Growing apart: The comparative political economy of income inequality and social policy development in affluent countries

Thewissen, S.H.

Author: Thewissen, Stefan Hubert
Title: Growing apart : the comparative political economy of income inequality and social policy development in affluent countries
Issue Date: 2015-09-29

5 Technological change as a determinant of redistribution preferences[1]

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 significant substitution of routine work by capital, whilst 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 persons employed in sectors particularly exposed to technological change, and for richer individuals who have more to lose from automation. In this way we combine occupational and sectoral elements of risk exposure, whilst we revisit the role of income in shaping redistribution preferences. The implications of our theoretical framework are tested using survey data for 23 European countries between 2002 and 2012.

5.1 INTRODUCTION

Technological change is widely regarded to be a main driver of long-term economic development (Romer, 1990). By complementing occupations with certain skill profiles whilst making others redundant, it structures employment and significantly shapes the occupational structure (Goldin and Katz, 2008; Oesch, 2013). This entails that technological innovations can have far-reaching social implications that differ across occupations. These implications played a key role for instance in the work of Marx. He regarded technology to be the instrument through which the organisation and execution of work could

---

1 This chapter appeared as Thewissen, S., Rueda, D. (2015) Technological change as a determinant of redistribution preferences, *Leiden Department of Economics Research Memorandum no. 2015.01*. Financial support from the Leiden University Fund and the KETEL 1 scholarship fund is gratefully acknowledged. An earlier version of this study was presented at the 4th European Political Science Association (EPSA) annual general conference, 19-21 June 2014 in Edinburgh. We thank all participants, Nils-Christian Bormann, Koen Caminada, Kees Goudswaard, Robert Hellpap, Lieke Kools, Stefanie Reher, and Margit Tavits for their helpful suggestions. All errors remain ours.

be separated, so that labour could be transformed into deskilled operative work. More optimistically, technological change enables specialisation and skill upgrading, which facilitated societies to shift from routine labour particularly in agriculture towards manufacturing, and later services (Erikson and Goldthorpe, 1992; Iversen and Cusack, 2000; Wren, 2013).

Current technological innovations particularly take place in computer-based information technology. Its precipitous implementation in the last decades has been spurred by significant real price declines in computing power (Autor *et al.*, 2003). Computers are capable in performing routine tasks, which are well defined and repetitive. On the other hand, computer capital complements complex and more ambiguous abstract tasks structures, whilst it does not have clear effects on interpersonal service tasks. Studies report significant decreases in the share of routine occupations, which tend to lie in the middle of the educational and wage distribution. Information technology therefore does not lead to linear upskilling of work, but rather to a process of polarisation (Spitz-Oener, 2006; Autor *et al.*, forthcoming).

Given the pervasive substitutive effects of information technology on routine occupations, we might expect individuals holding routine occupations to prefer additional nonmarket protection to insure against increased risk of employment and wage loss. The conception that preference for insurance against job risks can fuel preferences for redistributive social protection plays a prominent role in the comparative political economy literature. Allusion to risks resulting from technological change have been made within this literature, for instance by Iversen and Cusack (2000) 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'. Yet, occupational susceptibility for technological change is not directly examined by these authors. Kitschelt and Rehm (2014) are to our knowledge the only ones mentioning routine occupations as a group having higher redistribution preferences. The authors, however, do not operationalise this in terms of routine task intensity, but differentiate a routine group based on educational lines.

In this chapter we devote explicit attention to risks of technological change depending on the degree of routine task intensity of occupations as a determinant of redistribution preferences. Because of the widespread implementation, advances in information technology is widely regarded to be a main driver of rising earnings inequality and can therefore be seen as an influential occupational risk (Goldin and Katz, 2008; Michaels *et al.*, 2014). We develop a simple theoretical framework in which risk-averse individuals prefer to insure against occupational hazards by means of redistribution when markets cannot provide such insurance.

Moreover, we argue that insurance preferences resulting from risks of technological change will be accentuated by two factors. First, the degree of routine task intensity of occupations will be a stronger determinant of preferences for social protection for individuals employed in sectors particularly exposed to technological change. Second, we argue that income plays a moderating role, since individuals will have more to lose from automation when their income level is higher. By introducing these moderating variables we aim to bridge the gap between studies emphasising occupational and sectoral risks (Rehm, 2009). Furthermore, we revisit the role of personal income in shaping redistribution preferences, allowing income to have a negative effect on the level of preferred redistribution in the spirit of Meltzer and Richard (1981), whilst it amplifies the effects of risks on redistribution preferences.

The remainder of this chapter is divided into three sections. In Section 5.2 we propose a simple theoretical argument and derive its main empirical implications. We discuss our measure of routine task intensity and our dataset that covers 23 countries between 2002 and 2012 in Section 5.3. In Section 5.4 we examine the empirical validity of our hypotheses and conduct extensive sensitivity tests. We conclude in Section 5.5.

5.2 Our argument

Our line of reasoning is as follows. Current technological innovations involve an occupational risk for individuals depending on the degree to which their occupation is susceptible to automation. The ease of automation increases when an occupation contains more routine tasks. As individuals are risk averse, they favour more redistribution to insure against the risk of automation when the routine task intensity (RTI) of their occupation goes up. Moreover, we theorise that this positive effect of RTI on preferences for redistribution is moderated by two factors. The first factor is risk exposure, which increases when an individual is employed in a sector where technological change plays a prominent role. Second, RTI becomes a more important determinant of redistribution preferences when an individual has more to lose from automation, that is, when his or her income is higher.

5.2.1 Technological change as an unequally distributed occupational risk

The first element of our argument is that technological change causes an employment risk for individuals with routine occupations that can relatively easily be automated. As already mentioned in the introduction, current technological innovations in information technology are generally viewed to have strong and dissimilar effects across occupations (Goldin and Katz, 2008; Oesch, 2013; Wren, 2013). These developments complement individuals with abstract or personal tasks, whilst individuals in routine occupations face an increased risk of being substituted by capital (Autor *et al.*, forthcoming). Routine tasks can be partitioned into step-by-step rules, and do not require cognitive or service task skills that are more difficult to automate (Goos and Manning, 2007; Goos *et al*., 2014). Routine tasks susceptible to automation might well be complex and can require extensive educational training, such as bookkeeping. Because of this, information technology advancements do not impact occupations linearly across educational lines. In fact, routine occupations tend to lie in the middle of the educational and income distribution (Oesch, 2013).

Information technology has generally been found to have substantial effects on the occupational structure in affluent countries in the last decades (see also Autor *et al*., 2003; Spitz-Oener, 2006 for single-country studies). 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, whilst employment in non-routine analytical and interactive occupations went up by 23 to 41 per cent. Michaels *et al*. (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 *et al*. (2014) extend this to 1993-2010 for 16 Western European countries, estimating that technological change and offshoring can account for three quarters of the observed increase in high-skilled non-routine work and the observed decrease in medium-skilled routine employment. Interestingly, these studies all find much weaker or insignificant effects of international trade and offshoring once the impact of technological change is accounted for.

5.2.2 Routine task intensity as determinant of preferences for redistribution

Having put forward that technological change is an employment hazard for individuals in routine occupations, we will now argue that this occupational risk translates into increased preferences for redistribution.

In the classic comparative political economy approach redistribution preferences are a function of material self-interest (Meltzer and Richard, 1981). From this model we would predict that preferences for redistribution are decreasing in the relative level of present individual income at the micro level. An implication of this is that increased market earnings inequality will lead to greater political demand for redistribution at the macro level.

More recently, scholars have distinguished an insurance component of redistribution preferences that incorporates an intertemporal element. When individuals are risk averse, they will prefer to insure against uncertain future income levels. Individuals will favour additional nonmarket insurance when they are presently exposed to an increased risk of job or wage loss, assuming that markets cannot provide for insurance against such risks. Social protection arrangements such as unemployment benefits or social assistance offer insurance for individuals against job and wage loss. As these forms of social security are redistributive (*e.g.*, Nelson, 2011), the redistribution preferences for individuals exposed to risks will go up (Sinn, 1995; Moene and Wallerstein 2001; Iversen and Soskice, 2001; Iversen and Soskice 2009; Rehm 2009). This insurance perspective in understanding determinants of social protection was pioneered and formally modelled by two papers. We will contrast our reasoning to theirs.

Iversen and Soskice (2001; IS from here onwards) argue that individuals with more specific as opposed to general skills favour more insurance as protection against their investment in human capital. In the IS model there is a homogeneous risk of job loss across the electorate, but the opportunities for reemployment are lower for individuals who 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.

