

Firms vs. Workers? The Political Economy of Labor in an Era of Global Production and Automation *

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Abstract

The nature of production has changed in important ways due to the rise of global production and automation. Increasing capabilities to access foreign labor or to use more capital intensive production, have given firms many strategies to reduce domestic labor costs. Because firms are strategic, in the face of greater barriers to global production, firms will increase automation (and vice versa). Consequently, we cannot understand political economy today without considering how the welfare of workers is tied to firms' ability to utilize different production. I develop an integrated theory of the labor market implications of global production and automation using the tasks framework. I argue that workers in occupations intensive in routine or predictable tasks are more vulnerable to the negative labor market consequences created by these forces, including lower wages and reduced job security. These occupation-characteristics are an important determinant of workers' preferences and political behavior. I hypothesize that workers vulnerable to labor-replacing automation and global production will be more protectionist with respect to globalization, more likely to favor government redistribution, and support a left party or right-wing populist party. I find support for these claims using ISSP data from 1995 to 2016.

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1 Introduction

Across advanced democracies, we see growing discontent with how capitalism meets the needs of workers. The 2020 Democratic primary alone featured calls for limits on free trade, reforms to reduce the influence of corporations in politics, an economy that works better for workers, and demands for universal basic income. The U.S. is not alone as citizens in many countries express support for populist and far-right parties. To understand these trends, we must consider how changes in economic production have benefited firms at the expense of workers. Most notably, increasing capabilities to access foreign labor or to use more capital intensive production, have given firms many strategies to reduce labor costs.¹

The ability of firms to split up production and automate certain tasks has important consequences for the economic well-being of workers. Consider the following example which illustrates how automation and global production together make it difficult to implement policies that benefit workers (not just employers). In 2016, Carrier, a U.S. air conditioning manufacturer, received \$7 million in state tax incentives to keep 800 jobs onshore for ten years. One year later, however, Carrier offshored 600 different manufacturing jobs and simultaneously announced a \$16 million investment in plant automation to reduce labor costs. Outside of manufacturing, deeper economic integration and advancing technology also affect workers in industries and jobs not traditionally affected by either globalization and automation.

What global production and automation have in common is that they break up the tasks performed by workers. As a result, workers in certain occupations are more vulnerable to the negative labor market consequences created by these forces (Autor 2013; Owen and Johnston 2017; Thewissen and Rueda 2019). This means that the economic welfare of workers is now tied to the type of work they do—their occupation—rather than to the industry in which they work or their skill level. In this paper, I discuss the labor market implications of firms’ ability to engage in global production or automation using the tasks framework. I argue that occupation characteristics are important determinants of which workers benefit from or are harmed by global production and/or

¹Indeed, the decline of manufacturing employment and the polarization of jobs is well documented in a number of studies (e.g. Acemoglu and Autor 2011; Autor, Levy, and Murnane 2003; Goos, Manning, and Salomons 2014).

automation. Specifically, workers in occupations intensive in routine or predictable tasks will be most vulnerable to the labor-replacement pressures of global production and automation.

How do these welfare consequences shape workers' preferences over policy and political behavior? Literatures in comparative and international political economy (C/IPE) address different dimensions of the politics of global production and technological change separately. By considering firms' production strategies with respect to global production and automation in the same framework, we should expect to see occupation characteristics influence several different dimensions of preferences. I hypothesize that workers in vulnerable occupations will be more protectionist regarding global production and more likely to favor government redistribution. Extending work on the political economy of voting, I further expect that those individuals harmed by global production and/or automation will be more likely to support left parties and right-wing populist parties. I find support for these claims using data between 1995 and 2016 from the International Social Survey Programme (ISSP).

2 Recent literature

In many respects, there are parallel literatures in C/IPE which examine the impact of technological change and globalization, respectively on preference formation and mass political outcomes. In both research areas, scholars have focused on the winners and losers from globalization and technological change. Most recently, these literatures have focused on the backlash against globalization, concerns about automation, and the rise in support for populist and far-right parties.

2.1 Globalization

While the last several years of IPE research have yielded new insights into the political preferences and activities of firms (e.g. Kim 2016; Kim and Osgood 2019; Kim et al. 2019; Osgood 2016), another strand of research has focused on the backlash against globalization, including support for populist and far-right parties.² The fact that there was a backlash was not a surprise (Scheve and Slaughter 2007), but why the backlash occurred when it did, and the form it took is less well

²For reviews, see Frieden (2019) and Rodrik (2018).

understood. What is clear, however, is the feeling (and evidence) that many workers and families have been left behind as a result of globalization and automation. In the U.S. and Europe, workers face stagnant wages and increasing job insecurity, and in many countries, financial crisis has led to crushing fiscal austerity. These economic conditions lead to rising economic insecurity, one factor shown to contribute to support for populism (e.g. Guiso et al. 2017; Inglehart and Norris 2016). Other scholars have found that status threat (Mutz 2018) and cultural backlash (Inglehart and Norris 2016) are responsible for rise in populist sentiment.

At the individual level, a number of studies find that individuals experiencing economic hardship or anxiety are more likely to support populist rhetoric and policies. Yet the impact of economic factors may be direct or indirect. That dissatisfaction and hostility to globalization on the one hand, and support for populist or far-right parties on the other, stems from a combination of economic and non-economic factors seems clear, but disentangling these factors is difficult. For instance, Colantone and Stanig (2018b), Guiso et al. (2017), and Hays, Lim, and Spoon (2019) examine different channels through which economic factors (economic insecurity, trade shocks) affect support for populism. These papers make an important point that it is not about economic OR cultural factors, but rather when and how each of these drivers matter.³ In a different approach, Bisbee et al. (2020) argue that generations of insufficient redistribution (i.e. decompensation) have made people skeptical or hostile to globalization and examine the shift from embedded liberalism to support for right populism using survey data.

Moving to mass politics, multiple studies find that globalization losers have had their say in the ballot box. In the United States, support for incumbent parties in presidential elections decreases in districts where more voters have been hurt by globalization (e.g. Autor et al. 2016; Jensen, Quinn, and Weymouth 2017; Margalit 2011). These electoral pressures have resulted in increasing political polarization (Autor et al. 2016; Feigenbaum and Hall 2015). The China shock has been shown to increase support for Brexit (Colantone and Stanig 2018a) and greater support for nationalist parties in Western Europe (Colantone and Stanig 2018b). In Germany, Dippel, Gold, and Heblich (2016) find that imports (from China and Eastern Europe) lead to greater support for far-right par-

³There is no question that Immigration is a politically and/or culturally salient dimension of the politics of globalization. However, my focus is on global production (how things are made) rather than globalization writ large and thus I discuss immigration as it comes up below.

ties, while exports lead to increased moderation. See also Caselli, Fracasso, and Traverso (2020) who examine the impact of immigration and Chinese import shock on local labor markets and election outcomes in Italy.

2.2 Technology

In CPE, scholars interested in the recent populist backlash have largely focused on technological change. Two major components of technological change over the last 30 years have been the ICT (Information and Communications Technology) revolution and automation. Traditionally, automation in manufacturing has involved mechanization. Increasingly we see a role for computer-based machines, including machine learning and artificial intelligence, as well as mobile robots.⁴ While all of these processes can increase productivity, technological innovation can also generate labor displacement.

Drawing on the well-known work of Autor, Levy, and Murnane (2003) and Acemoglu and Autor (2011) on task content and labor market polarization, scholars have examined the impact of automation on support for redistribution at the individual level. For instance, Thewissen and Rueda (2019) find that those in routine-task intensive occupations are more supportive of redistribution in a sample of European countries. Other studies demonstrate that routine workers are more likely to support left and far-right parties (Gingrich 2019). Those who are more vulnerable to computerization (as measured by Arntz, Gregory, and Zierahn 2017) are more likely to support far-right parties as well (Im et al. 2019).⁵

Recent work also examines the impact of technological change on mass politics. In a working paper, Anelli, Colantone, and Stanig (2018) examine how exposure to industrial robots affects votes for the far-right, using a measure of exposure to automation developed by Acemoglu and Restrepo (2018). Similarly, Frey, Berger, and Chen (2017) look at how exposure to robots influenced support for Trump in the 2016 election. Similar to some IPE work, Gidron and Hall (2017) exam-

⁴ICT and traditional automation have similar labor market effects in the sense that certain tasks still require human effort, whereas robots require less in way of human intervention (Graetz and Michaels 2018).

