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Automation and the Welfare State: Technological Change as a Determinant of Redistribution Preferences

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Abstract

Technological change is widely considered to be a key driver of the economic and occupational structure of affluent countries. Current advances in information technology have led to a significant substitution of routine work by capital, while occupations with abstract or interpersonal manual task structures are complemented or unaffected. We develop a simple theoretical framework in which individuals in routine task-intensive occupations prefer public insurance against the increased risk of future income loss resulting from automation. Moreover, we contend that this relation will be stronger for richer individuals who have more to lose from automation. We focus on the role of occupational elements of risk exposure and challenge some general interpretations of the determinants of redistribution preferences. We test the implications of our theoretical framework with survey data for 17 European countries between 2002 and 2012. We find vulnerability to automation to be more significant than other occupational risks emphasized in the literature.

1. Introduction

Technological change is widely regarded as one of the main drivers of long-term economic development (Romer 1990). By complementing occupations with certain skill profiles while making others redundant, it structures employment and significantly shapes the occupational structure (Goldin and Katz 2008; Oesch 2013). Technological innovations can have far-reaching social implications that differ across occupations. For Marx, technology contributed to the creation of a "reserve army of the unemployed" which allowed capitalists to reduce the wages of the working classes. More optimistically, technological change enables specialization and skill upgrading, which facilitates a move away from routine labour (Erikson and Goldthorpe 1992; Iversen and Cusack 2000; Wren 2013).

Current technological innovations are strongly connected to computer-based information technology. Its momentous implementation in the last decades has been spurred by significant real price declines in computing power (Autor, Levy, and Murnane 2003). Computers can perform routine tasks, which are well defined and repetitive, and can complement complex and more ambiguous abstract task structures. They, however, have a limited effect on interpersonal service tasks. An earlier literature on skill-biased technological change associated these developments to the significant increase in wage inequality between those with university degrees and those with a high school degree or less (Katz and Murphy 1992). More recently, technological change is argued to promote a significant decrease in the share of routine occupations that occupy the middle of the educational and wage distributions. Information technology therefore does not lead to linear upskilling of work, but rather to a process of polarisation (Spitz-Oener 2006; Autor, Dorn, and Hanson 2015).

Technological change is therefore connected to income inequality (Goldin and Katz 2008; Michaels, Natraj, and Van Reenen 2014) and, as such, it affects the political economy of industrialized democracies in important ways. Inequality is frequently invoked as an explanation for a number of crucial issues in political science. It is often considered a determinant of processes as diverse as the decline of electoral turnout (Nie and Kim 1978; Rosenstone and Hansen 1993), the increase in the support of extreme-right parties (Betz 1994), or the likelihood of political conflict (for a review, see Lichbach 1989). This paper wishes to address one of the assumptions underlying most arguments about the influence of inequality on political outcomes. If inequality matters to individual political behavior, it seems reasonable to assume that it does so through the effects of income on redistribution and social policy preferences. These redistribution preferences may (or may not) then be reflected on party positions and, eventually, government policy. To begin at the beginning, the issue of whether technological change is a significant determinant of redistribution preferences is a topic in need of further analysis.

Given the pervasive substitution effects of information technology on routine occupations, we would expect individuals holding routine occupations to have strong preferences for nonmarket protection to insure against increased risk of employment and wage loss. The idea that insurance motivations are a significant determinant of preferences for redistribution has become prominent in the recent comparative political economy literature. While some authors mention risks resulting from technological change,[1] the vulnerability of concrete occupations to technological change is rarely examined directly. To our knowledge, only Kitschelt and Rehm (2014) analyze the relationship between routine occupations and redistribution preferences, but they focus on education as the key defining factor for these occupations, rather than measuring routine task intensity directly.

In this paper we focus on the risks associated to technological change and argue that the degree of routine task intensity in different occupations is a significant

[1] See, for example, Iversen and Cusack who state that "most of the risks being generated in modern industrialized societies are the product of technologically induced structural transformations inside national labor markets. (...) It is these structural sources of risk that fuel demands for state compensation and risk sharing" (2000: 313).

determinant of redistribution preferences. We develop a simple theoretical framework in which risk-averse individuals support redistribution because of their desire to insure against occupational hazards. We also argue that insurance preferences resulting from technological change risks will be accentuated by income. We argue that income plays a intermediating role, since individuals will have more to lose from automation when their income level is higher. These arguments aim to re-examine the effects of redistribution and insurance motivations on redistribution preferences, while emphasizing the importance of a factor that has received a remarkable amount of popular attention (see, for example, Martin Ford's *Rise of the Robots: Technology and the Threat of a Jobless Future*).

2. The argument

As suggested above, technological innovation entails occupational risks for those individuals whose occupations are susceptible to automation. Vulnerability to automation, in turn, is related to the routine tasks involved in any particular occupation. Individuals will therefore favor redistribution as insurance against the risk of automation when the routine task intensity (RTI) of their occupation is high. Below, we will further argue that this positive effect of RTI on preferences for redistribution is affected by income: RTI becomes a stronger influence on redistribution preferences when an individual has more to lose from automation (i.e., when her income is higher).

2.1. Technological change as an unequally distributed occupational risk

Current innovations in information technology are generally viewed to have strong and dissimilar effects across occupations (Goldin and Katz 2008; Oesch 2013; Wren 2013). They complement individuals with abstract or personal tasks, while individuals in routine occupations face an increased risk of being substituted by capital

(Autor, Dorn, and Hanson 2015). Routine tasks can be partitioned into step-by-step rules and do not require cognitive or service skills that are difficult to automate (Goos and Manning 2007; Goos, Manning, and Salomons 2014). It is important to emphasize that routine tasks susceptible to automation might well be complex and require extensive educational training (for example, bookkeeping). Because of this, innovations in information technology do not impact occupations linearly across educational levels. In fact, routine occupations tend to lie in the middle of the educational and income distribution (Oesch 2013).

Advances in information technology have been found to significantly affect the occupational structure of industrialized democracies in the last couple of decades. Oesch (2013) finds a decrease of relative employment between 29 and 41 per cent in routine occupations in Denmark, Germany, Spain, Switzerland, and the UK from around 1990 to 2008, while employment in non-routine analytical and interactive occupations increased by 23 to 41 per cent. Michaels, Natraj, and Van Reenen (2014), using data for the US, Japan, and nine European countries between 1984 and 2004, report strong polarising effects of information technology, accounting for a quarter of the growth in relative demand towards non-routine high-skilled labour. Goos, Manning, and Salomons (2014) analyze the period between 1993 and 2010 in 16 Western European countries and show that technological change and offshoring can account for three quarters of the observed increase in high-skilled non-routine work and decrease in medium-skilled routine employment.[2]

2.2. Routine task intensity (RTI) as determinant of preferences for redistribution

In the traditional political economy literature redistribution preferences are a function of material self-interest (Meltzer and Richard 1981). The Metzer-Richard model

[2]See also Autor, Levy, and Murnane (2003) and Spitz-Oener (2006) for single-country studies on this topic.

assumes that the preferences of the median voter determine government policy and that the median voter seeks to maximize current income. If there are no deadweight costs to redistribution, all voters with incomes below the mean maximize their utility by imposing a 100% tax rate. Conversely, all voters with incomes above the mean prefer a tax rate of zero. When there are distortionary costs to taxation, the MR model implies that, by increasing the distance between the median and the mean incomes, more inequality should be associated with more redistribution.

