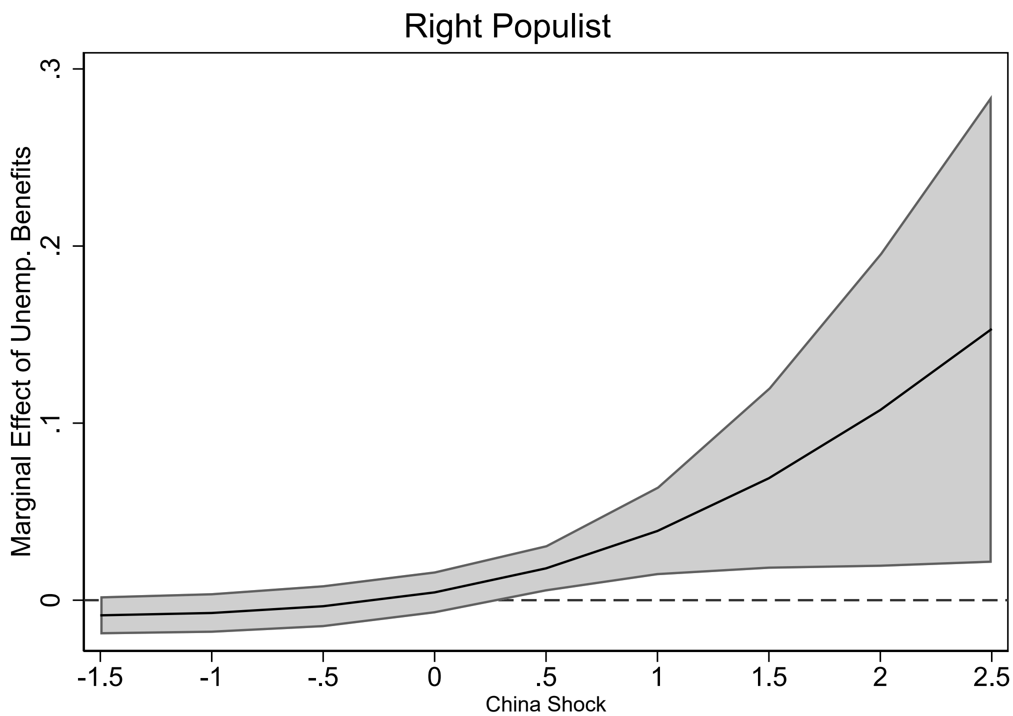

Figure A1: Marginal Effects of Unemployment Benefits on Vote Choice: Voting for the extreme right becomes more likely as imports rise in their region when the person receives unemployment benefits. Multinomial logistic regression, reference category= Other

F.3 Individual-Level Ordinary Least Squares Models

Table A14: ESS Individual Data: Unemployment Benefits, 2002-2016

	(1) Pop Right b/se	(2) Main Right b/se	(3) Main Left b/se	(4) Pop Left b/se
Globalization Variables				
China Shock	0.029***	-0.013	-0.021	-0.016*
	(0.011)	(0.028)	(0.021)	(0.009)
FDI Shock	0.005	-0.017	0.006	0.009
	(0.015)	(0.055)	(0.064)	(0.045)
Immigration Shock	-0.050	0.683	-0.189	-0.020
	(0.079)	(0.569)	(0.404)	(0.171)
Unemp. Ben.	-0.002	-0.097***	-0.050***	0.017***
	(0.004)	(0.011)	(0.011)	(0.006)
Unemp. Ben $\times$ China Shock	0.010**	-0.011	-0.002	-0.002
	(0.005)	(0.016)	(0.009)	(0.010)
Post-Crisis	0.100***	0.106***	-0.136***	0.148***
	(0.014)	(0.033)	(0.022)	(0.010)
Robots Shock	-0.030*	0.004	-0.016	-0.086***
	(0.017)	(0.068)	(0.052)	(0.033)
Individual Variables				
RTI	0.003***	-0.002	-0.002	-0.001
	(0.001)	(0.003)	(0.003)	(0.001)
Offshore	-0.002**	0.008***	0.013***	0.000
	(0.001)	(0.003)	(0.003)	(0.001)
Male	0.013***	0.038***	-0.019***	-0.005***
	(0.002)	(0.005)	(0.004)	(0.002)
Age	0.001***	0.006***	0.006***	0.001***
	(0.000)	(0.001)	(0.000)	(0.000)
Age^2	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Education	-0.002***	0.007***	-0.001	0.001***
	(0.000)	(0.001)	(0.001)	(0.000)
Urban	-0.005*	-0.052***	0.033***	0.005*
	(0.003)	(0.007)	(0.007)	(0.003)
Union	-0.000	-0.075***	0.080***	0.031***
	(0.002)	(0.006)	(0.006)	(0.004)
Religiosity	-0.001**	0.020***	-0.006***	-0.006***
	(0.000)	(0.001)	(0.001)	(0.001)
Constant	0.006	-0.143***	0.147***	-0.009
	(0.011)	(0.029)	(0.030)	(0.007)
N	153471	153471	153471	153471

Notes: OLS estimates with country-year fixed effects and robust standard errors clustered by region in parentheses for elections from 2002-2016. The dependent variables are individual vote choice by party family spanning from populist right → populist left. The globalization variables are lagged one year prior to the election and are calculated using a three year difference in imports or foreign direct investment inflows (i.e, t-1 - t-4). * p<.1, ** p<.05, *** p<.01.