⁵See also Levy (2018).

ine how economic and cultural developments together shape support for right-wing populism; they find that those with lower perceived social status are more likely to support a populist party, as are those in more routine task intensive occupations.

There is a great deal of overlap in terms of the factors identified by the two fields as determinants of winners and losers from global production and technological innovation. These include skill level, industries, occupations, and local economic impacts. Yet most existing research focuses on either globalization or technological change, implicitly or explicitly treating the other process as exogenous. Few scholars have examined the two channels together. Some notable exceptions include the analysis of the impact of trade, immigration, and industrial robots on election outcomes in Italy by Caselli, Fracasso, and Traverso (2019). They argue each of these forces requires short-term labor market adjustment and this could influence election outcomes through multiple channels. Meanwhile, Gamez-Djokic and Waytz (2019) look at the links between automation and attitudes toward immigration. If we ignore how these two processes evolve together, we end up with an incomplete understanding of how the production strategies of firms influence the welfare of workers.

3 Global Production, Technology, and Firms' Labor Demands

Firms can use a number of different inputs in the production process, including capital and labor of various skill levels. Standard models of production focus on a single (final) good, and equate inputs with the process they perform (Acemoglu and Autor 2011). But this standard framework overlooks two important features of the production decisions of firms that shape their demand for labor: the ability to (1) fragment the steps of the production process and (2) utilize different production techniques (labor or capital intensive) depending on the price of inputs. The tasks approach, developed by Autor (2013) and Acemoglu and Autor (2011), thus offers a useful framework for understanding how firms make production decisions and the consequences for workers.

In this framework, the production of a good or service is broken down into a series of tasks (i.e. discrete units of work). Factors of production are used to complete particular tasks. A final good is composed of many intermediate goods and services, and the production of each of those

intermediates requires that its own series of tasks be performed. For example, the iPhone must be engineered, parts produced, and then it is assembled. Tasks are thus implicitly bundled into the production of the good.⁶

A firm must choose whether to use capital or labor inputs to perform a particular task, where capital includes machines, computers or other technology. In a world with trade, global production or immigration, labor inputs can also be foreign or domestic. In a simple example, a company producing a widget can use domestic workers to manufacture the widget, foreign labor to manufacture the widget (sourced through trade, offshoring or immigration), or it can invest in a machine to manufacture the widget. Firms will choose different inputs depending on the relative costs of those inputs. Per Acemoglu and Autor (2011), a task will be performed by the input with the lowest economic cost (a function of technological capability and opportunity cost).⁷ If domestic labor is expensive, the firm can use capital or lower wage foreign workers. In equilibrium, each factor of production is used to produce a unique subset of tasks.

In this paper, I focus on the production process—global production—not the globalization *per se*, which of course includes the globalization of labor via immigration. Put differently, this is a theory of how the work is done rather than who does the work. The main channels of labor-replacement through global production include, trade, FDI and offshoring. There are multiple dimensions to labor-replacing technology, including what has been referred to as automation, digitalization, and computerization.⁸ Automation occurs through software and computerization or robots (Bisello et al. 2019). Industrial robots can be distinguished from previous waves of automation by their ability to adapt and manipulate, and in some cases move. Indeed, industrial robots are associated with a lower share of work by unskilled labor (Graetz and Michaels 2018), manufacturing employment (Dauth et al. 2018), and local employment (Chiacchio, Petropoulos, and Pichler 2018). To capture the many ways that firms can substitute capital for labor, I refer to these

⁶Thus, even in the absence of fragmented production, we can think about trade in terms of the task content of goods. For further discussion, see Owen and Johnston (2017).

⁷Otherwise known as comparative advantage.

⁸Digitalization is the adoption of ICT technology (Kurer and Gallego 2019), while computerization refers to “job automation by means of computer-controlled equipment” (Frey and Osborne 2017, 254).

processes as “automation,” following Levy (2018).

Wages are a key determinant of firms’ incentives to adopt labor-replacing production techniques. Firms can substitute foreign workers for domestic ones (trade, offshoring) or machines for workers (e.g. automation) to reduce their labor costs. While inputs of production may be complements or substitutes to one another, capital is traditionally viewed as a substitute for low skill labor and complement to high skill labor (for review, see Goos 2018). Global production and automation change the allocation of capital and labor to different tasks; tasks that used to be labor tasks can become capital ones and so on (Autor 2013). Firms may use capital-intensive production in higher wage countries, and labor-intensive techniques in lower wage countries (Autor 2013) or offshore the low-skill intensive tasks to a lower wage country (Feenstra and Hanson 1999). The relationship between demand for different inputs and production strategies can also be considerably more nuanced depending on the extent of offshoring and automation, and whether those strategies substitute for or complement unskilled workers (e.g. Acemoglu, Gancia, and Zilibotti 2015; Acemoglu and Restrepo 2018).⁹

Firms’ demands for factor inputs will shift in response to the policy environment because policies determine the marginal costs of different inputs. First, the level of openness to trade, global production, immigration, and the feasibility of offshoring shape whether or not firms will utilize these strategies to employ foreign labor. An increase in barriers to trade, offshoring, or FDI will increase the price of foreign labor relative to domestic. When the domestic economy is more closed, firms are likely to invest in more capital-intensive production, thus substituting capital for domestic labor, to reduce labor costs.¹⁰ Second, governments incentivize technology adoption (or not) through a number of other policies, including industrial policy and tax policy. Low taxation of capital relative to labor can lead to a non-optimal amount of automation as in the US economy (Acemoglu, Manera, and Restrepo 2020). Tax incentives for investment in plant retooling (e.g.

⁹Two strands of research addressing this are the literatures on skill-biased technological change and the adoption of labor-replacing technology.

¹⁰Firms are strategic about utilizing different strategies of accessing foreign labor. As Peters (2014) argues, firms most in favor of low skill immigration are those that are low skill intensive and not mobile (i.e. not able to produce abroad). Low-skill immigration also slows the rate of adoption of automation technologies (e.g. Lewis 2011).

Carrier) or other capital investment, as well as corporate tax policy are also important. Laws governing minimum wage laws or the collective bargaining (e.g. right-to-work laws) also influence firms' production strategies. For instance, Alesina, Battisti, and Zeira (2018) demonstrate that in highly regulated labor markets (e.g. more restrictions on firing), there is a greater incentive for firms to replace labor with capital, particularly in low skill sectors.

Given how closely linked firm production costs are linked to the policy environment, it is no surprise that firms are very active in the political process. A growing body of research shows that the largest, most productive firms (i.e. those most likely to benefit from trade liberalization) are the ones most likely to lobby on trade bills (e.g. Kim 2016; Kim and Osgood 2019; Kim et al. 2019), creating a strong role for pro-globalization interests and pro-business policies. There is also an abundance of scholarship which examines the influence of business interests on politics and policy-making in the U.S. (e.g. Drutman 2015) and elsewhere.

Finally, the processes of technological change and global production are mutually reinforcing. New technology makes fragmentation possible. In addition to manufacturing, exposure of new segments of the workforce to global competition for the first time was facilitated by the adoption of ICT (e.g. Fort 2017). At the same time, import competition leads to greater innovation (Bloom, Draca, and Van Reenen 2016; Dorn et al. 2016) and can increase concerns about production costs.

4 Distributional consequences for workers

What are the consequences of changes in production for the welfare of workers? Although research has typically focused on the labor market implications of global production (Autor, Dorn, and Hanson 2013) and technology (e.g. Kurer and Gallego 2019) separately,¹¹ the tasks approach can be used to understand both channels of economic pressure on workers. When firms engage in global production or adopt new labor-replacing technology, the demand for tasks provided by domestic labor will change. Demand for some types of domestic labor tasks will increase, while demand for

¹¹Exceptions include Autor, Dorn, and Hanson (2015) and Baldwin (2019) and Caselli, Fracasso, and Traverso (2019).

other types of tasks will decrease.¹² In this section, I integrate the literatures on global production and automation through the tasks framework to develop a theory of distributional consequences for workers.