More recently, scholars have questioned the idea that material self-interest motivations should be limited to a measure of present income. This approach distinguishes an insurance component of redistribution preferences that incorporates an intertemporal element in material self-interest. Individuals will insure against uncertain future income levels and will therefore favor social protection when they are exposed to an increased risk of job or wage loss. As these forms of social security (such as unemployment benefits or social assistance) are redistributive,[3] redistribution preferences for individuals exposed to these risks will be high (Sinn 1995; Moene and Wallerstein 2001; Iversen and Soskice 2001, 2009; Rehm 2009).

Two articles have been particularly influential in the insurance approach to the determinants of social protection. We will contrast our reasoning to theirs. First, Moene and Wallerstein (2001) propose that insurance is a normal good, leading individuals to prefer more of it when their income rises. Assuming that individuals are sufficiently risk averse, so that the insurance motive dominates the Meltzer-Richard redistribution motive, then income will positively affect preferences for redistribution, holding risk and risk aversion constant. In this model risk of job loss is a function of income: it is lower (or set to zero) for high-income than for low-income groups. Second, Iversen and Soskice (2001) argue that individuals with specific as opposed to general skills will favour insurance as protection against their investment in human

[3] See, for example, Nelson (2012).

capital. In their model there is a homogeneous risk of job loss across the electorate, but the opportunities for reemployment are lower for individuals who have invested in specific skills. Holding income and risk aversion constant, an increase in the ratio of specific versus general skills will lead individuals to prefer higher levels of nonmarket insurance.

Our point of departure lies closer to the Iversen and Soskice model, as we explicitly recognise an occupational hazard, independent of the level of income, that translates into higher preferences for nonmarket protection. We part ways with their argument by emphasizing that the risk of job or wage loss depends on the occupational level of RTI, instead of focusing on the effects of skill specificity on reemployment possibilities. The implication is quite distinct: given a level of income and risk aversion, the level of routine task intensity of an occupation positively affects preferences for redistribution.

While technological change has not been recognised as an important determinant of redistribution preferences in the comparative political literature, it is germane to ask whether RTI is in fact related to more traditional occupational risks. We will show below that, empirically, the correlation between RTI and occupational risk is low. Theoretically, they are distinct concepts as well.

Kitschelt and Rehm (2014) mention routine occupations in their analysis of the relationship between occupational characteristics and redistribution preferences. As we show in more detail in Appendix A, however, their operationalisation follows educational and income lines and does not capture the degree of occupational routine task intensity. Kitschelt and Rehm in fact do not argue that individuals in routine occupations favour more redistribution as insurance against increased risks due to automation. Rather, elaborating on Oesch (2006), they are interested in occupations as the source of socialisation profiles. They differentiate occupations based on discretionary disposal over own work (the 'logic of authority'), and they hypothesize individuals with more discretionary space and authority over subordinate employees will find preserving material incentives to be important, and therefore will be against redistribution.[4]

As mentioned above, a common component of the more traditional conception of occupational risk is skills (Cusack, Iversen, and Rehm 2006; Iversen and Soskice 2001). Skill specificity reflects investments in human capital and consequently affects occupational risks. In the Iversen and Soskice approach, therefore, the distinction that matters is that between general and specific skills, not whether a certain skill (be it specific or general) is routine, manual, or abstract. There are no *a priori* reasons to believe that the specificity of skills is related to the degree of occupational RTI. As an example, models, salespersons, and demonstrators have among the most general skills, while stationary-plant and related operators have very specific skills. In terms of routine task intensity, however, these occupations are very comparable - both are average as we will also show below.

It is also important to note that the outsourcing of production and its specific effects on certain occupations is significantly connected to risk (Grossman and Rossi-Hansberg 2008). The crucial factor is the degree to which parts of the production process can be executed abroad, and how this *offshorability* is concentrated on particular activities. Walter and co-authors have explored how offshorability affects redistribution preferences (Walter 2010; Rommel and Walter 2014; Walter 2014; Dancygier and Walter 2015). But here again we argue there is an analytic distinction between offshorable and automatable occupations (Oesch 2013; Goos, Manning, and Salomons 2014; Autor, Dorn, and Hanson 2015). There are occupations that can be executed abroad but require non-routine cognitive skills that are difficult to automate (like those in architecture, software developing, or statistical analysis). And there are

[4]Moreover, the differences across groups with varying degrees of authority are measured as dummy variables rather than by means of a continuous measure of the routine task intensity of occupations. See details in Appendix A.

occupations that are routine and can be computerised but require spatial proximity (like security guards or customer service clerks). Moreover, studies analyzing the determinants of occupational structure find much weaker or insignificant effects of international trade and offshoring once the impact of technological change is accounted for (see Goos, Manning, and Salomons 2014; Autor, Levy, and Murnane 2003; Spitz-Oener 2006).

2.3. The mediating effect of income

The last part of our argument concerns a factor that can exacerbate the (positive) effect of RTI on preferences for redistribution. We argue that the importance of RTI as a determinant of nonmarket insurance demand will be increasing in the level of present income. If an individual has relatively more to lose from an occupational risk, then this risk will become more decisive in determining her preferences for nonmarket protection. This view is related but, again, deviates in significant ways from existing models of redistribution. As is well-known, the Meltzer-Richard model emphasizes current income as the determinant of redistribution demand and does not consider insurance motivations. Income plays a similar role for Iversen and Soskice (2001), redistribution preferences are negatively associated to present income and they experience a general increase when an individual possesses specific skills (because of insurance-related reasons). In fact, the effect of skill-specificity in the Iversen and Soskice model is not income dependent, insurance motivations are expected to produce a similar increase in demand for protection whether an individual's income is high or low.

Moene and Wallerstein (2001) are most similar to the argument we are presenting, since they argue that insurance is a normal good that individuals will demand more of as their income goes up. Moene and Wallerstein, however, focus on the effects of a mean-preserving increase of macro-inequality on individual demand for insurance. We, on the other hand, emphasize the greater effect of RTI vulnerability on the demand for insurance promoted by increased levels of individual income. In their model, income is positively associated with demand for redistribution. In our model, on the other hand, income has a direct negative effect on preferred levels of redistribution, but it will positively influence the effects of RTI (our risk exposure variable) on redistribution preferences.

Some scholars have argued that educational levels moderate the effects of offshoring on redistribution preferences, since high-skilled individuals benefit from globalization while low-skilled individuals do not (Walter 2010; Dancygier and Walter 2015). Other have put forward country-level institutions as a moderating factor for the effects of skill specificity on preferences for insurance (Gingrich and Ansell 2012).[5] But, to our knowledge, the individual level of income has not been considered a intermediating factor for RTI effects in existing studies on redistribution preferences.

