Occupation-Specific Skills, Labor Market Context and Preferences for Redistribution

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Abstract

Understanding who and when supports income redistribution is at the core of political economy literature. Nevertheless, even though social stratification literature understands skill specificity as a key element of social class, there is no consensus on the role they play in shaping political preferences. I elaborate a framework that allows understanding these contradictions. I argue that the effect of occupation-specific skills (OSS) on redistribution preferences is moderated by occupational context, being more negative the tighter the occupational labor market is. I propose two mechanisms related to labor market prospects that allow explaining this relation: expected wages and risk exposure. Using flexible interactive effects models and different rounds from the European Social Survey and the International Social Survey Programme I show the relevance of this new approach. This analysis might allow explaining distinct political coalitions depending on the economic context.

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1 Introduction

Why the welfare state is broadly supported by different social classes in some cases, while in others they hold completely different political positions? Under what conditions do the policy preferences of different classes converge? These questions are fundamental because the policies that constitute the welfare state require broad political support (Rehm, 2011). Although social stratification literature has identified specific skills as a crucial component of social class (e.g., Goldthorpe, 2000), there is still disagreement about how they affect redistribution preferences. On the one hand, political economists have long maintained that individuals with relatively more specific skills are more likely to support risk-reduction policies because these skills are less portable relative to general skills (Iversen and Soskice, 2001; Pardos-Prado and Xena, 2019). On the other hand, political sociology asserts that the likelihood of job loss decreases with the amount of specific skills because this increases replacement costs for firms (Emmenegger, 2009; Polavieja, 2016). This distinction has complicated the study of cross-class alliances.

This article aims to shed light on the relationship between specific skills and redistribution preferences and seeks to better understand when cross-class alliances are likely to emerge. I argue that previous contradictory results linking specific skills and political preferences stem from overlooking some elements related to the role of specific skills in labor market prospects. First, the different strands of the literature generally do not speak to each other. I argue for an integration of the two approaches, that is, the approach that emphasizes that specific skills make workers less replaceable, and the approach that emphasizes that these skills are less portable. Second, it is not clear whether the authors focus on the relative or absolute level of skill specificity and whether greater specificity implies that a particular set of skills can only be used in a narrower set of firms, or whether it implies a larger amount of skills that cannot be used broadly. In this paper, following Emmenegger (2009), I examine the role of the *absolute amount* of specific skills as it is better linked to the concept of social class (Goldthorpe, 2000; Kitschelt and Rehm, 2014).

Finally, the extent to which skills are specific to a company, industry, or occupation is also unclear. Following the labor economics literature, I focus on occupation-specific skills (OSS), which are a key element of labor market prospects (Shaw, 1984; Kambourov and Manovskii, 2009a; Jäger and Heining, 2022).

Building on the literature linking the role of social mobility and insurance motives in explaining redistribution preferences, the main thesis of this paper is that OSS, moderated by occupational context, affect redistribution preferences by shaping labor market *risk exposure* – defined as the probability of becoming unemployed and the probability of being reemployed in the same occupation in case of job loss – and by changing *expected wages*.

First, I argue that when the occupational labor market is tight, that is, when occupational unemployment rates are low relative to vacancy rates, higher OSS are associated with a lower layoff probability. Due to the occupational context, companies would find it difficult to find other workers with the right skills and they would otherwise have to incur training costs, with the costs increasing the larger the amount of OSS. Similar to Goldthorpe (2000)’s replaceability thesis, occupations with higher OSS are less likely to support redistribution in this context (Emmenegger, 2009). However, when the occupational labor market is loose, larger OSS are not associated with a lower risk of job loss, as companies have a greater chance of finding a worker with the right skills. Additionally, in the event of a layoff, higher OSS increases the costs associated with job loss and may even increase the likelihood of long-term unemployment (Lamo, Messina, and Wasmer, 2011). This causal channel is similar to the portability argument emphasized in the political science literature (Iversen and Soskice, 2001; Pardos-Prado and Xena, 2019). As is well known, redistributive policies serve not only to redistribute income but also to reduce risk (Varian, 1980; Sinn, 1995). For this reason, individuals exposed to higher labor market risks are more likely to favor redistribution (Rehm, 2009; Pahontu, 2021).

In addition to risk exposure, OSS also affect expected wages. As highlighted in the literature, the prospects of upward mobility reduce support for redistributive policies

(Benabou and Ok, 2001; Alesina and La Ferrara, 2005; Rueda and Stegmueller, 2019). I argue that an increase in OSS raises expected wages because it increases workers' productivity and because they can retain some of the returns on investments made (Lazear, 1995). I contend that the rents earned by workers depend on their relative bargaining position vis-à-vis firms, which in turn depends on the occupational context. Following the previous discussion about risk exposure, I argue that workers have a good bargaining position when the occupational labor market is tight, but this is not the case when the occupational context is loose. I argue that in a tight occupational context, higher OSS are associated with steep earnings profiles, while this relationship is less strong in a loose occupational context.

This argument has important implications for the literature linking skills to redistributive preferences and for work on cross-class alliances. First, it follows a recent line of research that argues that being highly skilled no longer means being protected from the risk of unemployment (Wren and Rehm, 2014; Häusermann, Kurer, and Schwander, 2015; Webb, 2019), and highlights the scope conditions under which skills affect redistribution preferences. Second, I argue that focusing on OSS rather than on social class provides a better understanding of when and why different cross-class alliances are likely to emerge (Beramendi et al., 2015; Fernández and Jaime-Castillo, 2018; Gingrich and Häusermann, 2015). Rather than understanding social class location as something stable, the argument focuses on a key element of employment relations, OSS, and shows how and when they affect political preferences. The argument is elaborated on redistribution preferences, which are an important dimension of political economy because they have been shown to be an important determinant of voting decisions in Western countries (Rueda and Stegmueller, 2019).

2 The argument

This article draws on the literature that highlights the importance of social mobility and insurance motives in explaining redistribution preferences. However, this strand of research lacks work linking occupational context and occupational skills to redistribution preferences. To address this gap, this article proposes a novel framework based on labor literature. Specifically, occupational skills and occupational context are linked to explain two key dimensions of redistribution preferences: risk exposure and expected wages. This section concludes by discussing how this new argument relates to other arguments that examine the relationship between specific skills and redistribution preferences.

2.1 Social Mobility, Insurance and Redistribution Preferences

Economists and political scientists have consistently emphasized the importance of self-interest in explaining redistribution preferences, but early accounts considered only current income (e.g., Meltzer and Richard, 1981). The literature has moved beyond this static framework to examine the effects of individuals' income prospects on policy preferences, analyzing social insurance (Varian, 1980; Moene and Wallerstein, 2001; Rehm, 2009) and social mobility motives (Benabou and Ok, 2001; Alesina and La Ferrara, 2005).

As is now well understood, redistributive policies reduce not only inequality but also risks (Sinn, 1995). Since there are (labor market) risks, individuals do not know exactly what their income will be in the next periods and may therefore want government intervention to reduce income uncertainty. Without this intervention, individuals would over-save, leading to inefficient outcomes (Varian, 1980). This literature asserts that the greater the exposure to risk, the greater the support for redistributive policies (Iversen and Soskice, 2001; Rehm, 2009; Pahontu, 2021).

In this regard, occupations have been shown to be a key element of labor market risk and of redistribution preferences (Kambourov and Manovskii, 2009b; Rehm, 2009; Thewissen and Rueda, 2019). Rehm (2009) argues and empirically finds that individuals

in occupations with higher unemployment rates tend to demand more redistribution. He also shows that they find more likely to become unemployed in a near future (Rehm, 2016), suggesting that the insurance mechanism is at play. In contrast, he shows no relationship between similar industry-level measures and redistribution preferences. On the other hand, Thewissen and Rueda (2019) argues that there are occupational risks other than unemployment rates, such as the risk of automation. They show that occupations with more routine tasks, which are easier to automate, have greater redistribution preferences. They also argue that the effect should be stronger for those with more to lose, that is, those with higher earnings.

However, these accounts, do not directly address the role of skills. Häusermann, Kurer, and Schwander (2015) claims that high-skilled workers are not sheltered from labor market risks and expects them to show a stronger response to an increase in labor market vulnerability compared to low-skilled workers. This is because low-skilled workers already support a high redistribution level. In contrast, Wren and Rehm (2014) contends that while high-skilled are more exposed to labor market risks, their political response may be different. They analyze exposure to global markets, and show that high-skilled workers in exposed sectors are more fearful of becoming unemployed but have lower levels of redistribution preferences. This is because increasing social spending can reduce competitiveness, which further increases unemployment risk. Analyzing also recent globalization process, Walter (2017) argues that highly skilled workers in offshorable sectors or occupations are more sheltered from labor market risks and for this reason are less opposed to redistribution. Although these pieces of work focus on skills, they all define skill level as the amount of general skills, without taking into account skills at the occupational level.

Beyond labor market risks and insurance motives, there are scholars who focus on social mobility analyzing life-cycle profiles and how expectations of upward mobility explain why individuals below the median income do not support redistribution (Alesina and La Ferrara, 2005; Benabou and Ok, 2001). For instance, Alesina and La Ferrara (2005) analyzes past mobility experiences, subjective perceptions of the future standard of living

of individuals, and objective measures of mobility to explain redistribution preferences. In all cases, they find that those individuals with upward mobility prospects, either objectively or subjectively, are less likely to support redistribution preferences. However, in this exercise, the authors do not look at the determinants of social mobility. Overcoming this, Rueda and Stegmueller (2019) proposes a framework that incorporates how individuals compute their expected incomes and how expected income affect redistribution preferences.¹ They do so by means of mincer equations, including potential experience and educational level. Nevertheless, they do not consider the role played by occupational context and occupational skills (Kambourov and Manovskii, 2009b; Lazear, 1995).

2.2 Occupation-Specific Skills and Labor Market Prospects

The preceding discussion has highlighted a gap in the literature linking occupational risks and redistribution preferences. In this section, I elaborate on the foundations of the relationship between OSS and redistribution preferences in different occupational contexts and analyze how they are related to risk exposure and expected wages.

I follow recent developments in labor economics and analyze the impact of OSS on workers' labor market prospects (Shaw, 1984; Kambourov and Manovskii, 2009b; Jäger and Heining, 2022). Following the seminal work of Shaw (1984), Kambourov and Manovskii (2009b) finds that workers who change from occupation suffer an 18% wage decline five years after displacement, while the effect is three times smaller for workers who change from firm but not from occupation. Looking at unexpected worker deaths, Jäger and Heining (2022) shows that it is difficult for firms to replace workers with OSS and that the wages of incumbent workers in the same occupation as the deceased worker increase. Looking at heterogeneous effects, Zangelidis (2008) finds that occupational experience raises wages mainly in professional and managerial occupations, occupations that are assumed to have higher levels of specific human capital investment. In what follows,

¹Moreover, they claim that it serves to analyze together social mobility and insurance motives. Distinctly I prefer to analytically separate between these motives.

I develop a framework that links OSS and labor market prospects.

To understand how OSS affect workers' labor market prospects, Table 1 shows the alternatives that firms and workers have when the contract that binds them is broken, either because the firm fires the worker or because the worker decides to leave the firm. This has a backward induction logic: if we know the consequences of breaking the contract, we can understand what incentives different agents have to actually break it. On the one hand, firms may not be able to find workers with these skills in the labor market, so they have to incur training costs (Goldthorpe, 2000). At the same time, workers may have to change from occupation, resulting in a large loss of income (Iversen and Soskice, 2001). On the other hand, unlike Becker (1962), workers can switch to the same occupation without much loss of income, and firms have the option of replacing existing workers with workers who have the necessary skills, so there are no training costs.²

Table 1: Alternatives of firms and workers in case of broken contract

Alternatives in case of broken contract	
Firms' alternatives	Workers' alternatives
<ol style="list-style-type: none"> 1. Hire another worker with OSS without incurring training costs. 2. Hire a worker without OSS incurring training costs. 	<ol style="list-style-type: none"> 1. Find a job that requires OSS without experiencing income losses. 2. Find a job in another occupation without being able to use OSS, experiencing income losses.

Looking at the different options available to firms and workers, I argue that the relative costs of the different alternatives are determined by the interaction between the amount of OSS and the occupational context. This in turn affects workers' prospects in the labor market, specifically, risk exposure and expected wages.

As for risk exposure, I argue that it is difficult for firms in a tight occupational environment to find workers with the right skills. Therefore, the larger the amount of OSS,

²In fact, since individuals can use OSS in other firms, the literature understands OSS as a form of general skills (Christenko, Martinaitis, and Gaušas, 2020; Kambourov and Manovskii, 2009b).

the more difficult it is to *replace* workers, as this entails higher training costs. Moreover, skills are relatively *portable* in this context because workers are likely to find a job in the same occupation, so the consequences of a layoff are not as severe (Lazear, 2009). In this context, in which replaceability but not portability is important, the effect of OSS is similar to Goldthorpe’s argument. The situation changes when the occupational context is loose because firms have external options in the labor market that allow them to replace workers without incurring training costs. Therefore, higher OSS does not imply a lower likelihood of being laidoff. Moreover, the consequences of job loss are severe because skill *portability* is low. The higher the OSS, the greater the cost of changing occupation, which may provide incentives for individuals to remain unemployed until they find a suitable job, increasing the likelihood of long-term unemployment (Lamo, Messina, and Wasmer, 2011). The mechanism of this countervailing effect is consistent with the argument of Iversen and Soskice (2001).

