Automatability of Work and Preferences for Redistribution

Hoorn, André van

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Automatability of Work and Preferences for Redistribution*

ANDRÉ VAN HOORN

Institute for Management Research, Radboud University, PO Box 9108, Nijmegen 6500 HK, The Netherlands (e-mil: Andre.vanHoorn@ru.nl)

Abstract

Although the importance of technological change for increasing prosperity is undisputed and economists typically deem it unlikely that labour-saving technology causes long-term employment or income losses, people's anxiety about automation and its distributive consequences can be an important shaper of economic and social policies. This paper considers the political economy of automation, proposing that individuals in occupations more at risk of job loss due to automation have stronger preferences for government redistribution. I analyse individual-level cross-national data from the European Social Survey and other sources, covering up to 32 countries and more than 170,000 individuals. I find a robust positive association between occupational automation risk and preferences for redistribution. As long as the conditional (mean) independence assumption is satisfied, my estimates suggest that a one standard deviation increase in automatability increases preferences for redistribution with roughly 0.05 standard deviations, which is comparable to the difference in preferences for redistribution between women and men.

I. Introduction

Whereas few people deny that technological change can radically transform economies, economists typically emphasize the long-run benefits of creative destruction and technological change for increasing prosperity (Autor, 2015). Advances in robotics, task automation and artificial intelligence, however, have been fuelling widespread concerns about the possibility of long-lasting technological unemployment and the disruptive effect of labour-saving technology on society (Brynjolfsson and McAfee, 2014; Ford, 2015). The core of such automation anxiety is that technological change

has distributional effects between groups in society, meaning that the benefits of technological change are not spread evenly.[1] Recent debate and anxiety thereby highlight a specific automation concern, which is that some workers or occupations end up losing from labour-saving technology not just compared to other groups but also in absolute terms. If large groups in society are indeed in danger of long-run losses from automation this would be a powerful shaper of economic and social policies. Jobs that are more automatable come with higher unemployment risk and economic uncertainty, stoking up demand for government action that mitigates or insures against income losses. Different estimates of the labour market effects of automation exist. Frey and Osborne (2017), for example, find that approximately 47% of the US labour force is at risk of displacement by machines. A report by McKinsey (2017) similarly finds that roughly six of ten occupations in the United States involves tasks that can be automated for at least 30%.

This paper links the automatability of work, specifically individuals' risk of losing their job due to automation, to preferences for redistribution. Redistributing material wealth has traditionally been one of the most important roles played by governments and individuals' preferences for redistribution have been widely studied (Corneo and Grüner, 2000; Pittau, Massari and Zelli, 2013; Kuziemko *et al.*, 2015; Gärtner, Mollerstrom and Seim, 2017). The workhorse model for understanding differences in preferences for redistribution comes from Meltzer and Richards' (1981) seminal work, which emphasizes the role of individuals' income (relative to the median). However, expectations concerning future income or wealth and socioeconomic mobility are also commonly proposed as determinants of preferences for redistribution (Bénabou and Ok, 2001) and confirmed by empirical evidence. Ravallion and Lokshin (2000), for instance, find that negative expectations about future welfare increase demand for redistribution. My hypothesis is that greater occupational automatability leads to a stronger preference for redistribution. The underlying logic involves two steps. The first is that individuals recognize the implications of their occupational task content for the automatability of their work. The second is that individuals recognize the implications of the automatability of their work for their income and wealth prospects and for the net pecuniary gains that they can expect from government redistribution.

For examining the association between exposure to automation risk and preferences for redistribution, this paper follows earlier work on occupational task content (e.g. Acemoglu and Autor, 2011) and draws on individual-level survey data to construct an aggregate indicator of the degree of automatability of different occupations. The idea is that combining insights on the risk of job loss due to automation from employees actually working in a particular type of job renders a valid measure of occupational

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[1]I use the terms automation and labour-saving technology interchangeably. Formally, however, the latter includes both automation and mechanization. Meanwhile, it seems that the COVID-19 pandemic has brought added significance to the issue of the automatability of work. The impact of COVID-19 (or other contagious diseases) on work and human labour varies among occupations. At the same time, the issue of replacing humans with robots that are immune to diseases is particularly relevant for jobs that have been deemed critical to society (e.g. logistics or medical personnel). More generally, there is of course occupational variation in the extent to which computer and information technologies (e.g. online communication tools) facilitate and enable people to work from home or not.

automatability. Empirical evidence presented in this paper suggests that this is indeed the case. Data on self-reported preferences for redistribution and various other factors recognized to affect these preferences come from the European Social Survey or ESS (European Social Survey, 2018). The indicator of occupational automation risk is matched to these data using codes from the 1988 version of the International Standard Classification of Occupations (ISCO). Data from the 1992 and 1999 International Social Survey Programme modules on Social Inequality (ISSP-SI) (ISSP Research Group, 2014) enable me to triangulate results and take into account an alternative set of potential confounders. Similarly, data from the 1996 and 2006 Role of Government module of the ISSP or ISSP-ROG (ISSP Research Group, 2008) enable extending results from redistribution preferences, which are relatively broad and abstract, to preferences concerning a specific policy issue, namely government support of declining industries.

The key challenge for identifying a possible causal effect of occupational automation risk on preferences for distribution is properly controlling for omitted variables. In particular, the issue is that individuals can choose and may select into certain occupations and that some of the same factors that affect such occupational selection may also correlate with individuals' preferences for redistribution (see, e.g. Todd and Zhang, 2020 for a study of occupational choice). To address this issue, the empirical analysis includes an extensive set of control variables, mostly concerning individual-level differences but also concerning differences between occupations. Rather uniquely, these controls do not only involve standard variables such as years of education and educational degree but also, among others, the comprehensive measures of human motivations provided by the basic human values framework (Schwartz, 1992). In addition, both the ESS and the ISSP-ROG dataset provide means to control for people's political preferences directly. The closing piece of the paper's strategy for addressing omitted variable bias is that, instead of considering the relationship between individuals' own automation risk and redistribution preferences, I consider the relationship between redistribution preferences and automation risk through individuals' exposure to automation risk via the occupation of their spouse or partner. In this case, there remains a theoretical possibility that individuals' with certain unobserved traits select into partnering with people employed in certain occupations (Mansour and McKinnish, 2018), which, in turn, affects the former's redistribution preferences. However, using the automatability of individuals' own occupation as an additional control variable renders serious biases due to such assortative matching less likely. Moreover, we can of course also consider spousal automation risk as an additional control variable. If spousal automation risk is capturing unobserved differences between individuals that also affect these individuals' redistribution preferences, than adding spousal automation risk as a control variable helps reduce omitted variable bias in the analysis of the relationship between individuals' own automation risk and their preferences for redistributions (see Section III and Figures A.3-A.7 in Appendix A for an elaboration of the paper's main empirical analyses and models).

The key findings of this paper are as follows. First, individuals that are more exposed to automation risk, either through their own job or through their partner's job,

do indeed exhibit stronger redistribution preferences, indicating an important channel through which automation anxiety can end up affecting societies, independent of automation's direct labour market effects. Recent technological change seems to increase economic uncertainty for a growing part of the population, prompting citizens to pressure their governments into compensatory social and economic policies. Second, the standard occupational characteristics of task routineness and complexity do not affect preferences for redistribution when occupational automation risk is taken into account. A final finding concerns preferences for a concrete economic policy with redistributive consequences. Results indicate that the apparent association between automatability of work and redistribution preferences extends to preferences for government support of declining industries.

This paper builds on and contributes to different literatures. Measurement of distinct job characteristics and characterizing the task content of employment is an important topic in different fields, particularly the labour economics literature on job polarization and the new trade literature (Autor, Levy and Murnane, 2003; Blinder and Krueger, 2013; Goos, Manning and Salomons, 2014; Jerbashian, 2019). The indicator of automation risk constructed for the present analysis adds to this literature by providing a valid dimension of occupational task content that complements extant indicators of occupational task routineness and complexity.