Moene and Wallerstein (2001; MW from here onwards) have a slightly different ambition. Using a micro level model, they seek to explain a macro level phenomenon that runs counter to the Meltzer-Richard model, that is, why a more skewed income distribution can in fact lead to lower levels of redistribution. MW theorise that insurance is a normal good, leading individuals to favour more public insurance 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. From this MW conclude that a means-preserving increase in earnings inequality that lowers the income of the median voter decreases preferences for insurance. In the MW 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.

Our point of departure lies closer to the IS model, as we explicitly recognise an occupational hazard, independent of the level of income, that translates into higher preferences for nonmarket protection. We slightly deviate from the IS model by theorising that the risk of job or wage loss is heterogeneous across the electorate, depending on the occupational level of RTI, instead of proposing that reemployment possibilities differ conditional on occupational risk. The implication is similar, however; given a level of income and risk aversion, the occupational risk leads individuals to favour higher levels of nonmarket insurance.

Hypothesis 1: The level of routine task intensity of an occupation positively affects preferences for redistribution

As already stated, technological change has not yet been recognised as an occupational threat in the redistribution preferences literature as far as we know. How does the degree of RTI compare to occupational risks that have been described in the comparative political economy literature? We will show later that correlations among occupational risks are low.

Kitschelt and Rehm (2014) mention routine occupations in their study which also looks at occupational characteristics and redistribution preferences. As we show in more detail in Appendix 5.1, their operationalisation follows educational and income lines and does not capture the degree of routine task intensity of occupations. Kitschelt and Rehm also do not argue that individuals in routine occupations favour more redistribution as an insurance against increased risk of job loss due to automation. Rather, elaborating on Oesch (2006), they are interested in occupations as socialisation profiles. They differentiate occupations based on discretionary disposal over own work (the 'logic of authority'), where the hypothesis is that individuals with more discretionary space and authority over subordinate employees will find the preserving of material incentive to be important, and therefore will be against redistribution. The two groups with the lowest degree of authority are coined skilled and unskilled routine, versus professionals and associate professionals. The differences across these groups are measured by dummies rather than by means of a continuous measure of the routine task intensity of occupations.

We already introduced the degree of skill specificity from the IS model (see also Cusack *et al*., 2006). Skill specificity pertains to job risks following investments in human capital. It comprises a scale of specific versus general skills, instead of whether a certain skill (be it specific or general) is routine, manual, or abstract. There are no *a priori* reasons to believe that the degree of specificity of skills (and therefore occupations) is related to the degree of RTI. As an example, models, salespersons, and demonstrators have the most general skills, whilst stationary-plant and related operators have the most specific skills. In terms of routine task intensity, however, these occupations are very comparable – both are very average as we will also show later.

A second occupational risk is the outsourcing of certain parts of the production process as performed by certain occupations (Grossman and Rossi-Hansberg, 2008). The crucial occupational factor here is the degree to which parts of the production process can be executed abroad, which is generally called offshorability. Walter and co-authors have applied the concept of offshorability to redistribution preferences (2010; 2014; Dancygier and Walter, forthcoming; Rommel and Walter, 2014). There is an analytic distinction between offshorable and automatable occupations (Oesch, 2013: 18-19; Goos *et al*., 2014; Autor *et al*., forthcoming). Certain occupations can relatively easily be executed abroad, but require non-routine cognitive skills that are difficult to automate. Examples are architecture, software developing, or statistical analysis. Other occupations are routine and can be computerised relatively straightforwardly, but require spatial proximity. Examples here are security guards or customer service clerks.

5.2.3 Moderating factors

The last part of our argument concerns factors that moderate the (positive) effect of RTI on preferences for redistribution. We will argue that the importance of RTI as a determinant of nonmarket insurance preferences will be increasing in the degree of sectoral risk exposure and the level of present income. By considering factors that moderate the translation from job risk to preferences for insurance, we part from the IS and MW models. Moreover, the role of the level of present income in affecting redistribution preferences in our model differs from theirs.

We hypothesise that RTI becomes a stronger predictor of redistribution preferences for individuals employed in sectors more exposed to technological change. This can be the result of an increased actual risk of job or wage loss (*e.g.*, Michaels *et al.*, 2014; Thewissen and Van Vliet, 2014), or it can be a consequence of increased visibility of this risk as relatively more individuals employed in the same sector are exposed to risk of automation too. Sectoral differences in risk exposure are examined more frequently in studies on preferences for insurance (*e.g.*, Rehm, 2009; Walter, 2010).[2] Yet, occupational factors are generally seen as more important determinants of nonmarket protection preferences than sectoral factors. Human capital is more tied to an occupation than to an industry, and occupations are considered to be more important socialisation factors (Oesch, 2006; Rehm, 2009; Kitschelt and Rehm, 2014).

> *Hypothesis 2: Sectoral exposure to technological change strengthens the positive effect of the occupational level of routine task intensity on preferences for redistribution*

We propose to view income as a second factor that accentuates the preferred level of insurance for individuals holding more routine occupations. If an individual has relatively more to lose from an occupational risk, then this risk will become a more decisive factor in preferred levels of nonmarket protection. This view deviates from existing models of redistribution preferences. In the Meltzer-Richard model individuals do not have an insurance motive so that the level of income always negatively affects preferred levels of redistribution. Income enters the IS model in a comparable fashion; in their regression results the level of redistribution preferences is also negatively associated with levels of present income. MW, however, argue that insurance is a normal good so

2 We do not include industry-level risks other than technological change in our regressions, such as FDI in value added (Walter, 2010), unemployment rates (Rehm, 2009), or the share of foreign-born workers (Dancygier and Walter, forthcoming). This is because we can only define sectors at a highly aggregated level as we will explain later. Yet, we incorporate occupational equivalents of these variables as sensitivity tests.

that individuals will favour more when their income level goes up. In a follow-up paper (2003) the authors do not explicitly argue that richer individuals prefer more insurance than poorer individuals. Rather, a more skewed income distribution will lead to lower levels of insurance against income loss compared to a more equalised country with the same mean income and risk distribution. We still follow Meltzer-Richard in hypothesising that income has a negative direct effect on redistribution preferences. Yet, we add a moderating effect of income to this. We pose that RTI translates into higher favoured levels of insurance particularly when individuals have more to lose. Thus, in our model, income has a direct negative effect on preferred levels of redistribution, but it will positively influence the effects of RTI on redistribution preferences.

> *Hypothesis 3: The individual level of present income strengthens the positive effects of the occupational level of routine task intensity on preferences for redistribution*

To our knowledge, individual levels of income or sectoral exposure have not been considered as moderating factors in existing studies on redistribution preferences. Other scholars have argued that educational levels moderate the effects of offshoring on redistribution preferences, since high-skilled individuals benefit from globalisation whilst low-skilled individuals lose (Walter, 2010; Dancygier and Walter, forthcoming). In addition, country-level institutions that mitigate risks have been put forward as a moderating factor in the effects of skill specificity on preferences for insurance (Gingrich and Ansell, 2012).[3]

5.3 Data

5.3.1 Routine task intensity across occupations

In our theoretical section we argued that individuals holding routine occupations particularly bear risks of wage or employment loss from automation. We use the routine task intensity index from Goos *et al*. (2014), who rely on Autor and Dorn (2013) and Autor *et al*. (forthcoming). Goos *et al*. (2014) 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 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 *et al*. (2014) rescale these actual measures to mean 0 and standard deviation 1.

3 We test for the effects of these possibly confounding factors in our sensitivity analysis.

Measures are available at the 2-digit occupational International Standard Classification of Occupations (ISCO)-88 level.[4]

Another occupational measure of the degree of routine task intensity comes from Oesch (2013). Oesch codes occupations at the 4-digit ISCO-88 level into multiple non-routine and routine occupations drawing on Spitz-Oener (2006), also differentiating between routine, manual, and abstract (or analytical and interactive) tasks. 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 *et al*. (2014) are quite highly correlated (0.73). As we have more variation and more observations for the continuous Goos *et al*. RTI index, 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-section data of redistribution preferences of individuals. It has a standardised 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.[5] By means of this occupational identifier we can link individuals to the RTI index of Goos *et al*. (2014). Our analysis draws on ESS surveys between 2002-2012 for the 23 countries for which at least two waves of information is available.[6]

To obtain a better understanding 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 operationalisation of education and income. We define the level of education by years of education maximised to 25. Our measure of present income is constructed using respondents' answers to the ESS survey question on household's total net income. Respondents answer on the basis of a show-card, which contains categories identifying income ranges for weekly, monthly, or annually income. We transform the income bands into their survey-specific midpoints, following Rueda *et al*. (2014) and Rueda (2014). The highest income band, which has no upper limit, is assumed to follow a

4 For six groups at the 2-digit ISCO-88 level no information on RTI is available. These agricultural, supervisory, and residual occupational groups are also excluded by Goos *et al*. (2014), Autor *et al*. (forthcoming), and Autor and Dorn (2013).