G ESS Models, China Shock × Post-Crisis

Table A16 investigates the relationship between the financial crisis and import competition. The financial crisis has a large effect on every party family, increasing support for right and left populist parties and decreasing support for center left parties. Less consistent with the aggregate vote share models, I also find an increase in support for Center Right parties.

However, there is little evidence that import competition has moderated the effects of the crisis, save for left populist parties where I find that increased import competition decreases support.

G.1 Individual-Level Multinomial Logit Models

Table A15: ESS Individual Data: Post-Crisis, 2002-2016

	(1) Pop Left b/se	(2) Main Left b/se	(3) Main Right b/se	(4) Pop Right b/se	(5) Pop Right b/se
Globalization Variables					
ChinaShock	0.316*	0.162	0.126	0.536**	0.428*
	(0.171)	(0.187)	(0.154)	(0.250)	(0.256)
FDI Shock	0.116	0.039	-0.041	0.164	0.156
	(0.708)	(0.365)	(0.215)	(0.584)	(0.586)
Immigration Shock	1.058	1.203	4.847	-0.783	-3.061
	(3.501)	(2.937)	(3.972)	(6.158)	(6.340)
Post-Crisis	3.366***	-0.323	0.618**	3.538***	3.275***
	(0.816)	(0.219)	(0.290)	(1.030)	(1.037)
Post-Crisis× China Shock	-0.821***	-0.340	-0.282	0.036	0.311
	(0.282)	(0.217)	(0.280)	(0.318)	(0.298)
Unemp. Ben.	0.450***	-0.087	-0.348***	0.221*	0.323***
	(0.102)	(0.082)	(0.079)	(0.127)	(0.119)
Robots Shock	-2.296***	-0.557	-0.509	-0.650	-0.244
	(0.670)	(0.358)	(0.437)	(0.518)	(0.438)
Individual Variables					
RTI	-0.002	0.007	0.007	0.087***	0.084***
	(0.018)	(0.015)	(0.014)	(0.025)	(0.023)
Offshore	-0.010	0.039*	0.019	-0.081***	-0.099***
	(0.028)	(0.021)	(0.017)	(0.028)	(0.024)
Male	0.034	0.070***	0.292***	0.478***	0.367***
	(0.045)	(0.025)	(0.033)	(0.041)	(0.034)
Age	0.005	0.002	0.005	0.001	0.001
	(0.007)	(0.004)	(0.004)	(0.009)	(0.009)
Age^2	-0.000	0.000	0.000**	-0.000	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Education	-0.008	-0.036***	-0.004	-0.095***	-0.083***
	(0.006)	(0.006)	(0.006)	(0.010)	(0.009)
Urban	0.175**	0.215***	-0.105***	-0.016	-0.055
	(0.073)	(0.037)	(0.030)	(0.069)	(0.071)
Union	0.704***	0.297***	-0.273***	0.003	-0.038
	(0.052)	(0.033)	(0.028)	(0.054)	(0.052)
Religiosity	-0.157***	-0.026***	0.079***	-0.025**	-0.035***
	(0.016)	(0.007)	(0.007)	(0.012)	(0.012)
Constant	-3.241***	0.512***	-0.792***	-3.096***	-4.219***
	(0.742)	(0.186)	(0.183)	(1.017)	(1.039)
N	141505	141505	141505	141505	141505

Notes: Multinomial logistic regression estimates with country-year fixed effects and robust standard errors clustered by region in parentheses for elections from 2002-2016. The dependent variables are individual vote choice by party family spanning from populist left → populist right (reference category=Other). The globalization variables are lagged one year prior to the election. Column five reflects logistic regression in which party families are designated right populist or not right populist (reference category= not right populist). * p<.1, ** p<.05, *** p<.01.