In analyzing expected wages, I argue that contracts involving specific skills tend to be steeper and that both workers and firms derive some benefit from investing in these skills (Lazear, 1995; Goldthorpe, 2000). Following labor rent-sharing literature, I argue that the impact on future wages depends on the relative bargaining power of workers and firms (Card, Devicienti, and Maida, 2014). From the previous discussion, I contend that the tighter the occupational labor market, the stronger the bargaining power of workers relative to firms. Therefore, in a tight occupational context, I expect an increase in OSS to lead to a large increase in wages, while in a loose occupational labor market, I expect the relationship between OSS and expected wages to be smaller.

The argument put forward has several differences with other approaches that also study skill specificity. It differs from approaches that link the specificity of skills to the demand for those skills (Bisbee and Rosendorff, 2020; Christenko, Martinaitis, and Gaušas, 2020; Lazear, 2009; Streeck, 2012). I focus on how the *amount* of skills that are specific to the occupation shapes labor market prospects as a function of occupational context, i.e., the skills analyzed do not become more specific because the labor market

shrinks, skills are specific in so far as can only be used in a given occupation. Following an approach similar to Lazear (2009), Bisbee and Rosendorff (2020) defines skill specificity as the availability of similar jobs, defined in terms of the tasks performed at the occupational level. Therefore, they analyze specificity in terms of how specific are the tasks performed, either because the tasks are similar to a few occupations, or because the occupations are small relative to the economy.

Moreover, it is also different from other accounts that focus on amounts of specific skills (Emmenegger, 2009; Goldthorpe, 2000). Rather than focusing on an abstract level of skill specificity (Emmenegger, 2009) or on FSS (Goldthorpe, 2000), I argue that occupations are a key driver of labor market prospects (Kambourov and Manovskii, 2009b; Rehm, 2009). Following Rehm (2009), I focus on how occupational context changes the relative costs to firms and workers (see Table 1) and how this changes the relationship between OSS and risk exposure. I also argue that this affects the bargaining power of workers vis-à-vis firms, diminishing the effect of OSS on expected wages.

2.3 Specific Skills and Redistribution Preferences: Competing Arguments

I started analyzing the literature that explains how social mobility and insurance motives shape redistribution preferences. Then I proposed a framework linking OSS and occupational context to two key elements related to each of these two mechanisms: expected wages and risk exposure. Putting the two analyses together it directly follows that OSS are expected to have a negative effect on redistribution preferences when OUR is tight but that this effect attenuates as the occupational context deteriorates. Indeed, it might even be that greater OSS are associated with greater redistribution preferences.

I argue that in a tight occupational context, higher OSS makes workers harder to replace, and workers know that they can use these skills in another firm if they are laid off. Moreover, because they have a strong bargaining position with firms, higher OSS

are associated with higher expected wages. In this context, therefore, higher OSS can be expected to be associated with fewer redistribution preferences because OSS are associated with lower risk exposure and higher expected wages. If the occupational context deteriorates, firms can find other workers with the right skills, so higher OSS do not increase replaceability costs and also make skills less portable (Iversen and Soskice, 2001; Lamo, Messina, and Wasmer, 2011). Because they have less bargaining power, the relationship between OSS and expected wages is weak. Thus, if occupational conditions deteriorate, OSS will be associated with relatively stronger redistributive demands, to the point that this could even lead to a positive relationship between the amount of OSS and redistribution preferences.

I now turn to explore different accounts that link specific skills to redistribution preferences to expose that difference with the argument presented here. Figure 1 summarizes the main implications of the competing arguments.³ In the first two panels, I show portability and replaceability arguments. Because the level at which skills are specific can vary in these models, I show a general relationship between specific skills and redistribution preferences.

Panel a) shows the implication of the portability argument proposed by Iversen and Soskice (2001), which states that an increase in relative skill specificity leads to greater redistribution preferences because specific skills are less portable than general skills. They define an increase in relative skill specificity as the increase in specific skills that results in individuals having the same expected income. Since specific skills are less portable than general skills, an increase in skill specificity with constant expected income implies greater volatility in income profiles, leading to greater redistribution preferences (Varian, 1980). In contrast to my approach, however, they do not consider replaceability motives nor the role played by the labor market context. Indeed, they claim that “employed workers risk losing the income from their specific skills, regardless of their exposure to unemployment”

³In Appendix A.1 I develop a formal model in which, depending on the assumptions, the different competing explanations arise. Roughly speaking, is a model with loss-averse individuals in which expected wages in case of remaining employed, the probability of working in a given occupation and the probability of being unemployed depend on OSS and the occupational context.

(2001:880).

Sociological research, on the other hand, argues that the previous account neglects the fact that specific skills protect workers from job loss because they make them harder to replace. The implications of their approach are illustrated in Panel b). The replaceability argument states that higher specific skills increases workers' labor market security and, in turn, lowers their preferences for risk-reducing policies (Emmenegger, 2009; Polavieja, 2016). This is so because in case of layoff firms would have to incur training costs (Goldthorpe, 2000). Unlike the previous argument, this one compares individuals with different skill levels, and thus, with different income expectations. Therefore, the effect on redistribution preferences is expected to occur through two channels: first, by increasing expected income and, second, by reducing unemployment risk (Alesina and La Ferrara, 2005; Rehm, 2009). However, the role of the labor market context is usually not considered.

Figure 1: Implications competing arguments

Finally, panel c) shows the empirical expectations of the proposed model that combines both insights and links *occupation*-specific skills and redistribution preferences.⁴ In a tight occupational labor market, the argument resembles the replaceability argument, in which replaceability motives dominate those of portability and the impact of OSS on expected wages is large. This explains the downward slope in gray. However, I expect this relation

⁴This is in terms of the relative slopes of the relation between OSS and redistribution preferences, not about the intercept. The graph includes different intercepts assuming that, regardless of OSS, the worse the occupational context, the more redistribution preferences (Rehm, 2009).

to weaken the worse the occupational context is. This is because replaceability motives diminish and skills become less portable. Moreover, this leads to lower expected wages. Theoretically, it could even be that, as shown in the graph, larger absolute OSS leads to greater redistribution preferences. Empirically, however, I show that the effect diminishes until approaches zero, but never becomes positive.

3 Data Sources and Operationalization

The main empirical analysis of this paper draws on the first nine rounds of the European Social Survey (ESS), with data from 2002 to 2018.⁵ The data from ESS are of high quality and, crucially for the purposes of this article, include a question on respondents' redistribution preferences and detailed occupational identifiers in successive rounds. To capture occupational variables, I use two external data sources. Concretely, I retrieve data on OSS from the Programme for the International Assessment of Adult Competencies (PIAAC), and to capture occupational context I use information from Labor Force Surveys (LFS). In addition, I use different rounds of the Role of Government questionnaires of the International Social Survey Programme (ISSP) to analyze specific policy preferences. In this section, I describe occupational variables and the main variable used to capture redistribution preferences. Due to space limitations, the control variables and data from the ISSP are presented in Appendix B.2.

Occupation-Specific Skills (main independent variable). To compute the amount of OSS, I use the Survey of Adult Skills questionnaire from the PIAAC, which aims to measure cognitive skills that are useful in the workplace. It is carried out by the OECD in 40 countries between 2011 and 2015.⁶ In this survey, respondents are asked: “supposing that someone with this level of qualification was applying today, how much related work experience would they need to *get* this job?”, where “this level of qualifica-

⁵Concretely, I analyze all countries in the European Union (e.g., I drop Turkey, Russia or Israel from the sample). See Appendix B.1.

⁶I use all countries that also appear in my ESS sample, see Appendix B.1.

tion” refers to the formal qualifications needed to get the job, including internships and work placements. This question captures how costly would be for firms to hire another worker without the required skills, and also, the experience that would be lost if workers change to a different sector where the “related experience” is not important. I code responses in months and average them at the ISCO two-digits (concrete operationalization and descriptive statistics in Appendices B.4 and B.5).⁷

Sociological literature tends to use the Erikson-Goldthorpe-Portocarero (EGP) class schema instead (Emmenegger, 2009). However, it does not directly capture the amount of specific skills required and it is not clear whether it captures occupation-specific or firm-specific skills.⁸ In Appendix B.6, I show that the variable used yields an order similar to the EGP class schema, with the advantage that it is a continuous variable that directly captures the dimension under study.

Alternatively, Iversen and Soskice (2001)’s measure is often used in political science research to capture the specificity of skills. Concretely, the measure of absolute skill specificity proposed by these authors is proportional to the number of four-digit units within each two-digit group in the ISCO classifications divided by the proportion of workers in the occupation. The authors contend that if an ISCO group contains many occupations it must be that either the tasks performed in this occupation are very specific or there are many workers in this occupation. By dividing by the share of workers in the occupation, therefore, they capture the “degree of specialization”.⁹ I do not use this variable because it does not aim to capture how long/costly it is to acquire skills, which is crucial for my argument. In what follows, I will show that both measures capture a different dimension

⁷Concretely, I use ISCO88 and ISCO08 classifications. These classifications have different levels of detail, from one-digit (containing 9 occupations) to four-digit (containing 390 and 436 occupations, respectively). Crucially, available crosswalks allow homogenizing these classifications if they are provided in their most detailed form. For this reason, as will be discussed, measures of occupational context can only be calculated separately at the ISCO88 and ISCO08. I measure OSS accordingly.

⁸For an exception, see Polavieja (2016), who use a continuous measure of the amount of specific skills required with a question from the ESS similar to the one used in this paper (see Appendix B.4).

⁹Note, however, that it depends on the concrete class classification used by the International Labor Organization (ILO). Indeed, using Oesch (2006) class schema, Kitschelt and Rehm (2006) argue that the resulting measure of specific skills is implausible since “socio-cultural professionals” are considered to have lower skill specificity than “routine service”.

of skills and in Appendix D.3.1 I show that these differences are reflected in the way these variables affect political preferences.

Figure 2 displays the values of the two variables broken down by two-digit ISCO88 occupations, rescaled from 0 to 1 to facilitate the comparison between them.¹⁰ It should be noted that there are two main differences between the measure proposed in the paper and the one proposed by Iversen and Soskice (2001). The first one is the comparison between Plant and Machine Operators occupations (major group 8) and Craft Workers (major group 7). In the variable obtained from the PIAAC, Craft Workers require a greater amount of OSS compared to Plant Operators, while Iversen and Soskice (2001)’s measure suggests that Plant Operators workers require a higher degree of specialization compared to Craft Workers. Since I want to grasp the amount of specific skills, I claim that is more sensible the order and magnitude using the PIAAC. Following occupation definitions from the ILO, Craft Workers tasks “call for an understanding of all stages of the production process, the materials and tools used, and the nature and purpose of the final product”, while for Plant Operators it suffices to have “experience with and an understanding of industrial and agricultural machinery and equipment, as well as an ability to cope with machine-paced operations”.

The second difference relates to Professionals and Associate Professionals. In the variable retrieved from the PIAAC, these are the groups with one of the highest levels of OSS, as assumed in labor economics literature (Zangelidis, 2008). In contrast, their level of specialization is rather low according to Iversen and Soskice (2001)’s measure. Moreover, Professionals have lower levels of specialization than Associate Professionals according to this latter measure, which would be implausible if it captured the absolute amount of OSS.

Occupation Unemployment Rates (moderator). In the theoretical discussion, I defined occupational labor market tightness as the ratio of unemployment to vacancy rates

¹⁰Since Iversen and Soskice (2001)’s measure varies at occupation-country-year, I aggregate its values at the level of occupation. I provide a comparison of the two variables at the ISCO08 in Appendix B.5.

Figure 2: Comparison Measures of Occupation-Specific Skills

at the occupational level. In the absence of consistent data capturing job vacancies at the occupational level, I use occupational unemployment rates (OUR), a measure widely used in political economy (Rehm, 2009). This variable reflects the intuition of the proposed interactive effect, as it is directly related to the possibility of replacing workers and the difficulty for workers to find a job in the same occupation afterwards.¹¹ This variable is computed in the same way as country unemployment rates but at the ISCO two-digits level. To calculate it, I use Labor Force Surveys provided by Eurostat, which are large enough to compute unemployment rates at this level of disaggregation. One shortcoming is that these data identify occupations at the three-digit ISCO level, using ISCO88 until 2010 and ISCO08 thereafter, which does not allow homogenization at the same ISCO classification. Therefore, I calculate OUR at the ISCO88 until 2010 and at the ISCO08 afterwards.

At this point, it must be noted that when testing interactive effects, having a skewed moderator can make the results model-dependent (Hainmueller, Mummolo, and Xu,

¹¹Must be noted that there are other variables that also grasp the occupational context, such as the probability of automation (e.g., Goos, Manning, and Salomons, 2014). To see that the results are not sensitive to the measure of occupational context used, I use also the measure proposed by these authors in the robustness section.

Figure 3: Histogram of Occupation Unemployment Rates and the logarithmic transformation

2019). To avoid this issue I transform the variable. Similarly to Rehm (2009) I smooth the series and recode extreme values, setting the minimum and the maximum value to the first and the last percentile of OUR in the sample and I take the logarithm to reduce the remaining skewness (steps of the transformation fully elaborated in Appendix B.7). Figure 3 displays the histogram of the untransformed OUR variable (top) and of the transformed variable (bottom). As can be seen, the untransformed OUR is right-skewed while the transformed one reduces this skewness. To see whether there might be problems related to severe extrapolation, Hainmueller, Mummolo, and Xu (2019) propose to check if the L-Kurtosis of the moderator is greater than 0.16. In this specific setting, the L-Kurtosis is 0.20 for the untransformed variable and 0.12 for the transformed one, suggesting the use of the latter as the moderator.

