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by

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THREE ESSAYS ON THE ROLE OF INSTITUTIONS IN LABOR MARKET POLARIZATION

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To my grandfather.

I am not always sure of where I go, but I certainly do not forget from where I come.

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Chapter 1

Introduction

This dissertation examines the impact of institutions on the distribution of jobs and wages, with a special focus on European countries. We are more specifically interested in labor market polarization, a phenomenon which has originally been observed in the US[1] between 1980 and 2010. *Wage polarization* describes an increase in wages at both ends of the distribution relative to the middle, while *job polarization* refers to an increase in the employment share of both low- and high-skill jobs relative to middle-skill jobs. A now standard explanation of this phenomenon is routine-biased technical change (RBTC). According to this approach, technical progress favors the substitution of machines — and, indirectly, of high-skill workers — for middle-skill labor. The underlying mechanism is the following (see e.g. Acemoglu and Autor, 2011). Since the tasks typically performed by middle-skill workers have an important routine content, they can easily be codified. They can thus be performed by capital (especially computers), to which high-skill workers are complement. Technical change favors this substitution, and redirects middle-skill workers towards tasks — and thus jobs — previously performed by low-skill labor. High-skill workers thus benefit from an upward pressure on their wages due to the increasing demand for their services, while middle-skill wages are subject to a relative decrease. The RBTC approach is therefore able to explain both wage and job polarization.

As previously emphasized, this two-fold phenomenon has been observed in the US (see e.g. Autor, Katz and Kearney, 2006; Autor and Dorn, 2013). Figure 1.1 shows the (smoothed) change in employment share and log hourly wage for occupations ranked according to their 1980 mean wage. While this is not the only way of representing the evolution of the distribution of jobs and wages, Autor and Dorn (2013) data — used in Figure 1.1 — allows a particularly clear illustration of the U-shaped curves implied by polarization. Job polarization has also been observed in Europe, but not necessarily in all European countries, and not necessarily to the same extent. For example, Oesch and Rodriguez Menes (2011) and

[1]For the sake of completeness, note that the phenomenon of *job* polarization has been early documented in the UK by Goos and Manning (2003) (published as Goos and Manning, 2007) for the period 1979-1999. However, the twofold phenomenon of labor market polarization — that is, the combination of job *and* wage polarization — has been originally highlighted in the US, notably by Autor, Katz and Kearney (2006).