The possible economic effects of automation have been widely considered, both theoretically and empirically. However, earlier work has focused mostly on direct labour market effects and pays little explicit attention to significant indirect effects involving individuals' attitudes and demand for government policies.[2] Even when the direct labour market effects of labour-saving technology and thus the objective threat of future unemployment and income losses are limited, automation can still have radical effects on society and its policies. The reason is that the subjective perception of automation as an economic threat is already a powerful force influencing people. Automation anxiety affects citizens' economic and social policy preferences, transforming the political landscape and pushing governments into action. Key societal trends such as automation and globalization have important direct economic effects. This paper complements studies of these direct effects to consider indirect but more fundamental changes to society that can result from citizens' anxiety about such trends.

This study resonates most strongly with the literature on preferences for redistribution. The role of net pecuniary gains in shaping individuals' preferences for redistribution has long been recognized. Much attention has also been paid to an individual's income and wealth prospects as determinants of their preference for redistribution through their effect on expected costs and benefits of government redistribution. Furthermore, there is a growing body of research that seeks to flesh out

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[2]Two notable exceptions are Frey *et al.* (2018) and Anelli *et al.*, (2019). The former link changes in regional levels of exposure to robotization, a specific form of automation, to changes in the share of votes in a region going to the Republican presidential candidate in the 2012 and 2016 US elections. The latter consider how regional changes in the operational stock of industrial robots increase voting for nationalist and radical-right parties. Focusing on preferences, the present paper speaks to possible mechanisms linking robotization, or automation more broadly, to changes in voting (and a variety of other political behaviours) via individuals' attitudes.

the role of income expectations and mobility perceptions in shaping individuals' preferences for redistribution. Alesina, Stantcheva and Teso, (2018), for example, find that perceptions of intergenerational mobility shape preferences for redistribution, even when these perceptions do not accurately match reality. More generally, there is prior work still that finds that risk aversion affects individuals' preferences for redistribution (Gärtner *et al.*, 2017). The nature of individuals' occupations, in contrast, does not yet figure prominently in this literature.[3] The evidence presented in this paper, however, suggests that job characteristics are an important factor shaping individuals' expectations about future income and socioeconomic mobility.

II. Occupational automatability

Measuring occupational automation risk

Measurement of the automatability of occupations in this paper follows the seminal work by Autor *et al.*, (2003) and other studies of the task content of employment that have appeared since (e.g. Goos *et al.*, 2014; Jerbashian, 2019). Two main approaches to assessing the automatability of jobs can be discerned. The first approach revolves around well-established job or task characteristics such as routineness or complexity (Acemoglu and Autor, 2011; Quintana-Domeque, 2011; Jerbashian, 2019). Following this approach, a job can be seen as comprising a set of tasks, each of which can be more or less susceptible to automation, not least because each task involves more or less routineness and complexity. The automatability of a given job is therefore a function of the automatability of individual job tasks, weighted by the importance of each task as part of the overall content of the job. The second approach uses aggregated opinions of technology experts judging the overall automatability of different jobs (cf. Frey and Osborne, 2017).

This paper applies a third approach that involves aggregated knowledge of employees actually working in a particular type of occupation. The idea underlying this approach, which, following the seminal work of George Katona (e.g. Katona, 1979), can be called a 'Katonian' approach (Boulding, 1972) is that it harnesses the wisdom of crowds and helps overcome biases likely to occur using any of the other two approaches. Calculating occupational automatability on the basis of task content is an intricate process. It requires not only that task attributes such as routineness are measured accurately but also that each task is assigned proper weight as part of the overall task content of a given occupation. Expert judgments face other limitations. A particular concern is the possibility that there are blind spots that are shared by the group of experts asked for their opinion, which is quite likely when the assessment involves a large number of jobs. Specifically, it seems unreasonable to expect that experts have detailed knowledge on the task content of all possible occupations, particularly rare ones. Two further challenges involve lack of cultural diversity among the experts consulted and the use of a system of job classification that follows a

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[3]Labour market concerns have been linked to attitudes concerning other policy issues, however, including immigration (Haaland and Roth, 2020) and, more generally, to political polarization (Dorn *et al.*, 2020).

national standard rather than an international standard. Specific concern is that the resulting measure of occupational automation risk is not universally applicable or valid. To elaborate, consider an automatability indicator constructed by American experts and referring to jobs as classified by the American classification system. This indicator likely is a more accurate measure of automatability risk for workers in the United States than for workers in Russia or Germany. Hence, applying this particular indicator to individuals and jobs in other countries might cause biases in the empirical analysis.

The implementation of my proposed approach relies on data collected by the International Social Survey Programme in the 1997 module on Work Orientations or ISSP-WO (ISSP Research Group, 1999). This module surveyed respondents from a diverse group of 21 country regions about various aspects of their jobs. One specific item asked respondents about the likely effect of automation on employment: 'New kinds of technology are being introduced more and more in [country]: computers, robots, and so on. Do you think these new technologies will over the next few years...' The Likert-type answer scale provided to respondents comprised five possible answers: '1, Greatly increase the number of jobs?', '2, Slightly increase the number of jobs?', '3, Make no difference to the number of jobs?', '4, Slightly reduce the number of jobs?', or '5, Greatly reduce the number jobs?' For more than 19,000 respondents, the survey further recorded their occupation using four-digit codes from the 1988 version of the international standard classification of occupations (ISCO). For an additional 5,000 respondents, the 1997 ISSP-WO module recorded their occupation using three-digit ISCO88 codes.

My proposed indicator of occupational automation risk involves aggregating individual assessments of automation-driven job loss at the level of two-digit ISCO codes, which is the most common level of analysis in studies of the economic implications of occupational task content. Hence, I combine the available three-digit and four-digit occupational data and recode them into two-digit ISCO codes. To make sure that calculated averages of the individual responses are reliable, the empirical analysis limits the sample to consider two-digit occupations for which the aggregate automatability score is based on data from minimum 20 respondents. However, as a robustness check, I also repeat my baseline empirical analyses using different thresholds for the minimum number of individual responses. Similarly, I also estimate models in which automation risk is measured at the three-digit ISCO level. Since prior work typically measures automatability at the two-digit level, measuring automatability at the three-digit level adds a level of detail not yet found in the literature on occupational task content. However, a disadvantage of measuring automatability at the three-digit ISCO level is that using a three-digit classification leaves fewer individual respondents per occupational code, on average. Hence, the three-digit level indicator is likely noisier than a two-digit level indicator of automatability. Table 1 presents automatability scores for the two-digit occupations in my sample (scale 1–5).

Validity of measured occupational automation risk

The indicator of occupational automation risk constructed above has much intuitive appeal. Its main appeal is that, instead of imposing a personal view on what makes a

TABLE 1

Automatability of selected occupations

Occupation	Two-digit ISCO code	Automatability score (1-5)
Legislators and senior officials	11	3.24
Physical, mathematical and engineering science professionals	21	3.35
Armed forces	1	3.48
Education professional not elsewhere classified	25	3.53
Corporate managers	12	3.53
Other professionals	24	3.58
Agricultural, fishery and related labourers	92	3.59
Legislators, senior officials and managers	10	3.61
Teaching professionals	23	3.61
Life science and health professionals	22	3.64
Physical and engineering science associate professionals	31	3.64
General managers	13	3.66
Teaching associate professionals	33	3.73
Other associate professionals	34	3.74
Life science and health associate professionals	32	3.77
Sales and services elementary occupations	91	3.79
Precision, handicraft, printing and related trades workers	73	3.81
Stationary-plant and related operators	81	3.81
Personal and protective services workers	51	3.82
Market-oriented skilled agricultural and fishery workers	61	3.83
Labourers in mining, construction, manufacturing and transport	93	3.83
Customer services clerks	42	3.83
Metal, machinery and related trades workers	72	3.84
Office clerks	41	3.84
Models, salespersons and demonstrators	52	3.84
Skilled manual worker	75	3.87
Extraction and building trades workers	71	3.88
Machine operators and assemblers	82	3.91
Other craft and related trades workers	74	3.96
Drivers and mobile plant operators	83	3.96
Craft and related trades workers	70	4.18
Clerks	40	4.21
Technicians and associated professionals	30	4.57

Notes: Source is own calculations based on data from the 1997 ISSP Work Orientations module (ISSP Research Group 1999). See also Table 2 and Figure A.1 in Appendix A in the supplementary file.

job more or less automatable, the approach harnesses the wisdom of crowds. In addition to intuitive appeal, however, there is also evidence testifying to the validity of the automatability indicator thus constructed.