How do tasks relate to workers? We can think of occupations as bundles of tasks, and if we assume that workers are not fully mobile across occupations,¹³ then the nature of the tasks they perform in their job become a key determinant of whether an individual benefits from or is harmed by these different processes. Therefore, the impact of globalization and technological change on workers' welfare depends on the task content of their occupation (i.e. the profile of tasks associated with the occupation). When changes in production facilitate labor-replacement, workers compete based on how well workers in other countries or machines can perform those same tasks, because tasks are now more easily provided from abroad or via automation (e.g. Acemoglu and Autor 2011; Autor, Levy, and Murnane 2003; Grossman and Rossi-Hansberg 2008). Thus, we must ask which types of tasks are likely to be more cheaply provided by foreign labor through global production, or by machines.

I argue that there are three characteristics of tasks that affect the likelihood that the tasks are subject to labor-replacing changes in production: routineness, predictability and offshorability.¹⁴ First, routine tasks are both more likely produced abroad (through either trade or offshoring) and more likely to be automated. Routine tasks are characterized by repetition or rule-following procedures, and are therefore more easily explained to foreign workers or programmed via a computer. In the seminal work of Autor, Levy, and Murnane (2003), they suggest computers substitute for labor in completing routine cognitive and manual tasks. Routine cognitive tasks (e.g. record keep-

¹²A different question is whether aggregate demand for domestic labor will rise or fall. Labor-replacing production changes reduce demand for labor through the displacement effect and increase demand for labor through the productivity effect (e.g. Acemoglu and Restrepo 2017; Grossman and Rossi-Hansberg 2008).

¹³For discussion of licensing and occupational mobility, see for instance Kleiner (2000). On general barriers, see Cortes and Gallipoli (2017).

¹⁴Previous work contrasts task-based measures with industry- and location- based impacts. For instance, the China shock in local labor markets vs. routine tasks (David, Dorn, and Hanson 2013) and industrial robots in the local labor market (Acemoglu and Restrepo 2017).

ing, calculation, basic customer service) are susceptible to substitution by computers. Similarly, manual routine tasks offer substantial room for substitution between labor and capital (e.g. manufacturing production). Concerning global production, Owen and Johnston (2017) argue that workers in routine task-intensive occupations will be negatively affected by trade because advanced economies have a comparative disadvantage in such tasks. Workers in more routine jobs are likely to experience lower wages and increased job insecurity as a result of trade and global production (e.g. Ebenstein et al. 2014). In contrast, workers who perform non-routine interactive or analytic tasks may benefit from a complementarity to computerization. Such workers may also benefit from offshoring and trade in services as I discuss further below.

The second key characteristic is predictability. New advances in technology threaten workers in occupations that are intensive in non-routine, but predictable physical and personal tasks (Chui, Manyika, and Miremadi 2016; Frey and Osborne 2017). Robotics allow for the automation of physical tasks not previously automated by mechanical devices because the use of computers increases flexibility and scope, while digitization allows for automation of previously non-routine tasks and service provision (Bisello et al. 2019, 16-17).¹⁵ Focusing on the automation potential of non-routine tasks, Frey and Osborne (2017) identify engineering bottlenecks that limit the extent to which non-routine jobs can be computerized (261). Tasks that are difficult to automate require complex perception and manipulation, creative intelligence or social intelligence (e.g. negotiation, persuasion and care). The extent to which the environment or interaction is predictable or unpredictable therefore is important in determining automation potential. Predictable physical tasks are those that include specific actions in a well-defined environment. For example, the adoption of robotic technology is spreading to warehouse distribution centers and factories, but not homes, which are unstructured environments that make perception and manipulation more difficult. Broadly, tasks in manufacturing, food service, accommodation and retail are highly susceptible to automation because many tasks are physical and predictable (Chui, Manyika, and Miremadi 2016). Consider the increasing prevalence of self-check out lanes, airport kiosks, ordering kiosks in fast food restaurants or cashless tolling.

¹⁵In a study of U.S. commuter zones, Acemoglu and Restrepo (2017) find that the use of robots negatively affects local labor markets, and this effect is distinct from those related to imports from China and Mexico and also the decline in routine jobs.

The final characteristic that shapes occupational vulnerability is offshorability. Offshorability refers to whether job tasks can reasonably be performed from a distance. Non-offshorable tasks require face-to-face interaction (e.g. haircut) or must be performed at a specific place (e.g. crop harvesting) (Blinder 2007). Those in offshorable occupations are more exposed to competition from foreign workers (Owen and Johnston 2017; Rommel and Walter 2018; Walter 2017). Concerning occupation characteristics, those in routine task intensive occupations are more vulnerable to shifts in global production when those jobs tasks are also offshorable (Owen and Johnston 2017). Tasks that are not predictable but are offshorable—such as those requiring problem solving or human interaction—can be provided from a distance.¹⁶

How do the pressures of global production and automation converge or diverge across these different occupation characteristics? In Table 1, I present stylized examples of occupations' vulnerability to labor replacement via global production and automation. I focus on the current technology rather than potential technology, because utilization will lag behind capabilities (Arntz, Gregory, and Zierahn 2016).

First, the most vulnerable workers are in occupations intensive in routine and predictable tasks. In both cognitive and manual tasks, these workers face competition from automation and global production. As shown in Cell D, examples of routine cognitive and manual task intensive occupations include bookkeepers and production workers.

Second, some occupations are vulnerable to either automation *or* global production. Cell B presents examples of occupations that have a high vulnerability to automation but not global production. This includes occupations intensive in non-routine but predictable tasks—physical or social—that cannot be provided from abroad. Because tasks are not offshorable, workers are not directly exposed to global production via occupation pressures.¹⁷ Vulnerable occupations in this category include those service-intensive occupations that could be replaced by a kiosk like a cashier or airport ticket agent or wait persons. It also includes occupations intensive in predictable physical tasks. For instance, sanitation workers are being replaced by trucks with lifts and warehouses

¹⁶Note that job does not have to be moved offshore in order to experience negative labor market outcome. Even the possibility creates downward pressure on wages (e.g. Blinder 2007).

¹⁷But note such workers could be exposed via industry- or firm-effects.

like Amazon are increasingly employing industrial robots. Newer waves of automation will not continue hollowing out the middle (polarization), but will also actively threaten those in lower skill occupations.

Cell C presents examples of occupations that are vulnerable to replacement via global production but not automation. This includes tasks which may face an engineering bottleneck in terms of automation (Frey and Osborne 2017) because they are considered unpredictable, but which could be provided from abroad and are fairly routine. Examples include software programmers, certain legal services occupations, and draughtpersons engaged in computer aided design and computer-aided manufacturing. These occupations are intensive in routine tasks but also require some autonomy to adapt to unpredictable elements or specific problems. The offshoring of these tasks is facilitated by ICT and ease of communicating across borders (Fort 2017).¹⁸

Finally, in Cell A, workers in occupations intensive in non-routine, unpredictable tasks are not vulnerable to labor-replacing changes in production. Some occupations are sheltered from substitution for capital or foreign labor, while others may benefit from these processes. In the first category, sheltered occupations are those that are intensive in interpersonal tasks related to care, management, and persuasion (Frey and Osborne 2017), including providers of child care, beauty or plumbing services, teaching and management.¹⁹ In the second category are workers that could benefit from labor-enhancing changes in production. For instance, workers in non-routine task intensive occupations may benefit from global production via comparative advantage and/or complementarity with automation. These are workers in many occupations intensive in creative and analytical cognitive tasks that are both a source of comparative advantage for developed countries (Owen and Johnston 2017).²⁰ For instance, workers in knowledge creation occupations are likely to benefit from trade and advances in computer-based technology (e.g. data scientist). It is worth

¹⁸Of course, this classification is conditional on the widely adopted technology at the moment of writing. Some occupations vulnerable to global production may become more vulnerable to automation in the future as the potential for machine learning to replace non-routine cognitive tasks expands (Frey and Osborne 2017, 259).

¹⁹In the language Frey and Osborne (2017), tasks related to social or creative intelligence.