3. Data

3.1. Routine task intensity across occupations

In the theoretical section we have argued that individuals holding routine occupations bear the risks of wage or employment loss from automation. We use the routine task intensity index from Goos, Manning, and Salomons (2014), who rely on Autor and Dorn (2013) and Autor, Dorn, and Hanson (2015). Goos, Manning, and Salomons distinguish between routine, manual, and abstract task inputs, derived per occupation from the Dictionary of Occupational Titles (DOT). The RTI index measures the log routine task input per occupation, minus the log manual and abstract task inputs, so that the measure is increasing in the relative importance of routine tasks

[5]We test for the effects of these potentially confounding factors in our sensitivity analysis.

vis-à-vis manual and abstract tasks. As the RTI index gauges the tasks structure of an occupation, the index is time- and country-invariant. Goos, Manning, and Salomons (2014) rescale these measures to mean 0 and standard deviation 1. The index is available at the 2-digit occupational International Standard Classification of Occupations (ISCO)-88 level.[6]

A different occupational measure of the degree of routine task intensity is available from Oesch (2013). Again differentiating between routine, manual, and abstract (or analytical and interactive) tasks, Oesch codes occupations at the 4-digit ISCO-88 level into multiple non-routine and routine occupations drawing on Spitz-Oener (2006). These occupational categories can be combined into a dummy equal to 1 if an occupation is routine, and equal to 0 if otherwise. This dummy indicator and the continuous variable from Goos, Manning, and Salomons (2014) are highly correlated (0.73). As we have more variation for the continuous RTI index from Goos, Manning, and Salomons, we use this one as our benchmark and use the Oesch (2013) dummy as a sensitivity test.

The European Social Survey (ESS) provides us with pooled time-series cross-sectional data of individual redistribution preferences. It has a standardized occupational identifier at the 4-digit ISCO-88 level for 2002-2010 and ISCO-08 for 2012. We recode the 2012 wave into ISCO-88 definitions using the ILO 4-digit correspondence table[7] and use this occupational identifier to link individuals to the RTI index from Goos, Manning, and Salomons (2014). Our analysis draws on ESS surveys between 2002-2012 for the 17 Western countries for which at least two waves are available.[8]

[6] No information on RTI is available for six groups at the 2-digit ISCO-88 level. These agricultural, supervisory, and residual occupational groups are also excluded by Goos, Manning, and Salomons (2014), Autor and Dorn (2013) and Autor, Dorn, and Hanson (2015). We also have to exclude individuals in all waves for which information is only available at the 1-digit ISCO level. In total 12% of observations are excluded because of this.

[7] We use the correspondence table from Ganzeboom, `http://www.harryganzeboom.nl/ISCO08/index.htm`. This correspondence table is based on the ILO correspondence table. None of our results change when we exclude 2012 in which the ISCO-08 coding is used, as shown in the sensitivity tests.

[8] Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the

To obtain a better understanding of what type of occupations score high and low on the RTI index, we postpone our definition of redistribution preferences for a moment and first discuss our operationalization of education and income. We use measures of years of education and present income (using respondents' answers to a survey question on household total net income). We transform the income bands in the survey's show-cards into their survey-specific midpoints. The highest income band, which has no upper limit, is assumed to follow a Pareto distribution (Hout 2004; Kopczuk, Saez, and Song 2010).[9] Self-reported household total net income is recoded into annual 2010 PPP-adjusted US dollars using exchange rate information from OECD (2014b). We equivalize the income level using the square root of the household size to account for differences in household size and economies of scale.[10]

Table 1 lists the occupations ranked by their level of RTI. It shows that on average non-routine occupations have a higher wage and educational level. Yet these relationships are not very strong; middle-income and middle-skill occupations have high values of RTI (see also Autor, Dorn, and Hanson 2015 or Goos, Manning, and Salomons 2014). In general, there is a relatively low correlation between the RTI index and both equivalized income (-0.13) and educational level (-0.17). General managers have the least routine occupation, a profession with above-average wage and skill level, but the second-least routine occupation is drivers and mobile-plant operators (low-skilled and low-paid). The most routine occupations are customer service and office clerks, and precision workers.

Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the UK. We also conduct a sensitivity test where we include the Eastern European countries for which at least two waves are available, namely, Czech Republic, Estonia, Hungary, Poland, Slovak Republic, and Slovenia.

[9] From 2002-2006 respondents were shown 12 categories that were the same across all countries. The waves from 2008-2012 distinguish between 10 categories (deciles) that differ per country. We calculate the survey specific midpoints. For the upper band we apply the formula in Hout (2004).

[10] In the regressions below, we use individual income in relative terms, as a percentage of the country and wave specific mean. We calculate the mean as the mean of all individuals in the sample - not just the subset included in the regressions. For ease of interpretation, we divide this coefficient by 100.

Table 1: Levels and changes in employment shares and income for occupations ranked by their level of RTI

	ISCO	RTI	Education (years)	Equivalized Income ($ 2002)	(% change 2002-2012)	Employment share (2002)	(% change 2002-2012)
Non-routine		**-0.75**	**14.35**	**29530**	**17.26**	**64.34**	**3.63**
General managers	13	-1.52	13.44	29667	10.44	3.44	-0.52
Drivers and mobile-plant operators	83	-1.5	11.32	20531	23.54	4.09	-0.32
Life science and health professionals	22	-1	17.71	36571	14.97	2.31	0.99
Physical, mathematical and engineering science professionals	21	-0.82	16.52	36716	12.62	4.73	0.71
Corporate managers	12	-0.75	15.16	41161	5.33	7.07	1.46
Other professionals	24	-0.73	16.61	34721	16.69	7.23	1.21
Personal and protective services workers	51	-0.6	12.34	20987	21.57	10.13	1.4
Other associate professionals	34	-0.44	14.15	29263	19.34	10.82	-0.01
Physical and engineering science associate professionals	31	-0.4	13.93	27171	25.19	5.37	-1.09
Life science and health associate professionals	32	-0.33	15.03	26423	18.77	4.14	-0.17
Extraction and building trades workers	71	-0.19	11.59	21619	21.41	5.01	-0.03
Routine		**0.83**	**11.74**	**22071**	**13.94**	**35.66**	**-3.63**
Sales and services elementary occupations	91	0.03	10.92	18935	6.02	4.67	0.53
Models, salespersons and demonstrators	52	0.05	12.16	21384	19.65	4.39	0.16
Stationary-plant and related operators	81	0.32	11.64	24685	10.93	1.16	-0.25
Labourers in mining, construction, manufacturing and transport	93	0.45	11.03	19533	0.28	2.22	0.18
Metal, machinery and related trades workers	72	0.46	11.98	21002	34.85	6.09	-1.9
Machine operators and assemblers	82	0.49	11.18	18670	12.48	3.37	-0.41
Other craft and related trades workers	74	1.24	10.33	18790	26.92	1.88	-0.61
Customer services clerks	42	1.41	12.92	25492	3.72	1.88	0.56
Precision, handicraft, printing and related trades workers	73	1.59	12.37	26894	7.51	0.96	-0.2
Office clerks	41	2.24	12.86	25326	17.07	9.05	-1.7

Note: For non-routine (negative RTI score) and routine (positive RTI score) occupations, bold figures show average values for RTI, years of education, equivalized income, and income changes. They show the sums of employment shares and employment changes. Calculations are based on the countries for which information for both 2002 and 2012 is available (all except Austria, France, Greece, Ireland, Luxembourg, and Spain).