5 The correspondence table can be found here: http://www.ilo.org/public/english/bureau/stat/isco/isco08/index.htm. A number of occupations are not included in the ILO correspondence table but can easily be transformed to ISCO-88 at the 2-digit level; coding is available upon request. Only a couple of occupations (for 0.1 per cent of the sample) cannot unequivocally be coded and are left out. None of our results change when we exclude 2012 in which the ISCO-08 coding is used, as shown in the sensitivity tests. We have to exclude individuals in all waves for which information is only available at the 1-digit ISCO level (0.8 per cent of the total sample).

6 Austria, Belgium, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Luxembourg, the Netherlands, Norway, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, and the UK.

Pareto distribution (Hout, 2004; Kopczuk *et al.*, 2010).[7] Self-reported household's total net income is recoded into annual 2010 PPP-adjusted US dollars using exchange rate information from the OECD (2014e). In our regressions we place income in natural log.

Table 5.1 lists the occupations ranked by their level of RTI. We can see that on average non-routine occupations have a higher wage and educational level. Yet, these relationships are not very strong; particularly middle-paid and middle-skilled occupations have high values of RTI (Autor *et al.*, forthcoming; Goos *et al.*, 2014). This is also reflected in relatively low correlations between the RTI index and income (-0.14) 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 are drivers and mobile-plant operators, a low-skilled low-paid occupation. The most routine occupations are customer service and office clerks, and precision workers. These middle-skilled occupations require relatively few cognitive or interpersonal skills and can fairly easily be partitioned into step-by-step rules.

In our theoretical section we already discussed findings from the labour economics literature that automation is a significant risk for individuals holding routine occupations (Autor *et al.*, 2003; Spitz-Oener, 2006; Goos *et al.*, 2014; Michaels *et al.*, 2014). Using the ESS data we can also look at developments in employment measured by headcounts and wages. As shown in Table 5.1, we can see that within the relatively short time frame of 2002-2012 non-routine occupations (with a negative RTI score) saw on average an increase in their employment share and a higher increase in their wage compared to routine occupations (with a positive RTI score).

7 From 2002-2006 respondents were shown 12 categories that were the same across all countries. The waves 2008-2012 distinguish between 10 categories that differ per country. Moreover, the income bands of the show-card cover substantially different income ranges. We calculate the survey specific midpoints. For the upper band we apply the Hout (2004) calculation, with frequency f and lower limits L, and the country- and wave-specific highest income band indexed as *top* and next-to-last as *top*–1: $M_{top} = L_{top}\frac{V}{V-1}$ where $V = \frac{\ln(f_{top-1} + f_{top}) - \ln(f_{top})}{\ln(L_{top}) - \ln(L_{top-1})}$. There are a small number of observations for which this calculation leads to incorrect top income calculations, 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). Leaving out these country waves does not affect our main results.

Table 5.1 Levels and changes in employment shares and wages for occupations ranked by their level of RTI

				Wages		Employment shares	
	ISCO	RTI	Average years of education	2002 average (dollar)	% change 2002-2012	2002 average	% change 2002-2012
Non-routine		*-0.68*	*14.1*	*42522*	*12.61*	*61.06*	*0.26*
General managers	13	-1.52	14.0	45287	21.56	3.78	3.99[1]
Drivers and mobile-plant operators	83	-1.50	11.4	30073	11.95	4.23	0.31
Life science and health professionals	22	-1.00	17.7	55880	3.65	2.06	0.93
Physical, mathematical and engineering science professionals	21	-0.82	16.6	52930	6.67	3.94	0.44
Corporate managers	12	-0.75	15.4	60583	8.99	6.42	-4.90
Other professionals	24	-0.73	16.5	49217	9.21	6.43	0.04
Personal and protective services workers	51	-0.60	12.4	31930	13.51	9.37	0.56
Other associate professionals	34	-0.44	14.3	42901	13.23	10.23	0.17
Physical and engineering science associate professionals	31	-0.40	14.0	40254	20.93	5.05	-1.33
Life science, health associate professionals	32	-0.33	14.9	39797	12.92	3.93	-0.19
Extraction and building trades workers	71	-0.19	11.5	30531	12.28	5.64	0.24
Routine		*0.91*	*12.0*	*31708*	*5.53*	*38.94*	*-0.26*
Sales and services elementary occupations	91	0.03	10.7	26293	6.00	5.24	1.65
Models, salespersons and demonstrators	52	0.05	12.3	31327	5.80	5.14	0.59
Stationary-plant and related operators	81	0.32	11.7	31056	13.98	1.29	-0.14
Labourers in mining, construction, manufacturing and transport	93	0.45	11.1	27040	-1.37	2.60	0.38
Metal, machinery, related trades workers	72	0.46	12.0	31894	16.30	6.26	-2.13
Machine operators and assemblers	82	0.49	11.4	28833	5.78	3.34	1.61
Other craft and related trades workers	74	1.24	10.9	27845	4.20	2.29	-0.19
Customer services clerks	42	1.41	13.1	34873	2.57	2.28	0.81
Precision, handicraft, printing and related trades workers	73	1.59	12.3	34770	13.97	0.94	-0.45
Office clerks	41	2.24	13.1	36991	13.14	9.56	-2.40

Note Average values for RTI, average years of education, and wages for non-routine and routine weighted by employment share

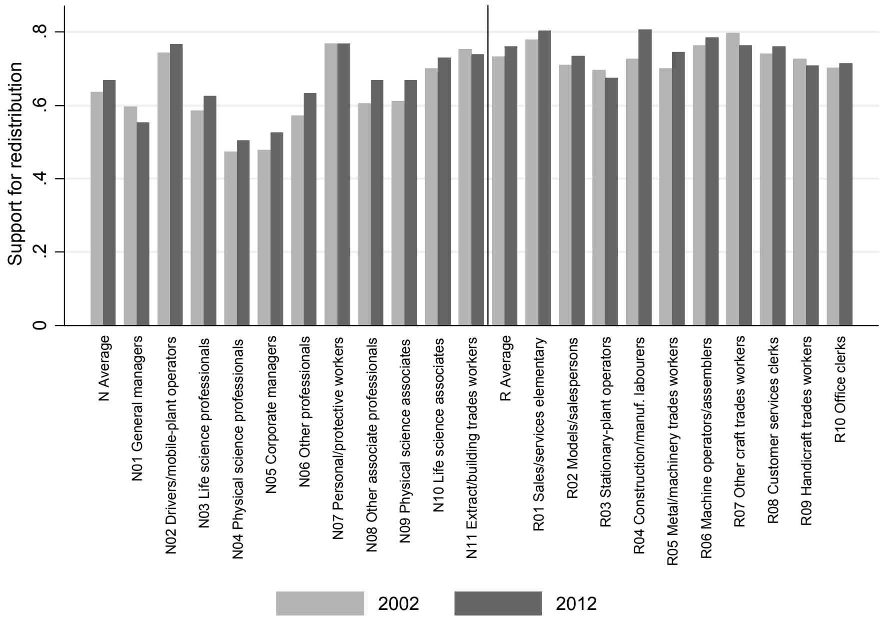
[1] The substantial increase in employment for general managers combined with the large drop in number of corporate managers is at least partly due to coding differences between ISCO-08 (for 2012) and ISCO-88 (for earlier waves). If we calculate the employment difference between 2002 and 2010 the employment share of general managers increased by 0.97, whilst the employment share of corporate managers dropped by -0.16. As already stated, none of our results change when we leave out 2012.

5.3.2 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 to the following statement: 'Using this card, please say to what extent you agree or disagree with each of the following statements: The government should take measures to reduce differences in income levels'. This variable is recoded to capture support for government redistribution. Our final measure contains the following categories: 1: Disagree strongly; 2: Disagree; 3: Neither agree nor disagree; 4: Agree; and 5: Agree strongly.[8] This question is the only one tapping into social policy preferences available in all waves of the ESS, and the question is frequently used in studies seeking to explain redistribution preferences (Rehm, 2009; Burgoon *et al.*, 2012; Burgoon, 2014; Kitschelt and Rehm, 2014; Rueda, 2014; Wren and Rehm, 2014; Hausermann *et al.*, forthcoming). The mean of our ordinal measure of support for redistribution for the full sample is 3.73. Support for redistribution went slightly up on average from 3.65 (2002) to 3.81 (2012).