First, gauging Table 1, measured automatability differences have strong face validity. Occupations intuitively expected to have low/high automation risk indeed have low/high automation risk (e.g. *Legislators and senior officials* vs. *Machine operators and assemblers*). In addition, even though occupational automation risk is

measured using data collected in 1997, these data appear to capture expectations concerning recently emerged technological trends, particularly self-driving cars. To wit, out of 33 occupations, an occupation that was expected to suffer rather much job loss from automation were *Drivers and mobile plant operators* (ISCO 83), which can be subdivided in such jobs as *Locomotive-engine drivers* (ISCO8311), *Car, taxi and van drivers* (ISCO8322) and *Bus and tram drivers* (ISCO8323).

For a formal test of the (construct) validity of the occupational automatability indicator, I further check how this indicator relates to four other indicators measuring features of an occupation that are conceptually related to occupational automation risk. Following the literature on occupational task content and job polarization, the first two indicators considered concern task complexity and routineness. Although job complexity and job routineness are distinct from automatability – a task may not be automatable even though it is routine and a task may be complex but nonetheless automatable – , measured automation risk should correlate reasonably strongly both with differences in occupational task routineness and with differences in occupational task complexity (cf. Goos *et al.*, 2014; Jerbashian, 2019). The last two indicators, in contrast, do not involve occupational task content. Instead, these indicators involve systematic differences in economic expectations between individuals employed in different occupations. These expectations concern the likelihood of becoming unemployed in the next 12 months and the potential deterioration of these individuals' financial situation over the next 5 years. Table 2 presents the results, while Figure A.1 in Appendix A in the supplementary file plots scores on these four occupational indicators as a function of occupational automation risk.

As expected, automatability correlates strongly positively with job routineness and strongly negatively with job complexity. At the same time, the correlations found are not so strong to suggest that occupational routineness or complexity are essentially the same as occupational automatability.[4] Hence, the automatability indicator appears to add to common routineness and complexity indicators, capturing features of occupational task content not fully captured by either of these two job characteristics. Turning to economic expectations, correlations again suggest that the occupational automatability indicator is valid. The higher automation risk is, the more negative individuals perceive their employment and financial prospects. Meanwhile, the plots of job complexity, job routineness, employment prospects and financial prospects as a function of occupational automation risk in Figure A.1 do not clearly identify any specific occupation as a consistent outlier. Hence, it seems that measurement error is mostly random and not systematic.

Importantly, the strong correlations reported in Table 2 exist even though quite some time may have passed between the collection of the data for measuring automation risk (in 1997) and the collection of the data for the other occupational indicators. This speaks to the power of the Katonian approach. However, in the empirical analyses, I also consider how the relationship between occupational

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[4]To be sure, a complementary explanation for the less than perfect correlations between these conceptually related measures can be that there is measurement error in each of these three measures characterizing occupations and their task content.

TABLE 2

Construct validity of occupational automation risk

Correlations for N = 26 occupations	**Automation risk**	Complexity	Routineness	Expected likelihood of unemployment
Automation risk (1997)	**1**			
Complexity (2000, 2005, 2010 & 2015)	**-0.584** [95%CI: −0.803,- 0.243]	1		
Routineness (2004 & 2010)	**0.525** [95%CI: 0.238,0.769]	-0.761	1	
Expected likelihood of unemployment (1972–2018)	**0.617** [95%CI: 0.379,0.815]	-0.550	0.699	1
Expected deterioration of financial situation (2015)	**0.599** [95%CI: 0.389,0.777]	-0.289	0.513	0.528

Notes: Year(s) of measurement in parentheses. Confidence intervals are obtained using bootstrapping with 10,000 repetitions. Correlations concern occupational averages that are calculated using binary and ordinal variables obtained from individual responses. Indicators of occupational task routineness, task complexity, average unemployment expectations and financial situation expectations are constructed to concern occupations at the two-digit level of the 1988 version of the ISCO.

Data on job routineness and 1988 ISCO codes are available from Waves 2 and 5 (2004 and 2010) of the European Social Survey or ESS (European Social Survey 2018). I measure routineness using the ESS item asking respondents to indicate how much the statement 'there is a lot variety in my work' applies to their job. Respondents can answer using the following answer scale: '1, Not at all true', '2, A little true', '3, Quite true' or '4, Very true'. The occupational routineness indicator is constructed by reverse coding individual answers on this item and aggregating them at the two-digit ISCO level.

Data on job routineness and 1988 ISCO codes are available from Waves 3–6 (2000, 2005, 2010 and 2015) of the European Working Conditions Survey or EWCS (European Foundation for the Improvement of Living and Working Conditions 2018). I measure job complexity using the EWCS item asking respondents whether their job generally involves complex tasks (1) or not (0). The occupational complexity indicator is constructed by aggregating individual answers on this item at the two-digit ISCO level.

Data on unemployment expectations and 1988 ISCO codes are available from the 1972 to 2018 Waves of the General Social Survey or GSS (Smith et al. 2019). I measure unemployment expectations using the GSS item asking respondents how likely they think it is that they will lose their job or be laid off in the next 12 months. Respondents can answer using the following answer scale: '1, Very likely', '2, Fairly likely', '3, Not too likely' or '4, Not at all likely'. The occupational indicator of expected likelihood of unemployment is constructed by reverse coding individual answers on this item and aggregating them at the two-digit ISCO level.

Data on financial situation expectations are available from the 2015 Work Orientations module from the International Social Survey Programme (ISSP Research Group 2017). I measure expected deterioration of financial situation using the item asking respondents what they think their financial situation will be in 5 years. Respondents can answer using the following answer scale: '1, Much better than today', '2, Somewhat better than today', '3, The same as today', '4, Somewhat worse than today' or '5, Much worse than today'. Because the 2015 Work Orientations module measures occupation using 2008 ISCO codes I use the crosswalk provided by Ganzeboom and Treiman (2015) to convert these ISCO codes in 1988 ISCO codes. The occupational indicator of expected deterioration of financial situation is constructed by aggregating individual answers on this item at the two-digit ISCO level.

For all occupational indicators, I drop occupations with fewer than 20 underlying individual responses. This leaves 26 two-digit occupations. See also Table 1 and Figure A.1 in Appendix A.

To be complete, I also considered correlations between the measure of occupational automation risk and average preferences for redistribution or industry support in a two-digit occupation, measured using individual-level data from the ESS, ISSP-SI and ISSP-ROG respectively. These correlations are rather strong with $\rho = 0.759$ for the ESS data, $\rho = 0.734$ for the ISSP-SI data and $\rho = 0.782$ for the ISSP-ROG data (n = 26). See also Figure A.2 in Appendix A.

automation risk and preferences for redistribution may be different in samples with data collected much later than 1997. More generally, there are of course sources of measurement error in individuals' assessments of automation risk. It is well known, for instance, that individuals tend to think that automation risk is mostly going to affect the jobs of other people, not their own jobs (e.g. Smith, 2016). Overall, however, the evidence indicates that the aggregated measure of occupational automation risk can capture systematic occupational variation in the threat of automation-driven job loss.