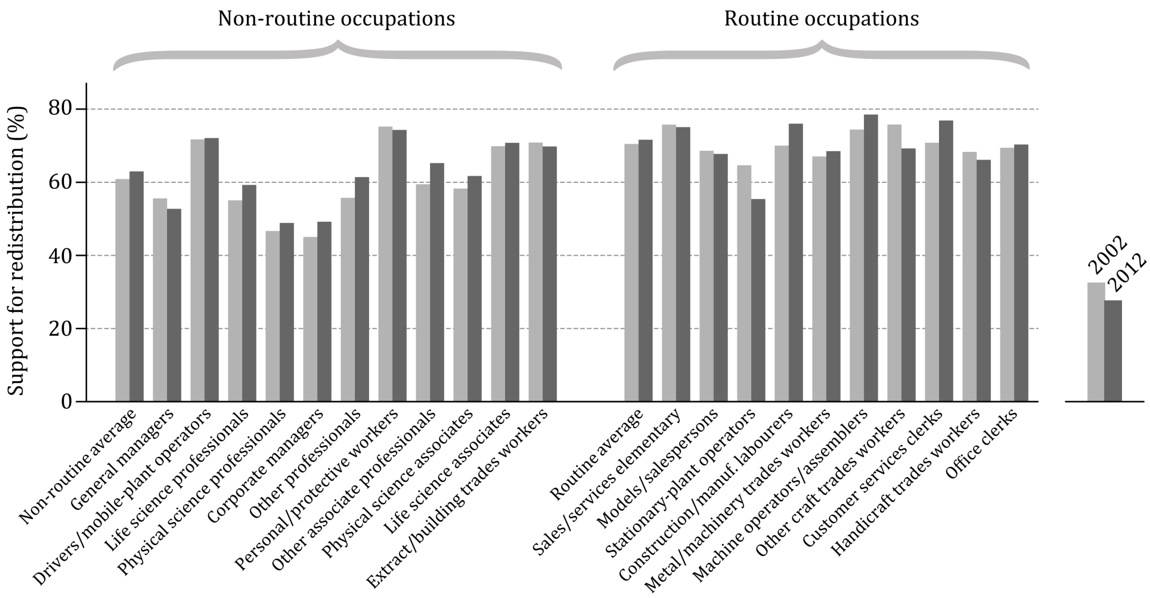
As mentioned above, existing contributions in the labour economics literature illustrate the relationship between automation and wage/job risk for individuals holding routine occupations (Autor, Levy, and Murnane 2003; Spitz-Oener 2006; Goos, Manning, and Salomons 2014; Michaels, Natraj, and Van Reenen 2014). Using ESS data we can also explore these outcomes. Table 1 is consistent with previous findings and shows that within the relatively short time period in our anlaysis (2002-2012), non-routine occupations (with a negative RTI score) saw on average an increase in their employment share and a higher increase in wages when compared to routine occupations (with a positive RTI score).

3.2. Redistribution preferences

The ESS contains a question designed to directly capture what we aim to explain: whether or not an individual supports government redistribution. Respondents are asked whether they agree or disagree on a five-point scale with the following statement: "The government should take measures to reduce differences in income levels." This variable is recoded to capture support for government redistribution. This question is the only one tapping into social policy preferences available in all waves of the ESS, and it has frequently been used in studies seeking to explain redistribution preferences (Rehm 2009; Burgoon, Koster, and Egmond 2012; Burgoon 2014; Kitschelt and Rehm 2014; Rueda 2014; Wren and Rehm 2014; Häusermann, Kurer, and Schwander 2015). The mean of our ordinal measure of support for redistribution for the full sample is 3.68 and it increased slightly from 3.63 in 2002 to 3.72 in 2012.

To better illustrate the differences in redistribution preferences across occupations, we generate a binary measure for support for redistribution equal to 1 if an individual agrees or strongly agrees with support for redistribution. This variable has an overall mean of 0.66. In Figure 1 we rank the occupations on their level of RTI, again

Figure 1: Support for redistribution across occupations in 2002 and 2012



distinguishing between occupations with a negative RTI index score (non-routine, N) and a positive one (routine, R).[11] The figure reflects that individuals in routine occupations have higher levels of support for redistribution. In both groups, support for redistribution increased over time.

3.3. Controls

We include a vector of individual-level controls common in the redistribution preferences literature (e.g., Rehm 2009; Burgoon 2014; Rueda 2014). We include measures for years of education, age, the degree of religiosity (scaled 1-10), and indicator variables for gender, (former) trade union membership, and whether an individual is unemployed. As in Cusack, Iversen, and Rehm (2006), this last dummy variable can be interpreted as a measure of realised risk (i.e., if an individual looses her or his job).

[11] Calculations are based on the countries for which information for both 2002 and 2012 is available (all except Austria, France, Greece, Ireland, Luxembourg, and Spain).

At the country level, we again follow previous studies by including social spending as a percentage of GDP (Burgoon, Koster, and Egmond 2012; Rueda 2014) and the unemployment rate (Burgoon, Koster, and Egmond 2012; Burgoon 2014), both lagged one year. By including ex ante levels of social spending we can account for possible diminishing marginal returns to redistribution. It could also be that higher levels of social spending also affect the occupational distribution, for instance by leading to higher levels of public versus private employment. Similarly, there are reasons to believe that individuals will favour higher levels of redistribution when unemployment is high and that unemployment might affect occupational patterns.

4. Analysis

To account for the fact that individuals are nested within countries, we estimate a multilevel model with random intercepts for countries, and we cluster standard errors at the country level. Our dependent variable is categorical and ordered. We could analyse its determinants with ordered probit or ordinary least squares (OLS) estimation techniques. In an ordered probit model predicted probabilities are restricted to the range of the dependent variable and potential heteroskedasticity resulting from the categorical nature of the dependent variable is corrected. Some authors, however, argue that interaction effects in nonlinear models cannot be directly interpreted (Ai and Norton 2003; Greene 2010). Moreover, in a multilevel framework, the models sometimes do not converge and marginal effects cannot be easily calculated when a model contains both random and fixed terms. A linear OLS model does not have these drawbacks, and we correct for heteroskedasticity by clustering our standard errors at the country level. We estimate our equations using both techniques. Our results are very comparable and therefore we present findings from the OLS estimations, since the interaction effects are more intuitive.[12]

[12]Results for the multilevel ordered probit models are available in Appendix B.

4.1. Main results

The results of our estimation of the effects of RTI on redistribution preferences are presented in Table 2. Regarding our control variables, the estimates are all consistent with previous findings in the literature. First, we find that poorer individuals favour higher levels of redistribution than richer ones. This is in line with the Meltzer-Richard model. The coefficient in Table 2 implies that a 1 percentage point increase in individual income relative to the country- and year-specific mean is associated with a 0.002 decrease in expressed redistribution preferences.[13] Thus, the model predicts that an individual with 1.5 times mean income has an on average 0.2 lower level of redistribution preferences compared to an individual with 0.5 times mean income, ceteris paribus. Furthermore, having less education, being older, female, unemployed, not religious, or a trade union member all increase the likelihood of agreeing that the government should reduce income disparities. Neither the country levels of social spending or unemployment have statistically significant effects on individual redistribution preferences in our analysis.

Moving on to our main variable of interest, the results in Table 2 indicate that RTI is positively associated with redistribution preferences. This is the case no matter the number of additional variables in the analysis (in columns 1-4). This result provides empirical support for our first hypothesis that individuals in routine occupations favour more redistribution to insure against the increased risk of job or income loss.

How robust are the results for RTI presented in Table 2? In Table 3, we explore the sensitivity of the effect of RTI on redistribution preferences to a number of different specifications and additional explanatory variables suggested in the literature. First, we use the Oesch (2013: 156) coding to generate a dummy variable for routine occupations (model 1). With this indicator the effects of RTI on redistribution

[13] Recall that in the regressions, we use individual income as a percentage of the country and wave specific mean.