To better view the differences in redistribution preferences across occupations, we generate a binary measure for support for redistribution equal to 1 if an individual agrees or agrees strongly with support for redistribution (see also Rehm, 2009; Wren and Rehm, 2014). This variable has an overall mean of 0.68; its average values increased from 0.67 in 2002 to 0.70 in 2012. In Figure 5.1 we rank the occupations on their level of RTI, again distinguishing between occupations with a negative RTI index score (non-routine, N) and a positive RTI index level (routine, R). We can see that on average individuals in routine occupations have higher levels of support for redistribution. In both groups support for redistribution increased over time.

Figure 5.1 Support for redistribution across occupations in 2002 and 2012



8 Refusals and don’t knows are recoded as missings (1.7 per cent of the sample).

5.3.3 Sectoral exposure

In our theoretical section we hypothesised that income and sectoral exposure can moderate the relationship between RTI and preferences for public insurance. We already explained how we measure income. The ESS contains a sectoral identifier whose definition unfortunately differs across waves. We generate a standardised sectoral identifier based on the 1-digit Nomenclature statistique des Activités économiques dans la Communauté Européenne (NACE) 1.1 level.[9]

We follow Wren and Rehm (2013) by defining the degree of exposure at the sectoral level using our occupational indicator for RTI. We use the means of the RTI index for this. We can see in Table 5.2 that manufacturing, financial intermediation, and wholesale and retail trade are sectors containing on average relatively large volumes of routine work, and can therefore considered to be exposed to technological change. Interestingly, public administration is also relatively exposed to RTI, which again illustrates the substantive difference between RTI and offshoring. We can see that exposure is low in agriculture, hotels and restaurants, but also in health and social work. This corresponds to their large shares of manual and interpersonal work.

Table 5.2 Sectoral exposure

Sector	NACE	Exposure
Agriculture and fishing	AtB	-0.46
Hotels and restaurants	H	-0.46
Health and social work	N	-0.40
Transport, storage, communication	I	-0.25
Education	M	-0.22
Other community, social and personal service activities	O	-0.22
Real estate, renting, business activities	K	-0.21
Construction	F	-0.18
Mining	C	-0.15
Electricity, gas, water supply	E	-0.04
Public administration, defence, social security	L	-0.01
Wholesale and retail trade	G	0.01
Financial intermediation	J	0.06
Manufacturing	D	0.20

9 ESS 2002 is based on NACE Rev. 1.0, 2004-2008 on NACE Rev. 1.1, and 2010-2012 on NACE Rev. 2.0. To link NACE Rev. 1.0 and 1.1 we only need to drop the tiny industry P: Activities of households. NACE Rev. 1.1 and 2.0 can be (slightly imperfectly) linked, but only at the 1-digit level. We use the correspondence table from the UK National Statistics (2009: 2-3) for this.

5.3.4 Other individual-level controls

We include a vector of common controls in the redistribution preferences literature (*e.g.*, Rehm, 2009; Burgoon, 2014; Rueda *et al.*, 2014). We include variables for years of education, age in years, the degree of religiosity (scaled 1-10), and we include dummies for gender, (former) trade union membership, and whether an individual is unemployed. This last dummy can be seen as a measure of realised risk; if an individual lost her or his job (Cusack *et al.*, 2006).

5.3.5 Country-level factors

At the country level, we follow the literature by including social spending as a percentage of GDP (Burgoon *et al.*, 2012; Rueda *et al.*, 2014) and the unemployment rate (Burgoon *et al.*, 2012; Burgoon, 2014), both lagged one year.[10] By including ex-ante levels of social spending we can account for possible diminishing marginal returns to redistribution, yielding a negative association between social spending and preferences for redistribution (Burgoon *et al.*, 2012). It could be that higher levels of social spending also affect the occupational distribution, for instance by leading to higher levels of public versus private employment. We expect that individuals favour higher levels of redistribution as means of insurance when unemployment is soaring. The unemployment rate might affect the occupational distribution when certain occupations are more severely affected by cyclical movements.

5.4 Empirical estimations

5.4.1 Model specification

We account for the fact that individuals are nested within countries by applying a multilevel model with random intercepts for countries, and we cluster standard errors at the country level.[11] Our dependent variable is categorical and ordered. We could analyse its determinants by applying ordered probit or ordinary least squares (OLS) estimation techniques. An ordered probit model has the advantages that predicted probabilities are restricted to the range of the dependent variable and it corrects for heteroskedasticity resulting from the categorical nature of the dependent variable. Yet, interaction effects in

10 Data for social spending for Switzerland in 2009 (linked to 2010 in our dataset) are missing. We impute this observation by linear interpolation; this does not affect our results.

11 As we will in our sensitivity tests, none of our results change when we use a crossed random effects model for occupations and countries.

nonlinear models cannot be directly interpreted (Ai and Norton, 2003; Greene, 2010). Moreover, in a more complicated multilevel setting, the models sometimes do not converge. A linear OLS model does not have these drawbacks, and we already correct for heteroskedasticity by clustering our standard errors at the country level. We estimate our equations using both techniques. Our results and even coefficients are very comparable. All predicted probabilities for our OLS tests fall neatly in the range of the dependent variable. Therefore, we follow Burgoon (2014) and show the results of our OLS estimations of which the interaction effects are easier to plot. We list the results for the multilevel ordered probit models in Appendix 5.2.

In our regressions we demean sectoral exposure and ln income. The only effect of this is that the RTI coefficient can be interpreted as the effect of RTI on redistribution preferences when income and sectoral exposure are at their mean, instead of when income and sectoral exposure are zero which is a substantively meaningless case.

5.4.2 Main results

The results of our estimation of the effects of RTI on redistribution preferences are presented in Table 5.3. We first briefly reflect on the coefficients of our control variables. These estimates are all consistent with previous findings in the literature. First, we find that poorer individuals favour higher levels of redistribution than richer. This is in line with our expectations based on the Meltzer-Richard model. The coefficient implies that a 1 per cent increase in income is associated with a 0.002 decrease in expressed redistribution preferences, or an individual with twice the income is predicted to have a 0.14 lower level of redistribution preferences, *ceteris paribus*. Furthermore, being lower educated, older, female, unemployed, and being a trade union member all increase the likelihood of approving that the government should reduce income disparities (*e.g.*, Rehm, 2009; Burgoon, 2014). The ordered probit models yield fully comparable estimations of the individual-level variables. The OLS models do not show signs of significant effects of social spending or the unemployment rate. The ordered probit models, however, point to positive associations for the unemployment rate. This is in line with the hypothesis that individuals favour more nonmarket protection when unemployment rates are higher.[12]

12 The difference between probit and OLS for the country-level variables potentially arises from the fact that probit models tend to require a larger number of countries than linear OLS models to derive reliable estimates. For our model which only includes random country intercepts, the bias of estimated country effects is limited as long as 15-20 countries are present (Stegmueller, 2013).

We now move to our main variables of interest. In model 1 we test for the direct effects of RTI on preferences for redistribution. Our findings indicate that RTI is positively associated with redistribution preferences. 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. As we will show in the sensitivity tests, the positive effect of RTI on redistribution preferences remains robust in different specifications and when other occupational risks are added. We will look into the size of the coefficient compared to other occupational risks in this section as well.