III. Empirical model and strategy for addressing omitted variable bias

The basic empirical model used to assess the association between the automatability of individuals' jobs and their preferences for redistribution reads:

$$P_{ioct} = \beta_0 + \beta_1 A_o + \beta_2 \mathbf{X}_i + \beta_3 \mathbf{Z}_o + d_c + \delta_t + \varepsilon_{ioct} \tag{1}$$

In this model, P_{ioct} is the preference for redistribution of individual i working in occupation o, living in country c at time t, A_o is the automatability of occupation o, $\mathbf{X}_i$ is a vector of individual characteristics, and $\mathbf{Z}_o$ is a vector of occupational characteristics other than automatability, and ϵ_{ioct} is a random error term. The basic model further includes country (d_c) and year/wave (δ_t) dummies. Per my hypothesis, I expect that β_1 is positive. In addition, if the error term ϵ_{ioct} is mean independent from A_o, conditional on $\mathbf{X}_i$, $\mathbf{Z}_o$, d_c and δ_t, we can interpret the coefficient for β_1 as the causal effect of automation risk on preferences for redistribution. Because the analysis involves data that are structured hierarchically with individuals nested in occupations, I use robust standard errors that are clustered at the level of occupations.[5]

As indicated, the key challenge for valid identification of a potential causal effect of automation risk on preferences for distribution is properly addressing the endogeneity problem in the analysis. This, in turn, requires that we can properly measure and control for omitted variables. Two factors stand out as possible sources of omitted variable bias. The first is a personal trait or generic preference factor that might affect both individuals' preference for redistribution and their preference for jobs with a particular task content. This generic preference factor, in turn, might correlate with the degree to which these jobs are automatable (a selection effect). The second factor is an individual's skill level, which likely affects both their net pecuniary gain from redistribution and their ability to find employment in jobs with particular task content. Specifically, it seems likely that individuals with comparatively low skill levels have more difficulty finding employment in occupations with low automation risk and vice versa, which would again imply a selection effect.

To account for these sources of omitted variable bias, the empirical analyses include several control variables, not least of which are some unique measures of individuals' preferences. The control variables that I include are not perfect measures but proxies for the two main sources of omitted variables bias discussed in the previous paragraph. Hence, my control variables typically contain some measurement

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[5]As an alternative, I use the wild bootstrap approach of Roodman et al. (2019) to correct the standard errors for clustering at the occupation level. Results are comparable to the main results (Table A.6 in Appendix A).

error. However, because I use an extensive set of control variables and use multiple proxies simultaneously it seems implausible that this measurement error poses a serious challenge to the analysis. Concerning skill level, basic control variables are years of education but also educational degree and measures of individuals' employment status, which is of course partly a realized outcome of occupational automation risk. In addition, I check results with key features of individuals' occupation, specifically occupational task routineness and occupational task complexity, controlled for. Finally, for two of the available samples, I can add different measures of income and perceived relative social status of one's family, which are again partly a realized outcome of occupational automation risk. In general, there is a downside to including realized outcomes as controls because such variables can be and endogenous and thus potentially 'bad controls' (Angrist and Pischke, 2008:64–68; Rohrer, 2018). In addition, such variables are possible mediators of the relationship between occupational automation risk and preferences for redistribution. Nevertheless, I consider endogenous outcome variables as controls because they serve as powerful proxies for individuals' skill level. However, for the sake of completeness, I also present results for models that do not consider the variables that are most likely also outcome variables as control variables (Table A.7 in Appendix A).[6] Details on the specific variables and measures used, which vary between datasets, are presented below and in Tables A.1-A.3.

The closing piece of the strategy for reducing omitted variable bias is to consider the relationship between redistribution preferences and automation risk through individuals' exposure to automation risk indirectly via the occupation of their spouse or partner. The rationale is as follows. First, spousal automation risk is likely to affect the wealth prospects of the individual's household and hence their expected net pecuniary gains from government redistribution. Compared to the direct effect of the automatability of one's own occupation, the effect of spousal automation risk is likely much weaker. However, the effect may still be significant. Second, when focusing on spousal automation risk, the measure of individuals' own occupational automation risk provides a rather interesting means for controlling for differences in skill levels or preferences not yet captured by the various other control variables. Theoretically, it is of course possible that individuals with certain unobserved skills select into partnering with people employed in certain occupations (Mansour and McKinnish, 2018). Such assortative matching, in turn, would mean that the association between spousal automation risk and an individual's preferences for redistribution suffers an omitted variable bias. However, including individuals' own occupation risk as a control variable makes it unlikely that any found relationship between spousal automation risk and preferences for redistribution is, in fact, spurious. Meanwhile, the analysis can also be seen as considering spousal automation

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[6]Another, related issue is collider bias. However, in my analysis there do not seem to be many (prospective) control variables that are likely affected both by occupational automatability and by preferences for redistribution. The control variables that come closest to being a collider would be the measures of people's political preferences and personal values that I consider in some models. Hence, to be complete, Table A.7 also presents results for models that do not include these specific variables as control variables.

risk as an additional control variable, while still focusing on the effect of the automatability of individuals' own occupation. In this case, the rationale is that unobserved differences in preferences or skill levels may affect individuals' likelihood of partnering with somebody with a particular type of occupation (and corresponding preferences and skill level). This sort of assortative matching would imply that including spousal automation risk helps ensure that the association between own automation risk and redistribution preferences is not spurious. In the most extreme case, spousal automation risk does not have any genuine effect on redistribution preferences and any relationship between spousal automation risk is entirely driven by spousal automation risk capturing unobserved differences between individuals that also affect redistribution preferences. If so, however, the value of considering spousal automation risk actually increases, as it becomes a powerful control variable, able to capture important but otherwise unobserved differences between individuals that also affect these individuals' preferences for redistribution.

In the appendix I present a set of five directed acyclic graphs or DAGs (e.g. Rohrer, 2018) to clarify the various causal assumptions in my analysis and the different empirical models that I use (Figures A.3-A.7). Figures A.3, A.6 and A.7 thereby provide visual representations of the main empirical models that illuminate the underlying causalities but also illustrate how the empirical specification of these models helps address omitted variable bias. The other two figures on the other hand are versions of the baseline model (Figure A.3; equation 1) that I use to consider problems due to endogenous control variables (Figure A.4) and to potential colliders (Figure A.5).

IV. Data and measures

Data sources

The main data for this paper are individual-level survey data from the European Social Survey or ESS, Waves 1-8 (European Social Survey, 2018). These data have been collected bi-annually during the period 2002–16 and cover 32 mostly European and some Eurasian countries. In addition to data on self-reported preferences for redistribution and various other important variables, the ESS has recorded respondents' occupation using ISCO codes. The measure of occupational automation risk applies the same occupational classification so that the individual-level ESS data can be matched to the automatability indicator constructed and validated in the previous section. The survey item on preferences for redistribution is the standard item that is commonly used to study redistribution preferences. Dropping about 175,000 respondents with missing data, particularly on occupation, leaves about 173,000 individuals, depending on the model specification used.

Whereas the analyses using ESS data are the main analyses, part of the robustness checks involves considering samples of individuals from two alternative data sources. The first of these alternative sources are the 1992 and 1999 ISSP modules on Social Inequality or ISSP-SI (ISSP Research Group, 2014), which include data on respondents from 22 country regions and are commonly used to study preferences for

redistribution (Corneo and Grüner, 2000).[7] A chief motivation for using data from the ISSP-SI is that the ISSP-SI includes interesting individual-level control variables not available in the ESS, particularly on household income and perceived relative social status of one's family. In addition, the ISSP-SI covers a different group of countries than the ESS does, which increases the international generalizability of the results. Dropping about 22,000 respondents with missing data, leaves about 16,000 individuals, depending on the model specification used. Table A.2 presents a description of the variables in the ISSP-SI used for the empirical analysis and some summary statistics. The second alternative data source is the third and fourth Role of Government module of the ISSP or ISSP-ROG (ISSP Research Group, 2008). These data have been collected in 1996 and 2006 and cover 20 country regions.[8] The main motivation for using ISSP-ROG data is that these data provide an alternative dependent variable concerning individuals' preference for government support of declining industries. The advantage of this variable is that it is much more specific about the preferred policy action. In addition, considering this particular preference as the dependent variable enables including measures of more generic preferences for redistribution as control variables, providing powerful means to address omitted variable bias. Starting with some 45,000 observations and dropping about 16,000 respondents with missing data, particularly on occupation, leaves more than 29,000 individuals (depending on the model specification used). Table A.3 in Appendix A presents a description of the variables in the 1996 and 2006 ISSP-ROG modules used for the empirical analysis and some summary statistics.