Table 2: RTI and redistribution preferences

	(1) RTI only	(2) + individual income	(3) + individual controls	(4) + country-level controls
RTI	0.085***	0.067***	0.042***	0.042***
	(0.000)	(0.000)	(0.000)	(0.000)
Income		-0.211***	-0.180***	-0.180***
		(0.000)	(0.000)	(0.000)
Years of education			-0.022***	-0.022***
			(0.000)	(0.000)
Male			-0.208***	-0.208***
			(0.000)	(0.000)
Age			0.003**	0.003**
			(0.014)	(0.017)
Trade union member			0.176***	0.176***
			(0.000)	(0.000)
Degree of religiosity			-0.008**	-0.008**
			(0.016)	(0.019)
Unemployed			0.137***	0.135***
			(0.000)	(0.000)
Lag of social spending				-0.004
				(0.503)
Lag of unemployment				0.006
				(0.554)
Constant	3.743***	3.977***	4.193***	4.246***
	(0.000)	(0.000)	(0.000)	(0.000)
Log likelihood	-93913	-93176	-92414	-92412
Intraclass correlation	0.101	0.104	0.113	0.106
N	64639	64639	64639	64639
Number of countries	17	17	17	17

Note: Multilevel OLS model with random country intercepts and standard errors clustered at the country level. P values in parentheses, *p<0.1, **p<0.05, ***p<0.01.

preferences become stronger. We then include a number of the occupational risks discussed in the theory section into our regression model. A first alternative is skill specificity (model 2; Iversen and Soskice 2001; Cusack, Iversen, and Rehm 2006). We use the measure of relative skill specificity also used by Rehm (2009). This is a time-invariant measure available at the 2-digit ISCO-88 level.[14] Second, Burgoon, Koster, and Egmond (2012) identify migration as an occupational risk. We follow their empirical strategy and include the number of foreign born as a percentage of the population, which is available for around 2000 at the 2-digit ISCO-88 level from the OECD migration database (OECD 2008). We find that individuals with occupations with higher ratios of foreigners have higher levels of redistribution preferences, as also found by Burgoon, Koster, and Egmond (2012). More importantly, the significance of our variables of interest in model (3) is not affected by including this occupational hazard. Third, we rely on Walter's binary index of offshoring (model 4; Walter 2010, 2014; Dancygier and Walter 2015). This index is defined at the 4-digit ISCO-88 level.[15] We argued above that RTI substantively differs from skill specificity and offshoring. This is also reflected in modest correlations (0.14-0.19). In model (4), our main results are confirmed.[16] Fourth, in model (5) we include the occupational unemployment rate from Rehm (2009).[17] This is a stringent test, since our argument is that RTI at the occupational leads to a higher levels of job risk. We lag the occupational unemployment rates by one year as information for 2012 is missing. Unfortunately, data are only available at the 1-digit occupational level. The occupational unemployment rate and the RTI index are positively correlated (0.23)

[14]The data are from `http://www.people.fas.harvard.edu/~iversen/SkillSpecificity.htm`. This website also contains information regarding measurement.

[15]We are grateful to Stefanie Walter for sharing her coding with us.

[16]We find in model (2) that individuals whose occupations require more specific skills favour more insurance. Interestingly, individuals in offshorable occupations decrease rather than increase their preferred level of redistribution. This finding is also reported by (Walter 2014). Walter argues that exposure to offshoring increases risk perceptions among low-skilled, whereas high-skilled (or 'globalisation winners') lower their demand for redistribution.

[17]We thank Philipp Rehm for sharing his occupational information. Data for Luxembourg are missing.

Table 3: Robustness checks for main results

		RTI coefficient	p value
	Original result from Table 2, column (4)	0.042***	(0.000)
(1)	Dummy RTI from Oesch (2013)	0.071***	(0.000)
(2)	Skill specificity	0.039***	(0.000)
(3)	Foreign ratio	0.048***	(0.000)
(4)	Offshoring	0.057***	(0.000)
(5)	Occupational unemployment rate	0.024***	(0.002)
(6)	Task groups from Kitschelt&Rehm	0.071***	(0.000)
(7)	Public sector employee	0.048***	(0.000)
(8)	Left-right scale	0.039***	(0.000)
(9)	All individuals	0.035***	(0.000)
(10)	Only employed	0.040***	(0.000)
(11)	Eastern Europe	0.040***	(0.000)
(12)	Excluding 2012	0.042***	(0.000)
(13)	Before 2008 (excluding 2008-2012)	0.038***	(0.001)
(14)	Binary dependent variable	0.018***	(0.000)
(15)	Absolute redistribution	0.042***	(0.000)
(16)	Relative redistribution	0.042***	(0.000)
(17)	Gini market income	0.042***	(0.000)
(18)	Gini net income	0.042***	(0.000)
(19)	EPL index	0.041***	(0.000)
(20)	UB replacement rate	0.042***	(0.000)
(21)	OLS with country fixed effects	0.042***	(0.000)

and, as expected, including the occupational unemployment rate decreases the size of the RTI index coefficient on redistribution preferences. But our main finding are still robust to the inclusion of this additional variable. Fifth, we introduce a measure for the routine occupations in Kitschelt and Rehm (2014). As we explain in more detail in Appendix A, this occupation operationalisation follows educational and income lines and does not capture the degree of occupational routine task intensity. Nevertheless, the results in model (6) confirm our main findings. Sixth, we include an indicator variable capturing whether individuals are public sector employees in model (7). This again makes little difference to our main findings.

Our main analysis does not include the left-right position of individuals, as we think of redistribution preferences, which we seek to explain, as a key element of expressed ideology. We explore whether left-right self-placement constitutes an independent determinant of redistribution preferences (see e.g., Margalit 2011) in model (8). We then test the robustness of our results to the sample definition. In model (9), we expand our sample by 64 per cent by including all individuals for which information is available (we insert an additional dummy for people not active in the labour market). In model (10), we repeat our estimations for only employed individuals, which reduces our sample size by 6 per cent. In model (11), we test whether our results still hold when we include Eastern European countries for which at least two waves of data are available.[18] We also test whether leaving out 2012, which is based on another occupational coding scheme (model 12), or leaving out all crisis years (model 13) affects our results.[19]

By applying OLS to a categorical dependent variable, we implicitly make the proportional lines assumption that the effect of the independent variables is constant for each answer category of our dependent variable. This assumption can be relaxed by transforming our categorical dependent variable into a dummy equal to 1 when an individual prefers or strongly prefers redistribution (model 14). This does not affect the sign and significance of our variable of interest.

We also test for robustness with country-level controls in Table 3. We again lag all these factors by one year. Support for redistribution might decrease when present levels of redistribution are high because of disincentive effects or because actual levels of redistribution may act as a benchmark when answering questions about whether the government should reduce income differences. Alternatively, individuals may potentially favour more redistribution when existing levels of inequality are

[18]The Eastern European countries are Czech Republic, Estonia, Hungary, Poland, Slovak Republic, and Slovenia. There are a small number of observations for which the calculation of top income levels leads to problems (becoming strongly negative) for these countries, as the number of people in the last or next-to-last income band is too low. We exclude the top income band persons in Czech Republic 2002 (two persons), Hungary 2004 (one), Slovak Republic 2004 (seven), and Slovenia 2006 (one).

[19]More generally, dropping countries, years, or occupations one by one does not affect signs or significance for the variable of interest.

Table 4: Substantive effects of RTI

Occupational risk	Effect on redistribution preferences	95% confidence bounds	
RTI	0.052***	0.039	0.066
Skill specificity	0.024***	0.015	0.033
Offshoring	-0.065***	-0.076	-0.053

higher. We include measures for the absolute and relative levels of redistribution and the levels of market and net income inequality from the Solt (2014) database (models 15 to 18).[20] Adding these factors does not affect the estimates of interest.