²⁰Advances in automation could take over cognitively demanding tasks and free workers to perform other tasks that are not as amenable to computerization (Kurer and Gallego 2019).

noting that Cell A includes both high and low skill workers.

Table 1: Vulnerability to labor replacement via global production and automation

	Automation- Low	Automation - High
Global - Low	<i>NR, unpredictable or non-offshorable</i> Child care, hairdresser, plumber, nursing, education, management (A)	<i>NR, predictable</i> Warehouse, truck drivers, cashier, airport (B)
Global - High	<i>Routine, unpredictable, offshorable</i> Legal, accountant, draughtperson (C)	<i>Routine & predictable</i> Bookkeeper, production worker, call center (D)

NR: Non-routine. *

Although the three occupation characteristics are conceptually distinct, there are important areas of overlap and divergence. Given my interest in policy and partisan preferences, an index of vulnerability is the best way to capture the nature of workers' distributional consequences. Vulnerability is increasing in routineness and predictability, and magnified by offshorability for those in routine jobs. Vulnerable workers pay a wage penalty and also face lower job security. Those in predictable and routine jobs are most vulnerable (Cell D), especially if offshorable. Those in either routine offshorable or predictable and non-offshorable occupations are next in terms of vulnerability (Cells C and B). Least vulnerable are those in non-routine, unpredictable and non-offshorable occupations (Cell A).

Before moving on, I note that while many low and medium skill workers are vulnerable to labor-replacing changes in production (per the polarization literature), a subset of high skill workers are vulnerable as well. An important implication of fragmented production is that more high and medium skilled workers are vulnerable to offshoring (even those employed in exporting or non-tradable industries/firms), which contrasts with the conventional wisdom that more skilled workers benefit from trade. This includes such workers as software developers, accountants, and white-collar workers in business services, as well as some medical and legal professionals. Although high skill workers are indeed better able to adjust, there may be significant costs associated with displacement or lower wages. Within classes (Oesch and Rennwald 2018), there are substantial differences in vulnerability to these processes. Although some vulnerable occupations are

concentrated in specific industries, others are found in every industry. Indeed, an occupation-based theory of production identifies the negative pressures that affect many different workers. Although global production and automation create new jobs, these are typically filled by different workers than those who are displaced.

5 Vulnerability, Policy and Party Preferences

How preferences are formed is the subject of a large debate in the fields of C/IPE. To the extent that individuals' preferences are shaped by economic considerations, those who benefit from a particular policy are expected to support it and those who are harmed will oppose the policy. Labor market outcomes also shape people's attitudes toward political parties. Policy and partisan references are determined by the welfare consequences of global production and technological change for workers. I refer to these generally as wage effects, but of course there are also additional labor-market consequences like increased job insecurity. It is not necessary for workers to fully understand exactly how trade or automation shape their welfare. The outcomes—declining or stagnating wages, insecurity or actual loss of jobs—that result from global competition and automation (together or individually) can cause workers to hold preferences as if they understand.²¹

Because firms can substitute foreign labor and capital for domestic workers in ways that are influenced by task characteristics, we should expect occupation characteristics to shape several different types of policy and partisan preferences. This includes preferences over policies governing economic openness (in terms of trade, offshoring and foreign direct investment), those policies that address the pressures of automation and globalization (including support for redistribution and minimum wage levels), as well as votes for different political parties. I focus on overall occupational vulnerability to labor-replacing changes in the production process. Those who are more vulnerable to labor-replacement are more protectionist with respect to trade and multinational activity. Concerning individual characteristics, those in routine jobs should be more protectionist, and this should be magnified for those who are offshorable per Owen and Johnston (2017).

²¹On the role of information, see Guisinger (2017) and Rho and Tomz (2017) and Schaffer and Spilker (2019).

Government redistribution can ameliorate the labor market consequences of both globalization and automation. Therefore, those with greater vulnerability to labor replacement should be more likely to support redistribution. This means that those in routine task intensive jobs are more likely to support redistribution, as are those in occupations with more predictable tasks. Further, we could expect such individual to support progressive tax policies or higher minimum wages.

Finally, pressures from globalization and automation should influence support for different political parties. Rommel and Walter (2018) show low-skill workers in offshorable occupations (those harmed by globalization) are more likely to vote for left parties that support redistribution, while high skill workers in offshorable occupations (globalization winners) are likely to support parties that support openness (i.e. liberal and center-right parties). Gingrich (2019) finds that workers most exposed to automation (i.e. those in routine-task intensive occupations) are more likely to support mainstream left and far-right parties. The motivation for those in vulnerable occupations to support left parties is that left parties are more supportive of redistribution. Vulnerable workers might also support right populists because such parties are generally hostile to globalization. This raises the question of which vulnerable individuals are more likely to support left parties versus far-right parties. Many studies of the rise of populism consider exactly this question. (e.g. Dancygier and Walter 2015; Rovny and Rovny 2017) and I discuss further in the empirical section below.²²

While others have looked at different pieces of the puzzle individually, it is important to bring together all dimensions in a more holistic assessment of how occupation characteristics can influence attitudes. In particular, it has the potential to provide insight into the rise in support for populist parties, and as discussed further in the conclusion, it highlights the challenges workers and governments face regarding policy-making given that many policies benefit firms more than the employees of those same firms. I thus test the following hypotheses.

H1. Protection. Individuals will be more protectionist (in terms of trade, multinational activity) as occupational vulnerability to labor-replacement increases.

H2. Redistribution Individuals will be more likely to support government redistribution as

²²For instance, pressures may manifest themselves in different ways depending on what the second cleavage is per Dancygier and Walter (2015) and Noury and Roland (2020).

occupational vulnerability to labor replacement increases.

H3. Political behavior Individuals will be more likely to support mainstream left or far-right parties as occupational vulnerability to labor replacement increases.

There are several additional factors to consider. First, occupation characteristics will only determine preferences to the extent that labor market mobility is limited across occupations. When mobility across occupations is high (i.e. easier to change occupations), then the reallocation of workers across occupations will lead to preferences based on skill level as shown by Acemoglu and Autor (2011). Second, a focus on occupations does not get at variation in technology adoption across industries or firms. While I have argued that these pressures on occupations transcend industries and firms, it is important to consider these other channels of transmission of the effects of automation (and global production) on workers. Third, the growing literature on the political geography of trade highlights how trade can impact local labor markets, and depress the economic well-being of communities (regardless of any one individual's exposure to trade). See for instance Bisbee et al. (2020), Colantone and Stanig (2018a,b), Frieden (2019), and Jensen, Quinn, and Weymouth (2017). Finally, we must also consider how the domestic context like levels of openness or social spending also influence preferences (e.g. Compton and Lipsmeyer 2019; Gingrich 2019; Schaffer and Spilker 2016).

6 Research design

In this section, I discuss my empirical strategy for examining how occupation characteristics shape the above preferences and vote choices. I primarily analyze surveys from waves of the ISSP from 1995 to 2016. Among surveys that include occupation data for respondents, one advantage of the ISSP is that it asks questions about global production, redistribution, and political parties. It also contains countries outside of Europe. Building on the data of Gingrich (2019), my sample includes all waves of the ISSP from 1995 to 2016 for 20 advanced democracies.²³ Descriptive statistics are

²³Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Iceland, Ireland, Israel, Italy, Japan, Norway, South Korea, Spain, Sweden, Switzerland, United Kingdom, and the United States.

provided in the supplemental appendix.

The key independent variable is occupational vulnerability to labor-replacing changes in production. The *Occupational vulnerability index* combines the characteristics of routineness, predictability, and offshorability. In political science, Owen and Johnston (2017) and Thewissen and Rueda (2019) and Walter (2017) are among the first to use routineness and offshorability in the analysis of individual preferences. These occupation measures are constructed from detailed information on occupation work activities and context available from the United States O*Net (Occupational Information Network) database.²⁴ Using the Acemoglu and Autor (2011) occupation scales, I measure *Routineness* as routine task intensity (RTI), which captures how important routine tasks are relative to manual or abstract tasks. RTI equals $\ln(Routineness) - \ln(Abstractness) - \ln(Manualness)$, where routineness is the sum of scores for routine manual and cognitive tasks, abstractness is the sum of scores for non-routine personal and analytical tasks, and manualness is the sum of scores for non-routine physical and personal tasks. Higher values of RTI indicate that the occupation is more intensive in routine tasks and thus indicate greater vulnerability.