Variables and measures

Dependent variable
The paper's main dependent variable is an individual's preference for redistribution. As mentioned, the ESS item measuring these preferences is standard and widely used. It asks respondents about the extent to which they agree or disagree with the statement that 'the government should take measures to reduce differences in income levels'. Possible answers are given by the following Likert-type scale: '1, Agree strongly', '2, Agree', '3, Neither agree nor disagree', '4, Disagree' or '5, Disagree strongly'. To facilitate interpretation, I reverse code scores on this item so that higher scores indicate a stronger preference for redistribution. Similarly, the main analyses reported in this paper treat this item as a continuous measure of preferences for redistribution.

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[7]Data from the other ISSP-SI modules cannot be used because these modules have not collected data on key control variables. The countries covered by the 1992 and 1999 Social Inequality modules are Australia, Austria, Canada, Chile, Cyprus, Czech Republic, France, Germany (East and West separately), Hungary, Latvia, New Zealand, Norway, Philippines, Poland, Portugal, Russia, Slovak Republic, Slovenia, Spain, Sweden and United States.
[8]Data from the other ISSP-ROG modules cannot be used because these modules have not collected data on occupation. The countries covered by the third and fourth Role of Government module are Australia, Canada, Czech Republic, France, Germany, Hungary, Ireland, Israel, Japan, Latvia, New Zealand, Norway, Poland, Russia, Slovenia, Spain, Sweden, Switzerland, Great Britain and United States.

However, I obtain similar results when I estimate the empirical models using ordered probit or ordered logit techniques (detailed results available on request).

The ISSP-SI item measuring preferences for redistribution is almost identical to the item from the ESS. It asks respondents whether the government should reduce income differences and the first part of this item reads: 'It is the responsibility of the government to reduce the differences in income between people with high incomes and those with low incomes'. The answer scale is again a 5-point Likert-type scale: '1, Strongly agree', '2, Agree', '3, Neither agree nor disagree', '4, Disagree' or '5, Strongly disagree'. As before, I reverse code scores on this item.

Finally, as indicated, data available from the ISSP-ROG offer the opportunity to assess the effect of occupational automation risk on a concrete economic policy with redistributive consequences in the form of government support of declining industries. The relevant item starts with a generic text asking about economic policies: 'Here are some things the government might do for the economy. Please show which actions you are in favour of and which you are against'. The specific policy is thereby described as 'support for declining industries to protect jobs' and answers are recorded on a 5-point Likert-type scale that is reverse coded for the empirical analysis: '1, Strongly in favour of', '2, In favour of', '3, Neither in favour of nor against', '4, Against' or '5, Strongly against'.

Independent variables

For most of the empirical analyses in this paper, the key independent variable is the indicator of occupational automation risk constructed and validated in Section II. As indicated, I match this indicator to the individual-level data from the ESS, ISSP-SI and ISSP-ROG datasets using two-digit codes from the 1988 version of the ISCO. However, Waves 6–8 of the ESS (2012–16) have not recorded occupation using ISCO88 codes but using ISCO08 codes. Hence, for these later waves I first convert ISCO08 codes into ISCO88 codes using the crosswalk provided by Ganzeboom and Treiman (2015). All the analyses include year/wave fixed effects that capture measurement error that is specific to particular waves. In addition, in an extension to the baseline analysis, I consider how the relationship between occupational automation risk and redistribution preferences may be different for data collected in later years and/or using ISCO08 instead of ISCO88 codes.

As discussed, as part of the strategy for addressing omitted variable bias, instead of considering the effect of individuals' own automation risk, I consider the effect of individuals' exposure to automation risk through the occupation of their spouse or partner (see, also, Figures A.2 and A.3). All three data sources – ESS, ISSP-SI and ISSP-ROG – have collected data on the occupation of individuals' spouses using ISCO codes. As before, matching of the occupational automatability indicator is done on the basis of two-digit ISCO codes.

Basic control variables

The main empirical models that I estimate include various control variables. Some basic demographics are sex (1=female), age and age squared. Because the available data are cross-national and collected at different points in time, the basic set of

controls not only includes year (or wave) dummies but also country dummies. Preferences for redistribution and occupational automation risk likely correlate with education. Hence, I also control for measures of educational differences. To be exhaustive and take into account possible measurement error in the control variables, I thereby use two different measures, one concerning years of education and one concerning level of education. Similarly, although employment status is partly a realized outcome of occupational automation risk, all models include controls for employment status as a proxy for individual skill differences. Because prior studies find a role for religion in shaping preferences for leisure and redistribution, I further include sets of dummies both for individuals' religious denomination and for their attendance of religious services. Tables A.1-A.3 in Appendix A provide details on the measures used.

As much as possible, the factors that I control for to address omitted variable bias are measured at the individual level. The skill intensity of one's occupation may, for instance, affect redistribution preferences. However, this effect is taken into account by including measures both of individuals' years of education and of their formal education level. Notwithstanding, to make sure that any found effect of automation risk on redistribution preferences is genuinely due to automatability I also consider two other features of individuals' occupation, namely its routineness and its complexity. The specific measures that I use are the same indicators of job routineness and job complexity considered earlier. There are two important downsides to including these two control variables. The first is that these two indicators are available for fewer occupations than the measure of occupational automatability is. The second is that task routineness and complexity are conceptually related to occupational automatability and may therefore capture effects on redistribution preferences that are, in fact, partly due to automation risk.

Sample-specific control variables
Whereas the basic control variables are independent from the sample considered, ESS, ISSP-SI or ISSP-ROG, further control variables used are typically only available for a specific sample.

ESS: Relevant control variables that are specific to the ESS sample are income rank and (indirect) experience with socioeconomic mobility as well as two other measures that speak to the net pecuniary gains that an individual can expect from redistribution and their skill level. In addition, the analyses of the ESS sample consider some unique measures of individuals' preferences and motivations. To create an indicator of income rank, meaning the percentile score of an individual's income relative to other individuals in the same country, I use the ESS item asking respondents about their income (measured on a 10- or 12-point scale). Similarly, I consider individuals' indirect experience with socioeconomic mobility by including two sets of dummies capturing features of the socioeconomic status of their parents. The first set concerns the level of education of an individual's father and mother respectively. The second set concerns the employment status of the individual's father and their mother when the individual was 14 years old. A further ESS-specific control variable that I consider is individuals' health status, where I expect that individuals with poorer health benefit

more from redistribution and therefore have stronger redistribution preferences. Similarly, I consider an individual's prior unemployment experience (1=yes; 0=no). This variable speaks to the individual's skill level but also to the likelihood of future unemployment and hence their income and wealth prospects.

Concerning individuals' preferences I include a variety of measures. The first measure is the classic left/right political self-placement scale in which respondents identify their political preferences on a spectrum that ranges from left to right. Left/ right political orientation has been identified as part of a cluster of preferences involving the role of government in the economy, including preferences for redistribution (Scheepers and Te Grotenhuis, 2005; see, also, Roth and Wohlfart, 2018). Hence, including this measure provides powerful means to rule out that there is a generic preference factor that causes individuals with a strong preference for redistribution to select into occupations that are highly automatable and vice versa. However, as for some of the control variables discussed above, I should warn that left/ right political preferences may also be an outcome of automation risk and could mediate the relationship between automation risk and redistribution preferences.

The second measure is a composite index of individuals' trust in politics, specifically trust in their country's parliament and politicians. The idea is that automation risk affects individuals' political attitudes, which may then go on to affect their preferences for redistribution. By controlling for trust in politics, however, the analysis can focus on a potential direct effect of automation risk on preferences for redistribution.