Two other country-level factors might be important as they could decrease the level of redistribution individuals favour by providing insurance (Gingrich and Ansell 2012). We include the overall employment protection legislation (EPL) index and the summary measure of OECD unemployment benefit replacement rates (OECD 2014a, c) in models (19 and 20). Once again, our main findings are confirmed.[21] They are also confirmed, finally, when we include country fixed effects in model (21) to control for any unspecified time-invariant country-specific characteristic.

In the previous section we mentioned that, in Table 2, RTI was positively associated with redistribution preferences no matter the number of additional variables in the analysis. The sensitivity tests in Table 3 leave no doubt about the robustness of our results. It is, however, not straightforward to get an intuitive impression of the substantive importance of RTI. We attempt to do this in a comparative fashion, by running a regression where we include two of the other occupational risks discussed in the theoretical section, skill specificity and offshoring. We calculate the effects of a standard deviation increase in each occupational risk and compare these effects.

For RTI, a standard deviation increase is roughly comparable to an occupational

[20] We calculate unweighted averages per country-year observation for our sample from the Solt database. Unfortunately, within our multilevel framework we cannot take standard errors of the levels of inequality and redistribution into account. We also conduct these tests leaving out or original country-level variables, which does not alter the results.

[21] Leaving out the original country-level variables does not alter these results.

switch from extraction and building trades workers to machine operators and assemblers (-0.13 to 0.83). For relative skill specificity, it is approximately equivalent to an individual switching from physical, mathematical and engineering science professionals to sales and services elementary occupations (4.2 to 7.5). For offshoring, it can be interpreted as an occupational switch from metal, machinery, and related trades workers to general managers (0.45 to 0.95).

We can conclude from Table 4 that a one standard deviation increase of the RTI index has an effect that is roughly two times stronger than a comparable increase in skill specificity on the favoured level of redistribution. An (uncorrected) F test indicates that the effect of RTI on redistribution preferences is stronger than the effect of skill specificity at the 1 per cent significance level. As mentioned above, offshoring has a negative association with redistribution preferences. Its (absolute) size is comparable to the size of the RTI index coefficient.

4.2. Evidence for the mediating effect of income

Having found a positive effect of RTI on redistribution preferences, we now enquire whether this relation is intermediated by income. Following an insurance logic, we argued that income would exacerbate the effects of RTI, as richer individuals have relatively more to lose from job loss due to automation. As already stated, we also argued that income itself would be negatively associated with preferences for redistribution. The results from all 3 models in Table 5 support this line of reasoning, showing a positive effect of the interaction between income and the RTI index on preferences for redistribution.

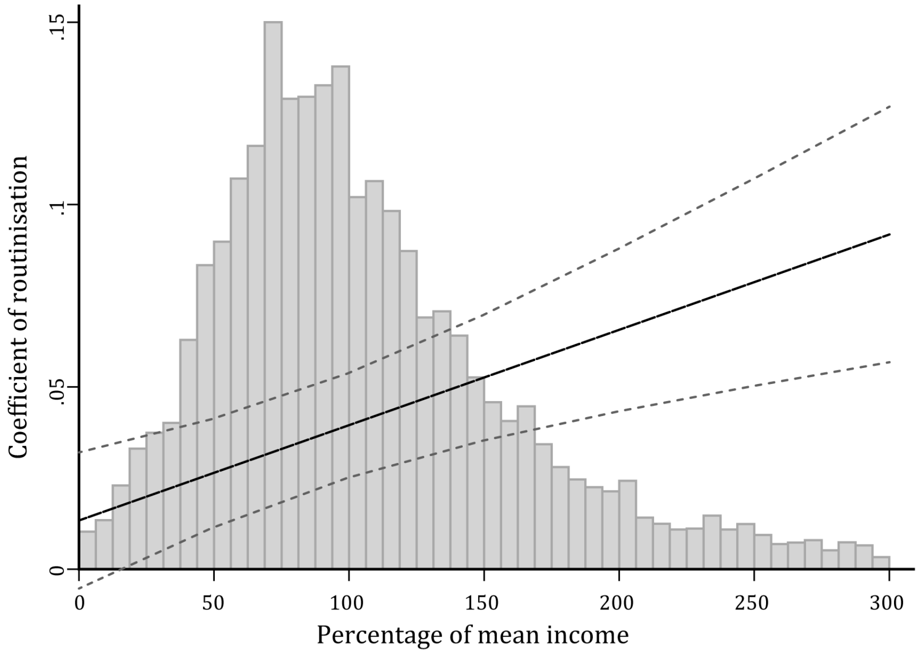
To facilitate the interpretation of the interaction, we evaluate the effect of RTI on redistribution preferences at different levels of income in Figure 2. We use model (3) in Table 5, with the highest number of controls, for our calculations. All continuous control variables are held at their mean and the dummies at their

Table 5: RTI and income interaction

	(1) RTI * income	(2) + individual controls	(3) + country-level controls
RTI	0.068***	0.043***	0.043***
	(0.000)	(0.000)	(0.000)
Income	-0.201***	-0.172***	-0.172***
	(0.000)	(0.000)	(0.000)
RTI * income	0.032***	0.026***	0.026***
	(0.000)	(0.000)	(0.001)
Years of education		-0.022***	-0.022***
		(0.000)	(0.000)
Male		-0.207***	-0.207***
		(0.000)	(0.000)
Age		0.003**	0.003**
		(0.013)	(0.016)
Trade union member		0.176***	0.176***
		(0.000)	(0.000)
Degree of religiosity		-0.008**	-0.008**
		(0.016)	(0.019)
Unemployed		0.139***	0.137***
		(0.000)	(0.000)
Lag of social spending			-0.004
			(0.500)
Lag of unemployment			0.006
			(0.560)
Constant	3.744***	3.988***	4.042***
	(0.000)	(0.000)	(0.000)
Log likelihood	-93162	-92403	-92402
Intraclass correlation	0.104	0.113	0.107
N	64639	64639	64639
Number of countries	17	17	17

Note: Multilevel OLS model with random country intercepts and standard errors clustered at the country level. P values in parentheses, *p<0.1, **p<0.05, ***p<0.01.

Figure 2: Effects of RTI on redistribution preferences conditional on income



Note: Multilevel OLS model with random country intercepts and standard errors clustered at the country level. All continuous control variables are held at their mean and dummies at their median. The black line shows the coefficient of RTI on redistribution preferences (y-axes) at different levels of income (x-axes). The dashed lines are the 95 per cent confidence intervals. The grey histogram plots the distribution of observations across levels of income.

median value. The figure makes clear that the effects of RTI on redistribution preferences are monotonically increasing in the level of income. For individuals with a very low income (less than 25% of mean income), the association between RTI and redistribution preferences is insignificant. For the largest part of our sample, however, RTI is a positive and significant determinant of redistribution preferences, and this influence becomes more substantive as income grows.

We can provide a more formal test for whether the effect of RTI on redistribution preferences differs for individuals with different income levels (and we will also use this framework for our interaction sensitivity tests below). To do this, we define meaningful values of low, average, and high individual relative income. We select 50%, 100%, and 175% of country and year-specific income per year. These are not extreme values, 12% of the observations lie below 50% relative income and 13% of the observations lie above 175% income (and 175% is almost equal to the median plus one standard deviation of relative income).