The second component of the index is *Predictability*. As noted, routineness is an important predictor of vulnerability to automation and global competition. To measure predictability or non-routine automation potential, I estimate a measure of the likelihood of computerization that is unexplained by routineness. To do so, I regress Frey and Osborne's (2017) occupational probability of computerization on RTI and use the residuals as a measure of the risk of automation that cannot be explained by routineness.²⁵

The third component of the index is *Offshorability*, the degree to which job tasks can be provided from a distance or are specific to a particular location. I code occupations as one if they are classified as offshorable or highly offshorable by Blinder (2007) and zero otherwise.

To compute the vulnerability index, I sort 352 occupations (4-digit ISCO-88 codes) into quintiles for both routineness and predictability. I add together the quintiles for both measures such that higher values indicate greater vulnerability. To account for the additional pressures (or oppor-

²⁴Acemoglu and Autor (2011) and Blinder (2007). See also seminal work on task content by Autor, Levy, and Murnane (2003).

²⁵I estimate using a GLM logit link function to constrained predicted values to the (0,1) range. The results of the estimation is in the supplemental appendix.

tunities) facing those in offshorable occupations, the final component of the index is the level of routineness in quintiles (minus three) times the offshorable dummy.²⁶ This increases vulnerability for those in offshorable occupations in the top two quintiles of routineness and decreases vulnerability for those in non-routine offshorable occupations that might benefit from global production. I rescale so that the final index ranges from zero to one. I use 4-digit ISCO-88 codes where available and fill in at 2 digit if the 4 digit not is available.²⁷

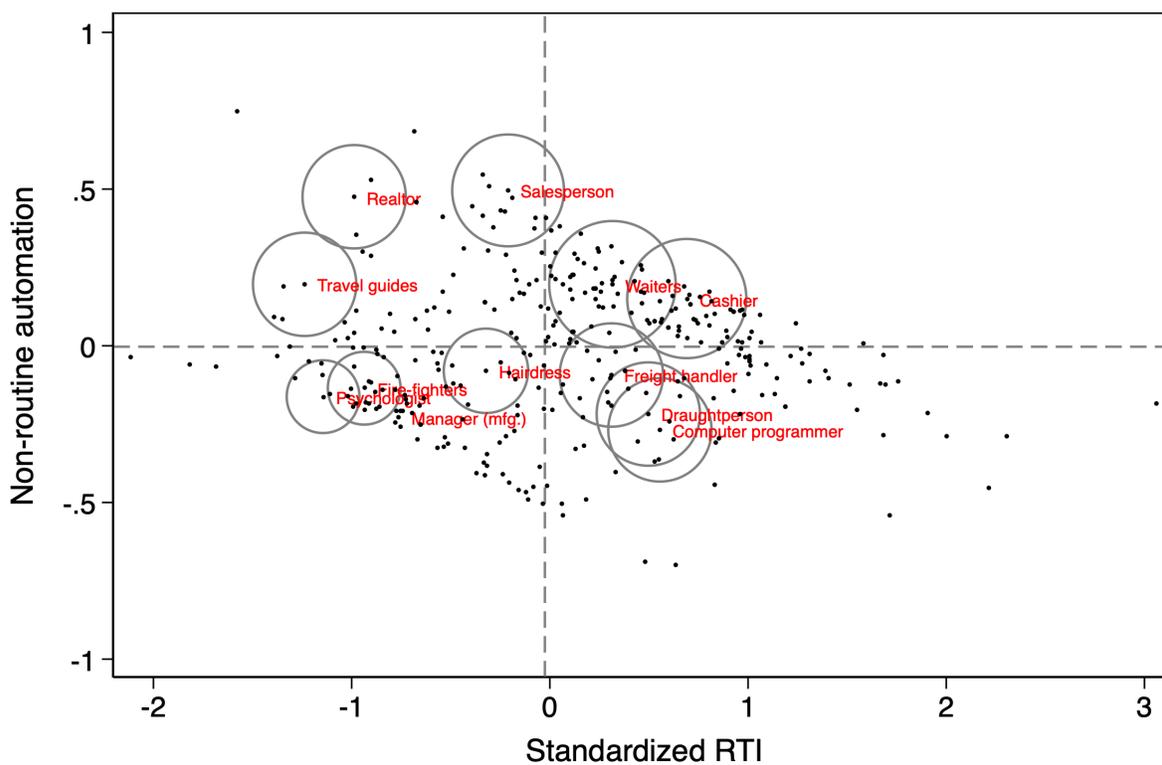
In Figure 1, I plot routineness and predictability to demonstrate the differences between them. For select occupations, the circles show the degree of occupational vulnerability to labor replacement. For instance, fire-fighters have a vulnerability score of 0.273, managers have a vulnerability score of 0 and waiters have a vulnerability score of 0.818.

It is important to note a few limitations of task-based measures and the implications for my analysis. For in-depth reviews, see Autor (2013), Arntz, Gregory, and Zierahn (2016) and Bisello et al. (2019). First, these are static concepts. The Acemoglu and Autor (2011) measures were constructed in the early 2000s and thus reflect the technology of that period. Although technology diffusion/adoption lags behind the frontier of what is possible, this is important to keep in mind. Moreover, the composition of tasks performed by each occupation has evolved over time in response to changes in technology and global production. This shift means that exposure to automation pressures may be different even within occupations (Arntz, Gregory, and Zierahn 2017) because many workers in routine-task intensive occupations increasingly shift toward non-routine tasks. The passage of time should make it more difficult to find the hypothesized effect using such measures. Second, the measures used in this analysis are based on U.S. task structures, despite the fact that there are differences in the tasks profiles of occupations across countries. Again, this noise should make it more difficult to find the hypothesized effect. I utilize the measure of Arntz, Gregory, and Zierahn (2017) which addresses some of these concerns for a smaller number of countries in the supplemental appendix. There, I also show that my estimated measure of pre-

²⁶Occupational vulnerability equals the sum of quintiles for routineness and predictability, plus a term equal to the routineness quintile (centered) times offshorable: $Vulnerability = (R_q + P_q + ((R_q - 3) \times Off)/11)$.

²⁷In the potential sample of 304,298, 17 percent are coded using 2-digit codes. I use the less precise two digit measure in the supplemental appendix for robustness.

Figure 1: Measures of routineness, predictability, and vulnerability



Note: The size of the bubble is proportional to occupational vulnerability for selected occupations. Sample is 352 occupations at 4-digit ISCO-88 level for which data is available. Dashed lines represent the means of routineness and predictability.

dictability corresponds with job tasks from a different taxonomy by Fernández-Macías and Bisello (2017) in a manner consistent with the discussion above.

Finally, although this analysis is not causal, the measure of occupational vulnerability is exogenous (e.g. Rodrik 2020). Thus I avoid the problems associated with a regression of attitudes on attitudes.²⁸ Additionally, I am not investigating the mechanisms which produce a linkage between occupation characteristics and preferences. Indeed, outside of a survey experiment, it is difficult to untangle different channels such as cultural and economic factors (Dancygier and Walter 2015; Rodrik 2020). Rather, this analysis shows how vulnerability can shape preferences and vote choice in a number of different ways.

In the following sections, I use these measures to examine the economic implications of my arguments, and test hypotheses related to preferences and party support. In the sample, vulnerability ranges from 0 to 1, has a mean of 0.53, and a standard deviation of 0.20. Distributions for each of the independent and dependent variables are presented in the supplemental appendix. All summary statistics are available in the supplemental appendix. For each analysis that follows, I estimate OLS or logit models with country and year fixed effects. I discuss the measurement of the DV and the control variables for each model when introducing the model.

7 Economic implications

I first examine the effect of occupation characteristics on income and perceived job security as a way of examining support for the posited labor market consequences. The first dependent variable is income, measured using the log of personal income in constant US dollars and also relative income.²⁹

I expect that those in more vulnerable occupations will have a lower income due to wage

²⁸Colantone and Stanig (2018b) emphasize that including attitudes in a regression model alongside economic factors is not a valid test of the effect of economic factors because those values are influenced by the economic factors. See also Owen and Walter (2017).