Redistribution Preferences (Dependent variable): To capture preferences for redistribution, I use an item of the ESS that exposes respondents the following statement: “the government should take measures to reduce differences in income levels”. This is a Likert item where respondents have five possible answers from “strongly agree” to “strongly disagree” with an intermediate option which is “neither agree nor disagree”.

This variable has been widely used in the literature (e.g., Rehm, 2009 or Rueda and Stegmueller, 2019). Table 2 displays the distribution of the variable.

Table 2: Distribution Redistribution Preferences (in percentages)

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
2.41	11.68	14.49	43.89	27.53

Note: Data from rounds 1 to 9 of the ESS. Design and population weights applied. $N = 149,144$.

As can be seen, 70% of the respondents show some degree of support for redistribution. In the main analysis showed, I code as one the answers “agree” or “strongly agree” and zero otherwise (Rueda and Stegmueller, 2019). This transformation allows to better interpret the interactive effects proposed.¹²

Figure 4 shows the binscatter plot of the relationship between redistribution preferences and OSS with low and high levels of OUR, defined as observations in the lowest and the highest tercile of OUR, respectively. Concretely, the blue dots show the average level of redistribution support for different levels of OSS and the maroon dashed lines show the linear fit of a bivariate OLS. It can be seen that, as expected, when OUR are low, individuals with more OSS tend to be less supportive of redistribution. Differently, when the occupational labor market is loose the relation is much more muted, implying that there are fewer differences in redistribution preferences between occupations. Both the estimated slope of the relation (b) and the correlation (r) is around three times higher when OUR are low than when they are high. Moreover, it can be observed that the relation between OSS and redistribution preferences does not become positive when OUR are high, the effect simply diminishes.

4 Methods

The main thesis of the paper is that OSS affect redistribution preferences differently depending on the occupational labor market context. Like other papers that rely on

¹²The results are robust to using the untransformed version of the variable, with the results displayed in the robustness section.

Figure 4: Binscatter plot and linear relation of OSS and Redistribution Preferences

Note: $N_{\text{Low}} = 45,522$ and $N_{\text{High}} = 45,507$.

the occupational dimension of preferences, I analyze changes in the variable of interest that involve comparing individuals with different occupations (Rehm, 2009; Walter, 2017; Thewissen and Rueda, 2019).¹³ Concretely, I will be comparing individuals with similar observable characteristics (income, age, education, preferences for risk, values, occupational context...), but that have different levels of OSS. This comparison will be done for different levels of OUR.

To perform this analysis I start running a set of models using redistribution preferences as a dependent variable and OSS, OUR and their interaction as independent variables (as well as a full set of control variables).¹⁴ Assuming that the effects of OSS are a linear function of the logarithm of OUR, the regression to be estimated is:

$$(1) \quad \text{RED}_i = \mu + \alpha \text{OSS}_o + \eta \text{OUR}_{o,c,t} + \beta \text{OSS}_o \times \text{OUR}_{o,c,t} + \delta' Z_i + \varphi_{c,t} + e_i$$

where o, c and t should be understood as functions that map individuals, i , into their occupations, countries and year of the survey, respectively. To avoid “omitted interaction bias”, Z_i is made up of controls and their interactions with OUR (Blackwell and Olson,

¹³That is, I am not interested in how individuals react when in a given occupation OSS change.

¹⁴I assume that redistribution preferences are continuous. A discussion about this assumption is provided in Appendix C.1.

2021).¹⁵ For instance, female workers tend to be in occupations that require less OSS and may react distinctly to labor market risks. Therefore, not including the interaction between gender and OUR could lead to classical omitted variable bias. $\varphi_{c,t}$ are country-year dummies and μ, α, η, β , and δ are the coefficients to be estimated, being α and β the parameters of interest. Concretely, from the theoretical discussion it is expected that the marginal effect of OSS at the lowest level of OUR to be negative ($\alpha < 0$) but less so as OUR become higher ($\beta > 0$). Moreover, it could even be that for sufficient high levels of OUR the effect of OSS turns out to be positive ($\alpha + \beta \times OUR > 0$).

This approach, even standard in the literature, assumes a specific functional form of the interactive effect that is not theoretically founded. To deal with this issue, Hainmueller, Mummolo, and Xu (2019) propose two distinct regressions that relax this linearity assumption. The first alternative they propose is to utilize a binning estimator. In this method, OUR are discretized in three terciles, creating a dummy for each of them. That is, for each tercile j , creating a dummy variable $G_{i,j}$ that takes the value of one when the OUR of individual i is in the j -th tercile and zero otherwise.¹⁶ Then, an interactive model which allows different interactive effects within each tercile is regressed. Specifically, the equation to be estimated via OLS is the following:

$$(2) \quad \text{RED}_i = \sum_{j=1}^3 \left\{ \mu_j + \alpha_j \text{OSS}_o + \eta_j \text{OUR}_{o,c,t} + \beta_j \text{OSS}_o \times \text{OUR}_{o,c,t} \right\} G_{i,j} + \delta' Z_i + \varphi_{c,t} + e_i$$

being $\text{OUR}_{o,c,t}$ the deviation of i 's individual OUR from her tercile's median.¹⁷ Because the interaction within each tercile is done using as moderator the transformed measure of OUR, the coefficient of α_j gives the effect of OSS at the median level of the j -th tercile. According to the argument, therefore, it is expected that $\alpha_1 < \alpha_2 < \alpha_3$, that is, the marginal effect increases the higher the level of OUR. Equation (2) is a generalization of the linear interaction model, so it can be tested which of the two models is preferred. The choice of the model is a classical bias-variance trade-off. On the one hand, the binning

¹⁵That is, being z_i the controls included, the estimation takes the following form: $\text{RED}_i = \mu + \alpha \text{OSS}_o + \eta \text{OUR}_{o,c,t} + \beta \text{OSS}_o \times \text{OUR}_{o,c,t} + \gamma' z_i + \phi' z_i \times \text{OUR}_{o,c,t} + \varphi_{c,t} + e_i$. With $\delta Z_i = \gamma z_i + \phi z_i \times \text{OUR}_{o,c,t}$.

¹⁶More formally, being $t(\cdot)$ a function that maps individuals into terciles of OUR, $G_{i,j} = 1\{t(i) = j\}$.

¹⁷That is $\text{OUR}_{o,c,t} = \text{OUR}_{o,c,t} - \text{OUR}_j^{p50}$

estimate is more flexible, implying that it tends to be less biased, however, it has a greater variance. On the other hand, the linear model is more efficient, however, if the linearity assumption does not hold, it is biased.

The second strategy proposed by Hainmueller, Mummolo, and Xu (2019) is to use a kernel smoothing estimator which allows marginal effects to vary, almost freely, at all levels of the moderator. Useful for this analysis, this method allows to properly test at which range of OUR the effect of OSS is estimated to not be different from zero. Concretely, the regression to be estimated is the following:

$$(3) \quad \text{RED}_i = f(\text{OUR}_{o,c,t}) + \text{OSS}_o \times g(\text{OUR}_{o,c,t}) + h(\text{OUR}_{o,c,t}) \times z_i + \varphi_{c,t} + e_i$$

where $g(\cdot)$ is a kernel smoothing function that captures the marginal effect of OSS on redistribution preferences for distinct values of OUR, and $h(\cdot)$ a vector of kernel smoothing functions for distinct controls.¹⁸ From the theoretical discussion it is expected that $g(\cdot)$ is monotonically increasing with OUR, implying that the larger the OUR, the larger the effect of OSS at all levels of occupational context. The critical component of kernel smoothing estimates is the selection of the bandwidth. I allow greater bandwidths when the density of the moderator is lower and they are selected through 10-fold cross-validation.

5 Results

5.1 Main Results

Figure 5 graphically summarizes the main results of the three estimation procedures discussed, with the regressions including all controls, their interaction with OUR, and country-round FE (see Appendix C.2 for the table of coefficients with a different set of controls). Standard errors are clustered at the country-year-occupation and design and

¹⁸See Hainmueller, Mummolo, and Xu (2019) for the technical details.

population weights are applied.¹⁹

The left panel of Figure 5 shows the marginal effects of OSS on redistribution preferences for different levels of OUR from linear and binning regressions. The black line is the marginal effect of increasing OSS by one standard deviation for various values of OUR under the assumption that the interactive effect is linear in the logarithm of OUR. The associated 95% confidence intervals are displayed in dark gray. It can be seen that under this specification, the worse the occupational context, the less negative the effect of an increase in OSS on redistribution preferences. It can also be observed that the effect is mostly negative, meaning that an increase in OSS decreases redistribution preferences for most observations in the sample. In particular, for the lowest values of OUR, a one standard deviation increase in OSS reduces the probability of supporting redistribution preferences by an average of 6 percentage points, *ceteris paribus*. These negative effects are consistent with Goldthorpe’s replaceability thesis. Yet, for the highest values of OUR the effect is not significantly different from zero. This implies that moving to an occupation with higher OSS does not change redistribution preferences if the occupational context is sufficiently loose.

The results from the binning regression are displayed in red. Concretely, they are the coefficients and 95% confidence intervals associated with the median value of each tercile of the moderator.²⁰ It can be seen that the marginal effect of increasing OSS is the lowest for the median value of the lowest OUR’s tercile and the highest for the median value of the highest tercile. Moreover, the difference between the marginal effects for low and high levels of OUR is statistically significant, indicating the existence of an interactive effect (Hainmueller, Mummolo, and Xu, 2019). Moreover, it turns out that for a typical high value of OUR, the marginal effect is close to zero (and statistically significant only at 90%

¹⁹Concretely, for clustering, are occupations at the ISCO one-digit. This is done because the number of clusters are six times higher (from one thousand to six thousand) if the clusters are done at the two-digits rather than at the one-digit. The average number of observations in the clusters moves from 25 to 150.

²⁰The terciles are defined as follows. The lowest tercile includes all values between -0.690 and 1.18, with a median value of 0.721. The middle tercile includes values greater than 1.18 and lower than 1.910, with a median of 1.568. The largest tercile ranges from 1.911 to 3.360 and the median is 2.321.

of confidence). As mentioned earlier, the binning estimate is a generalization of the linear interaction model, and we can test whether the two models are significantly different or not. In fact, the Wald test rejects the null hypothesis that both models are the same ($p\text{-value} < 0.001$), indicating that the linear interaction model is not appropriate.

Note: Left panel display estimates of the linear interaction and binning estimators and the associated 95 percent confidence intervals. The right panel depicts kernel smoothing estimates and the associated confidence intervals. The optimal bandwidth in the highest density areas, selected via 10-fold cross-validation, is 0.273. Regressions include all controls (defined in Appendix B.2), their interaction with OUR and country-year FE. Clustered standard errors at country-year-occupation. Design and population weights applied.

The right panel of Figure 5 shows the kernel smoothing estimate. Again, it can be seen that the relationship is in the expected direction.²¹ Overall, the results suggest that the interactive effect is significant, with OSS having a much weaker effect on redistribution preferences the worse the occupational context. Although the effect of OSS does not increase monotonically with OUR, in no case does this negative relationship become statistically significant. For the lowest levels of OUR, a one standard deviation increase in OSS is associated with 5 percentage point decrease in the probability of supporting

²¹The (adaptive) bandwidth has been selected through 10-fold cross-validation, assigning lower values to the highest density of the moderator in the region. The bandwidth for the highest density area is 0.273.

redistribution. This effect is about 3.75 percentage points for intermediate levels of OUR and does not become significantly different from zero for high levels of OUR. Even for sufficiently high levels of OUR the effect is positive, this effect never becomes statistically significant.

The main takeaway from these analyses is that for low values of OUR, more OSS leads to lower redistribution preferences, while this relationship fades away for sufficiently large values of OUR. The binning estimate suggests that for a typical large value of OUR (the median of the highest tercile of OUR), the effect is close to zero. A more concrete picture emerges from the kernel smoothing estimate, which shows that for values in the top 20th percentile of OUR (i.e., with OUR slightly greater than 2), the marginal effects are close to zero and not statistically significant. This implies that, on average, OSS are not associated with redistribution preferences in a high OUR contexts.

To show the substantive impact of the proposed interaction, Figure 6 compares the average marginal effects (AME) of increasing OSS by one standard deviation in different contexts with the effect of other controls related to redistribution preferences.²² This is done with the binning regression used in Figure 5.

I find that in a low OUR context, one standard deviation increase in OSS increases redistribution preferences by 3.8 percentage points on average, while when OUR are low the effect, the reduction is of 0.75 p.p. and not significant at 95% of confidence. Moreover, the difference between these two effects is significant and substantial. To put the results in context, the proposed interactive effect is around two and a half times larger than the effect of one standard deviation in education (with the differences being statistically significant). The effects are closer to the effects of increasing income by one standard deviation, of being unemployed or being a female.

Overall, the results suggest that the effects of absolute increases in the amount of OSS

²²Concretely, it shows the AME effect of income, education, being unemployed and being female. For the former two, the effect shown is the effect of one standard deviation increase, while the others are simply a dummy taking value of one if the individual is unemployed or is a female, respectively, and zero otherwise.