G.2 Individual-Level Ordinary Least Squares Models

Table A16: ESS Individual Data: China Shock × Post-Crisis, 2002-2016

	(1) Pop Right b/se	(2) Main Right b/se	(3) Main Left b/se	(4) Pop Left b/se
Globalization Variables				
China Shock	0.024**	-0.008	-0.006	-0.000
	(0.012)	(0.030)	(0.025)	(0.009)
FDI Shock	0.005	-0.018	0.005	0.009
	(0.015)	(0.055)	(0.065)	(0.044)
Immigration Shock	-0.053	0.687	-0.181	-0.011
	(0.081)	(0.564)	(0.404)	(0.172)
Post-Crisis	0.098***	0.109***	-0.128***	0.155***
	(0.014)	(0.039)	(0.024)	(0.010)
Post-Crisis × China Shock	0.011	-0.010	-0.031	-0.031***
	(0.011)	(0.044)	(0.026)	(0.011)
Unemp. Ben.	0.002	-0.100***	-0.051***	0.016***
	(0.004)	(0.010)	(0.010)	(0.004)
Robots Shock	-0.029*	0.004	-0.016	-0.087***
	(0.016)	(0.069)	(0.052)	(0.033)
Individual Variables				
RTI	0.003***	-0.002	-0.002	-0.001
	(0.001)	(0.003)	(0.003)	(0.001)
Offshore	-0.002**	0.008***	0.013***	0.000
	(0.001)	(0.003)	(0.003)	(0.001)
Male	0.013***	0.038***	-0.019***	-0.005***
	(0.002)	(0.005)	(0.004)	(0.002)
Age	0.001***	0.006***	0.006***	0.001***
	(0.000)	(0.001)	(0.000)	(0.000)
Age^2	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Education	-0.002***	0.007***	-0.001	0.001***
	(0.000)	(0.001)	(0.001)	(0.000)
Urban	-0.005*	-0.052***	0.033***	0.005**
	(0.003)	(0.007)	(0.007)	(0.003)
Union	-0.000	-0.075***	0.080***	0.031***
	(0.002)	(0.006)	(0.006)	(0.004)
Religiosity	-0.001**	0.020***	-0.006***	-0.006***
	(0.000)	(0.001)	(0.001)	(0.001)
Constant	0.007	-0.144***	0.143***	-0.013*
	(0.010)	(0.028)	(0.029)	(0.007)
N	153471	153471	153471	153471

Notes: OLS estimates with country-year fixed effects and robust standard errors clustered by region in parentheses for elections from 2002-2016. The dependent variables are individual vote choice by party family spanning from populist right → populist left. The globalization variables are lagged one year prior to the election and are calculated using a three year difference in imports or foreign direct investment inflows (i.e, t-1 - t-4). * p<.1, ** p<.05, *** p<.01.

H ESS Models, Low-Wage Import Shock× Unemp. Benefits

Tables A18 and A20 replicate the individual findings with an alternative import shock measure with the three-year difference in imports from 50 low-wage countries. I find consistent results as the individual ESS models with the China shock, particularly when compared against Other or Main Right parties. Aggregating Other, Main Left, Main Right, and Left Populist into a "non-right-populist" party family seems to diminish the effects, perhaps due to the broad reference category.

H.1 Individual-Level Multinomial Logit Models

Table A17: ESS Individual Data: Unemployment Benefits, 2002-2016
Low-Wage Imports

	(1) Pop Left b/se	(2) Main Left b/se	(3) Main Right b/se	(4) Pop Right b/se	(5) Pop Right b/se
Globalization Variables					
Lowwage Shock	1.032	-0.600	-0.490	2.001**	2.390**
	(1.250)	(0.851)	(0.871)	(0.980)	(0.991)
FDI Shock	0.179	0.024	-0.050	0.217	0.216
	(0.768)	(0.368)	(0.216)	(0.581)	(0.581)
Immigration Shock	1.118	1.110	4.750	-0.891	-3.118
	(3.493)	(2.907)	(4.039)	(6.109)	(6.279)
Unemp. Ben.	0.247*	-0.211**	-0.332***	0.066	0.204
	(0.128)	(0.097)	(0.097)	(0.175)	(0.171)
Unemp. Ben×Lowwage Shock	2.338**	1.494***	-0.127	1.524**	0.997
	(1.005)	(0.574)	(0.621)	(0.751)	(0.710)
Post-Crisis	3.177***	-0.399*	0.552**	3.483***	3.282***
	(0.808)	(0.212)	(0.271)	(1.040)	(1.063)
Robots Shock	-2.612***	-0.460	-0.419	-0.661	-0.310
	(0.716)	(0.355)	(0.452)	(0.529)	(0.441)
Individual Variables					
RTI	-0.002	0.007	0.007	0.087***	0.083***
	(0.018)	(0.015)	(0.015)	(0.025)	(0.023)
Offshore	-0.010	0.039*	0.019	-0.082***	-0.100***
	(0.028)	(0.021)	(0.017)	(0.028)	(0.024)
Male	0.033	0.070***	0.292***	0.479***	0.368***
	(0.044)	(0.025)	(0.033)	(0.041)	(0.034)
Age	0.004	0.002	0.004	0.001	0.001
	(0.007)	(0.004)	(0.004)	(0.009)	(0.009)
Age^2	-0.000	0.000	0.000**	-0.000	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Education	-0.008	-0.036***	-0.004	-0.095***	-0.084***
	(0.006)	(0.006)	(0.006)	(0.010)	(0.009)
Urban	0.173**	0.213***	-0.106***	-0.016	-0.054
	(0.073)	(0.037)	(0.030)	(0.069)	(0.071)
Union	0.705***	0.297***	-0.272***	0.002	-0.039
	(0.052)	(0.033)	(0.028)	(0.054)	(0.051)
Religiosity	-0.157***	-0.026***	0.079***	-0.024**	-0.034***
	(0.016)	(0.007)	(0.007)	(0.012)	(0.012)
Constant	-3.140***	0.552***	-0.764***	-2.990***	-4.139***
	(0.743)	(0.189)	(0.183)	(1.026)	(1.059)
N	141505	141505	141505	141505	141505