²⁹This is the ratio of personal income relative to the country-year median in the sample (Thewissen and Rueda 2019, 203). Note that this variable is measured using bins for income. See Rueda (2018) for discussion.

penalties associated with exposure to global production and automation. In addition to country and year fixed effects, I control for different levels of educational attainment (Less than lower secondary, lower secondary, upper secondary, vocational, university degree or higher) and age, and dummy variables for gender (equal to one if female), trade union membership (equal to one if a member of a trade union), and unemployment (equal to one if unemployed).

The results are presented in Table 2. My main focus is the vulnerability index, but I present results for the individual components of routineness and predictability for comparison. In Models 1 and 2, the dependent variable is the log of personal income. The coefficient on vulnerability is negative and statistically significant, suggesting that those in more vulnerable occupations have a lower income. In Model 2, the coefficient of routineness is negative and statistically significant. This suggests that those in routine task-intensive occupations have a lower income. The coefficient on predictability is also negative and statistically different from zero, indicating that those in more non-routine automatable occupations have a lower income. The results for relative income follow a similar pattern as shown in Models 3 and 4. Per Model 3, the coefficient on occupation vulnerability is again negative and statistically different from zero. Those in more routine and more predictable occupations have a lower income in relative terms per Model 4.

Substantively, the effect sizes are large. A one standard deviation increase in occupation vulnerability reduces income by 8.2 percent in Model 1.³⁰ Yet, this effect is small in magnitude relative to, say holding a college degree or higher. An individual with a college degree or higher will have an income that is 52.66 percent larger than someone with less than secondary education.³¹ Other control variables have the expected effects: union members earn more, women earn less, those with vocational or advanced degrees earn more. Those living in rural areas earn less than non-rural counterparts.

To capture a different dimension of economic concerns, I examine beliefs about job security from the 1997, 2005, and 2015 waves of the ISSP. Concerns about job security are measured using a four-level response to the question: “Do you worry about the possibilities of losing your job?”³² Higher values indicate greater concern about losing a job. I expect that those who are more

³⁰95% CI: [-10.03, -6.81].

³¹95% CI: [30.23, 75.10]

³²In the appendix, as an alternative, I also look at beliefs about the ease of finding a new job,

Table 2: Economic implications

	Log income		Relative income		Job security	
	(1)	(2)	(3)	(4)	(5)	(6)
Vulnerability index	-0.560*** (0.073)		-0.793*** (0.063)		0.576*** (0.057)	
RTI		-0.083*** (0.018)		-0.146*** (0.011)		0.185*** (0.021)
Predictability		-0.324*** (0.053)		-0.392*** (0.045)		-0.004 (0.065)
Upper secondary	0.067 (0.050)	0.068 (0.050)	0.158*** (0.019)	0.157*** (0.019)	-0.161*** (0.048)	-0.155*** (0.046)
Vocational	0.282** (0.108)	0.290** (0.109)	0.237*** (0.021)	0.241*** (0.021)	-0.181*** (0.052)	-0.177*** (0.052)
Degree	0.423*** (0.075)	0.441*** (0.078)	0.566*** (0.048)	0.578*** (0.048)	-0.263*** (0.052)	-0.253*** (0.052)
Unemployed	-2.845*** (0.817)	-2.851*** (0.817)	-0.657*** (0.053)	-0.663*** (0.053)	1.018*** (0.208)	1.039*** (0.209)
Union member	0.172*** (0.033)	0.166*** (0.033)	0.099** (0.037)	0.092** (0.036)	0.119** (0.059)	0.118** (0.059)
Female	-0.434*** (0.044)	-0.438*** (0.044)	-0.482*** (0.042)	-0.489*** (0.043)	-0.077** (0.039)	-0.062* (0.037)
Age	0.014*** (0.004)	0.014*** (0.004)	0.010*** (0.001)	0.011*** (0.001)	-0.005** (0.002)	-0.005** (0.002)
Unemployment rate	-0.162*** (0.041)	-0.162*** (0.041)	0.005 (0.008)	0.005 (0.008)	0.092*** (0.012)	0.092*** (0.013)
Rural	-0.082* (0.046)	-0.082* (0.046)	-0.078*** (0.019)	-0.079*** (0.018)	-0.153*** (0.037)	-0.152*** (0.036)
Constant	9.288*** (0.565)	8.975*** (0.572)	1.248*** (0.160)	0.811*** (0.161)		
Threshold 1					0.273 (0.194)	-0.036 (0.189)
Threshold 2					1.741*** (0.179)	1.434*** (0.178)
Threshold 3					3.037*** (0.206)	2.732*** (0.210)
Observations	170653	170653	170053	170053	26228	26228
# countries	20	20	20	20	19	19
Log likelihood	-3.84e+05	-3.84e+05	-2.12e+05	-2.13e+05	-29886.37	-29856.32
BIC	768732.27	768833.27	424206.61	425246.91	59915.19	59865.26

Cluster robust standard errors in parentheses. Country and year fixed effects included

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

vulnerable to global production and/or automation will have higher feelings of job insecurity. I present the results of ordered logit analyses in Models 5 and 6 of Table 2.

In Model 5, the coefficient on occupation vulnerability is positive and statistically significant, suggesting that those in more vulnerable occupations are more likely to express concern about losing their job. A one-unit increase in occupational vulnerability increases the odds of being worried about the possibility of losing your job by 1.78. Note that this is akin to an increase in vulnerability from minimum to the maximum, or the difference in the vulnerability of a general manager compared to a clerk or machine-operator. Overall, control variables have the expected effect. Those who are more educated (college degree or higher, vocational degree, and upper secondary) are less concerned about losing their job than those with less than a secondary degree, while union members feel more secure in their jobs. In Model 6, the coefficient on routineness is positive and statistically significant, suggesting that those in routine task-intensive occupations are more likely to worry about job security. A one-unit increase in routineness (from the minimum to the maximum) increases the odds of being very worried about the possibility of losing your job by 1.20. The coefficient on predictability is not statistically different from zero.

In summary, the results broadly support the theory of distributional consequences laid out above. Those in occupations vulnerable to global production or automation have lower incomes in absolute and relative terms, all else equal, and are more likely to feel insecure in their job.

8 Policy preferences

The above results show that those in vulnerable occupations face a wage penalty and experience greater feelings of job insecurity, all else equal. Given these welfare consequences, does occupation vulnerability influence preferences over the policies governing globalization and redistribution? First, I use the 1995, 2003, and 2013 National Identity waves of the ISSP to examine preferences toward trade and multinational firms. Results are presented in Table 3 and Figure 2. All models are estimated using ordered logistic regression, with country and year fixed effects. I

using a five-level response to the question: “How easy or difficult do you think it would be for you to find an acceptable job?”

control for degrees, age, and dummy variables for unemployment, union membership, and gender.

Model 1 of Table 3 measures support for trade protection based on the question “[Country] should limit imports to protect jobs”, with higher values coded to indicate greater support for trade protection. The coefficient on vulnerability is positive and statistically significant, suggesting that those who are more vulnerable are more protectionist with respect to trade. A one-unit increase in occupational vulnerability increases the odds of strongly agreeing to limit imports by 1.79. In Model 2, the coefficients on routineness and predictability are both positive and statistically significant. It is interesting to note the effect of predictability because individuals in these types of occupations are not directly exposed to competition from trade. Further research into the mechanisms driving this is needed.

The results in Models 3 and 4 examine attitudes toward multinational firms, based on the question “Large international businesses are doing more and more damage to local business.” In Model 3, the coefficient on vulnerability also is positive and statistically significant. In Model 4, the coefficient on routineness is positive and statistically different from zero. Those in more routine task intensive occupations are more protectionist. Similarly, the coefficient on predictability is positive and statistically significant.

Overall, the results support Hypothesis 1. Across both measures of protectionist sentiment, the effects of control variables are largely consistent with expectations.