Table 5.3 RTI and redistribution preferences

	RTI	Interacted with sectoral exposure	Interacted with income	Both interactions
	(1)	(2)	(3)	(4)
RTI	0.042***	0.050***	0.043***	0.050***
	(0.000)	(0.000)	(0.000)	(0.000)
ln income	-0.202***	-0.197***	-0.195***	-0.191***
	(0.000)	(0.000)	(0.000)	(0.000)
Sectoral exposure		-0.180***		-0.172***
		(0.000)		(0.000)
RTI * sectoral exposure		0.144***		0.144***
		(0.000)		(0.000)
RTI * ln income			0.046***	0.042***
			(0.000)	(0.000)
Years of education	-0.027***	-0.028***	-0.027***	-0.027***
	(0.000)	(0.000)	(0.000)	(0.000)
Male	-0.189***	-0.172***	-0.188***	-0.172***
	(0.000)	(0.000)	(0.000)	(0.000)
Age	0.002***	0.002***	0.002***	0.002***
	(0.009)	(0.009)	(0.007)	(0.007)
Trade union member	0.160***	0.159***	0.160***	0.159***
	(0.000)	(0.000)	(0.000)	(0.000)
Degree of religiosity	-0.006	-0.006	-0.006	-0.006
	(0.155)	(0.133)	(0.159)	(0.137)
Dummy unemployed	0.096***	0.098***	0.100***	0.101***
	(0.000)	(0.000)	(0.000)	(0.000)
Social spending in %GDP$_{t-1}$	0.007	0.007	0.007	0.006
	(0.280)	(0.329)	(0.295)	(0.342)
Unemployment rate$_{t-1}$	0.000	0.000	0.000	0.000
	(0.965)	(0.966)	(0.953)	(0.956)
Constant	3.933***	3.941***	3.928***	3.936***
	(0.000)	(0.000)	(0.000)	(0.000)
Log likelihood	-111158.0	-111072.2	-111121.9	-111041.1
Intraclass correlation	0.082	0.083	0.083	0.083
N	78050	78050	78050	78050
Number of countries	23	23	23	23

Note Multilevel OLS model with random country intercepts and standard errors clustered at the country level. Sectoral exposure and ln income are demeaned. *P* values in parentheses, *p<0.1, **p<0.05, ***p<0.01

Having found a positive effect of RTI on redistribution preferences, we now enquire whether this relation is moderated by sectoral exposure. Following the insurance logic our second hypothesis was that the positive linkage between RTI and redistribution preferences increases for individuals working in sectors more exposed to RTI. Thus, we expect a positive sign for our interaction between sectoral exposure and the RTI index. Again, our empirical results support our theoretical expectations as can be concluded from model 2 in Table 5.3. We find positive associations between our dependent variable and the interaction of the RTI index and sectoral exposure. Additional tests where we also demean the RTI index (results not shown here) show that the constituent element of sectoral exposure itself is negative, whilst the constituent RTI index variable remains positive.[13] This seems to suggest that sectoral exposure is not an important driver of preferences for public insurance by itself. This finding corresponds to Rehm (2009) that occupational factors matter more for insurance motivations. Still, our results indicate that sectoral exposure accentuates the effects of occupational hazards on individual preferences for nonmarket protection.

Next, we address the role of income as a factor that can strengthen the association between RTI and preferences for redistribution (hypothesis 3). As we already stated, income itself is always negatively associated with preferences for redistribution. Yet, income can moderate the effects of RTI on preferences for redistribution, as richer individuals have relatively more to lose from job loss due to automation. Our empirical results from model 3 in Table 5.3 support this line of reasoning as indicated by a positive effect of the interaction effect of income and the RTI index on preferences for redistribution.

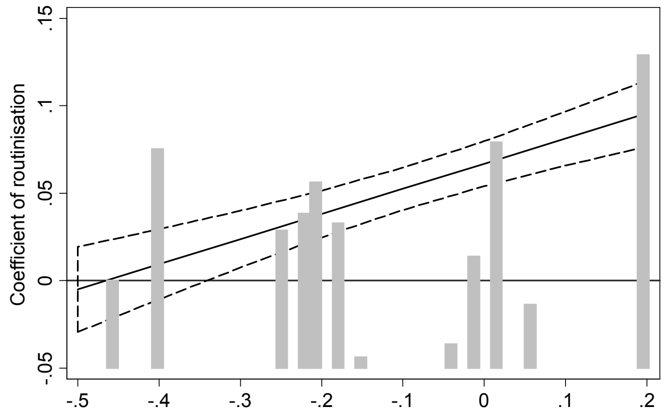
Having established that income and sectoral exposure strengthen the effects of RTI on redistribution preferences separately, we now move to a simultaneous estimation. In this way we test whether both interactions have explanatory power, or whether they are picking up a similar moderating pattern. We do this here by estimating both interactions in one equation as shown in model 4.[14] The two interactions and their constitutive parts remain significant, and the coefficients barely change. Thus, income and sectoral exposure have an independent moderating effect on the relationship between RTI and redistribution preferences. From this we can conclude that higher levels of RTI particularly translate into higher preferred levels of redistribution when individuals are working in exposed sectors and when they are richer. This does not necessarily mean that richer individuals have higher levels of redistribution preferences, as the level of income itself is still negatively associated with preferred levels of redistribution.

13 Demeaning the RTI index does not affect the constituent coefficient of sectoral exposure much, as the RTI-index is normalised.

14 Another way of simultaneously analysing the moderating effects of income and sectoral exposure on the relationship between RTI and redistribution preferences would be to estimate a triple interaction between these variables. We do this in Appendix 5.3; results confirm our findings presented here.

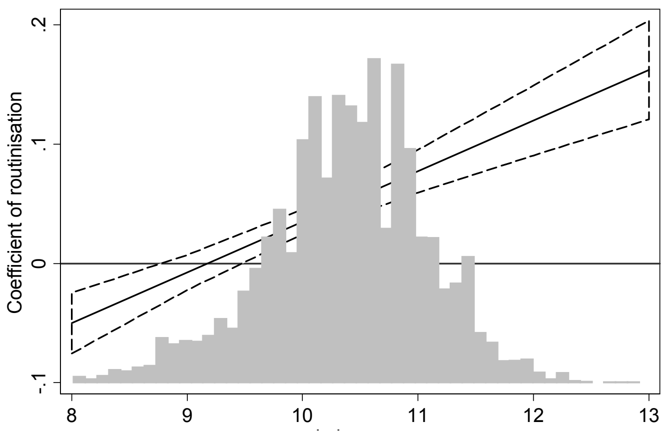
Figure 5.2 Effects of RTI on redistribution preferences conditional on sectoral exposure and income

5.2a Conditional on sectoral exposure



Degree of sectoral exposure

5.2b Conditional on income



ln 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 sectoral exposure or ln income (*x* axes). The dotted lines are the 95 per cent confidence intervals. The grey histogram plots the distribution of observations across levels of sectoral exposure and ln income

To ease the interpretation, we evaluate the effect of RTI on redistribution preferences at different levels of sectoral exposure and income in Figure 5.2.[15] All continuous control variables are held at their mean and the dummies at their median value. We can see in Figure 2a that for individuals in sheltered sectors (with a sectoral exposure below -0.35, or 18 per cent of the sample) RTI is not a significant determinant of redistribution preferences. Above this threshold, the RTI index at the occupational level becomes an increasingly stronger determinant of preferences for redistribution.

We also see that the effects of RTI on redistribution preferences are monotonically increasing in the level of income (Figure 2b). For individuals with a very low income we find that RTI is associated with lower rather than higher levels of redistribution preferences, but this only holds for a minor part of our sample (5 per cent of the sample). For a slightly larger part of our sample the association between RTI and redistribution preferences is insignificant (15 per cent of the sample). Above this income threshold RTI becomes a positive and significant determinant of redistribution preferences. The size of the coefficient of RTI increases when the level of individual income goes up.

5.4.3 Sensitivity tests

We conduct a battery of sensitivity tests to examine the robustness of our results. In Table 5.4 we show the effects of these tests on the coefficients of the RTI index and its interactions with sectoral exposure and income for OLS.[16] In Appendix 5.2 we also display the results of these sensitivity tests for our multilevel ordered probit models. We conclude from these tests that the effects of RTI on redistribution preferences and the moderating effects of sectoral exposure and income are robust.

---

15 We show the effects for model 4, holding the other interaction effect constant. The marginal effects for models 2 and 3 with only one interaction effect at the time produce fully comparable results.