Table 3: Substantive Effects		
Variable	Average Marginal Effect	95% Confidence Intervals
OSS (Low OUR)	-3.775**	[-4.374, -3.177]
OSS (High OUR)	-0.746*	[-1.518, 0.026]
OSS (Low vs High)	-3.029**	[-4.019, -2.040]
Income	-2.639**	[-2.982, -2.295]
Education	-1.191**	[-1.514, -0.867]
Unemployed	2.900**	[1.797, 4.002]
Female	3.208**	[2.668, 3.748]

Note: Low OUR refers to median value of the lowest tercile, while High OUR to the median value of the highest tercile. ** p-value < 0.05; * p-value < 0.10.

generally reduce redistribution preferences, consistent with Goldthorpe’s replaceability thesis. However, the effect has been consistently shown to approach zero when OUR are sufficiently high. This has major implications for the study of preference formation among different social classes and their alliances.

5.2 Robustness

To check the sensitivity of the results discussed so far, I do six types of robustness tests. A large number of robustness tests have been performed (discussed in Appendix D.1). Concretely, I check whether the results are robust to: i) changes in the coding of the dependent variable; ii) changes in the variable chosen to capture OSS; iii) changes in the variable used to grasp the occupational context; iv) changes in the controls used in the regression, including occupation FE, v) testing the argument against competing explanations; vi) changes in specific countries, time periods or occupations. As a placebo, I show that the relation holds for private workers but not for public servants.

I perform two more exercises. First, I test the proposed mechanisms. One of the reasons for examining specific skills is that they are a key dimension of social classes (Goldthorpe, 2000). I have argued that studying this concrete dimension is a better strategy than using class dummies, which can hide many other dimensions that make it difficult to assess what is driving the results. Nonetheless, the approach taken is useful as far as the mechanisms outlined are at work. In Appendix D.2, I tentatively test the

three proposed mechanisms and show suggestive evidence of their effect. To capture expected income, I follow a similar strategy to Rueda and Stegmueller (2019), which calculates expected income by means of mincer equations. To capture risk exposure, I use two questions from the ESS. The first one asks individuals how likely they are to be unemployed in the next 12 months (Wren and Rehm, 2014), and the second asks directly how difficult it would be to find a similar or better job (Iversen and Soskice, 2001; Walter, 2017). Second, I show that the effect of FSS and of the degree of specificity are distinct to the one proposed in this paper (Appendix D.3.1).

5.3 Assessing the Effect on Political Coalitions

Previous analyses suggest that when the level of OUR is high, an increase in OSS does not lead to changes in redistribution preferences. This implies that in this context occupations will have similar preferences regardless of their OSS. However, to examine in more detail which coalitions will tend to be formed, I enrich the previous analysis in two ways. First, I analyze the relationship between OSS and the average predicted probability (APP) of supporting redistribution in different occupational contexts. This allows to test, for example, whether occupations with a low level of OSS when OUR is low have, on average, different redistribution preferences than occupations with a high level of OSS in a high OUR context.²³ Second, since redistribution can be achieved by different means, class coalitions could differ depending on the policies supported by different classes (Beramendi et al., 2015). To test this, I also use several questions on *policy* preferences asked in the International Social Survey Programme (ISSP).

To illustrate the differences in the effects of OSS depending on the occupational context, Figure 6 shows the APP of supporting redistribution when the levels of OUR are high or low. Concretely, I show the average of the predictions from the binning model in Figure 5, setting the variables of interest at different values (i.e, OSS and OUR) and

²³Further, in Appendix E I show more flexible estimations. Concretely, I allow for quadratic effects of OSS and also I show non-parametric evidence by means of a binscatter. These two exercises relax the linearity assumption made about the effect of OSS on redistribution preferences.

holding the controls at their observed values. I select observations in the lowest and the highest tercile of OUR to represent low and high values. When OUR are low, the 95% confidence intervals are shown in dark gray and when OUR is low they are displayed in light gray. The OSS are divided into half standard deviations, and the dot lines show the three terciles of OSS (the mean value is 15.16).

Figure 6: Probability Support for Redistribution by OSS and OUR (with 90% Confidence Intervals)

Figure 6 shows that the empirical data are consistent with the theoretical expectations (see the right panel in Figure 1), with the effect of OSS varying by occupational context. When OUR are low, the effect of OSS on redistribution preferences is large. While for an individual in the first tercile of OSS (value of 10.5) the likelihood of supporting redistribution is 68%, for those in the second tercile (value of 17.5) the likelihood is 64%. Moving from the minimum to the maximum level of OSS, the probability of supporting redistribution drops by almost 20 percentage points, from 73% to 55%. The effects are much weaker when OUR are high and indeed they are not statistically significant.²⁴ In

²⁴The effects for very high levels of OSS when OUR are high have to be taken with caution since there are outliers. Indeed, without introducing managers – who represent 1% of the sample in a high

this context, APP of supporting redistribution is 80% for those individuals with the lowest amount of OSS, 79% for those in the first tercile, 78.5% for those in the second tercile, and 77% for those with the highest amount of OSS.

This analysis suggests that alliances between individuals in a high OUR context, regardless of their level of OSS, and individuals with low levels of OSS, regardless of their occupational context, are likely to occur. All these groups show the likelihood of supporting redistribution is greater than 70%. Moreover, those in bad occupational contexts, independently of their skills, are expected to be the groups with the highest redistribution preferences. These results also speak to the literature analyzing the effect of occupational hazards on redistribution preferences (Rehm, 2009; Thewissen and Rueda, 2019). They show that the effect of occupational risk (i.e., moving from low to high OUR contexts) has a greater impact on the high-skilled (in line with Häusermann, Kurer, and Schwander (2015)).

As has now been recognized, economic conflict cannot be summarized as “more versus less welfare spending” (Häusermann and Kriesi, 2015: 203). Indeed, there might be differences in preferences depending on whether policies are investment-oriented or consumption-oriented (Gingrich and Ansell, 2015). Consumption-oriented policies aim to increase aggregate demand and de-commodify individuals out of the labor market, whereas investment-oriented policies are long-term and aim to re-commodify workers by providing jobs or training opportunities. To find out whether there are differences in the type of policies supported, I analyze the proposed interactive effect for four different types of policies that reduce income inequality: i) policies aimed at creating new jobs; ii) policies that protect risky jobs; iii) increases in unemployment benefits; and iv) progressivity of the tax structure. The first group are investment policies, while the other three are clearly consumption policies. For this purpose, I use the last three rounds of the Role of Government module (1996, 2006, and 2016) of the ISSP. They consistently contain questions that capture each of these dimensions, as well as consistent occupational identifiers

OUR context – the maximum level of OSS goes from 35 to 26.5. Appendix E analyzes how the results depend on including managers in the sample.

needed for the analysis.

Concretely, respondents are asked to answer whether they believe it is the government’s responsibility to fund “projects to create new jobs”, to provide “jobs for all” and to support “declining industries to protect jobs”. The first two questions relate to investment policies, while the last item captures employment protection issues. To capture preferences related to unemployment benefits, respondents are asked to answer whether they want to see “more or less government spending” on “unemployment benefits”. Finally, to capture tax preferences, I use individuals’ preferences for taxing the rich and a measure of preferences for tax progressivity proposed by Barnes (2015).²⁵

Figure 7 I display APP of supporting redistribution for the six ISSP questions for the binning regression with controls defined in Appendix B.2, their interaction with OUR terciles and country-year FE.

Several conclusions can be drawn from this analysis. First, the slopes of OSS vary by occupational context, showing a consistently weaker relationship when OUR are high. Second, there are different questions in which broad alliances are likely to emerge. Concretely, policies aimed at supporting declining industries, taxing the rich, and increasing the progressivity of the tax system receive similar support from low-skilled and from occupations with high OUR regardless of the amount of skills. This suggests that broad-class coalitions supporting these policies are likely to emerge. Second, the effect on unemployment benefits is almost entirely driven by OUR (Rehm, 2016), and a great share of high-skilled workers in high OUR context demand significantly more increases in unemployment benefits than low-skilled in low OUR contexts. Finally, there are no clear patterns in investment policies, with occupational context and OSS having distinct effects in each of these cases.

²⁵Exact wording, the operationalization of the variables, their descriptive statistics and the countries analyzed are provided in the Appendix B.2.

Figure 7: Linear and Binning estimates: Employment protection, employment creation and unemployment benefits

Note: Binning estimates and the associated 95 per cent confidence intervals, clustering standard errors at country-year-occupation.

6 Conclusions

Recent developments in the labor market affect highly skilled workers unevenly, making it necessary to understand their behavior in different labor market contexts (Häusermann, Kurer, and Schwander, 2015; Webb, 2019; Wren and Rehm, 2014). Nevertheless, we do not know enough about when and why skills matter for shaping political attitudes. Concretely, this article focuses on why different social classes sometimes have aligned economic interests while others do not. Rather than focusing on dichotomized social class classifications, it identifies a key element of these classifications: occupation-specific skills. By combining different approaches that link specific skills to redistribution preferences, it

provides a micro-level explanation of how and when OSS affect redistribution preferences.

In summary, the argument is as follows. When the occupational context is tight, greater OSS are associated with higher replaceability costs for firms. This is because it would be difficult for them to find another worker with the right skills, and hiring another worker without these skills would involve training costs. In this scenario, two occupations with different OSS will hold different redistribution preferences. On the contrary, when the occupational context is loose, higher OSS do not increase replacement costs for firms since they can hire another worker with proper skills. Moreover, the consequences of job loss are more severe, as changing occupations involves large income losses. In line with the literature on social mobility and insurance, in a tight occupational context, greater OSS are associated with lower preferences for redistribution, but this effect diminishes as the occupational context deteriorates. Thus, two occupations are more likely to have similar preferences when the occupational context is loose than when it is tight.

Using the first nine rounds of the ESS, three rounds from the ISSP, and flexible interactive models, this new approach receives support from the data: the marginal effect of increasing OSS in a tight occupational context is high in magnitude relative to key elements of redistribution preferences. In contrast, there are no significant differences in redistributive preferences for different levels of OSS in loose occupational contexts. Moreover, I show that in this latter context increasing OSS does not generally lead to different policy preferences, and indeed, there is a higher agreement on support for consumption policies. Thus, it is not only that with higher OSS there are less differences in terms of redistribution preferences but also there are fewer differences on how redistribution should be achieved. I argue that these results support the view that coalitions between classes are more likely to emerge when they face bad occupational conditions.

This study focuses on general empirical patterns and does not examine the institutional factors that may influence this relationship (Gingrich and Ansell, 2012). In addition, it examines only the effects on redistribution preferences without analyzing whether there are also effects on voting propensity or party policy responses. Further research should

address how different political systems will accommodate the preferences of high-skilled pressured by occupational hazards and how parties will adjust in the current tripolar political competition.

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A Appendix Argument

A.1 A simple formal model

I argue that OSS, moderated by occupational context, induce changes in expected wages and risk exposure. In this section I model this relation starting with how OSS shape expected wages. Being s the amount of OSS an individual has, I assume that workers' wages derived from OSS are equal to $\delta(u)s$, being $\delta(\cdot)$ a function of the (inverse of) occupational tightness u , which captures bargaining position of workers, with $\partial\delta/\partial u < 0$.²⁶ This captures the fact that, for a given OSS, the worse the occupational context, the lower the expected wages because bargaining position of workers is lower.

The second dimension that has been highlighted to be an important determinant of redistribution preferences is related to insurance, and how income uncertainty leads individuals to support redistribution (Varian, 1980; Moene and Wallerstein, 2001; Iversen and Soskice, 2001). To bring the discussion about how OSS shape redistribution preferences, from the previous setup, I introduce individuals' preferences and a policy device that redistribute income and that can limit labor market risks. As most insurance models it is made up of four elements: i) risk of job loss, ii) likelihood of regaining employment, iii) degree of risk/loss aversion; iv) policy that redistributes resources to those who experience the job/wage loss (Thewissen and Rueda, 2019).

To capture these dimensions, the setup of the model resembles Iversen and Soskice (2001)'s model. Concretely, I assume that individuals hold two types of skills, OSS (s) and general skills (g), and that there are two types of firms, ones that use both types of skills and others that only use general skills. There are two time periods, $t = 1, 2$, and workers are uncertain about their labor market situation in the second period. Concretely, workers may face three distinct states of nature, $n \in \{s, g, o\}$. With probability α , they will be employed using both types of skills, $n = s$; with probability β , they will be employed

²⁶The concrete form of this wage is equivalent to the one obtained through an asymmetric Nash bargaining of the following form: $w_i^* = \arg \max_w [w]^\delta [s_i - w]^{1-\delta}$, being δ the bargaining position of the worker.

using only general skills, $n = g$; and with probability γ they will become unemployed, $n = o$, with $\alpha + \beta + \gamma = 1$.

I claim that these probabilities are shaped by OSS and that this effect is moderated by the occupational context. Concretely, I have argued that OSS shelter workers from experiencing job loss ($\frac{\partial \alpha(s,u)}{\partial s} \geq 0$), but that the overall effect on the probability of being unemployed is uncertain because both, replaceability and portability motives are at play ($\frac{\partial \gamma(s,u)}{\partial s} \leq 0$).²⁷ These effects, however, are moderated by occupational context, u . According to the theoretical discussion, the worse the occupational context, the less the sheltering effect of the increases in OSS ($\frac{\partial \alpha(s,u)/\partial s}{\partial u} < 0$). Because of this, and because unemployment spells might increase, it is expected that increases in OSS will increase the likelihood of being unemployed the worse the occupational context ($\frac{\partial \gamma(s,u)/\partial s}{\partial u} > 0$).