Notes: Multinomial logistic regression estimates with country-year fixed effects and robust standard errors clustered by region in parentheses for elections from 2002-2016. The dependent variables are individual vote choice by party family spanning from populist left → populist right (reference category=Other). The globalization variables are lagged one year prior to the election. Column fice reflects logistic regression in which party families are designated right populist or not right populist (reference category=not right populist). * p<.1, ** p<.05, *** p<.01.

H.2 Individual-Level Ordinary Least Squares Models

Table A18: ESS Individual Data: Low-Wage × Benefits, 2002-2016

	(1) Pop Right b/se	(2) Main Right b/se	(3) Main Left b/se	(4) Pop Left b/se
Globalization Variables				
Low-Wage Import Shock	0.151***	-0.128	-0.150	-0.004
	(0.056)	(0.128)	(0.111)	(0.044)
FDI Shock	0.008	-0.021	0.002	0.011
	(0.016)	(0.055)	(0.065)	(0.046)
Immigration Shock	-0.033	0.676	-0.203	-0.029
	(0.081)	(0.572)	(0.402)	(0.167)
Unemp. Ben.	-0.005	-0.079***	-0.063***	0.009
	(0.005)	(0.012)	(0.014)	(0.006)
Unemp. Ben × Lowwage Shock	0.071*	-0.231***	0.130	0.077
	(0.041)	(0.070)	(0.085)	(0.052)
Post-Crisis	0.096***	0.109***	-0.132***	0.149***
	(0.014)	(0.033)	(0.022)	(0.010)
Robots Shock	-0.036**	0.020	-0.005	-0.099***
	(0.017)	(0.071)	(0.054)	(0.035)
Individual Variables				
RTI	0.003***	-0.002	-0.002	-0.001
	(0.001)	(0.003)	(0.003)	(0.001)
Offshore	-0.002**	0.008***	0.013***	0.000
	(0.001)	(0.003)	(0.003)	(0.001)
Male	0.013***	0.038***	-0.019***	-0.005***
	(0.002)	(0.005)	(0.004)	(0.002)
Age	0.001***	0.006***	0.006***	0.001***
	(0.000)	(0.001)	(0.000)	(0.000)
Age^2	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Education	-0.002***	0.007***	-0.001	0.001***
	(0.000)	(0.001)	(0.001)	(0.000)
Urban	-0.005*	-0.052***	0.033***	0.005**
	(0.003)	(0.007)	(0.007)	(0.003)
Union	-0.000	-0.075***	0.080***	0.031***
	(0.002)	(0.006)	(0.006)	(0.004)
Religiosity	-0.001**	0.020***	-0.006***	-0.006***
	(0.000)	(0.001)	(0.001)	(0.001)
Constant	0.011	-0.146***	0.143***	-0.012*
	(0.010)	(0.027)	(0.028)	(0.007)
N	153471	153471	153471	153471

Notes: OLS estimates with country-year fixed effects and robust standard errors clustered by region in parentheses for elections from 2002-2016. The dependent variables are individual vote choice by party family spanning from populist right → populist left. The globalization variables are lagged one year prior to the election and are calculated using a three year difference in imports or foreign direct investment inflows (i.e, t-1 - t-4). * p<.1, ** p<.05, *** p<.01.