Finally, I include a set of indicators measuring individuals' basic values, as identified by Schwartz's framework of universal human values, the leading framework of personal values in psychology (Schwartz, 1992). The 10 basic values in this framework are universal in that they are recognized across cultures and distinct in that they refer to different motivations. The values further form a circumplex that reflects the compatibility of each motivation with the other motivations. Specifically, values that are close in the circumplex have compatible motivations, referring to goals that can be achieved simultaneously without one necessarily coming at the expense of the other (see Figure B.1 in Appendix B). Values that are opposite each other in the circumplex, in contrast, are not compatible and cannot be achieved simultaneously. Finally, the framework conceptualizes values as having a relative priority only and not an absolute priority. Hence, it is not possible for individuals to attach great value to everything. Appendix B provides detailed information on the empirical operationalization of the framework of universal human values using questionnaire items included in the ESS.

ISSP-SI: Relevant control variables that are specific to the ISSP-SI sample concern individuals' personal and household income rank, perceived relative social status of one's family and their experience of socioeconomic mobility, most of which are partly a realized outcome of automation risk as well as important determinants of preferences of redistribution (see, e.g. Alesina *et al.*, 2018). To create an indicator of personal income rank, I use the ISSP item asking respondents about their own earnings. Answers to this item are coded on an ordinal scale, which I recode to calculate a percentile score, meaning the percentage of individuals from the same country that

indicated having lower earnings. Similarly, to create an indicator of household income rank, I use the ISSP item asking respondents about the income of their family, also recoding answers on the ordinal answer scale into a percentile score. Perceived relative social status of one's family is measured by an item asking respondents to think of society as a ladder and to identify the position of themselves and their family, whether they tend towards the top or towards the bottom. Concerning socioeconomic mobility, I consider individuals' direct experience with mobility. This is measured by a set of dummies that measures how the prestige of an individual's job compares to the prestige of the job of their father. In addition, I consider a measure of individuals' self-reported beliefs about what is needed for getting ahead in society, specifically the importance of family income.

ISSP-ROG: Relevant control variables that are specific to the ISSP-ROG sample again concern different measures of individuals' preferences. The ISSP-ROG modules contain data on individuals' preferences towards a variety of social and economic policies. Taking individuals' preference for government support of declining industries as the dependent variable thus creates the opportunity to use measures of other policy preferences as control variables (even though, as discussed above, there is a downside to controlling for variables that are themselves partial outcomes of the main independent variable). I consider four such preferences. First and foremost, when analysing individuals' preference for government support of declining industries, I control for individuals' generic preference for redistribution. The second policy preference concerns individuals' preference for government financing of projects for new jobs. The third policy preference concerns individuals' preference for government spending on unemployment benefits. Finally, the analysis of the ISSP-ROG sample considers the preference for government responsibility in providing a decent living standard for the unemployed. Together, these four measures likely capture important individual differences both in preferences and in skills that could otherwise bias the analyses using individuals' preference for government support of declining industries as the dependent variable. Due to missing data, analyses of the ISSP-ROG sample are unable to control for some of the factors considered in the analyses of the ISSP-SI and ESS samples, for instance experienced socioeconomic mobility.

V. Results

Evidence from the ESS sample

Table 3 presents the baseline results. Consistent with my hypothesis, results indicate a strong positive association between the strength of individuals' preferences for redistribution and their occupational automatability or automation risk (Model 1). As expected, this association becomes less strong when controlling for measures that speak to the net pecuniary gains that individuals can expect from government redistribution (Model 2). For example, compared to individuals with no prior unemployment experience, the preference for redistribution of individuals with prior unemployment experience is more than 0.09 standard deviations higher. Adding variables concerning parental socio-economic status and an extensive set of measures

of individuals' preferences, lowers the estimated coefficient for occupational automation risk a bit further, which is also as expected. However, the relationship remains highly statistically significant (Models 3 and 4). Results are also largely the same when considering job routineness and job complexity as additional control variables (Model 5).

For further exploration of the role of omitted variable bias, I use Oster's (2019) approach to assessing the degree to which unobserved variables may be driving the observed relationship between automation risk and redistribution preferences. Specifically, I estimate how strong the selection on unobservables in my analysis needs to be in order for the effect of automatability to be equal to 0. The end result of this exercise is a value for the proportionality of selection known as δ. Values for δ can be obtained under the assumption of a theoretical maximum, R_{max}, for variance explained (R^2). Choosing an appropriate value for R_{max} involves some judgment. In case of data that contain no noise whatsoever, this theoretical maximum is close to 1. However, the assumption of no noise is unrealistic when it comes to individual-level survey data. Indeed, prior studies of the ESS data on preferences for redistribution tend to report much lower values for R^2 (or R^2 adjusted) than my analysis. Luttmer and Singhal (2011, p. 166), for instance, report an adjusted R^2 of 0.1324 for their analysis of preferences for redistribution of native-borns. Roth and Wohlfart (2018, p. 258) similarly report an R^2 of 0.143. Model 5, in contrast, adds a further 4% points variance explained to this prior research (R^2 = 0.1868).[9] Hence, it seems that an appropriate value for R_{max} is >0.1868 but well below 1. Recognizing the subjectivity of this choice, I set R_{max} at 1.3 times the R^2 of Model 5 (R_{max} = 0.243). The bottom row of Table 3 presents values for the proportionality of selection δ thus obtained. For the main model, Model 5, δ equals about 0.563.[10] This value suggests that unobservables need to account for more than half of the variation captured by the variables currently included in this model in order for selection on unobservables to be able to explain away the main result. This results boils down to unobservables needing to explain some 10.5% (≈ 0.563 * 18.68%) of total variation in preferences for redistribution. This seems unlikely for two main reasons. The first is that, compared to prior work (e.g. Luttmer and Singhal, 2011; Roth and Wohlfart, 2018), the R^2 for Model 5 is already rather high. Hence, it seems that there is not much room in my analysis for an unobservable confounder to explain substantial amounts of variation, particularly variation that is not already captured by other independents. The second, related reason involves the relative explanatory power of some of the most-studied predictors of preferences for redistribution. Income rank, for instance, is widely considered a chief predictor of preferences for redistribution. However, even this well-known variable accounts for only about 0.5% of variation in preferences for redistribution. Hence, the

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[9]An important explanation for this higher R^2 is that Model 5 controls for personal values and for left/right political preferences, which are powerful predictors of redistribution preferences. In fact, it is not uncommon for researchers to study left/right political preferences as an alternative measure of political attitudes towards the welfare state (see, e.g. Roth and Wohlfart 2018 and Scheepers and Te Grotenhuis 2005). In my analysis, R^2 decreases from 0.1868 to 0.1421 when I exclude personal values and left/right political preferences as controls.

[10]Because of the subjectivity of the value of R_{max} I have also estimated the value of δ for Model 5 with R_{max} set to 0.2 and 0.3 respectively. Corresponding values for δ are 2.26 and 0.282 instead of 0.563.

TABLE 3

Occupational automation risk and preferences for redistribution

Dependent = preference for redistribution	1	2	3	4	5
Automation risk	0.119 (0.017) [P < 0.001]	0.061 (0.011) [P < 0.001]	0.058 (0.011) [P < 0.001]	0.051 (0.008) [P < 0.001]	0.046 (0.009) [P < 0.001]
Years of education	-	-0.010 (0.007) [P = 0.159]	-0.003 (0.007) [P = 0.696]	-0.013 (0.005) [P = 0.006]	-0.011 (0.004) [P = 0.014]
Income rank	-	-0.107 (0.013) [P < 0.001]	-0.104 (0.012) [P < 0.001]	-0.084 (0.010) [P < 0.001]	-0.083 (0.010) [P < 0.001]
Poor health	-	0.030 (0.003) [P < 0.001]	0.029 (0.003) [P < 0.001]	0.014 (0.003) [P < 0.001]	0.014 (0.003) [P < 0.001]
Unemployment experience (1=yes)	-	0.097 (0.007) [P < 0.001]	0.095 (0.007) [P < 0.001]	0.072 (0.007) [P < 0.001]	0.071 (0.006) [P < 0.001]
Left/right political preferences	-	-	-	-0.175 (0.017) [P < 0.001]	-0.175 (0.017) [P < 0.001]
Political trust	-	-	-	-0.042 (0.006) [P < 0.001]	-0.042 (0.006) [P < 0.001]
Job routineness	-	-	-	-	-0.003 (0.015) [P = 0.869]
Job complexity	-	-	-	-	-0.017 (0.017) [p = 0.308]
Sex (1=Female)	0.140 (0.017) [P < 0.001]	0.128 (0.013) [P < 0.001]	0.128 (0.013) [P < 0.001]	0.071 (0.008) [P < 0.001]	0.067 (0.011) [P < 0.001]