In terms of preferences, differently than Iversen and Soskice (2001), I follow Alesina and La Ferrara (2005) assuming risk-neutral individuals. However, differently to Alesina and La Ferrara (2005), I assume that individuals are loss-averse, that is, they value negatively the possibility of losing income. Concretely, I argue that individuals have a reference point (r), and that they value negatively the possibility of having an income lower than this reference point in the future. Concretely, in a risk-neutral environment (Alesina and La Ferrara, 2005), being r_i the reference point of individual i and $y_{i,n}$ her income in a given state of nature n , I follow Tversky and Kahneman (1991) in defining dislike for losses as $-\lambda(r_i - y_{i,n})$, being λ the degree of loss aversion, $\lambda \in (0, \lambda^{\max})$. Kahneman and Tversky (1979) contend that a sensible reference point is current income, that is, $r = s + g$. Thus, for instance, individuals know that with probability β they will lose δs because they will be employed in a sector that only uses their general skills instead of both types of skills. Dropping subindex for the ease of exposition, expected utility for the second period in this setting is as follows:

²⁷Note that $\frac{\partial \alpha}{\partial s} = \frac{\partial \gamma}{\partial s} = 0$ when the probability of facing unemployment is already zero.

$$(4) \quad EU = \alpha(\delta s + g) + \beta g - \lambda[\beta \delta s + \gamma(\delta s + g)]$$

Equation (4) implies that for two individuals with the same expected income, the one who has more expected losses will have less utility as far as $\lambda > 0$. Nevertheless, I do not allow an individual with more skills than another (holding the probabilities of being in each state of the nature constant) to have a lower expected utility, that is, $\lambda^{\max} \leq \frac{\alpha}{1-\alpha}$.

With this preference structure, individuals have to decide over a policy. In this regard I assume that they decide over a policy which is standard in the literature (Meltzer and Richard, 1981; Alesina and La Ferrara, 2005; Dimick, Rueda, and Stegmueller, 2016). Concretely, individuals decide over a proportional tax in income which is then distributed through lump-sum transfers under government balanced constraint. As in Alesina and La Ferrara (2005), individuals decide their preferred level of taxes at the beginning of the first period and cannot be changed in the second, assuming some sort of stickiness of preferences or that changes of policies take some time. Taxes generate a disincentive effect of the form $w = \frac{\tau^2}{2}\bar{Y}$, being $\bar{Y}$ the average income of the economy, which is assumed to be constant in the two periods. Concretely, adapting Equation (4), individuals choose their preferred level of taxes maximizing the following problem

$$(5) \quad \max_{\tau \in [0,1]} \alpha(\delta s + g)(1 - \tau) + \beta g(1 - \tau) + \tau \bar{Y} - \frac{\tau^2}{2} \bar{Y} - \lambda[\beta \delta s(1 - \tau) + \gamma(\delta s + g)(1 - \tau)]$$

With $\lambda = 0$, this model is simply Alesina and La Ferrara (2005)'s model adapted to the setting of general and specific skills. What is key about this policy device is that it redistributes income and insurance against risk. Concretely, individuals having more expected income, expect to pay more in comparison to what they receive in monetary terms. However, expected losses are monotonically decreasing with τ and for instance, with $\tau = 1$, expected losses are always equal to zero. Moreover, those with more skills

(either general or specific) are the ones that benefit relatively more from this insurance device. Note that this does not allow that taxes affect the probability of facing unemployment (i.e., $\frac{\partial \alpha}{\partial \tau} = \frac{\partial \gamma}{\partial \tau} = 0$). Even common in formal models, it should be kept in mind that workers might think that greater taxes limits competition with other economies and may increase risks (Wren and Rehm, 2014).

To analytically get preferred level of taxes as a function of previous parameters one has to take the first order condition with respect to τ , which, after rearranging yields:

$$(6) \quad \tau^* = 1 - \frac{\alpha(\delta s + g) + \beta g}{\bar{Y}} + \lambda \left[\frac{\beta \delta s + \gamma(\delta s + g)}{\bar{Y}} \right]$$

The first part of Equation (6) parallels the optimal tax of Alesina and La Ferrara (2005). It says that increases in expected income before tax and transfers decrease redistribution preferences. Different from Alesina and La Ferrara (2005), the latter argument of the equation captures the fact that individuals are fearful of losing their income. To get the unconditional effect of OSS on redistribution preferences, it suffices to take the derivative of equation (6) with respect to s . That is,

$$(7) \quad \frac{\partial \tau^*}{\partial s} = \frac{1}{\bar{Y}} \left(-\delta \bar{\alpha} + (1 + \lambda) \left(\frac{\partial \gamma}{\partial s} g - \frac{\partial \alpha}{\partial s} \delta s \right) \right) \begin{matrix} \geq \\ \leq \end{matrix} 0$$

Being $\bar{\alpha} = \alpha - \lambda(1 - \alpha) > 0$ for all $\lambda \in [0, \lambda^{max})$. From equation (7), it can be seen that the first element inside parenthesis captures issues related to expected wages, while the second relates to risk exposure. First, increases in OSS are associated with increases in expected wages which decreases redistribution preferences.²⁸ The second element, however, the relation is not unequivocal.

²⁸This relation holds because $\lambda^{max} < \frac{\alpha}{1-\alpha}$, which states that two individuals with the same probabilities of being in each state of nature, greater skills cannot lead to less expected utility. It is similar to the assumption done by Dimick, Rueda, and Stegmueller (2016) which do not allow risk aversion to be too high such that the effect of income on redistribution preferences is positive.

Following the reasoning of proponents of the replaceability argument, I contend that increases in OSS decrease the probability of being dismissed. However, in case of facing job loss, they may increase the probability of long-run unemployment. In this regard, I do not assume which effect dominates, the one stressed by proponents of portability of skills or the one stressed by proponents of replaceability argument. Because of this, it cannot be inferred which effect will dominate. However, there is a special case in which the sign of $\partial\tau/\partial s$ is immediate: when the probability of job loss is already zero. In this scenario, $\partial\gamma/\partial s = 0$. The last relation holds because there is neither a lower probability of becoming unemployed nor an increase in the probability of facing long-run unemployment because there is no possibility of experiencing a layoff. In this scenario, $\partial\tau/\partial s = -1/\bar{Y}\delta\bar{\alpha} < 0$.

Turning to the main point of the paper, I proceed to analyze how occupational context shapes the effect of OSS on redistribution preferences by moderating its effect on expected wages and on the relative effects of portability and replaceability motives. Taking the derivative of equation (7) with respect to occupational context,

$$(8) \quad \frac{\partial\tau^*}{\partial u} = \frac{1}{\bar{Y}} \left(-\frac{\partial\delta}{\partial u}((1+\lambda)s + \bar{\alpha}) + (1+\lambda) \left(\frac{\partial\gamma/\partial s}{\partial u} g - \frac{\partial\alpha/\partial s}{\partial u} \delta s \right) - \frac{\partial\alpha}{\partial u} (1+\lambda)\delta \right) > 0$$

As has been argued, the effect of OSS on redistribution preferences increases the worse the occupational labor market conditions is. Equation (8) expose that this effect is positive because of the two mechanisms proposed. The first element inside parenthesis captures the fact that the effect of increasing OSS on expected wages decreases the worse the occupational context. The second element inside the parenthesis, on the other hand, captures risk exposure. The worse the economic context, there is a lower sheltering effect of increases in OSS and makes more likely to remain unemployed in case of job loss.

Finally, I show that with these preferences, economy, and tax system the portability and the replaceability models arise. The *portability model* of Iversen and Soskice (2001) contends that holding expected income constant, greater specificity of skills yields greater

redistribution preferences. Moreover, following Lamo, Messina, and Wasmer (2011) I assume that holding greater OSS might increase long-run unemployment because workers do not find suitable jobs where to use their skills and prefer to remain unemployed searching for an appropriate job. Therefore, I assume that the unemployment effect comes by reducing the probability of being employed in an occupation that requires only general skills, that is, $\frac{\partial \beta}{\partial s} = -\frac{\partial \gamma}{\partial s}$.

To begin with, I define under what conditions expected income remains constant after a unit increase in s . Expected income can be defined as $y = \alpha \cdot (s + g) + \beta \cdot g$, totally differentiating and equalizing it to zero yields, $dy = (\alpha + \frac{\partial \beta}{\partial s}) ds + (\alpha + \beta) dg = 0$, what implies that $dg = -\frac{\alpha + \frac{\partial \beta}{\partial s}}{\alpha + \beta} ds$. Therefore,

$$(9) \quad \left. \frac{\partial \tau^*}{\partial s} \right|_{\bar{y}} = \frac{\partial \tau}{\partial s} - \frac{\partial \tau}{\partial g} \frac{\alpha}{\alpha + \beta}$$

Expanding each of the elements of Equation (9),

$$(10) \quad \frac{\partial \tau}{\partial s} = -\frac{\alpha}{\bar{Y}} - \frac{\partial \beta}{\partial s} \frac{g}{\bar{Y}} + \frac{\lambda}{\bar{Y}} [\beta + \gamma + \frac{\partial \gamma}{\partial s}]$$

$$-\frac{\partial \tau}{\partial g} \left[\frac{\alpha + g \frac{\partial \beta}{\partial s}}{\alpha + \beta} \right] = \frac{\alpha + \beta}{\bar{Y}} \frac{\alpha}{\alpha + \beta} + \frac{\alpha + \beta}{\bar{Y}} \frac{g}{\alpha + \beta} \frac{\partial \beta(s)}{\partial s} - \frac{\alpha}{\alpha + \beta} \frac{\lambda}{\bar{Y}} \gamma - \frac{\lambda}{\bar{Y}} \gamma g \frac{1}{\alpha + \beta} \frac{\partial \beta}{\partial s} =$$

$$(11) \quad = \frac{\alpha}{\bar{Y}} + \frac{g}{\bar{Y}} \frac{\partial \beta}{\partial s} - \frac{\lambda}{\bar{Y}} \left[\frac{\alpha}{\alpha + \beta} \gamma + \gamma \frac{1}{\alpha + \beta} g \frac{\partial \beta}{\partial s} \right]$$

Summing Equations (10) and (11),

$$\begin{aligned}
\left. \frac{\partial \tau^*}{\partial s} \right|_{\bar{y}} &= -\frac{\alpha}{\bar{Y}} - \frac{g}{\bar{Y}} \frac{\partial \beta}{\partial s} + \frac{\alpha}{\bar{Y}} + \frac{g}{\bar{Y}} \frac{\partial \beta}{\partial s} + \frac{\lambda}{\bar{Y}} \left[\beta + \gamma + \frac{\partial \gamma}{\partial s} g \right] - \frac{\lambda}{\bar{Y}} \left[\frac{\alpha}{\alpha + \beta} \gamma + \gamma \frac{1}{\alpha + \beta} g \frac{\partial \beta}{\partial s} \right] = \\
&= \frac{\lambda}{\bar{Y}} \left[\beta + \gamma + \frac{\partial \gamma}{\partial s} g - \frac{\alpha}{\alpha + \beta} \gamma - \gamma \frac{1}{\alpha + \beta} g \frac{\partial \beta}{\partial s} \right]
\end{aligned}$$

Since, $\alpha + \beta = 1 - \gamma$, and $\frac{\partial \beta}{\partial s} = -\frac{\partial \gamma}{\partial s}$,

$$\begin{aligned}
\left. \frac{\partial \tau^*}{\partial s} \right|_{\bar{y}} &= \frac{\lambda}{\bar{Y}} \left[\beta + \gamma \left(1 - \frac{\alpha}{\alpha + \beta} \right) + \frac{\partial \gamma}{\partial s} g \left(\frac{1}{1 - \gamma} \right) \right] = \\
&= \frac{\lambda}{\bar{Y}} \left[\beta + \beta \left(\frac{\gamma}{1 - \gamma} \right) + \frac{\partial \gamma(s)}{\partial s} g \left(\frac{1}{1 - \gamma} \right) \right] > 0
\end{aligned}$$

In Iversen and Soskice (2001), there is no effect of s on the probability of experiencing long-run unemployment (i.e., $\partial \gamma / \partial s = 0$), therefore, it translates simply to

$$\left. \frac{\partial \tau^*}{\partial s} \right|_{\bar{y}} = \frac{\lambda}{\bar{Y}} \left[\beta + \beta \left(\frac{\gamma}{1 - \gamma} \right) \right] > 0$$

I turn to analyze the *replaceability* argument. In this setting increases in specific skills reduce the probability of layoff without increasing long-term unemployment prospects, that is $\partial \gamma(s) / \partial s = -\partial \alpha(s) / \partial s < 0$. Thus, taking the derivative of Equation 4 with respect to s ,

$$\frac{1}{\bar{Y}} \left[-\frac{\partial \alpha}{\partial s} (s + g) + \alpha + \lambda \beta + \lambda \gamma + \lambda \frac{\partial \gamma}{\partial s} (s + g) \right] = \frac{1}{\bar{Y}} \left[-\bar{\alpha} - (1 + \lambda) \frac{\partial \alpha}{\partial s} (s + g) \right] < 0$$

It can be seen, as exposed in the main text that the effect of specific skills in replaceability thesis comes from two sources: from increasing expected wages and from decreasing the probability of being replaced.