I ESS Models, Low-Wage Shock & Post-Crisis

I.1 Individual-Level Multinomial Logit Models

Table A19: ESS Individual Data: Post-Crisis, 2002-2016

	(1) Pop Left b/se	(2) Main Left b/se	(3) Main Right b/se	(4) Pop Right b/se	(5) Pop Right b/se
Globalization Variables					
Lowwage Shock	5.370***	0.312	-0.390	3.648*	3.451
	(1.718)	(1.313)	(1.255)	(2.026)	(2.138)
FDI Shock	0.178	0.026	-0.050	0.210	0.211
	(0.750)	(0.370)	(0.216)	(0.580)	(0.581)
Immigration Shock	0.844	1.060	4.736	-1.061	-3.231
	(3.478)	(2.919)	(4.031)	(6.011)	(6.170)
Post-Crisis	3.303***	-0.371*	0.554**	3.532***	3.315***
	(0.816)	(0.214)	(0.273)	(1.021)	(1.035)
Post-Crisis×Low-wage Shock	-4.921**	-1.105	-0.090	-1.891	-1.218
	(1.992)	(1.120)	(1.062)	(1.910)	(1.991)
Unemp. Ben.	0.450***	-0.087	-0.347***	0.223*	0.324***
	(0.101)	(0.082)	(0.079)	(0.126)	(0.118)
Robots Shock	-2.885***	-0.496	-0.423	-0.746	-0.372
	(0.750)	(0.368)	(0.464)	(0.547)	(0.465)
Individual Level Variables					
RTI	-0.002	0.007	0.007	0.087***	0.083***
	(0.018)	(0.015)	(0.014)	(0.025)	(0.023)
Offshore	-0.010	0.039*	0.019	-0.082***	-0.099***
	(0.028)	(0.021)	(0.017)	(0.028)	(0.024)
Male	0.034	0.070***	0.292***	0.479***	0.368***
	(0.045)	(0.025)	(0.033)	(0.041)	(0.034)
Age	0.004	0.002	0.004	0.001	0.001
	(0.007)	(0.004)	(0.004)	(0.009)	(0.009)
Age^2	-0.000	0.000	0.000**	-0.000	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Education	-0.008	-0.036***	-0.004	-0.095***	-0.084***
	(0.006)	(0.006)	(0.006)	(0.010)	(0.009)
Urban	0.176**	0.214***	-0.106***	-0.015	-0.053
	(0.073)	(0.037)	(0.030)	(0.069)	(0.071)
Union	0.705***	0.297***	-0.272***	0.002	-0.039
	(0.052)	(0.033)	(0.028)	(0.053)	(0.051)
Religiosity	-0.157***	-0.026***	0.079***	-0.024**	-0.034***
	(0.016)	(0.007)	(0.007)	(0.012)	(0.012)
Constant	-3.168***	0.543***	-0.765***	-3.004***	-4.148***
	(0.743)	(0.188)	(0.183)	(1.022)	(1.053)
N	141505	141505	141505	141505	141505

Notes: Multinomial logistic regression estimates with country-year fixed effects and robust standard errors clustered by region in parentheses for elections from 2002-2016. The dependent variables are individual vote choice by party family spanning from populist left → populist right (reference category=Other). The globalization variables are lagged one year prior to the election. Column five reflects logistic regression in which party families are designated right populist or not right populist (reference category= not right populist). * p<.1, ** p<.05, *** p<.01.

I.2 Individual-Level Ordinary Least Squares Models

Table A20: ESS Individual Data: Low-Wage × Crisis, 2002-2016

	(1) Pop Right b/se	(2) Main Right b/se	(3) Main Left b/se	(4) Pop Left b/se
Globalization Variables				
Low-Wage Import Shock	0.177**	-0.240	-0.094	0.113*
	(0.083)	(0.261)	(0.196)	(0.060)
FDI Shock	0.008	-0.021	0.002	0.011
	(0.016)	(0.055)	(0.065)	(0.045)
Immigration Shock	-0.034	0.681	-0.207	-0.036
	(0.079)	(0.577)	(0.403)	(0.166)
Post-Crisis	0.097***	0.104***	-0.131***	0.153***
	(0.014)	(0.035)	(0.023)	(0.010)
Post-Crisis × Lowwage Shock	-0.031	0.133	-0.069	-0.145**
	(0.079)	(0.221)	(0.157)	(0.069)
Robots Shock	-0.037**	0.030	-0.004	-0.105***
	(0.018)	(0.074)	(0.056)	(0.035)
Individual Variables				
RTI	0.003***	-0.003	-0.002	-0.001
	(0.001)	(0.002)	(0.003)	(0.001)
Offshore	-0.002**	0.008***	0.013***	0.000
	(0.001)	(0.003)	(0.003)	(0.001)
Male	0.013***	0.037***	-0.019***	-0.005***
	(0.002)	(0.005)	(0.003)	(0.002)
Age	0.001***	0.005***	0.006***	0.001***
	(0.000)	(0.001)	(0.000)	(0.000)
Age^2	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Education	-0.002***	0.007***	-0.001	0.001***
	(0.000)	(0.001)	(0.001)	(0.000)
Urban	-0.005*	-0.053***	0.032***	0.006**
	(0.003)	(0.007)	(0.007)	(0.003)
Union	-0.000	-0.075***	0.080***	0.030***
	(0.002)	(0.006)	(0.006)	(0.004)
Religiosity	-0.001**	0.021***	-0.006***	-0.006***
	(0.000)	(0.001)	(0.001)	(0.001)
Constant	0.011	-0.148***	0.141***	-0.012*
	(0.010)	(0.027)	(0.028)	(0.007)
N	153471	153471	153471	153471