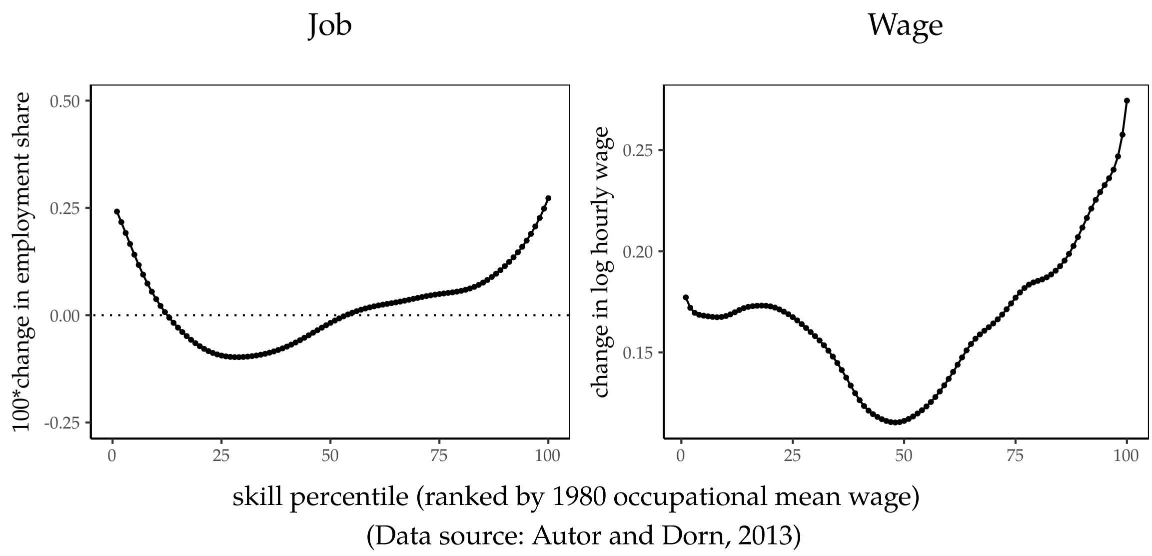

Figure 1.1: Labor market polarization in the US, 1980-2005

Fernández-Macías (2012) claim that polarization is only one of the patterns observed in European countries. Goos, Manning and Salomons (2009, 2014) argue that job polarization is pervasive in Europe, but their descriptive statistics indicate that the intensity of this phenomenon differs according to the country considered. Peugny's (2019) results point towards the same conclusion. Concerning wage polarization, only scant signs of it have been observed in Europe (see e.g. Naticchioni and Ragusa, 2014; Naticchioni, Ragusa and Massari, 2014; Antonczyk, DeLeire and Fitzenberger, 2018).

There thus exist cross-country differences in labor market polarization. Since developed economies have a similar access to technology, other determinants of the distribution of jobs and wages have to be considered to explain these differences. This dissertation considers institutions and demonstrates that a highly institutionalized labor market *mitigates* the twofold phenomenon of polarization. Institutions can therefore *partially*[2] explain the fact that economies with a similar access to technology exhibit either different patterns of change in the distribution of jobs and wages, or different degrees of the same pattern. In other words, institutions partially explain cross-country differences in labor market polarization.

This dissertation consists of three essays. In the first essay (Chapter 2), we use decomposition methods to show the impact of a highly institutionalized wage-setting process on the wage structure. More precisely, we assess the impact of institutions on the contribution of the pricing of workers' characteristics to the change in wages between the early 1990s and the second half of the 2010s. Our strategy makes use of the fact that the wage-setting process is more institutionalized in the public than in the private sector. Decomposing the change in wage quantiles for

[2]It is important to emphasize that other factors are likely to play a role, which may be non-negligible. Amongst these factors are the differences in initial skill supplies, which could lead technical change to yield different outcomes. Note that these initial skill supplies could partially depend on the institutional framework considered.

both sectors and operating a between-sector comparison of the results for a set of European countries, we reach the conclusion that institutions mitigate the polarization of the wage structure. We then use detailed decomposition methods to evaluate in which measure this impact takes place through the pricing of skills. According to the RBTC approach, this is the channel through which technical change leads to the polarization of wages. Our results corroborate the idea that institutions partially mute the effect of technical change through this channel.

In the second essay (Chapter 3), we develop a theoretical model based on the Acemoglu and Autor (2011) task-based framework. We contribute to this framework by including, in a Ricardian model of the labor market *à la* Acemoglu and Autor, an institutional device which mitigates wage polarization, based on the results of the first essay of this dissertation. While this device can be thought as unions operating in a centralized and coordinated bargaining regime, it is not restricted to this interpretation. Our model predicts that the institutions we consider, by mitigating wage polarization, have an anti-polarizing impact on the change in employment: while job polarization still follows skill-biased technical change, it is less pronounced in an institutionalized labor market than in an 'institutions-free' environment.

In the third and last essay (Chapter 4), we test the predictions of the model presented in the second essay by empirically assessing the impact of institutions on job polarization. For each country studied in the first essay and for each year of the period 1992-2017, we build a measure of each of the two components[3] of job polarization, based on the employment levels observed in selected, ranked and aggregated occupational categories. We then empirically characterize the impact of selected institutional devices — including the level of centralization and coordination of the collective bargaining regime — on these measures. In order to avoid dimensionality issues, we summarize these variables by combining them into a composite index of institutionalization. We first estimate the long-run relationship between each component of job polarization and this composite index, using panel cointegration techniques. We observe that de-institutionalization of the labor market is accompanied by an increase in both components of job polarization. To take into account both the reverse-causality problem implied by such a study and the potential delayed response of the variables, we then resort on panel vector autoregressive models and structural impulse response analysis: modeling all the variables of our empirical model as endogenous, we use impulse response functions to observe the dynamic impact of a structural institutional shock on job polarization. Our results indicate that de-institutionalization fosters both components of job polarization, confirming the structural interpretation of the model introduced in the second essay.