16 Signs and significance of the control variables are unaffected by these amendments (available upon request).

Table 5.4 Robustness checks for our OLS results

		RTI	ln income	Sectoral exposure	RTI * sectoral exposure	RTI * ln income
	Original results	0.050***	-0.191***	-0.172***	0.144***	0.042***
(1)	Dummy RTI from Oesch (2013)	0.081***	-0.212***	-0.313***	0.352***	0.050***
(2)	Sectoral definitions from Wren and Rehm (2014)	0.045***	-0.190***	-0.101***	0.044***	0.042***
(3)	Standardised ln income	0.050***	-0.141***	-0.173***	0.140***	0.034***
(4)	Equivalised ln income	0.051***	-0.196***	-0.176***	0.143***	0.037***
(5)	Skill specificity	0.047***	-0.189***	-0.199***	0.122***	0.043***
(6)	Offshoring	0.061***	-0.188***	-0.118***	0.120***	0.037***
(7)	Logic of task groups	0.072***	-0.175***	-0.131***	0.070***	0.035***
(8)	Foreign ratio	0.055***	-0.187***	-0.184***	0.146***	0.043***
(9)	Occupational unemployment rate	0.031***	-0.173***	-0.156***	0.134***	0.043***
(10)	Left-right scale	0.046***	-0.168***	-0.153***	0.119***	0.040***
(11)	All individuals	0.042***	-0.167***	-0.153***	0.107***	0.044***
(12)	Only employed	0.050***	-0.205***	-0.188***	0.146***	0.042***
(13)	Excluding Eastern Europe	0.052***	-0.189***	-0.211***	0.157***	0.045***
(14)	Excluding 2012	0.049***	-0.195***	-0.170***	0.137***	0.041***
(15)	Binary dependent variable	0.020***	-0.074***	-0.060***	0.060***	0.017***
(16)	Redistribution	0.050***	-0.191***	-0.171***	0.144***	0.042***
(17)	Gini market income	0.050***	-0.193***	-0.170***	0.143***	0.042***
(18)	EPL index	0.049***	-0.191***	-0.173***	0.149***	0.042***
(19)	UB replacement rate	0.050***	-0.194***	-0.173***	0.144***	0.042***
(20)	Crossed effects	0.077***	-0.159***	-0.155***	0.074***	0.024***

Note Multilevel OLS model with random country intercepts and standard errors clustered at the country level. Sectoral exposure and ln income are demeaned. *p<0.1, **p<0.05, ***p<0.01

First we use alternative measures of technological change and the moderating variables.[17] 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 preferences become stronger. The same holds for the moderating effects of sectoral exposure. We also use a different coding scheme to examine sectoral exposure to technological change (model 2). Wren and Rehm (2014) distinguish between four types of sectors on the basis of their exposure to information and communications technology and tradability. We follow their suggestions and generate a dummy equal to 1 for the sectors characterised by high rates of information technology intensity (the traditional sectors and technology-intensive services), and to 0 for other sectors (non-technology intensive services and welfare and government services). Signs and significance levels do not change. Furthermore, we employ alternative definitions for real income. First, we standardise income across countries to make sure that results are not driven by differences in average income across countries (model 3). Also equivalising income using the square root of the household size to correct for differences in household composition does not affect our results (model 4).

Next, we include other occupational risks into our regression model. We can see from Table 5.4 that this does not influence the significance of our

17 Plotting the interactions with these moderating variables yield results very comparable to the ones shown in Figure 5.2 (available upon request).

coefficients of interest. A first alternative occupational risk is skill specificity (Iversen and Soskice, 2001; Cusack *et al.*, 2006). We use the measure of relative skill specificity as also used by Rehm (2009).[18] This is a time-invariant measure available at the 2-digit ISCO-88 level. Second, we rely on Walter's binary index of offshoring (2010; 2014; Dancygier and Walter, forthcoming). This index is defined at the 4-digit ISCO-88 level.[19] We already argued that RTI substantively differs from skill specificity and offshoring. This is also reflected in modest correlations (0.15-0.21). We find that individuals whose occupations require more specific skills favour more insurance (model 5; *e.g.*, Iversen and Soskice, 2001; Cusack *et al.*, 2006). Interestingly, individuals in offshorable occupations decrease rather than increase their preferred level of redistribution (model 6). This finding is also reported by Walter (2014). Walter argues that exposure to offshoring increases risk perceptions among low-skilled, whereas high-skilled or the 'globalisation winners' lower their preferred levels of redistribution, which can explain the negative coefficient of offshoring on redistribution preferences.[20]

Furthermore, we include dummies for the technical and interpersonal task logic from Kitschelt and Rehm (2014). Dummies are defined at the 4-digit ISCO level. We find that these two groups have higher preferences for redistribution compared to the baseline group with an organizational task logic (model 7), as predicted by Kitschelt and Rehm. In fact, including these dummies almost doubles the size of the RTI index coefficient. We do not show the results if we include dummies for the logic of authority or the combined groups, as they eat up much of the variation given that one dummy captures all routine occupations (plus more, as shown in Appendix 5.1). If we were to include these dummies, then all interaction effects remain comparable, but RTI itself becomes insignificant.

In the literature more occupational risks have been discerned that substantively differ from RTI, but might still be seen as confounding factors. Burgoon *et al*. (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 at the 2-digit ISCO-88 level from the OECD migration database (OECD, 2008b). Data refer to around 2000. We find that individuals within occupations with higher ratios of foreigners have higher levels of redistribution preferences (model 8), as also found by Burgoon *et al*. (2012). More importantly, the significance of our variables of interest is not affected by including this occupational hazard.

18 The measure is taken from http://www.people.fas.harvard.edu/~iversen/SkillSpecificity.htm. This website also contains information regarding its measurement.

19 We are grateful to Stefanie Walter for sharing her coding with us. We cannot use ESS wave 2012 as the ISCO-08 definitions cannot be recoded into ISCO-88 at the 4-digit ISCO level.

20 Following Walter (2014), the negative association between offshoring and preferences for redistribution disappears when an interaction effect between offshoring and years of education is included.

Next, we include the occupational unemployment rate from Rehm (2009; model 9).[21] This is a stringent test, since our argument is that RTI leads to an increased job or wage loss risk, and because of this, to higher levels of preferred nonmarket protection. 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 (0.22).[22] As expected, including the occupational unemployment rate decreases the size of the RTI index coefficient on redistribution preferences, though it remains significant at the 1 per cent. The occupational unemployment rate positively affects the preferred level of redistribution.

Our main analysis does not include the left-right inclination of individuals, as we state that redistribution preferences, which we seek to explain, are a key element of expressed ideology (Rueda *et al.*, 2014). Nevertheless, left-right self-placement might constitute an independent determinant of redistribution preferences (see *e.g.*, Margalit, 2011). Our estimates are robust to the inclusion of left-right self-placement measured on a scale of 1-10 (model 10). Evidently, individuals that consider themselves more leftist prefer higher levels of redistribution.

Furthermore, we test the robustness of our results to the sample definition. First, we expand our sample by 67 per cent by including all individuals for which information is available (model 11). We insert an additional dummy for people not active in the labour market. Second, we repeat our estimations for only employed individuals, which reduces our sample size by 6 per cent (model 12). Both of these sample amendments do not affect our main results. Furthermore, results might be driven by the country and time sample. Excluding the Eastern European countries (model 13) or leaving out 2012 which is based on another occupational coding scheme (model 14) does not affect our results either.[23]

By applying OLS and ordered probit estimation 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 (see also Busemeyer and Garritzmann, 2014). 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 15). This does not affect the signs and significance of our variables of interest for our multilevel OLS and probit estimations.

---

21 We thank Philipp Rehm for sharing his occupational information. Unfortunately, no high-quality data are available at the two-digit level. Data for Luxembourg are missing.

22 The correlations between the occupational unemployment rate and the other occupational risks we discuss are significantly weaker.

23 More generally, dropping countries, years, or occupations one by one does not affect signs or significance levels.

We also account for other factors at the country level. We again lag all these factors by one year. Support for redistribution might decrease when present levels of redistribution are high. Higher levels of redistribution might lead to stronger disincentive effects (Thewissen, 2014), and individuals potentially take this into account when forming their redistribution preferences. Individuals might also use actual levels of redistribution as a benchmark when answering the question about whether the government should reduce income differences (Rueda *et al.*, 2014). Furthermore, we include the ex-ante level of market inequality (Burgoon *et al.*, 2012). Individuals potentially favour more redistribution when levels of inequality are higher. We include the absolute level of redistribution and the level of market inequality from the Solt (2014) database (models 16 and 17).[24] Adding these factors does not affect our coefficients of interest. For OLS both country factors are insignificant, but for the ordered probit model the preferred level of redistribution is negatively associated with the existing level of redistribution, and positively with the level of market inequality.

Two other country 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, 2014f; 2014g). The EPL index is never significant, whilst the ordered probit models provide support for our hypothesis that higher unemployment benefit replacement rates decrease preferred levels of nonmarket protection (models 18 and 19). More importantly, the country factors do not affect our coefficients of interest.

Last, we test for robustness to our model specification. We model occupations as a separate level in addition to the country level to account for the hierarchical nature of our data. Here, we use a crossed random effects model, since occupations are not nested within countries but can be seen as a distinct level. Our OLS results remain firm (model 20). The RTI coefficient increases while the coefficients of the interaction terms decrease slightly. Unfortunately, this specification does not converge for the ordered probit model.