B Sample, Data Sources and Operationalization

B.1 Countries Included in ESS, ISSP and PIAAC

Table 4: Sample analysis from ESS

Country	ESS Rounds
Austria	1 to 3 and 6 to 9
Belgium	1 to 9
Bulgaria	9
Switzerland	1 to 9
Cyprus	3 and 9
Czech Republic	1, 2 and 4 to 9
Germany	1 to 9
Denmark	1 to 7 and 9
Estonia	4 to 9
Spain	1 to 5 and 7 to 9
Finland	1 and 3 to 9
France	6 to 9
Great Britain	1 to 9
Greece	1, 2, 4 and 5
Croatia	9
Hungary	4 to 9
Ireland	2, 3 and 5 to 9
Iceland	8 and 9
Italy	6, 8 and 9
Lithuania	5 to 9
Luxembourg	2
Latvia	9
Netherlands	4 to 9
Poland	1 to 9
Portugal	1 to 4, and 6 to 9
Sweden	2 to 9
Slovenia	1 to 9
Slovakia	2, 3, 5, 6 and 9

Table 5: Sample analysis from ISSP

Country	ESS Rounds
Belgium	2016
Switzerland	2006 and 2016
Czech Republic	2006 and 2016
Germany	1996 to 2016
Denmark	2006
Spain	1996 to 2016
Finland	2006 and 2016
France	2016
Great Britain	2006 and 2016
Croatia	2006 and 2016
Hungary	2006 and 2016
Ireland	1996 and 2006
Iceland	2016
Lithuania	2016
Latvia	2006 and 2016
Norway	2006
Poland	2006
Portugal	2006
Sweden	2006 and 2016
Slovenia	2006 and 2016
Slovakia	2006 and 2016

The countries used from the PIAAC to calculate OSS are: Austria, Belgium, the Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, the Netherlands, Norway, Poland, Slovenia, Spain, Sweden and the United Kingdom.

B.2 Control Variables in Main Analysis

In this part of the Appendix, I provide the controls used in all the regressions and the logic for including them. Starting with ESS analysis:

1. **Income.** The ESS is especially good at providing the income of respondents harmonized by rounds and countries. I follow Rueda (2018), which uses the mid-points of the income bands of the ESS and uses Hout (2004) to impute top-income values. I normalize household income by dividing it by the square root of the number of individuals in the household. To calculate the relative distance from the country mean, I standardize the variable at the country-year (and set the maximum value

to the 99th percentile).

2. **Education years.** The variable aimed to capture general skills is the number of years the individual has been in formal education. Since the range is from 0 to 56, with few (and very uninformative) values at the right tail of the distribution I follow Walter (2017) and I put as the maximum level of education 25 years.
3. **Age.** In terms of affecting the coefficients of specific skills, it might be that age is capturing some other dimension not captured of risk aversion (Guiso et al., 2020), which may effect the occupation and redistribution preferences. I control linearly for age, but results are robust to the inclusion of age dummies.
4. **Unemployed.** This is a dummy variable that takes the value of one if the individual is unemployed and of zero otherwise. This is aimed to capture *realized risk* as an independent channel of risk exposure (Cusack, Iversen, and Rehm, 2006).
5. **Type of Contract.** As outlined by Rueda (2005), outsiders tend to have different redistribution preferences than insiders. Moreover, firms have to provide incentives in form of contracts to incentivize the acquisition of specific skills. Therefore, whether individuals have “unlimited”, “limited” or “no contract” should be included in the analysis.
6. **Member of a trade union.** As stressed by Freeman (1976), trade unions can have a positive effect on the information flow between workers and employers. This might be especially relevant for contract relations of long-run nature as the ones provided for individuals in order to acquire specific skills. Moreover, members of trade unions tend to be more leftist and support redistribution. When asked about whether the respondent is a member of a trade union, they had three options: “Yes, currently”, “Yes, previously” and “No”. I use these answers as controls.
7. **Gender.** Since female participation in the labor market tends to be more fragmented, they might be less represented in occupations requiring high investments

in specific skills, compared to general skills. Indeed, while the correlation between specific skills and a dummy for gender is -0.176, for education years is 0.025. Since women tend also to support more redistribution, I include it as a control.

8. **Religiousness.** Is usual in the literature to include some dimension of religiosity since it could affect individuals' values. I include a dummy that takes the value of one if the respondent belongs to a particular religion and zero otherwise.
9. **Risk aversion.** Individuals may select into occupations depending on their underlying preferences for risk (Bonin et al., 2007), which in turn may influence redistribution preferences. Following Guiso et al. (2020), I introduce a question about the willingness to take risks available in the ESS. Concretely, they are exposed to the following: "Now I will briefly describe some people. Please listen to each description and tell me how much each person is or is not like you. Use this card for your answer." Then they are exposed to different profiles. The one they use states: "He looks for adventures and likes to take risks. He wants to have an exciting life." Respondents have six options, from "Very much like me" to "Not like me at all".
10. **Human values (altruism, empathy, humbleness).** All rounds of the ESS provide a battery of questions that aims to capture human values. Since I rely on selection-on-observables, including these variables ensures that we are comparing otherwise similar individuals but in different occupations. Moreover, Duch and Rueda (2015) argue that personality traits (in their case, altruism and risk aversion) may affect redistribution preferences. Concretely, respondents are asked whether they think is "important to help people and care for others' well-being" (altruism), whether is "important to understand different people" (empathy) and whether is "important to be humble and modest" and to "do not draw attention" (humbleness). These are 6-scale questions. Must be noted that they do not capture exactly the same issues and the correlation between these variables varies from 0.24 (humbleness and altruism) to 0.4 (empathy and altruism).

For the analysis using ISSP, the list of control variables is the following:

1. **Income.** The ISSP provides a measure of the self-reported income of respondents. Even though this income variable is not coded as accurately as in the case of the ESS, varying the scale and the currency between and within countries, this is not especially problematic since I also standardize the variable at the country-year.
2. **Education Years.** As in the case of ESS, I limit education years to 25.
3. **Age.**
4. **Gender.**
5. **Union Member.** Different from ESS, the first two rounds used of the ISSP only differentiate between being currently a member of a trade union or not. Therefore, is a dummy that takes the value of one if the respondent is currently a member of a trade union and zero otherwise.
6. **Unemployed.** Dummy capturing whether the individual is currently unemployed.
7. **Part-time.** Dummy capturing whether the individual is working part-time.

B.3 Coding Dependent Variables of ISSP's analysis

In the ISSP the respondents face different areas where the government may intervene in the economy, concretely, supporting “declining industries to protect jobs”, “financing of projects to create new jobs” and whether is government’s responsibility to “provide jobs for all”. The former item captures issues of employment protection (used, for instance, by Emmenegger (2009)) and the latter two, active labor market policies aimed at creating jobs. The respondents have five options, from “Strongly in favour of” to “Strongly against”, with an intermediate option “Neither in favour of nor against”. I code as one respondents answering “Strongly in favor of” or “In favour of”, and zero otherwise.

To capture unemployment benefits, the statement faced by respondents is whether they would like “to see more or less government spending” in “unemployment benefits”. Again it has five options, from “Spend much more” to “Spend much less”, with an intermediate option “Spend the same as now”. I code as one those respondents answering “Spend much more” or “Spend more”, and zero otherwise.

Finally, I include measures about tax preferences. The ISSP asks respondents whether taxes on rich people are “much too high”, “too high”, “about right”, “too low” or “much too low”. I code as ones those answering “too low” and “much too low”, which imply that they would like to see more taxes on the rich. Finally, the ISSP shows this question not only about taxes on the rich but also on middle-income and low-income people. Following Barnes (2015), I compute a measure of greater tax progressivity preferences.

Table 6: Descriptive Statistics Dependent Variables from ISSP

Variable	Observations	Mean	Std.Dev
Support Decl. Industries	29,855	63.463	48.154
Projects New Jobs	30,111	84.042	36.622
Jobs for Everyone	30,305	64.484	47.857
Unemployment Benefits	30,724	37.485	48.409
Tax Rich	28,451	50.483	50.000
Progressivity	27,843	66.692	47.132

B.4 Coding Occupation-Specific Skills using the PIAAC and the ESS

Table 7 shows the possible answers individuals faced in the PIAAC questionnaire, how it has been coded into months, and how many observations are in each answer for the ISCO88 and for the ISCO08. Concretely, the variable is operationalized in months and captures the mid-point of the range of each answer. In the extreme case, “Three years or more”, it has been coded as 4 years (48 months). This case has been coded taking into account the distribution of answers to a similar question provided in the ESS.

As expected, there are fewer observations for ISCO88, since the PIAAC is originally

Table 7: Operationalization and Observations PIAAC answers

Answer	Operationalization (months)	Observations (ISCO88/08)
None	0	10,088/15,611
Less than 1 month	0.5	2,530/3,646
From 1 to 6 months	3.5	6,833/10,117
From 7 to 11 months	9	2,758/4,504
From 1 to 2 years	18	8,070/13,188
Three years or More	48	7,736/13,057

Note: These data come from the two rounds of the PIAAC. $N=38,015$ for ISCO88 and $N=60,123$ for ISCO08.

coded in ISCO08. All missing information arises because in some cases the occupation classification is not provided at the ISCO88 four-digit. This would pose a problem if there were some sort of selection of missings that would change the distribution of answers. Figure 8 displays the distribution of answers for both cases, showing that there are no substantial differences.

Figure 8: Distribution Answers PIAAC questionnaires

As has been mentioned, in the 2nd and the 5th rounds of the ESS there is also a question similar to the one provided by the PIAAC. This variable is the one used by Polavieja (2016). Concretely, respondents are asked: “if someone with the right education and qualifications replaced you in your job, how long would it take from them to learn

to do the job reasonable well?” I have coded answers into months following Ortega and Polavieja (2012). The main problem with this question is that it might also capture FSS. Nevertheless, the correlation between the variable obtained from ESS (after aggregating also at the occupational level) and the one retrieved from PIAAC is 0.94 for the case of aggregating at the first digit and 0.86 when aggregating at the second one. This is surprisingly high given that the occupation classification in the ESS is ISCO88, while in the PIAAC is ISCO08, leading to inevitable errors-in-measurement that attenuate the correlation. In the robustness section, I show results using this variable.

B.5 Descriptive Statistics Occupation-Specific Skills

In the main text I showed the relation between OSS measure retrieved from the PIAAC and the variable proposed by Iversen and Soskice (2001). Figure 9 shows the relation when using ISCO08 classification instead.

Figure 9: Compararison Measures: PIAAC and Iversen & Soskice

The next two tables shows the descriptive statistics of the main variable used, distinguishing by observations in ISCO88 and ISCO08.

Table 8: Descriptive Statistics ISCO88

Occupation	Mean	Median	Std. Deviation
11. Legislators and senior officials	26.256	18	21.357
12. Corporate managers	30.911	48	19.296
13. General managers	19.047	18	18.848
21. Physical science professionals	24.501	18	19.611
22. Life science professionals	19.339	18	19.240
23. Teaching professionals	15.705	9	18.186
24. Other professionals	23.181	18	19.365
31. Physical science associate	19.661	18	19.003
32. Life science associate	13.655	3.5	16.592
33. Teaching associate	23.677	18	19.522
34. Other associate professionals	17.916	18	18.137
41. Office clerks	12.859	3.5	15.917
42. Customer services clerks	7.852	3.5	12.437
51. Personal/protective workers	9.009	3.5	14.013
52. Models/salespersons	6.207	3.5	11.214
61. Skilled primary workers	8.676	0.5	14.555
71. Building trades workers	15.010	9	17.460
72. Metal/machinery trades workers	16.256	9	17.760
73. Handicraft trades workers	13.942	3.5	17.418
74. Other craft trades workers	10.642	3.5	15.043
81. Stationary-plant operators	10.802	3.5	15.485
82. Machine operators/assemblers	7.114	.5	12.616
83. Mobile-plant operators	12.152	3.5	15.599
91. Sales/services elementary	4.560	0	10.361
92. Primary sector labourers	4.815	0.5	9.686
93. Construction/manufacturing labourers	0.58	4,062	10.388

B.6 Relation between OSS from the PIAAC and EGP class schema

In this section I show the relation between the variable proposed and the EGP class schema, usually employed in social stratification literature. Concretely, I follow Tåhlin (2007) and Emmenegger (2009) and I assign different EGP classes a value of skill specificity, concretely, I assign the value of =1 to class “I. High Controllers”, of 0.8 to “II. Lower Controllers”, of 0.5 to “IIIa. Routine Nonmanual”, of 0.2 to “VI. Skilled Workers”