(Continued)

TABLE 3
(Continued)

Dependent = preference for redistribution	*1*	*2*	*3*	*4*	*5*
Personal values	No	No	No	Yes	Yes
Dummies education level father	No	No	Yes	Yes	Yes
Dummies education level mother	No	No	Yes	Yes	Yes
Dummies employment status father individual age 14	No	No	Yes	Yes	Yes
Dummies employment status mother individual age 14	No	No	Yes	Yes	Yes
Dummies education level	No	Yes	Yes	Yes	Yes
Dummies employment status	No	Yes	Yes	Yes	Yes
Other control variables	Yes	Yes	Yes	Yes	Yes
No. of occupations	31	31	31	31	27
No. of individuals	173,527	173,527	173,527	173,527	172,749
R^2	0.1170	0.1364	0.1394	0.1862	0.1868
Adjusted R^2	0.1167	0.1360	0.1390	0.1857	0.1863
Oster δ	3.68	0.554	0.547	1.09	0.563
(with $R_{max} = 1.3*0.1868 = 0.243$)					

Notes: Results obtained using the ESS sample. Standard errors (in parentheses) are robust standard errors that are clustered at the level of occupations. P-values are in square brackets. The dependent variable and continuous independent variables are standardized to have a mean of 0 and a standard deviation of 1. The term personal values refers to individuals' scores on the 10 basic values from Schwartz's framework of universal human values. Other control variables are dummies for religious denomination, dummies for religious attendance, age, age squared, dummies for country and dummies for year. To save space, the table presents a selection of coefficients, standard errors and p-values but complete results are available on request. See Oster (2019) and the main text for details on the procedure for obtaining values for the proportionality of selection δ.

value of δ found for Model 5 can be taken to mean that unobservables need to explain about 20 times more variation than income rank does before selection on these unobservables would be able to overturn the relationship found. In fact, even left/right political preferences, although closely related to preferences for redistribution (Scheepers and Te Grotenhuis, 2005; Roth and Wohlfart, 2018), account for as little as 2.71% of variation in preferences for redistribution, which is much <10.5%. Moreover, in all cases, unobservables need to capture differences between individuals that are not or not completely captured by the control variables already in the model, including years of education and educational degree but also occupational routineness and occupational complexity. A priori a value of 0.563 for δ does not seem very high and gives reason for caution. Nevertheless, given the above, there does not seem to be much valid reason to think that the kind of unobservables that could overturn the main result of Model 5 are likely to exist in practice.

Turning to effect sizes, Table 3 reports standardized coefficients, which enables interpreting estimated coefficients for different variables in the same way. In comparison, say, income rank seems more important but health status less important for understanding differences in preferences for redistribution than occupational automation risk. Gender on the other hand seems about equally important as a source of variation in preferences for redistribution as automation risk is. For income rank, the standardized coefficient is about 1.8 times higher, whereas the standardized coefficient for health is more than three times lower than the standardized coefficient for automation risk (−0.083 vs. 0.046 and 0.014 vs. 0.046; Model 5). Note, although that, part of the effect of occupational automation risk on redistribution preferences involves occupational automation risk negatively impacting individuals' income (as well as, for instance, their employment status and prior unemployment experience). Moreover, automatability is measured at the occupation level and not at the individual level where there is more variation.

Not considering standardized coefficients, the estimated relationship implies that a one-point increase in occupational automatability (measured on a 1–5 scale) is associated with a 0.341 points increase in preferences for redistribution (also measured on a 1–5 scale). The comparable effect of a one-point increase in, say, health (measured on a 1–5 scale) is 0.017 points.

Limiting attention to individuals with a partner, results indicate that the relationship between exposure to automation risk and redistribution preferences also occurs when considering the occupational automation risk of individuals' spouses instead of – or, more correctly, in addition to – individuals' own automation risk (Table 4). Shifting attention back to the relationship between individuals' own occupational automation risk and redistribution preferences, results show that individuals' exposure to automation risk remains significantly related with redistribution preferences also when adding spousal automation risk as an additional control variable (Model 8 in Table 4). Meanwhile, the estimated relationship between own automation risk and preferences for redistribution for the sample of individuals with a spouse (Model 9 in Table 4) is comparable to the relationship found for the sample that includes individuals without a partner (Model 4 in Table 3). Controlling for income, job routineness, left/right political preferences et cetera as in Table 3 likely goes a long way in ruling out that

TABLE 4

Exposure to automation risk via spousal automation risk and preferences for redistribution

Dependent = preference for redistribution	6	7	8	9
Spousal automation risk	0.035 (0.008) [P < 0.001]	0.023 (0.008) [P = 0.006]	0.020 (0.008) [P = 0.016]	-
Spousal job routineness	-	0.010 (0.014) [P = 0.507]	0.009 (0.015) [P = 0.562]	-
Spousal job complexity	-	-0.012 (0.013) [P = 0.390]	-0.010 (0.014) [P = 0.495]	-
Automation risk	-	-	0.056 (0.006) [P < 0.001]	0.059 (0.010) [P < 0.001]
Other control variables	Yes	Yes	Yes	Yes
No. of spousal occupations	31	27	27	-
No. of occupations	-	-	-	31
No. of individuals	73,160	72,611	70,191	70,191
Level of clustering of standard errors	Spousal occupation	Spousal occupation	Spousal occupation	Own occupation
R^2	0.2005	0.2011	0.2027	0.2018

Notes: Results obtained using the ESS sample. Standard errors (in parentheses) are robust standard errors that are clustered at the level indicated in the table. P-values are in square brackets. The dependent variable and continuous independent variables are standardized to have a mean of 0 and a standard deviation of 1. Other control variables are years of education, sex, income rank, poor health, unemployment experience, political trust, left/right political preferences, personal values, dummies for employment status, dummies education level father, dummies education level mother, dummies employment status father individual age 14, dummies employment status mother individual age 14, dummies for religious denomination, dummies for religious attendance, dummies for education level, age, age squared, dummies for country and dummies for year (see Model 5 in Table 3). To save space, the table presents a selection of coefficients, standard errors and p-values but complete results are available on request.

the apparent association between occupational automation risk and redistribution preferences is spurious, driven by unobserved differences in individuals' skills or preferences. However, given that this relationship also exists in case of indirect exposure (or when using spousal automation risk as an added control), it seems even more implausible that unobserved individual differences are driving the apparent association between automation risk and redistribution preferences.

The above results are robust to the use of occupational indicators constructed using minimum 100 or minimum 200 instead of minimum 20 underlying individual observations (Models A22–A25 in Table A.8) or considering automatability measured at the three-digit ISCO level instead of at the two-digit level (Models A26 and A27). Most noticeable differences concern the size of the estimated coefficients for occupational automation risk. When using occupational indicators constructed using minimum 100 or minimum 200 underlying individual observations estimated coefficients are a little bit larger than before (compare Model 8 in Table 4 and Model 5 in Table 3). In the models with occupational automatability measured at the three-digit level, in contrast, the estimated coefficient for automation risk is lower compared to results with occupational automatability measured at the two-digit level (again see Model 8 in Table 4 and Model 5 in Table 3). A possible explanation for the former

finding is that requiring minimum 100 or 200 individual observations per occupation when constructing occupational indicators filters out occupations that are relatively rare. As a result, Models A22–A25 probably concern fewer occupations that are relatively rare and for which occupational automatability is measured with more measurement error because of fewer underlying individual observations. This reduction in measurement error, in turn, could shift the size of the estimated coefficient for occupational automation risk upwards. On the other hand, the more fine-grained, three-digit occupational classification used for Models A26 and A27 implies that the occupational automatability indicator used in these models is calculated using fewer underlying individual observations per occupation on average. Hence, for these models, automatability is likely measured with more measurement error, resulting in a corresponding downward shift in the estimated coefficient for occupational automation risk.