Notes: OLS estimates with country-year fixed effects and robust standard errors clustered by region in parentheses for elections from 2002-2016. The dependent variables are individual vote choice by party family spanning from populist right → populist left. The globalization variables are lagged one year prior to the election and are calculated using a three year difference in imports or foreign direct investment inflows (i.e, t-1 - t-4). * p<.1, ** p<.05, *** p<.01.

J Unimputed Data

J.1 China Imports

Table A21: Regional Voting (1990-2018)
Unimputed Data

Right Populist	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
China Shock	5.193**	12.257***	4.805**	17.986***	4.636	9.177***	6.027*	15.792***
	(2.013)	(2.342)	(2.313)	(3.652)	(3.279)	(1.904)	(3.564)	(3.438)
FDI Shock	-5.863*	-11.149***	29.750***	45.182***	-5.920*	-15.632***	30.266***	49.361***
	(3.192)	(3.132)	(8.655)	(13.088)	(3.178)	(5.362)	(8.172)	(16.426)
Immigration Shock			-25.749	-30.463			-25.737	-32.991
			(20.432)	(19.725)			(20.450)	(20.913)
Post-Crisis	19.229***	19.795***	25.325***	30.828***	19.127***	18.721***	25.712***	30.819***
	(2.554)	(2.478)	(4.051)	(4.510)	(2.537)	(2.493)	(3.922)	(4.968)
Post-Crisis × China Shock					0.730	10.487*	-1.590	11.723
					(2.715)	(6.330)	(3.034)	(9.634)
Robot Shock	-2.676	-8.928***	-4.672*	-17.052***	-2.464	-10.220***	-5.185*	-19.671***
	(1.680)	(2.775)	(2.475)	(3.721)	(1.966)	(3.579)	(2.777)	(5.803)
RTI Region			5.617	4.755			5.632	4.202
			(3.496)	(3.098)			(3.477)	(3.294)
Constant	0.920		1.253		0.990		0.997	
	(0.995)		(1.551)		(0.913)		(1.344)	
N	621	621	480	480	621	621	480	480
Estimator	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS

Left Populist	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
China Shock	2.175	1.527	2.484*	8.392	2.173	1.937	3.573	9.390
	(1.482)	(5.898)	(1.445)	(7.277)	(3.072)	(6.121)	(3.308)	(6.420)
FDI Shock	-8.305***	-7.820	1.239	8.157	-8.306***	-7.222	1.699	6.258
	(3.137)	(5.380)	(15.457)	(12.225)	(3.132)	(5.793)	(15.460)	(12.638)
Immigration Shock			6.765	4.651			6.775	5.800
			(17.592)	(16.555)			(17.599)	(16.615)
Post-Crisis	9.315***	9.263***	6.718**	9.185***	9.315***	9.406***	7.063**	9.188***
	(2.221)	(2.101)	(2.959)	(2.820)	(2.142)	(2.110)	(2.893)	(2.909)
Post-Crisis × China Shock					0.003	-1.398	-1.417	-5.328
					(2.715)	(4.504)	(2.911)	(5.971)
Robot Shock	-6.118	-5.544	-0.260	-5.809	-6.117	-5.372	-0.717	-4.619
	(3.957)	(6.093)	(4.759)	(8.515)	(3.973)	(6.093)	(4.943)	(9.136)
RTI Region			-9.175	-9.561*			-9.162	-9.310*
			(5.555)	(5.290)			(5.544)	(5.236)
Constant	2.301*		3.502*		2.301*		3.274*	
	(1.372)		(1.832)		(1.334)		(1.746)	
N	621	621	480	480	621	621	480	480
Estimator	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS

Notes: * p<.1, ** p<.05, *** p<.01. OLS and Two-Stage Least Squares analysis, unimputed data.