Table 9: Descriptive Statistics ISCO08

Occupation	Mean	Median	Std. Deviation
11.Chief Executives, Senior Officials	31.596	48	19.990
12.Administrative and Commercial Managers	33.807	48	18.267
13.Production and Specialized Services	32.737	48	18.936
14.Hospitality, Retail and Other	23.190	18	19.058
21.Science and Engineering Professionals	24.562	18	19.743
22.Health Professionals	18.406	18	18.965
23.Teaching Professionals	15.517	9	18.062
24.Business and Administration Professionals	26.082	18	19.270
25.Information and Communications Tech.	25.927	18	19.350
26.Legal, Social and Cultural Professionals	21.033	18	19.265
31.Science and Engineering Associate Profs.	21.690	18	19.345
32.Health Associate Professionals	14.327	9	17.035
33.Business and Administration Assoc.	19.043	18	18.389
34.Legal, Social, Cultural Associate Profs.	16.775	9	18.114
35.Information and Communications Tech.	18.808	18	17.595
41.General and Keyboard Clerks	12.733	3.5	15.631
42.Customer Services Clerks	10.063	3.5	14.133
43.Numerical and Material Recording Clerks	14.417	9	16.342
44.Other Clerical Support Workers	12.770	3.5	16.363
51.Personal Services Workers	9.639	3.5	14.415
52.Sales Workers	7.009	3.5	12.083
53.Personal Care Workers	8.351	3.5	12.897
54.Protective Services Workers	10.250	3.5	15.783
61.Market-oriented Skilled Agricultural	9.043	3.5	14.785
62.Market-oriented Skilled Forestry,	14.498	3.5	9.512
63.Subsistence Farmers, Fishers, Hunters	4.055	0.5	9.168
71.Building and Related Trades Workers	15.154	9	17.506
72.Metal, Machinery and Related Trades	16.426	3.5	17.815
73.Handicraft and Printing Workers	13.940	3.5	17.193
74.Electrical and Electronic Trades Workers	17.223	18	17.914
75.Food Processing, Woodworking, ...	10.396	3.5	15.047
81.Stationary Plant and Machine Operators	8.053	3.5	13.588
82.Assemblers	6.199	0.5	11.479
83.Drivers and Mobile Plant Operators	11.746	3.5	15.318
91.Cleaners and Helpers	3.596	0	8.645
92.Agricultural, Forestry and Fishery	3.868	0	9.772
93.Mining, Construction, Manufacturing	4.933	0.5	10.613
94.Food Preparation Assistants	3.977	0.5	8.708
95.Street and Related Sales and Services	2.610	0	8.200

Figure 10: Comparison PIAAC and EGP class schema

and of 0 to “IIIb. Lower Sales-Service” and “VIIa: Unskilled Worker”.²⁹ The correlation between this (bit arbitrary) measure and the PIAAC variable is 0.789. Figure 10 shows the values of both variables (after recoding the PIAAC variable to be between 0 and 1). It can be seen that both variables coincide in which classes have the highest and the lowest levels of skill specificity, however, there are also some differences. First, the difference between classes I and II is higher using the variable proposed (nevertheless, the ordering remains the same) and, second, while EGP argues that class IIIa should have more specific skills than class VI, I find that it is the other way around. I argue that since this question directly captures the dimension under study, is a better strategy than simply using dummies capturing EGP classes.

²⁹These classes represent the 90% of the sample.

B.7 Operationalization Occupational Unemployment Rates

Since in some occupations OUR may rely on a few observations it could be that they are not accurately calculated. I only compute OUR for country-occupation-years with at least 30 observations and apply linear interpolation for missing cases. For the cases in which I have no data, I use OUR at the first digit kindly provided by Philipp Rehm. Moreover, all the analyses presented in the main text have been done aggregating OSS and OUR at the ISCO one-digit. Moreover, I smooth the data, considering one-year lag values of OUR, giving half of the weight to past values. That is,

$$(12) \quad \overline{OUR}_t = \frac{2}{3} \left(OUR_t + \frac{1}{2} OUR_{t-1} \right)$$

Being $\overline{OUR}$ the smoothed variable. This is slightly different from the approach in Rehm (2009). There, the smoothing is done considering not only a lag, but also a lead, which could attenuate the results.

Then I take the logarithm of this transformation. Since there are no zeros in any country-year-occupation observation, there is no need of using other transformations such as the inverse hyperbolic sine transformation.

Must be noted that OUR could be stratified across different dimensions. For instance, youth individuals tend to face different OUR than their older counterparts. Ideally, I should differentiate between OUR of different groups, distinguishing also for gender, age, and a more detailed regional measure. Nevertheless, LFS data do not allow disaggregating accurately at the 2-digits level for different population groups or more detailed regions.

C Appendix Results

C.1 Assumption linear dependent variable

I assume that the dependent variable is continuous and binary. This makes the interpretation of the interactive effects easier but it has two potential drawbacks. First, that the predicted values might be out of the probability boundary, and second, that standard errors are heteroskedastic by construction. Addressing the former issue, I display the predicted values of linear and the binning estimates in Figure 11. In both cases around 1.5% of the observations are above one, while less than 0.3% are below zero.

Figure 11: Predicted Values Binning and Linear Estimates

Regarding heteroskedastic standard errors, the confidence intervals shown in the main analysis are robust to heteroskedasticity and clustered at country-year-occupation (Abadie et al., 2017). To have enough observations in each cluster occupations used are at the ISCO one-digit.

C.2 Main Results

In the text, I only display results with all controls and I do not show a Table with the coefficients and the associated standard errors. Table 10 shows the coefficients of the linear interactive effects models. Column (1) shows the relation without any control, just the main variables analyzed. Column (2) includes country-round FE, showing that the interactive effect becomes even more strong. The third column uses controls usually employed in the literature, concretely, income, education years, age, employment relation, type of contract, member of a trade union, gender and religiousness. Moreover, these controls are interacted with OUR. The coefficient of the interaction diminish somehow the interactive effect proposed but is still big and significant. The last column also adds variables capturing attitudes towards risks and the levels of empathy, altruism and humbleness. The results are highly robust to the inclusion of these variables.

Table 10: Coefficient Linear Interactive Effects

	(1) No	(2) + Country-Round	(3) +Few	(4) +All
OSS	-6.871*** (0.572)	-7.957*** (0.353)	-5.168*** (0.366)	-4.929*** (0.364)
OUR	5.448*** (0.401)	2.255*** (0.321)	0.044 (1.188)	-4.325*** (1.372)
OSS× OUR	1.551*** (0.362)	1.870*** (0.208)	1.372*** (0.217)	1.336*** (0.215)
Observations	149148	149148	149148	149148
R^2	0.030	0.093	0.113	0.119

As stated in the text, in order to see the significance of the interactive effects is better to represent them graphically. Figure 12 does so. It can be seen that the interactive effect proposed works in all cases and only when only including country-round FE, for high levels of OUR the effect of OSS is significantly negative.

Table 11 and Figure 13 show the binning estimates using the same controls as before, showing that the results are robust to all these specifications.

Figure 12: Linear Interaction Results

Table 11: Binning Estimates

	(1) No Controls	(2) + Country-Round FE	(3) +Few Controls	(4) +All Controls
Low	-5.895*** (0.494)	-6.330*** (0.300)	-4.366*** (0.305)	-4.105*** (0.304)
Mid	-5.167*** (0.601)	-5.583*** (0.334)	-3.576*** (0.336)	-3.414*** (0.337)
High	-0.278 (0.737)	-2.041*** (0.402)	-0.470 (0.396)	-0.468 (0.392)
Observations	149144	149144	149144	149144
R^2	0.032	0.093	0.112	0.118

D Appendix Robustness

D.1 Robustness Checks

Figure 14 checks whether the results obtained are sensitive to some of the empirical decisions taken. Robustness checks can be divided into six subgroups, in which I test if the

Figure 13: Binning Estimates

results are robust to: i) changes in the coding of the dependent variable; ii) changes in the variable chosen to capture OSS; iii) changes in the variable used to grasp the occupational context; iv) changes in the controls used in the regression, including occupation FE, v) testing the argument against competing explanations; vi) changes in specific countries, time periods or occupations. Moreover, I show that the relation holds for private workers but not for public servants. Concretely, in the analyses that follow, I show the results of the marginal effect of one standard deviation increase in OSS in the binning regression used in the main analysis.

Panel a) shows different transformations of the dependent variable. Concretely, in red it shows how results change when using a binary transformation as dependent variable that codes those that “neither agree nor disagree” together with those that explicitly show redistribution support. In green are the results coding those that either agree nor disagree as an independent group, assuming that the difference between different options is the same. Finally, in yellow, there are the results using the untransformed variable. Despite the fact that each of them the meaning of the coefficient is slightly different, the

results are robust to all of these transformations.

To check that the result does not hinge on the specific operationalization of the dependent variable, Panel b) displays the effects using different variables to capture OSS. First, I employ the question retrieved from the ESS at the ISCO two-digits (described previously in Appendix B.4). The results are shown in red. Then I show that the result also holds when computing the variable from PIAAC and from ESS at the ISCO one-digit (in green and yellow respectively).

I also check that the results do not rely on the moderator used and that the expected relation also holds using other related variables in the first two graphs in the second row. I do so using measures to capture automation risk mostly used in the literature in Panel c) (Goos, Manning, and Salomons, 2014; Oesch, 2006).³⁰ Using Routine Task Intensity as a moderator (results are shown in red), go much in line with the main specification. Moreover, I use the dummy variable proposed by Oesch (2006) to capture which occupations are considered to be routine. In this latter case, since the moderator is binary, I interact OSS with the variable as well as all controls. The green point estimates and associated confidence intervals are shown only for Low (non-routine) and High (routine) levels of the moderator.

Panel d) analyzes changes in controls used. First, it must be noted that a potential problem with fully saturated models is that they may overfit the data (Blackwell and Olson, 2021). I show that this does not seem to be the case and that both specifications yield similar results. Another potential problem is that the interactive effects might simply capture a quadratic effect of OUR (Beiser-McGrath and Beiser-McGrath, 2020). I introduce the quadratic effect of OUR as controls, showing the results in green.

Further, I also include different controls. I include a variable capturing individuals' ideology.³¹ This is retrieved from a question that asks respondents to place themselves

³⁰For Goos, Manning, and Salomons (2014)'s variable, since there are missing values for some occupation groups defined at the two digits, I impute the mean value of other occupations in the same major group.

³¹All the controls included are also fully interacted allowing for flexible effects by distinct OUR.

ideologically in a left-right scale, having eleven options from extreme-left(0) to extreme-right(10). Even though this could bias the results because redistribution preferences and ideological scale may capture the same thing, it can be argued that the argument proposed should work within ideological groups. The results are robust to the inclusion of these dummies. Moreover, I show that the results are robust to the inclusion of RTI (Goos, Manning, and Salomons, 2014). Since offshorable occupations might be the ones that require less OSS, I include a measure of occupations' offshorability from Walter (2017) and also I include a dummy capturing if the occupation is considered to be routine (Oesch, 2013). Since current income could be thought as a "bad control" I exclude income from the controls. In all cases the results are robust and highly stable. Finally, I include occupation ISCO one-digit fixed effects, thus, exploiting only variation within occupations. Even in this case in which I limit the variation of the main explanatory variable the relation holds. This is especially important since it suggests that the effect found is not driven by selection into occupations, since it holds even within ISCO major groups.

In Panel e), instead of just introducing controls, I test competing arguments that propose a distinct interactive effect that could affect my result. Note that indirectly I am controlling in all regressions by the mechanisms proposed by Häusermann, Kurer, and Schwander (2015) since I interact OUR with education. I start by checking that introducing "degree of specificity" proposed by Iversen and Soskice (2001) does not change the result. Moreover, I control for Thewissen and Rueda (2019)'s argument. The authors claim that the greater the income, the larger the effect of being in a routine occupation. Concretely, I control for the interaction between the routine task intensity measure of Goos, Manning, and Salomons (2014) and income. Finally, I test whether Walter (2017) argument about the interactive effect of general skills and offshorability mutes the effect of this thesis. In all these cases, the effect remains significant and very stable.

Finally, I check how sensitive are the results to the inclusion of any particular country, period of time, or occupation. I do so by running a series of leave-one-out regressions and showing the coefficients in panels f), g), and h). In panel f) I leave one country at a

Figure 14: Robustness Checks

time, and I find similar results. In Panel g) I study different time periods. I show that the exclusion of one round at a time does not change the relation proposed. Moreover, I check whether the results hold splitting the sample between pre-crisis (from 2002 to 2008) and post-crisis (from 2010 to 2018). In both cases, the results hold, albeit a little bit less strong when analyzing the pre-crisis period. The last panel does the same analysis but changes one ISCO major group occupation at a time. Except when dropping major group 7 (Craft and Related Trades Workers), in all cases when the OUR are in the highest tercile, the effect is distinct from zero. Nevertheless, in all cases, the interaction is statistically significant in the sense that for typical low and typical high values of the moderator, the effect is statistically different.

Finally, I perform a placebo test, dividing between those that work as public servants and those that work in the private sector. The ESS provides a question on what type of organization the respondents work. They have six possibilities: i) central or local government; ii) another public sector (such as education); iii) a state-owned enterprise; iv) a private firm; v) self-employed and vi) other. I code as public workers those in the first three options and zero otherwise. They represent the 30% of the observations. Arellano et al. (2021) finds that, in Spain, public servants face very low-income risk compared to workers in the private sector, and that their income risk does not increase during recessions. Therefore, I should expect a more reduced effect compared to workers in the private sector. Indeed, for public servants, the interaction is not statistically significant while for workers in the private sector the effect is even more significant than in the main analysis.

D.2 Mechanisms

So far, I have shown that the effect proposed remains robust to alternative explanations proposed in the literature. Theoretically, I have argued that OSS are different from other types of skills in the sense that occupational context shapes their effects on labor market prospects and through this mechanism, their effects on redistribution preferences.

Figure 15: Effects on Public Servants and Private Workers

With this inquiry in mind, I study the proposed mechanisms by turning again to ESS data. To capture wage expectations in the case of remaining employed, I use a measure similar to Rueda and Stegmueller (2019). The authors use Mincer-type equations, having income as the dependent variable and potential experience, education, and their interaction as the main independent variables. They do so to compute expected income until retirement. Differently, since I am interested in expected wages I restrict the sample to those whose main income source is wages. Moreover, following Lazear (1995), I introduce occupational dimension of wages. Concretely, I introduce the interaction of OSS and OUR, and following Alesina and La Ferrara (2005), I compute expected wages for the next ten years (the description of the methodology is explained separately in Appendix D.4). The implicit assumption is that individuals not only consider their formal education and experience as a determinant of their expected income, but also their occupations, the amount of their skills, and the occupational context.