Heterogeneity in the relationship between occupational automation risk and preferences for redistribution

So far, I have considered the direct association between individuals' preferences for redistribution and their exposure to automation risk via their occupations. However, estimates of this direct relationship hide potentially interesting heterogeneity between different groups of individuals and countries. Hence, as a complement to the baseline results presented in Table 3, Table A.9 in Appendix A presents results exploring possible moderators of the relationship between occupational automation risk and preferences for redistribution.

The first moderator that I consider is sex, particularly the effect of being female or not. Women may be differently affected by automation risk than men are because, on average, men's labour income constitutes a larger share of their household's total income and because men are more likely to be the sole breadwinner. Hence, the negative consequences of automation-driven job loss for household finances are probably larger when men in a household lose their job than when women in a household lose their jobs, on average. In addition, within automatable jobs, women may, on average, perform activities that are more difficult to automate, particularly tasks involving non-routine cognitive and interpersonal skills (e.g. Autor, 2015). Hence, women may face fewer economic risks from automation, even when working in the same occupation as men do. Both mechanisms suggest that occupational automatability has a less strong negative relationship with preferences for redistribution among women than among men. This expectation is supported by the results (Model A28 in Table A.9).

The second moderator that I consider is education level, specifically whether an individual has low education as measured by having less than lower secondary education and less than eight years of education. Following the argument on systematic heterogeneity in task content within occupations, it could be that, within occupations, these individuals are more likely to be involved in routine tasks and therefore more exposed to automation risk. If so, the relationship between occupational automatability and preferences for redistribution may be stronger for this group. On the other hand,

there are also reasons to expect that this group is less affected by occupational automation risk. A first reason is that this group is already in a rather precarious position on the labour market and that automation risk therefore appends only relatively little additional economic risk. A second, related reason is that this group is already relatively strongly in favour of redistribution and that their redistribution preferences are therefore relatively insensitive to additional economic risks. Results are not conclusive but suggest that the latter type of influences dominate (Model A29). At the same time, the coefficient for the direct effect of having low education is negative, which is as expected.

The third and final moderator that I consider concerns potential heterogeneity due to differences in type of welfare regime. I follow Hall and Soskice's (2001) seminal typology, which distinguishes between so-called liberal market and coordinated market economies (Table A.11). The former economies include Anglo-Saxon countries such as the United Kingdom and are characterized by a relatively small welfare state and little government intervention on the labour market. The latter economies include countries such as Sweden and are characterized by a relatively large welfare state and comparatively much government intervention on the labour market. Accordingly, I expect that the relationship between occupational automation risk and preferences for redistribution may be less strong in coordinated market economics compared to liberal market economies. Results do not support this expectation, however (Model A30). A possible explanation is that type of welfare regime is itself already an outcome of the preferences for redistribution held by citizens in a country. Since preferences for redistribution on average appear much weaker in liberal market economies than in coordinated market economies (-0.335 standard deviations, $P < 0.001$), this does not seem unlikely.

Evidence from other samples and further robustness checks

To extend the main analyses involving the ESS sample and provide further evidence of the robustness of the association between automation risk and preferences for redistribution, Table A.4 present results for analyses using the ISSP-SI sample. In all cases, results confirm the finding that increased exposure to automation risk is associated with stronger preferences for redistribution. Compared to the analysis using the ESS sample, this analysis includes added variables controlling for household socioeconomic status, specifically perceived relative social status of the individual's family and household income rank. Hence, for this analysis, it seems more unlikely that the association between preferences for redistribution and spousal automation risk (Models A4 and A5) is spurious.

Turning to the ISSP-ROG sample and using a dependent variable that concerns a concrete policy action with redistributive consequences, results again support the earlier finding that automation risk affects individuals' preferences for redistributive government policy (Table A.5 in Appendix A). The relationship between (direct and indirect) exposure to automation risk and the strength of individuals' preference for government support of declining industries remains when controlling for individual

differences in the generic preference for redistribution and for government financing of projects for new jobs.

A final issue to consider is how the relationship between occupational automation risk and preferences for redistribution may be different for data collected in later years and/or using ISCO08 instead of ISCO88 codes. As discussed earlier, the indicator of occupational automatability is based on individual-level data collected in 1997. However, some of the individual-level data from the ESS and ISSP-ROG have been collected much later and it could well be that the occupational automatability indicator provides a more accurate measure of exposure to automation risk in years close to 1997 than in later years. Similarly, in Wave 6 (2012), the ESS started using a scheme for measuring individuals' occupation that differs from the scheme used to measure occupational automation risk (ISCO08 vs. ISCO88). Hence, for these later survey waves, the occupational automatability indicator likely provides a more noisy measure of exposure to automation risk than for ESS Waves 1-5 (2002–10).

Whereas all empirical models include year/wave fixed effects, a more detailed analysis of the role of potential year-specific measurement error involves interaction terms that allow the relationship between automation risk and redistribution preferences to vary across years or survey waves. As we would expect, results from this analysis (Table A.10 in Appendix A) indicate that the relationship between occupational automation risk and preferences for redistribution is stronger in earlier years/waves compared to later years/waves. However, the difference is only statistically significant at usual levels for the ESS sample. Moreover, in all cases, and again as expected, the estimated coefficient for automation risk increases somewhat when the relationship between automation risk and redistribution preferences is allowed to vary across years/ waves.

VI. Conclusion

This paper finds that individuals in occupations that are more at risk of losing their job due to automation have stronger preferences for redistribution. This result is supported by evidence from three different large-scale cross-country survey datasets and extends to preferences for a concrete policy action with redistributive consequences. Furthermore, findings are robust to the inclusion of a large variety of control variables. Among the control variables included are some unique measures of individuals' preferences as well as variables such as personal income rank that are able to capture individual skill differences not yet captured by formal measures of educational attainment such as years of education and educational degree. Finally, the association between automation risk and redistribution preferences is also present when considering individuals' indirect exposure to automation risk through the occupation of their spouses and/or using spousal automation risk as an added means for controlling for otherwise unobserved individual differences in relevant skills preferences. Nevertheless, because of the inferential limitations of this paper's cross-sectional analysis, there remains an interesting opportunity for designing a laboratory experiment

that manipulates individuals' perceived automation risk and tests the causal effect of this manipulation on their preferences for redistribution.[11]

Recent years have seen an increasingly intense debate about the possible disruptive effects of technological advances in robotics and artificial intelligence, among others. A most prominent issue thereby involves the distributional effects of technological change and the concern that some groups in society will not only lose from automation in relative terms but also in absolute terms. However, as this paper finds, automation can have important societal implications even when the objective threat of automation causing unemployment and income losses is limited. The reason is that fear and anxiety about automation alone are sufficient to radically alter people's policy preferences and increase pressure on governments to take action.

Considering future research, I find that the measure of occupational automatability developed in this paper may be particularly valuable for future studies involving COVID-19 and societies' resilience to pandemics. The current COVID-19 pandemic has highlighted important variation in the degree to which different jobs are critical for the functioning of society. However, humans doing these critical jobs may fall ill. Worse, working these critical jobs, individuals can easily infect their colleagues, which makes it even more difficult to keep basic functions (e.g. logistics, medical help) in society intact. Robots on the other hand do not fall ill or infect others. Automatability therefore seems a key factor when thinking about making society more resilient to future pandemics. More generally, automation and technological advances, for instance in online collaboration and communication tools, are very relevant when considering working from home as a policy response to reduce disease spreading or for enabling people to continue working while quarantined.

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[11] I thank an anonymous referee for suggesting a follow-up study that uses an experimental research design.

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Supporting Information

Additional Supporting Information may be found in the online version of this article:

Supplementary Material