We can then calculate the effect of RTI on redistribution preferences for an individual with average income, having an income of 100% of the country and year specific mean keeping all other control variables at their mean or median values. Moreover, we can compare the effect of RTI on redistribution for an individual with low income to one with high income, holding everything else equal, and we can calculate a simple (unadjusted) chi square post-estimation test to see whether the effect of RTI on redistribution preferences is statistically different for a low versus a high-income individual.

Table 6 presents the effect of RTI at the different levels of income explained above. We reproduce the robustness tests described in more detail when analyzing the results in Table 3 (and with the same theoretical justifications summarized then). In all tests, the effect of RTI is significant at average levels of income. With one exception, the effect of RTI is less sizeable for individuals with low income and higher for individuals with high income (the exception being the insignificance of low income when controlling for occupational unemployment, which, as mentioned above, is a highly demanding test for us). The chi square tests in the last column show that the effect of RTI on redistribution preferences for individuals with low income is statistically significantly lower than for individuals with high income, without exceptions.

5. Conclusions

Current technological innovations in information technology involve a substantial employment risk for individuals holding routine occupations by facilitating the ease of automation. We find that individuals in routine occupations respond to this risk by

Table 6: Robustness checks for interaction results

		Effect of RTI at different income: average	low	high	Chi square low vs. high
	Original results	0.039***	0.026***	0.059***	12.05***
(1)	RTI from Oesch	0.069**	0.033***	0.122***	18.31***
(2)	Skill specificity	0.036***	0.023***	0.057***	12.59***
(3)	Foreign ratio	0.045***	0.031***	0.067***	14.44***
(4)	Offshoring	0.055***	0.044***	0.072***	9.32***
(5)	Occupational unemp.	0.021***	0.009	0.039***	12.04***
(6)	Task groups (K&R)	0.068***	0.057***	0.086***	11.06***
(7)	Public sector employee	0.046***	0.033***	0.064***	10.76***
(8)	Left-right scale	0.037***	0.026***	0.052***	6.00**
(9)	All individuals	0.034***	0.019***	0.057***	19.14***
(10)	Only employed	0.038***	0.025***	0.056***	9.23***
(11)	Eastern Europe	0.037***	0.021***	0.062***	9.07***
(12)	Excluding 2012	0.039***	0.024***	0.061***	16.89***
(13)	Before 2008	0.035**	0.023***	0.054***	10.96***
(14)	Binary dep. variable	0.017***	0.012***	0.024***	7.72***
(15)	Absolute redistribution	0.039***	0.026***	0.059***	12.03***
(16)	Relative redistribution	0.039***	0.026***	0.059***	12.05***
(17)	Gini market income	0.039***	0.026***	0.059***	11.76***
(18)	Gini net income	0.039***	0.026***	0.059***	11.67***
(19)	EPL index	0.039***	0.025***	0.06***	14.18***
(20)	UB replacement rate	0.039***	0.026***	0.059***	12.01***
(21)	Country fixed effects	0.039***	0.026***	0.059***	12.04***

demanding higher levels of redistribution as a means of nonmarket insurance. Even though technological change is widely considered to be a key occupational driver with large distributive effects, whether it influences the preferred level of redistribution has not been subject of inquiry in the comparative political economy literature thus far. Indeed, our analysis suggests that on average the routine task intensity of an occupation has a larger positive effect on the preferred level of redistribution than other risks described in the literature, in particular skill specificity. We show our results to be robust to a large number of sensitivity tests.

In this paper we also show that the degree of routine task intensity of an occupation becomes a particularly influential determinant of redistribution preferences when an individual has more to lose from automation, that is, when his or her income is higher. Even though richer individuals on average might favour lower levels of redistribution, the routine task intensity of their occupation becomes a more important determinant of their demand for redistribution. Our findings therefore offer an interesting counterpoint to the traditional Meltzer-Richard redistribution story. While recent increases in inequality in industrialized democracies may promote more anti-redistribution attitudes from the affluent, incresing levels of automation risk mitigate these effects. Our results in fact suggest the possibility of cross-class coalitions in support of a redistributive welfare state between low-wage individuals in non-routine occupations and high-wage individuals holding routine occupations. This has potentially significant implications for our understanding of economic voting and insider-outsider politics in industrialized democracies.

This study's empirical work is built on survey data, rather than an experimental design where individuals could be randomly assigned to occupations. One might argue that individuals self-select into occupations, leading to possibly confounded causal interpretations of our results. This reasoning would imply that risk-averse persons who already have higher preferences for the provision of public insurance choose occupations less exposed to risk. Or it could be that individuals in routine occupations (with high redistribution preferences), lose their jobs because of automation, and move to non-routine occupations while keeping higher levels of preferred nonmarket protection. While these arguments point to interesting extensions of our research, it is important to mention that they predict a negative association between the degree of routine task intensity and the preferred level for redistribution, militating against this paper's statistically significant findings of a positive association.

Finally, in this paper we focus on the differences in automation risk (depending on the degree of routine task intensity) across occupations. We devote less attention to country-specific patterns like, for instance, the amount of investment in research and development, or qualitative educational factors that potentially shape how individuals cope with technological change. This would also be an interesting line of future inquiry. More generally, our analysis only begins to explore how technological risks shape actual redistribution and the welfare state. Future research should consider whether exposure to risk of automation affects voting behaviour, and party and policy agendas, and ultimately, actual welfare state policies.

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A. Differences between Kitschelt and Rehm and the RTI index

In this section we compare the Kitschelt and Rehm (2014) dummies based on Oesch (2006), which are meant to capture routine occupations, to the continuous RTI index from Goos et al. (2014) used in this paper. We argue that the RTI index is substantively and empirically superior to the Kitschelt and Rehm (henceforth, KR) dummies if the obejtive is to examine the routine task intensity of occupations. First, the RTI index is continuous and provides significantly more variation across occupational groups. This holds even though the KR dummies are defined at the more detailed 4-digit ISCO-88 occupational level. Second, the KR dummies do not measure the degree of routine task intensity but follow educational and income lines. Third, we have slightly more (5.4 per cent) observations at our disposal for the RTI index.

KR distinguish between four *a* groups which capture a vertical 'logic of authority' dimension (the degree of discretionary space): professionals, associate professionals, skilled routine, and unskilled routine. In addition, KR generate a second 'logic of tasks' dimension with three *t* groups (capturing whether tasks are more or less clearly defined): organisational, technical, and interpersonal task logics. This dimension does not have any clear linkage with RTI. The four *a* and three *t* groups are combined and merged into four *c* groups:

1. Skilled organisational: Professionals and associate professionals with an organisational logic of task structure, who are against redistribution;

2. Skilled technical: Professionals and associate professionals with a technical task structure, with more uncertainty and loose horizontal structures, who are less opposed to redistribution;

3. Skilled interpersonal: Professionals and associate professionals with interpersonal task structure, who accept redistribution;

4. Routine: The skilled and unskilled routine workers in all three aforementioned task structures are grouped here. This group is hypothesised to be in favour of redistribution.

Table 7 shows the mean values for all KR dummies for occupations at the 2-digit ISCO-88 level, where we sort occupations by their level of RTI. Only eight occupations at the 2-digit level for *a* groups and only four occupations for the *c* groups are not fully captured by a dummy (marked in bold). Thus, the more detailed 4-digit level at which the KR dummies are defined barely produces additional variation at a more aggregated level. In fact, the variation is significantly decreased because of the dichotomous nature of the measures.