To capture risk exposure I employ two questions that capture subjective unemployment risk and its consequences. Distinguishing them is useful because sometimes they can provide conflicting evidence. For instance, while Wren and Rehm (2014) finds that high-skilled individuals exposed to globalization expect to become unemployed, Walter (2017) shows that they are less concerned with finding an appropriate job. Concretely, to grasp unemployment risk I use a question in which respondents are asked “How likely

unemployed and looking for work next 12 months?”. This is the question used by Wren and Rehm (2014). I code as one those that say that is “likely” or “very likely” and as zero those that answer “not at all likely” and “not very likely”. To capture perceived consequences of job loss, I use answers to the question about how difficult/easy would be to “get a similar or better job with another employer”, with positive values indicating being more difficult.³² This is the question used by Walter (2017) and is very similar to a question used by Iversen and Soskice (2001), in which respondents were asked about how difficult is to find an “acceptable job”.

Figure 16: Proposed Mechanisms

It can be seen that there is suggestive evidence that expected wages in case of remaining employed increases with OSS but that this effect diminishes the looser the occupational context is. Turning to analyze risk exposure, it seems that the worse the occupational context, the higher the effect of OSS. Increases in OSS tend to decrease unemployment risk when the occupational context is tight and increase it when it is loose and at the same time, it makes workers more concerned with finding a similar job.

Must be noted that the proposed mechanisms are in a sense dynamic so the effect found for risk exposure should be read with caution. I have claimed that when the occupational context is loose, higher OSS do not translate into less unemployment insecurity and that individuals might find it difficult to find a new job. This, in turn, decreased their bargaining position vis-a-vis firms, which translated into lower expected wages. The fact

³²I follow Walter (2017) and I transform the 10-points scale into a 3-point scale, distinguishing between low (0-2), intermediate (3-7) and high(8-9).

that workers adapt to this situation by changing their wages aspirations, decreases job loss risk and makes finding an “similar” job relatively easier.

D.3 Analyzing the role of the “degree of specialization” and of firm-specific skills

D.3.1 Degree of Specificity vs Amount of Skills being Specific

As discussed in the main text, the variable used in Iversen and Soskice (2001) (I&S, hereafter) was aimed at capturing the “degree of specificity”. This is similar to what Bisbee and Rosendorff (2020) aims to capture, with higher specificity implying that skills can be used in a few occupations/sectors/firms and that the share of these occupations/sectors/firms is small. To capture this fact, I&S use the division between occupations provided by the ISCO classification, assuming that the more divided the occupations within (sub-)major groups, the more specific the skills to be performed. Then this variable is divided by the share of workers in a given occupation, to get a sense of the “actual size of the labor market” (Kitschelt and Rehm, 2006:81). Even though this latter element is introduced as a normalization (i.e., more fine-grained description of occupations could be due to their size), as a matter of fact, when the occupation share shrinks, the specificity of skills increases (Kitschelt and Rehm, 2006). I&S use the labor market share of each occupation for the whole sample, which implies assuming no mobility costs (Kitschelt and Rehm, 2006). In this aspect, I follow Bisbee and Rosendorff (2020) who define labor markets at the state level in the U.S., assuming that there are mobility costs. I define labor markets at the country level, as I do for OUR.

Differently, in the paper, I do not focus on the degree of specificity. Instead, I have focused on the *absolute amount* of skills that are specific to an occupation. I have shown that both variables capture different things, and now I will turn to show that they have a distinct effect on preferences.

The left panel in Figure 17 shows the effect of the variable proposed by I&S without controlling by the total amount of skills that are specific to the occupation, allowing for heterogeneous effects for distinct values of OUR. This is done with the same specification as in the principal analysis. It can be seen that, even though much less strong, there is suggestive evidence that the interactive effect proposed works also for the Iversen and Soskice (2001)’s measure. Nevertheless, the correlation between the two variables is 0.25, so it could be that simply the interactive effect shown arises because of this correlation. The right panel Figure 17 shows the effect of I&S measure after properly capturing the effect of OSS moderated by the occupational context. In this case, the effect is positive and is not a function of the occupational context, as I&S expected.

Must be noted, however, that this is not the causal effect that I&S aim to capture. Indeed they argue that not dividing it by general skills will tend to downward bias the result (Iversen and Soskice, 2001:881, footnote 16). I am agnostic about the concrete empirical specification that should be used to capture this causal effect, but this exercise points out that the measure their propose actually captures a different dimension than the one in this paper.

D.3.2 The role of Firm-Specific Skills

Following labor economics literature, in the main text, I have argued that I focused on OSS rather than on FSS because it was found to have greater effects on labor market prospects. Is this distinction between FSS and OSS relevant? Does the relation proposed holds also for FSS? I argue that the effect of FSS on redistribution preferences is indeed different from the one proposed in the paper. First, in terms of the theoretical Table 1, with FSS firms cannot find another worker with the appropriate skills (having to incur training costs), and workers in case of a layoff would not be able to use these skills in any other firm. With FSS, therefore, workers and firms are in a mutually beneficial position. According to Tåhlin (2007), analyses that focus on “reciprocal ties” ignore the more consequential cases in which either the worker or the firm dominates. In a context

Figure 17: Interactive effect using Iversen and Soskice (2001)’s and PIAAC’s variables to capture specificity

of reciprocal ties, the bargaining position of each of the parts does not change with labor market context since there are neither workers with the appropriate skills nor firms that value these precise skills (Lazear, 2009). Second, as outlined by Pahontu (2021), if firms use strategies such as “last-in first-out”, it could even be expected that FSS have a *more negative* on redistribution preferences *the worse the occupational context*.

Rounds 2 and 5 of the ESS allow me to see whether the interaction proposed works also for FSS. I follow Kambourov and Manovskii (2009a) defining FSS as tenure. Moreover, I use the answers of the question “if someone with the right education and qualifications replaced you in your job, how long would it take from them to learn to do the job reasonable well?”, codifying answers as Ortega and Polavieja (2012) (see Appendix B.4). The answers to this question are made up of three elements: firm-specific, occupation-specific and individual-specific. By controlling by OSS and all set of individual controls, I aim to capture FSS better than simply using tenure. Table 12 shows the correlations between the three variables. It can be seen that the correlation between the variable used in the paper and tenure is low ($r = 0.06$). Not surprisingly the correlation with

the question about how long it would take another person to learn her job is higher ($r = 0.16$). This is because there is a part of this question that grasps the occupational dimension of learning a job. Nevertheless, the correlation is still low and suggests that the two variables grasp different dimensions. Finally, among these variables, the highest correlation is among those aimed at capturing FSS, but still, the correlation is relatively low ($r = 0.23$).

Table 12: Correlation OSS and FSS measures

Variables	OSS PIAAC	Tenure	Time learn job
OSS PIAAC	1		
Tenure	0.06	1	
Time Learn Job	0.160	0.232	1

Figure 18 shows the effect of the two variables aimed to capture FSS on redistribution preferences. Since the p-value of a Wald test comparing the linear and the binning specifications is high in both cases, I analyze linear interactive effects models. It can be seen that the effect is different than the effect of OSS. Concretely, the effect seems to not be statistically different from zero at any level of OUR. For the case of tenure, the relation is basically flat, showing no interactive effect. For the question about time to learn a job, the effect is also close to zero and the interactive effect is small and negative in sign. This would imply that in contexts of high OUR, the higher the FSS the lower the level of redistribution support. This effect is the opposite that the one found with OSS.

D.4 How Expected Wages are Calculated

In this section, I elaborate on how to calculate expected wages. I compute them following closely Rueda and Stegmueller (2019). They build on labor economic literature predicting (current) wages on schooling and (potential) experience (Mincer, 1974; Heckman, Lochner, and Todd, 2006). Following the literature that outlines the importance of OSS, I introduce OSS interacted with experience (Lazear, 1995; Kambourov and Manovskii, 2009a). Further, I interact OSS with OUR, alongside with the interaction with experience.

Figure 18: Effect of Firm-Specific Skills

The model to be regressed is the following:

$$w_i = \alpha_1 f(exp_i) + \alpha_2 g(S_i) +$$

$$(13) \quad \alpha_3 OSS_i \times f(exp_i) + \alpha_4 OUR_i \times f(exp_i) + \alpha_5 OUR_i \times OSS_i \times f(exp_i) + \epsilon_i$$

Being, S_i the schooling years, exp_i the years of potential experience (i.e., $age_i - S_i$). I assume $f(x) = g(x) = x + x^2$. Since I want to capture expected wages, I regress this for the subsample of workers whose main source of income is wage. The predicted values from equation (13) are a function of S_i, exp_i, OSS_i and OUR_i :

$$\hat{w}_i = \hat{w}_i(S_i, exp_i, OSS_i, OUR_i)$$

Must be noted that the predicted value depends on potential experience, having heterogeneous effects depending on the levels of OSS and occupational context. At this stage, Rueda and Stegmueller (2019) compute expected income by computing the average predicted income until retirement. Differently, I follow Alesina and La Ferrara (2005) and compute expected wages for the next 10 years. Concretely, the measure of expected wages used has the following form:

$$W_i = \frac{\sum_{z=1}^{10} \hat{w}_i(S_i, exp_i + \mathbf{z}, OSS_i, OUR_i)}{10}$$

Since it has been retrieved from a regression, there are error-in-measurement problems. In the context of Rueda and Stegmueller (2019)'s analysis, they used it as an independent variable, thus, error in measurement leads to attenuation bias. For this reason, they use bootstrap to deal with this problem. In this setting, differently, since it will be the dependent variable it will only lead to more conservative standard errors. Finally, there is another difference with respect to Rueda and Stegmueller (2019)'s approach. They only compute expected income for males, while I do compute mincer equations separately for males and females, to account for the fact that not only females tend to be in occupations that require less OSS but also that the returns might be different.

E Implications

E.1 Analyzing the role played by Managers

As seen in Figure 4, managers are an outlier in terms of the amount of OSS they have (which is 1,5 standard deviations higher than the 90th percentile). This situation gets exacerbated when analyzing a context with high OUR. Figure 19 shows the histogram of OSS when OUR are high, with a dotted line on the new maximum value after dropping managers from the sample. It can be seen that including managers in the regression leads to the inclusion of outliers. These occupations have very high levels of OSS but there are only a few of them in the sample. When we drop them, the distribution of the variable is less right-skewed.

How important are these observations? Figure 20 in the left panel shows the APP from the main regression allowing for quadratic effects of OSS, including managers, and in the right panel, it shows the results without including managers, which only represent the 7,9%

Figure 19: Histogram OSS when OUR are high

of the sample. It can be seen that even allowing for quadratic effects, the main conclusions arise, with broad coalitions between low skilled, and medium and high-skilled in high OUR contexts. Moreover, the negative slope at the very end of the OSS distribution is essentially driven by managers. Without including them the relation between OSS and redistribution preferences is basically flat when OUR are high. This implies that different occupations in this context will have similar redistribution preferences: regardless of the amount of OSS, approximately an 80% of respondents will support redistribution. On the contrary, the relation found when OUR are low remains essentially unchanged, with greater OSS monotonically decreasing redistribution preferences.

E.2 Non-parametric assessment of coalitions: a binscatter approach

In the main analysis, I show the results using parametric models on the effect of OSS. First, I studied AME, assuming that the effect of OSS were linear (nevertheless, I allowed

Figure 20: APP without including managers

the effect to vary by different levels of OUR). In the previous section, I use quadratic effects to get a more clear picture of which classes were likely to support redistribution and when. Nevertheless, the previous analysis still imposes restrictions on the relationship between OSS and redistribution preferences. In this section, I move to analyze the relation by means of a binscatter regression, which does not impose a function form on the association found. This alleviates some concerns that the findings are due to the imposed (parameterized) relation between OSS and redistribution preferences.

Concretely, to control by all factors, I regress both, redistribution preferences and OSS on all controls, separately in different occupational contexts (i.e., low and high OUR levels).³³ Then, with the residuals, I create equally sized bins with respect to OSS, and I plot the average value of redistribution preferences and OSS (after adding the mean value of each bin).³⁴ Figure 21 shows the results of this analysis with dotted lines representing

³³Therefore, as in the main regression, I allow for different effects of controls in different occupational contexts.

³⁴I use 35 bins which is half of the different values OSS have. With 35 bins I have enough variance to see different patterns but I do not rely on the inclusion of outliers.

the 33 and 66 percentile of OSS in the sample. Reassuringly, the picture gotten from this analysis is similar to the parametric one, with low OUR there is a clear negative relation between OSS and redistribution preferences, but the relationship becomes much flatter with high OUR. Crucially, all bins in a high OUR context hold, on average, higher redistribution preferences than the ones in a low OUR context. Moreover, as suggested, it can be seen that there are few observations when OUR are high.

Based on the observations of individuals with intermediate OSS levels, it is clear that the proposed theory holds. Both low and high OUR contexts have individuals with intermediate levels of OSS, yet the relationship between increasing OSS and redistribution preferences differs by occupational context. When OUR is low, 71% of the lowest OSS group support redistribution and fall below 64% for the highest OSS group. In contrast, when OUR are high, there is no relationship between OSS and redistribution preferences, which remain constant at 80% of support.

Figure 21: Binscatter relation of OSS and Redistribution Preferences after partialling out the effects of controls and country-round FE