Next, I examine support for redistribution to test Hypothesis 2. The dependent variable comes from the Role of Government waves of the ISSP in 1996, 2006, and 2016, and is based on the question “Do you think it is the government’s responsibility to reduce income differences between the rich and poor?” Higher values indicate greater support for redistribution. In Model 5, The coefficient on occupational vulnerability is positive and statistically different from zero. Those who are more vulnerable to global production and/or automation are more likely to support government efforts to reduce inequality. In Model 6, the coefficients on routineness and predictability are positive and statistically different from zero, suggesting those more vulnerable to labor replacement are more supportive of redistribution.

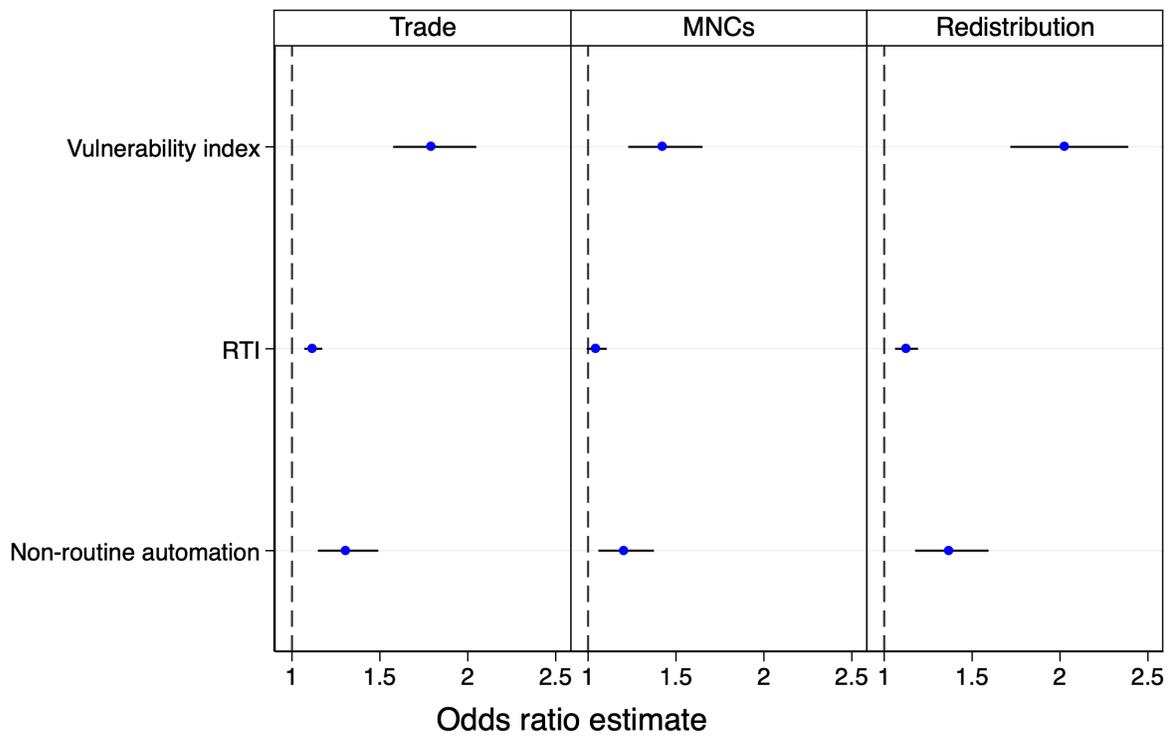
Table 3: Analysis of preferences

	Trade		MNCs		Redistribution	
	(1)	(2)	(3)	(4)	(5)	(6)
Vulnerability index	0.576*** (0.069)		0.336*** (0.077)		0.711*** (0.088)	
RTI		0.114*** (0.023)		0.047* (0.028)		0.119*** (0.030)
Predictability		0.268*** (0.067)		0.188*** (0.067)		0.311*** (0.076)
Upper secondary	-0.464*** (0.059)	-0.462*** (0.059)	-0.270*** (0.054)	-0.270*** (0.053)	-0.280*** (0.059)	-0.281*** (0.058)
Vocational	-0.592*** (0.076)	-0.592*** (0.076)	-0.440*** (0.053)	-0.445*** (0.054)	-0.423*** (0.077)	-0.431*** (0.077)
Degree	-1.004*** (0.073)	-1.009*** (0.072)	-0.645*** (0.050)	-0.659*** (0.051)	-0.558*** (0.080)	-0.580*** (0.078)
Unemployed	0.127** (0.062)	0.130** (0.062)	0.231*** (0.057)	0.235*** (0.058)	0.572*** (0.105)	0.581*** (0.106)
Union member	0.143*** (0.044)	0.147*** (0.044)	0.255*** (0.048)	0.258*** (0.047)	0.433*** (0.054)	0.439*** (0.054)
Female	0.305*** (0.031)	0.310*** (0.031)	0.046 (0.042)	0.048 (0.042)	0.302*** (0.039)	0.309*** (0.041)
Age	0.001 (0.002)	0.000 (0.002)	0.003* (0.002)	0.003 (0.002)	0.001 (0.002)	0.001 (0.002)
Unemployment rate	-0.007 (0.010)	-0.007 (0.010)	-0.007 (0.008)	-0.007 (0.008)	0.012 (0.017)	0.013 (0.017)
Rural	0.278*** (0.044)	0.280*** (0.044)	0.162*** (0.047)	0.163*** (0.048)	-0.069* (0.038)	-0.067* (0.038)
Threshold 1	-3.782*** (0.243)	-4.096*** (0.220)	-4.389*** (0.245)	-4.580*** (0.231)	-1.200*** (0.239)	-1.593*** (0.235)
Threshold 2	-1.991*** (0.170)	-2.307*** (0.153)	-2.434*** (0.099)	-2.625*** (0.090)	0.236 (0.189)	-0.159 (0.183)
Threshold 3	-0.899*** (0.200)	-1.215*** (0.185)	-1.136*** (0.110)	-1.328*** (0.097)	1.763*** (0.175)	1.367*** (0.175)
Threshold 4	0.925*** (0.201)	0.608*** (0.191)	0.860*** (0.088)	0.668*** (0.074)		
Observations	25200	25200	18543	18543	26201	26201
# Countries	19	19	19	19	18	18
Log likelihood	-36034.92	-36041.68	-25062.77	-25066.71	-32116.79	-32139.99
BCIC	72221.85	72245.51	50263.13	50280.83	64376.01	64432.57

Cluster robust standard errors in parentheses. Country and year fixed effects included

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure 2: Odds ratio estimates for models of preferences



95% confidence intervals. Country and year FE not shown.

9 Partisan preferences

In the final analysis I examine how these occupation characteristics shape support for various political parties. Different scholars have examined whether globalization (Dancygier and Walter 2015; Rommel and Walter 2018) and automation (Gingrich 2019) winners and losers support different political parties. If those hurt by globalization and automation support redistribution, they should be more likely to support mainstream parties that also support redistribution. At the same time, others have focused on globalization and automation losers' propensity to support far-right parties. Thus, I look at which party the respondent voted for in the last election, using the ISSP from 1995-2016. To do so, I use the replication data of Gingrich (2019) for the outcome variable. Parties are classified into five families: non-social democratic left (Green, Left, and Communist parties), the mainstream left (Social Democrats), mainstream right parties (Liberal, Christian Democrat, and Conservative), right-populist parties, and non-voters. I estimate a multinomial logit model with country and year fixed effects and a dummy variable for the election cycle and party type. The base category is mainstream right parties. The results are presented in Table 4 and Figure 3.

The results for the main variables of interest are presented in Table 4, with mainstream right as the base category. Hypothesis 3 is that the losers from automation and global production will be more likely to support mainstream left and far-right parties. Indeed, those in more vulnerable occupations are more likely to report voting in favor of a mainstream left or right populist party relative to a mainstream right party. They were also more likely to report not voting in the last election.

To facilitate comparison, Panel A of Figure 3 presents the marginal effects of vulnerability on the probability of voting for each party. A one-unit increase in vulnerability increases the probability of supporting the mainstream left by 6.27 percentage points; reduces the probability of supporting the mainstream right by 11.91 percentage points, and increases the probability voting for a right populist by 2.49 and of not voting by 4.92 percentage points.