Table A22: Regional Voting (1990-2018)
Unimputed Data

Center Left	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
China Shock	-2.321	13.211	0.366	31.994***	10.196*	18.154**	15.095**	36.567***
	(3.659)	(8.075)	(3.470)	(10.503)	(5.996)	(7.463)	(6.826)	(7.916)
FDI Shock	2.960	-8.662	21.793	58.824**	4.228	-1.468	28.008	50.113**
	(4.475)	(6.864)	(22.106)	(28.712)	(4.373)	(6.178)	(22.198)	(22.651)
Immigration Shock			38.063	26.750			38.210	32.019
			(54.729)	(56.130)			(53.073)	(52.095)
Post-Crisis	-16.230***	-14.986***	-10.725	2.479	-13.932***	-13.263***	-6.060	2.496
	(4.802)	(4.639)	(6.584)	(7.989)	(4.750)	(4.780)	(6.731)	(7.415)
Post-Crisis × China Shock					-16.429**	-16.828**	-19.161**	-24.432*
					(6.329)	(8.199)	(7.431)	(13.883)
Robot Shock	-3.589	-17.335*	-8.265	-37.971***	-8.373	-15.262*	-14.450	-32.514***
	(7.539)	(9.742)	(10.635)	(12.081)	(8.557)	(8.649)	(12.013)	(10.235)
RTI Region			-0.832	-2.900			-0.657	-1.747
			(13.216)	(12.690)			(12.873)	(12.442)
Constant	43.253***		40.123***		41.686***		37.038***	
	(4.757)		(4.272)		(4.626)		(4.064)	
N	621	621	480	480	621	621	480	480
Estimator	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS

Center Right	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
China Shock	-3.087	10.676	-4.880	18.717	8.757	18.155**	11.574	24.872**
	(3.444)	(9.059)	(4.225)	(14.650)	(5.440)	(7.279)	(7.584)	(10.974)
FDI Shock	-5.850	-16.148**	-9.469	18.159	-4.650	-5.262	-2.527	6.437
	(3.788)	(6.956)	(16.627)	(17.097)	(3.853)	(6.282)	(19.024)	(21.444)
Immigration Shock			26.112	17.672			26.276	24.762
			(27.853)	(29.619)			(26.307)	(26.284)
Post-Crisis	-6.132	-5.030	-11.201**	-1.350	-3.957	-2.422	-5.989	-1.327
	(3.750)	(3.607)	(5.529)	(6.811)	(3.944)	(3.948)	(6.705)	(6.986)
Post-Crisis × China Shock					-15.546**	-25.464***	-21.406***	-32.879**
					(6.223)	(9.863)	(7.644)	(14.797)
Robot Shock	-4.006	-16.186	-7.933	-30.097*	-8.533	-13.049	-14.843	-22.753*
	(9.566)	(11.966)	(13.586)	(16.037)	(10.703)	(10.196)	(15.104)	(13.092)
RTI Region			-8.160	-9.703			-7.964	-8.152
			(12.706)	(12.005)			(11.914)	(11.271)
Constant	28.356***		31.369***		26.873***		27.923***	
	(3.340)		(3.537)		(3.332)		(3.671)	
N	621	621	480	480	621	621	480	480
Estimator	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS

Notes: * p<.1, ** p<.05, *** p<.01. OLS and Two-Stage Least Squares analysis, unimputed data.

J.2 Low-Wage Imports

Table A23: Regional Voting (1990-2018)
Unimputed Data

Right Populist	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
Low-Wage Imp Shock	39.287***	96.419***	40.636***	104.223**	30.927	107.841***	39.395*	124.731***
	(10.065)	(30.602)	(11.559)	(41.607)	(20.840)	(34.895)	(22.821)	(46.610)
FDI Shock	0.014	2.911	34.887***	51.729***	0.251	2.521	34.790***	53.428***
	(2.530)	(3.395)	(8.584)	(12.889)	(2.509)	(3.592)	(8.084)	(12.434)
Immigration Shock			-23.989	-23.923			-23.944	-24.635
			(21.551)	(22.020)			(21.300)	(21.792)
Post-Crisis	19.692***	20.970***	21.270***	18.063***	18.841***	22.199***	21.220***	18.847***
	(2.208)	(2.052)	(3.623)	(4.372)	(2.450)	(3.438)	(3.365)	(4.549)
Post-Crisis × Low-Wage Imp Shock					9.382	-13.760	1.441	-23.268
					(18.630)	(26.801)	(19.927)	(34.524)
Robot Shock	-4.667***	-14.245***	-5.460***	-13.755**	-3.967*	-15.130***	-5.348*	-15.627***
	(1.710)	(5.252)	(1.922)	(5.498)	(2.122)	(5.397)	(2.744)	(5.903)
RTI Region			2.732	-2.274			2.728	-2.251
			(3.112)	(4.330)			(3.133)	(4.256)
Constant	-1.826		2.046		-1.107		2.053	
	(1.112)		(1.602)		(1.370)		(1.543)	
N	621	621	480	480	621	621	480	480
Estimator	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS

Left Populist	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
Low-Wage Imp Shock	21.553**	12.988	24.262*	30.896	19.600	28.551	20.626	113.021
	(10.740)	(38.671)	(14.132)	(50.088)	(18.168)	(76.298)	(18.731)	(83.723)
FDI Shock	-5.585***	-6.019**	4.758	6.515	-5.529***	-6.551***	4.472	13.315
	(2.102)	(2.483)	(13.163)	(12.521)	(2.045)	(2.043)	(13.673)	(13.727)
Immigration Shock			7.678	7.685			7.807	4.835
			(17.471)	(16.538)			(17.507)	(16.570)
Post-Crisis	9.623***	9.431***	4.457	4.123	9.424***	11.106**	4.311	7.261
	(2.411)	(2.249)	(3.713)	(4.909)	(2.198)	(5.442)	(3.775)	(4.416)
Post-Crisis × Low-Wage Imp Shock					2.192	-18.749	4.223	-93.180
					(13.465)	(54.490)	(14.848)	(59.568)
Robot Shock	-7.806*	-6.370	-1.092	-1.957	-7.643*	-7.576	-0.763	-9.455
	(4.305)	(7.258)	(5.607)	(8.442)	(4.457)	(9.579)	(5.511)	(10.435)
RTI Region			-10.923**	-11.445*			-10.934**	-11.352*
			(5.141)	(6.132)			(5.149)	(5.896)
Constant	0.732		3.907**		0.900		3.926**	
	(1.359)		(1.949)		(1.302)		(1.927)	
N	621	621	480	480	621	621	480	480
Estimator	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS

Notes: * p<.1, ** p<.05, *** p<.01. OLS and Two-Stage Least Squares analysis, unimputed data.

Table A24: Regional Voting (1990-2018)
Unimputed Data

Center Left	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
Low-Wage Imp Shock	-17.722	61.646	-18.619	104.186	26.760	216.142*	35.770	435.485**
	(18.929)	(53.468)	(29.562)	(75.055)	(39.416)	(119.682)	(38.187)	(169.498)
FDI Shock	0.324	4.349	16.433	48.961**	-0.937	-0.929	20.702	76.392***
	(3.886)	(5.239)	(21.386)	(20.338)	(3.982)	(5.304)	(22.046)	(23.351)
Immigration Shock			38.174	38.301			36.241	26.804
			(55.822)	(48.091)			(55.792)	(49.529)
Post-Crisis	-16.440***	-14.665***	-9.939	-16.132*	-11.914**	1.957	-7.747	-3.474
	(4.825)	(4.634)	(8.130)	(9.238)	(4.746)	(10.686)	(8.232)	(9.185)
Post-Crisis × Low-Wage Imp Shock					-49.915	-186.126*	-63.170*	-375.892**
					(33.957)	(98.223)	(35.411)	(157.849)
Robot Shock	-2.673	-15.978*	-5.492	-21.513**	-6.395	-27.952**	-10.407	-51.756***
	(6.875)	(9.065)	(9.135)	(9.488)	(7.962)	(14.182)	(10.975)	(18.598)
RTI Region			0.658	-9.011			0.822	-8.636
			(13.806)	(15.482)			(13.656)	(14.117)
Constant	44.494***		40.219***		40.669***		39.933***	
	(4.852)		(4.378)		(4.702)		(4.316)	
N	621	621	480	480	621	621	480	480
Estimator	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS

Center Right	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
Low-Wage Imp Shock	-49.957**	35.310	-80.576**	51.077	-35.500	218.425**	-21.340	345.133**
	(24.924)	(64.137)	(37.048)	(93.515)	(34.287)	(108.865)	(36.169)	(174.270)
FDI Shock	-10.693**	-6.369	-25.098	9.773	-11.103**	-12.625**	-20.449	34.120
	(4.867)	(5.388)	(15.993)	(21.130)	(5.069)	(5.626)	(17.151)	(23.814)
Immigration Shock			24.284	24.419			22.178	14.215
			(30.214)	(25.605)			(30.124)	(26.235)
Post-Crisis	-7.002*	-5.095	-5.100	-11.739	-5.531	14.607	-2.713	-0.505
	(4.044)	(3.646)	(7.227)	(9.023)	(4.480)	(9.909)	(8.040)	(10.054)
Post-Crisis × Low-Wage Imp Shock					-16.222	-220.604**	-68.801*	-333.637**
					(31.337)	(89.581)	(40.325)	(155.131)
Robot Shock	1.636	-12.658	-2.006	-19.180*	0.427	-26.850*	-7.359	-46.024**
	(8.234)	(10.586)	(10.545)	(11.499)	(9.527)	(15.142)	(12.835)	(21.176)
RTI Region			-2.136	-12.500			-1.957	-12.167
			(13.821)	(15.880)			(13.574)	(13.954)
Constant	32.174***		30.629***		30.930***		30.317***	
	(3.893)		(3.506)		(3.938)		(3.473)	
N	621	621	480	480	621	621	480	480
Estimator	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS

Notes: * p<.1, ** p<.05, *** p<.01. OLS and Two-Stage Least Squares analysis, unimputed data.

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