5.4.4 Interpretation of the size of the coefficients

Having found a positive association between RTI and preferences for redistribution, we now interpret its size. We do this in a comparative fashion, by running the regression with both interactions, where we include the two other occupa-

24 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.

tional risks discussed in the theoretical section, skill specificity and offshoring.[25] We calculate the effects when one of these three occupational risks increases by one standard deviation. In substantive terms, for the RTI index this is roughly comparable to an occupational switch from models, salespersons, and demonstrators to other crafts and related trades (0.11 to 1.08). For the relative skill specificity this is approximately equivalent to an individual switching from physical and engineering science associate professionals to sales and services elementary occupations (4.3 to 7.7). Last, for offshoring, it can be interpreted as an occupational switch from metal, machinery, and related trades workers to general managers (0.50 to 0.95).

We evaluate the effects of RTI on redistribution preferences at three levels: with ln income and sectoral exposure at their average value, one standard deviation below, and one standard deviation above this. This approximately implies that we evaluate the effects of the RTI index for an individual with an annual real income of 15003 dollar working in transport, storage, and communication (one standard deviation below), 31242 dollar in mining (average), and 65061 dollar in financial intermediation (one standard deviation above).

Table 5.5 Effects of an increase of one standard deviation on redistribution preferences

	Occupational risk	Sectoral exposure and ln income	Effect on redistribution preferences	Minimum (95% confidence interval)	Maximum (95% confidence interval)
(1)		Minus one standard deviation	0.010	-0.008	0.028
(2)	RTI	Average	0.056***	0.043	0.070
(3)		Plus one standard deviation	0.103***	0.080	0.125
(4)	Offshoring	-	-0.053***	-0.066	-0.039
(5)	Skill specificity	-	0.034***	0.024	0.044

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

From Table 5.5 we can conclude that a one standard deviation increase of the RTI index at average ln income and sectoral exposure has a roughly 1.5 times stronger effect than a comparable increase in skill specificity on the favoured level of redistribution. An *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. The effect of the RTI index becomes a factor three larger than skill specificity if ln income and sectoral exposure are one standard deviation above their means. On the other hand, RTI is no longer a significant determin-

25 We also conducted an estimation where we included the foreign ratio and occupational unemployment rate. The coefficient for the RTI index at average ln income and sectoral exposure decreased slightly to .040. The effect of a one standard deviation increase in foreign ratio on redistribution preferences is much lower, 0.022, whilst not surprisingly, the effect for the occupational unemployment rates is larger: 0.084. The coefficient for the RTI index when ln income and sectoral exposure are one standard deviation above is higher (0.10), though an *F* test indicates that the difference in size is not statistically significant.

ant of nonmarket protection preferences for low levels of ln income and sectoral exposure. As found earlier, offshoring has a negative association with redistribution preferences. Its (absolute) size is comparable to the size of the RTI index coefficient at average values of income and sectoral exposure.

5.5 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 preferring 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 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 offshoring and skill specificity.

In this chapter we show that the degree of routine task intensity of an occupation becomes a particularly influential determinant of redistribution preferences when two moderating factors are present. First, if an individual is employed in a sector exposed to technological change, and second, when an individual has more to lose from automation, that is, when his or her income is higher, the impact of routine task intensity on preferences for nonmarket protection increases. By introducing sectoral exposure as a moderating variable we combine an occupational and sectoral side of risk exposure. Moreover, the role of personal income in shaping redistribution preferences becomes fundamentally different. 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 favoured level of redistribution preferences. This view of income can be seen as more nuanced than existing perspectives where income only has a direct effect, which might be negative because of material self-interest (Meltzer and Richard, 1981), or positive when insurance is a normal good (Moene and Wallerstein, 2001).

This study's empirical work is built on survey data, rather than an experiment where individuals are 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 provision of public insurance choose occupations less exposed to risk. Second, it could be that individuals in routine occupations increased their redistribution preferences, lost their jobs because of automation, and moved to non-routine occupations whilst keeping higher levels of preferred nonmarket protection. Unfortunately we cannot directly test for this as we do not have micro panel data at our disposal. Yet, both of these arguments predict a negative association between the degree of routine task intensity and the preferred level for redistribution, militating against our statistically significant findings of a positive association. It might be, however, that because of these counteracting effects we underestimate the effect of routine task intensity on preferences for redistribution.

In this chapter we allow the risk of automation to differ across occupations, depending on their degree of routine task intensity. We devote less attention to country-specific patterns, depending on 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 be an interesting line of future inquiry. More generally, our analysis only begins to explore how risks of technological change shape actual redistribution and the welfare state. An extension of this study would be to consider whether exposure to risk of automation affects voting behaviour, and party and policy agendas, and ultimately, actual welfare state policies. Such a research agenda could follow the quantitative lines as applied in this chapter, or it could involve historical accounts of policies adopted by welfare states in response to risks resulting from technological change.

In the meantime, our findings point toward the possibility of cross-class coalitions between low-wage individuals in non-routine occupations and high-wage individuals holding routine occupations in support of a redistributive welfare state (Hausermann *et al.*, 2014). This potentially has implications for our understanding of insider-outsider politics and political mobilisation. Whether these coalitions materialise should be subject to further research.

APPENDIX 5.1 – DIFFERENCES BETWEEN KITSCHELT AND REHM AND THE RTI INDEX

In this appendix we more closely compare the Kitschelt and Rehm (2014) dummies (KR dummies) based on Oesch (2006), which are said to capture routine occupations, to the continuous RTI index from Goos *et al*. (2014). We will argue here that the RTI index is substantively and empirically superior to the KR dummies if one's ambition 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 (8 per cent) observations at our disposal for the RTI index.

KR distinguish between four *a*-groups which capture a vertical 'logic of authority' dimension or 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 groups (the *t*-groups) depending on whether tasks are more or less clearly defined: organisational; technical; or interpersonal task logics. This dimension does not have any linkages 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 have a considerable generosity to accept redistribution;
4. Routine: The skilled and unskilled routine workers in all three aforementioned task structures are grouped. This group is hypothesised to be in favour of redistribution.

Table A5.1 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 the *a*-groups, and even 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 produce additional variation at a more aggregated level. In fact, the variation is significantly decreased because of the dichotomous way of measuring.

Second and 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. Kitschelt and Rehm (2014) stress that they are interested in discretionary space rather than the intensity of routine tasks per occupations. 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.

Table A5.1 Comparing the continuous RTI index to the Kitschelt and Rehm dummy classifications

		Logic of authority groups				Logic of tasks groups			Combined groups			
		Profe-ssio-nals	Assoc-iate profe-ssio-nals	Skil-led rout-ine	Uns-killed rout-ine	Orga-nisat-ional	Tech-nical	Inter-pers-onal	a1t1 + a2t1	a1t2 + a2t2	a1t3 + a2t3	a3 + a4 for all *t*-groups
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	**0.54**	**0.46**	0.00	**0.65**	**0.35**	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	**0.82**	**0.19**	0.00	0.00	**0.53**	0.00	**0.47**	**0.53**	0.00	**0.47**	0.00
51	-0.60	0.00	0.00	**0.33**	**0.67**	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	**0.81**	**0.03**	**0.16**	**0.81**	**0.03**	**0.16**	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**	**0.11**	0.00	0.00	**0.09**	**0.91**	0.00	**0.09**	**0.80**	**0.11**
71	-0.19	0.00	0.00	**0.89**	**0.11**	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	**0.05**	**0.95**	0.00	0.00	0.00	1.00
52	0.05	0.00	0.00	**0.03**	**0.97**	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	**0.23**	**0.77**	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	**0.92**	**0.08**	1.00	0.00	0.00	0.00	0.00	0.00	1.00

Group 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.

Appendix 5.2 – Multilevel ordered probit results

Here we show the regression results of our multilevel ordered probit models, with random country intercepts and standard errors clustered at the country level. The equivalent of Table 5.3 estimated using multilevel ordered probit is shown in Table A5.2. The sign and size of coefficients for our variables of interest are all very comparable. The only difference is that the unemployment rate at country level becomes positive and significant.