In Model 2, those in routine task-intensive jobs were more likely to report voting in favor of a mainstream left or right populist party relative to a mainstream right party. They were also more likely to report not voting in the last election relative to mainstream right. The marginal effects are presented in Panel B. The coefficients for the predictability were only statistically significant

in reducing the likelihood of voting for “Other left” parties relative to the right-mainstream parties. See the marginal effects in Panel C of Figure 3.

Table 4: Vote choice

	Other Left	Mainstream Left	Right Populist	Non Voters
			Model 1	
Vulnerability index	0.158 (0.127)	0.574*** (0.094)	0.823*** (0.174)	0.647*** (0.086)
Observations	160087			
BIC	403881.82			
			Model 2	
RTI	0.001 (0.028)	0.133*** (0.017)	0.204*** (0.036)	0.176*** (0.024)
Predictability	-0.259** (0.107)	-0.012 (0.079)	0.196 (0.211)	-0.023 (0.065)
Observations	160087			
BIC	403781.61			

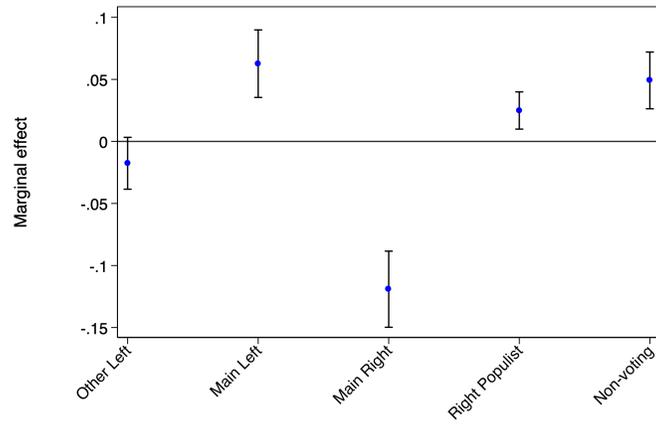
Cluster robust standard errors in parentheses. Country and election cycle fixed effects included

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

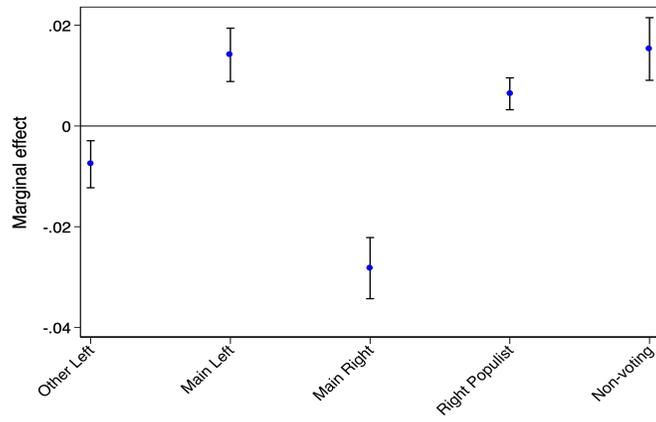
There are two important considerations to bear in mind. First, partisan preferences are nuanced in several ways. Recent work examines the changing nature of cleavages across the advanced economies. Regardless of the type of economy, immigration and/or other anti-globalism are emerging as a cultural dimension (Ford and Jennings 2020; Häusermann and Kriesi 2015; Noury and Roland 2020). Yet the emergence of this dimension is not independent from the economic element. We need theory to understand how economically disadvantaged voters will vote: the salience of the cultural dimension can lead to a vote for the far-right, while the economic dimension leads to support for the left. As Rodrik (2020) points out, the supply of politicians/parties that increase the salience of cultural dimension still comes from the economic dislocation, just through a different channel. Second, economic insecurity may also influence the propensity to vote, in addition to partisan preference. Labor market disadvantage can influence voting behavior through impacts abstention, protest voting, or support for pro-redistribution parties (Emmenegger, Marx, and Schraff 2015). This is consistent with my findings on policy and partisan preferences.

Figure 3: Marginal effect on party support

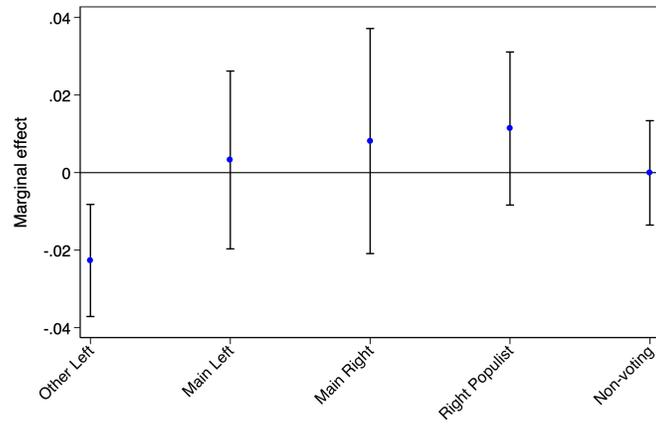
(a) Occupational vulnerability (Model 1)



(b) Routineness (Model 2)



(c) Predictability (Model 2)



10 Robustness

In the supplemental appendix, I test several additional implications of my theory and examine the robustness of the findings to different measures and model specifications. First, I show that vulnerability leads to lower political efficacy and explore whether the effect of vulnerability on policy and partisan preferences is conditional on compensation. I also consider potential heterogeneity in the effect of vulnerability on support for the left versus populist right. I utilize alternative measures of vulnerability and find the results are generally robust when the sample is split into the pre- and post-Great Recession period (2007 and earlier, 2010 and after). Finally, I show that vulnerability leads to lower income, more support for redistribution, and more support for the radical right when I use the European Social Survey and include controls for industry and regional exposure to globalization.

11 Conclusion

In this paper, I discuss how firms' production strategies shape the welfare outcomes of workers, and workers' policy and partisan preferences. Together, these results show that the occupation characteristics of vulnerability, and in particular, routineness and predictability can help explain variation in attitudes that may be driven by the competitive pressures of globalization and automation. Additionally, these same characteristics influence citizens' support for different political parties, which can provide insight into the growing backlash against globalization and business, as usual, more generally.

Yet there are several additional considerations. Theoretically, under what conditions will workers who are vulnerable to automation but not global production support trade protection? By detailing this more precisely, we may get leverage into the channels through which economic factors influence preferences and behavior (including cultural, psychological or sociotropic mechanism). A second area that needs further theorizing is how these different dimensions of preferences can serve as a substitute or complement one another. Third, I have assumed that workers' occupations are sticky, and thus a source of welfare consequences, but it may be the case that this varies across occupations (and across countries). Finally, occupational characteristics must be vetted in a con-

text which more directly accounts for other channels of transmission of the economic effects of global production and automation, including firm, industry, and geography.

Despite these limitations, there are several important implications of these findings. First, it is important to emphasize that policies that benefit firms do not necessarily benefit the workers in those firms (Dean 2015, see also). For example, policies directed at strengthening manufacturing production in employment terms have been largely ineffective and will continue to be in the future because they do not address all aspects of a firm's production decisions, such as location or levels of automation. The churn created by automation and global production changes the composition of jobs in the economy.

Second, the economic welfare of workers in the same industry, and even in the same firm, may be affected differently. Policies to help workers adjust must be flexible to address this. A further implication is that as workers' interests become more fragmented, it will be more difficult for workers to exert political influence. As a result of these changes, policymakers must work to broaden the safety net and make job training more widely available, particularly in Anglophone countries where such support systems are often lacking.

Overall, we need to protect workers, not jobs. Advances in technology and machine learning, coupled with global production, have the potential to generate job dislocations on the scale of the Industrial Revolution as job displacement occurs faster than job replacement; so we should expect demand for populism to increase (Baldwin 2019). Failure to respond accordingly will continue the backlash and threaten the gains from globalization. Large, productive firms, which are the most likely to benefit from globalization and which are also most likely to be politically active, should therefore support policies that mitigate the demand for populist policies. A higher level of redistribution and a more generous safety net are better for businesses than closure and isolation. To see this, one needs only to look at the impact of Brexit on the UK economy thus far.

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