More importantly, substantively the KR dummies are intended to measure 'unskilled routine' (*a4*) or 'routine' groups (*c4*) as compared to 'authoritarian' (*a1-3*) or 'skilled' groups (*c1-3*) - not to demarcate routine from non-routine occupations. KR stress that they are interested in discretionary space rather than the intensity of routine tasks per occupation. The 'unskilled routine' group *a4* captures all occupations whose ISCO-codes start with an 8 and 9 (plant and machine operators and assemblers, and elementary occupations), almost all occupations with a 5 and 6 (service workers and shop and market sales workers, and skilled agricultural and fishery workers for which we do not have RTI data), and parts of occupations starting with 4 and 7 (clerks, and craft and related trades workers). The 'routine' *c4* group combines groups *a3* and *a4*. It includes all occupations of which the ISCO-88 code begins between 4-9, thus all occupations except legislators, senior officials and managers, professionals, or technicians and associate professionals. This group is very large, covering almost twice the number of observations as the *c1-c3* groups combined for our sample.

Groups *a4* and *c4* do not measure the degree of routine task intensity of occupations contrasted to non-routine abstract or manual task intensive occupations, but closely follow educational and income lines. We can see this in particular for group *c4*, which indeed contains all occupations with a positive RTI index, but also includes for instance occupations 51 (personal and protective services workers) and in particular 83 (drivers and mobile plant operators). As we argue and empirically show, it is not true that all low-skilled occupations are routine (Michaels et al., 2014; Goos et al., 2014). Moreover, as all KR categories are measured as dummies, they do not do justice to the fact that certain occupations are significantly more or less routine than others. The KR dummies distinguish between large groups that largely following educational and income lines - this might include an element of RTI, but it will capture most certainly more, indeed, all (unobserved) differences between these groups.

B. Multilevel probit results

In this section, we present the results of our multilevel ordered probit models, with random country intercepts and standard errors clustered at the country level. Table 8 is the equivalent of Table 2 with our main results. The sign and size of coefficients for our variables of interest are all very comparable. The only difference in terms of individual control variables is the degree of religiosity, which is insignificant in column (4). Regarding the country-level controls, the lag of social spending as % of GDP becomes significantly negative in our ordered probit model.

Table 9 is the equivalent of Table 5 with our interaction results. The sign and size of coefficients for our variables of interest are, once again, comparable (the interaction is slightly smaller in terms of size, for column (3), it is 0.017 at the 5% confidence level for the probit model instead of 0.026 at the 1% for the OLS). And this time there are no differences in terms of individual or country control variables.

Table 7: Comparing RTI index to the Kitschelt and Rehm classification

		Logic of authority groups				Logic of tasks groups			Combined groups			
		Professionals (a1), Associate profess. (a2), Skilled routine (a3), Unskilled routine (a4)				Organisational (t1), Technical (t2), Interpersonal (t3)			a1t1 + a2t1 (c1), a1t2 + a2t2 (c2), a1t3 + a2t3 (c3), a3 + a4 all t-groups (c4)			
ISCO	RTI	a1	a2	a3	a4	t1	t2	t3	c1	c2	c3	c4
13	-1.52	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	0.00
83	-1.50	0.00	0.00	0.53	0.47	0.00	0.64	0.36	0.00	0.00	0.00	1.00
22	-1.00	1.00	0.00	0.00	0.00	0.00	0.12	0.88	0.00	0.12	0.88	0.00
21	-0.82	1.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00
12	-0.75	1.00	0.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	0.00
24	-0.73	0.81	0.19	0.00	0.00	0.52	0.00	0.48	0.52	0.00	0.48	0.00
51	-0.60	0.00	0.00	0.31	0.69	0.00	0.00	1.00	0.00	0.00	0.00	1.00
34	-0.44	0.00	1.00	0.00	0.00	0.79	0.04	0.17	0.79	0.04	0.17	0.00
31	-0.40	0.00	1.00	0.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00
32	-0.33	0.00	0.90	0.10	0.00	0.00	0.09	0.91	0.00	0.09	0.81	0.10
71	-0.19	0.00	0.00	0.91	0.09	0.00	1.00	0.00	0.00	0.00	0.00	1.00
91	0.03	0.00	0.00	0.00	1.00	0.00	0.04	0.96	0.00	0.00	0.00	1.00
52	0.05	0.00	0.00	0.02	0.98	0.00	0.00	1.00	0.00	0.00	0.00	1.00
81	0.32	0.00	0.00	0.00	1.00	0.00	1.00	0.00	0.00	0.00	0.00	1.00
93	0.45	0.00	0.00	0.00	1.00	0.00	1.00	0.00	0.00	0.00	0.00	1.00
72	0.46	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	1.00
82	0.49	0.00	0.00	0.00	1.00	0.00	1.00	0.00	0.00	0.00	0.00	1.00
74	1.24	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	1.00
42	1.41	0.00	0.00	0.24	0.76	1.00	0.00	0.00	0.00	0.00	0.00	1.00
73	1.59	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	1.00
41	2.24	0.00	0.00	0.93	0.07	1.00	0.00	0.00	0.00	0.00	0.00	1.00

Table 8: RTI and redistribution preferences

	(1) RTI only	(2) + individual income	(3) + individual controls	(4) + country-level controls
RTI	0.085***	0.063***	0.049***	0.037***
	(0.000)	(0.000)	(0.000)	(0.000)
Income		-0.215***	-0.182***	-0.181***
		(0.000)	(0.000)	(0.000)
Years of education			-0.028***	-0.025***
			(0.000)	(0.000)
Male			-0.209***	-0.206***
			(0.000)	(0.000)
Age			0.004***	0.003***
			(0.001)	(0.004)
Trade union member			0.130***	0.209***
			(0.000)	(0.000)
Degree of religiosity			-0.013***	-0.008
			(0.007)	(0.168)
Unemployed			0.165***	0.152***
			(0.000)	(0.000)
Lag of social spending				-0.021***
				(0.000)
Lag of unemployment				0.061***
				(0.000)
Log pseudolikelihood	-8.6e+04	-8.6e+04	-8.5e+04	-8.5e+04
Country variance	0.032***	0.053***	0.197***	0.236***
N	64639	64639	64639	64639
Number of countries	17	17	17	17

Table 9: RTI and income interaction

	(1) RTI * income	(2) + individual controls	(3) + country-level controls
RTI	0.067***	0.050***	0.041***
	(0.000)	(0.000)	(0.000)
Income	-0.205***	-0.177***	-0.179***
	(0.000)	(0.000)	(0.000)
RTI * income	0.022***	0.017**	0.017**
	(0.008)	(0.030)	(0.039)
Years of education		-0.028***	-0.024***
		(0.000)	(0.000)
Male		-0.209***	-0.207***
		(0.000)	(0.000)
Age		0.004***	0.004***
		(0.001)	(0.000)
Trade union member		0.130***	0.161***
		(0.000)	(0.000)
Degree of religiosity		-0.013***	-0.008*
		(0.007)	(0.081)
Unemployed		0.166***	0.169***
		(0.000)	(0.000)
Lag of social spending			-0.001
			(0.822)
Lag of unemployment			0.008
			(0.310)
Log pseudolikelihood	-8.6e+04	-8.5e+04	-8.5e+04
Country variance component	0.034***	0.197***	0.061***
N	64639	64639	64639
Number of countries	17	17	17