Table A5.2 RTI and redistribution preferences for multilevel ordered probit

	RTI	Interacted with sectoral exposure	Interacted with income	Both interactions
	(1)	(2)	(3)	(4)
RTI	0.042***	0.048***	0.041***	0.047***
	(0.000)	(0.000)	(0.000)	(0.000)
ln income	-0.209***	-0.206***	-0.205***	-0.201***
	(0.000)	(0.000)	(0.000)	(0.000)
Sectoral exposure		-0.172***		-0.165***
		(0.000)		(0.000)
RTI * sectoral exposure		0.135***		0.135***
		(0.000)		(0.000)
RTI * ln income			0.042***	0.039***
			(0.000)	(0.000)
Years of education	-0.028***	-0.029***	-0.027***	-0.028***
	(0.000)	(0.000)	(0.000)	(0.000)
Male	-0.192***	-0.171***	-0.189***	-0.171***
	(0.000)	(0.000)	(0.000)	(0.000)
Age	0.003***	0.002***	0.003***	0.002***
	(0.001)	(0.002)	(0.000)	(0.001)
Trade union member	0.147***	0.180***	0.143***	0.180***
	(0.000)	(0.000)	(0.000)	(0.000)
Degree of religiosity	-0.007*	0.000	-0.007	0.000
	(0.085)	(0.951)	(0.112)	(0.940)
Dummy unemployed	0.141***	0.135***	0.139***	0.138***
	(0.000)	(0.000)	(0.000)	(0.000)
Social spending in %GDP$_{t-1}$	-0.006*	0.000	-0.009**	-0.000
	(0.054)	(0.987)	(0.025)	(0.991)
Unemployment rate$_{t-1}$	0.016***	0.019***	0.018***	0.019***
	(0.000)	(0.001)	(0.000)	(0.001)
Log pseudolikelihood	-102337.1	-102620.4	-102353.4	-102598.2
Country variance component	0.036***	0.227***	0.048***	0.228***
N	78050	78050	78050	78050
Number of countries	23	23	23	23

Note Multilevel ordered probit model with random country intercepts and standard errors clustered at the country level. Sectoral exposure and ln income are demeaned. *P* values in parentheses, *p<0.1, **p<0.05, ***p<0.01

We also run our sensitivity tests using multilevel ordered probit. The equivalent of Table 5.4 is shown in Table A5.3. Again, the signs and sizes of the coefficients are very comparable. Also the added variables themselves yield comparable estimates (results not shown). Unfortunately, we cannot show results for a crossed effects model as this does not converge.

Table A5.3 Robustness checks for the multilevel ordered probit models

		RTI	ln income	Sectoral exposure	RTI * sectoral exposure	RTI * ln income
	Original results (multilevel ordered probit)	0.047***	-0.201***	-0.165***	0.135***	0.039***
(1)	Dummy RTI from Oesch (2013)	0.074***	-0.221***	-0.323***	0.360***	0.041**
(2)	Sectoral definitions from Wren and Rehm (2014)	0.043***	-0.206***	-0.098***	0.043***	0.038***
(3)	Standardised ln income	0.049***	-0.148***	-0.173***	0.139***	0.032***
(4)	Equivalised ln income	0.048***	-0.202***	-0.172***	0.134***	0.033***
(5)	Skill specificity	0.046***	-0.197***	-0.201***	0.117***	0.040***
(6)	Offshoring	0.059***	-0.203***	-0.130***	0.116***	0.031***
(7)	Logic of task groups	0.072***	-0.183***	-0.121***	0.059**	0.029***
(8)	Foreign ratio	0.056***	-0.195***	-0.184***	0.147***	0.042***
(9)	Occupational unemployment rate	0.032***	-0.186***	-0.165***	0.128***	0.038***
(10)	Left-right scale	0.050***	-0.184***	-0.148***	0.118***	0.039***
(11)	All individuals	0.040***	-0.167***	-0.151***	0.106***	0.043***
(12)	Only employed	0.048***	-0.226***	-0.187***	0.147***	0.037***
(13)	Excluding Eastern Europe	0.053***	-0.198***	-0.206***	0.157***	0.043***
(14)	Excluding 2012	0.046***	-0.209***	-0.162***	0.128***	0.035***
(15)	Binary dependent variable	0.055***	-0.232***	-0.159***	0.176***	0.039***
(16)	Redistribution	0.051***	-0.203***	-0.168***	0.141***	0.039***
(17)	Gini market income	0.049***	-0.202***	-0.166***	0.140***	0.038***
(18)	EPL index	0.047***	-0.208***	-0.156***	0.143***	0.037***
(19)	UB replacement rate	0.048***	-0.200***	-0.179***	0.140***	0.037***

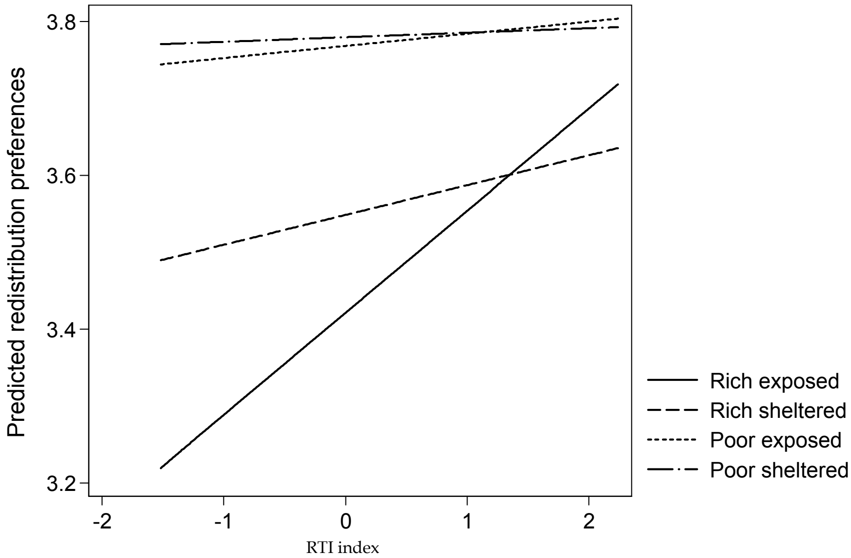
Note Multilevel ordered probit model with random country intercepts and standard errors clustered at the country level. Sectoral exposure and ln income are demeaned. *p<0.1, **p<0.05, ***p<0.01

Appendix 5.3 – A triple interaction

Another way of testing the moderating effects of income and sectoral exposure on the relationship between RTI and preferences for redistribution simultaneously is to run a triple interaction model. We run this model with OLS estimation, as our ordered probit model does not converge. We include all constitutive elements. Again, our results remain robust across model specifications and whether or not we include other occupational risks. For ease of interpretation we evaluate the predicted level of redistribution preferences for four groups: rich and exposed, rich and sheltered, poor and exposed, and poor and sheltered. Rich and poor are defined as one standard deviation above and below mean income. The same holds for sheltered and exposed sector. We evaluate their redistribution preferences at the minimum and maximum values of the RTI index.

Figure A5.1 supports our main hypotheses. We find that higher levels of RTI are associated with higher levels of preferred redistribution, as indicated by positive slopes. Second, we find that the poor always have higher predicted levels of redistribution than the rich. Third, for the poor, preferred levels of redistribution are reasonably stable across different levels of sectoral exposure and RTI. The interesting part concerns the rich, who have relatively more to lose from automation. The difference in predicted levels of redistribution preferences between individuals in non-routine versus routine occupations is substantial for the rich. This particularly holds for the exposed rich. Their predicted preferred level of redistribution rises substantially when they move from a non-routine to a routine occupation (from below 3.2 to around 3.7).

Figure A5.1 Predicted levels of redistribution preferences for a triple interaction



Note Multilevel OLS model with random country intercepts and standard errors clustered at the country level

We can also more formally test for the differences in effects of RTI on redistribution preferences (or the slopes) of these different groups, as we do in Table A5.4. The p values, however, are not adjusted for the fact that we conduct post-hoc tests. A very conservative interpretation would be to multiply these p values by the number of post-hoc tests (six). If we were to do so, we can still safely conclude that effects of RTI on redistribution preferences differ for rich exposed compared to every other group. We cannot conclude that there is a significant difference in effects of RTI on redistribution preferences for the poor exposed compared to the poor sheltered or compared to the rich sheltered.

Table A5.4 Post-hoc tests (unadjusted)

Groups	Coefficient	Standard deviation	z score	p value
Rich exposed vs. rich sheltered	0.093	0.013	7.18	0.000
Poor exposed vs. poor sheltered	0.024	0.013	1.89	0.059
Rich exposed vs. poor exposed	0.117	0.014	8.43	0.000
Rich exposed vs. poor sheltered	0.034	0.012	2.83	0.005
Rich sheltered vs. poor exposed	0.010	0.012	0.85	0.395
Rich sheltered vs. poor sheltered	0.127	0.014	9.17	0.000

Note Multilevel OLS with random country intercepts and standard errors clustered at the country level