As implicitly mentioned in the previous paragraphs, each essay rests on a specific approach and its related set of methods. In the first essay, we rely on the decomposition techniques introduced by DiNardo, Fortin and Lemieux (1996) and Firpo, Fortin and Lemieux (2018). These methods belong to a more general decomposition framework, which has been formalized in terms of the treatment effect

[3]The first component is the increase in employment in high- relative to middle-skill jobs, while the second component is the decrease in employment in middle- relative to low-skill jobs.

literature by Fortin, Lemieux and Firpo (2011). We augment the Firpo, Fortin and Lemieux (2009) RIF-regression approach, used in the Firpo, Fortin and Lemieux (2018) detailed decomposition methods, with a built-in smoothing mechanism based on the Barnichon and Brownlees (2019) smooth local projection estimator. The theoretical model of the second essay is an extension of the Ricardian model of the labor market introduced by Acemoglu and Autor (2011). This model belongs to the more general task-based framework, in which technical change impacts the optimal allocation of skills to tasks. Finally, the third essay rests on two distinct but yet related econometric approaches. In the first part of our analysis, we estimate long-run equilibrium relationships using panel cointegration techniques. In the second part of our analysis, we use structural vector autoregressive analysis to handle the reverse-causality problem between our variables of interest. These methods allow us to explicitly consider the endogenous relationship between the change in occupational structure and institutional reforms that are undertaken. Combining these different approaches allows us to confirm the hypothesis that the impact of technical change on the wage and occupational structure is mediated by country-specific institutional settings.

Chapter 2

Polarization of the Wage Structure and the Role of Institutions: a Decomposition Analysis in a Cross-Country Comparative Perspective

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2.1 Introduction

In a seminal paper, Autor, Katz and Kearney (2006) describe and interpret the simultaneous growth of high and low wages, relative to the middle, that they observe in the US for the 1988-2004 period. This phenomenon of "wage polarization", which takes the form of a U-shaped growth in wage quantiles[1], is considered as the earnings counterpart of "job polarization", which denotes a U-shaped growth of employment by occupation when occupations are ranked according to their skill content. As a proxy for the latter, Goos and Manning (2003, 2007) for the UK, and Wright and Dwyer (2003) for the US, use the occupational mean wage, a practice which is now standard in the literature. The two phenomenons of wage and job polarization, grouped together under the more general concept of labor market polarization, are modeled as the joint product of a same cause, that is, routine biased technical change (RBTC)[2]. In such a framework, skill-biased technical progress changes the relative task-specific productivities of the different skill groups and

[1]Note that the wage quantiles are interpreted as skill quantiles; see e.g. Autor and Dorn, 2013.

[2]See e.g. Autor, Katz and Kearney (2006) and Acemoglu and Autor (2011). RBTC can be considered as an adjustment of the skill-biased technical change (SBTC) theory to the polarization phenomenon.

leads to the substitution of middle-skill workers with capital (machines, especially computers), to which high-skill workers are complement.

The previously mentioned theory emphasizes the role played by the technology-driven change in demand for skills and its impact on their price (in other words, the wage structure). If, however, RBTC was the only cause of the polarization phenomenon, then developed economies, which have access to the same level of technology, should exhibit a similar polarized pattern of change in earnings. If this pattern differs according to the country considered, then other factors (such as institutions or initial skill supplies) or other mechanisms (such as the selection effects examined in Böhm, von Gaudecker and Schran, 2019 and detailed in Section 2.5) may have an effect on the way RBTC impacts the distribution of wages. Considering the *overall* change in the distribution of wages for the UK and several European economies between 1995 and 2016, it appears — as shown in Figure 2.1 (solid lines) — that only the UK, Ireland, Finland, Belgium and somehow Luxembourg exhibit such a pattern, and to different degrees. This is also the case of Greece and Portugal when the last quartile of the distribution is ignored. Amongst these countries, only Ireland, Luxembourg and the UK show a strong first component of wage polarization, i.e. a substantial increase in wages at the top of the distribution relative to wages in the middle. One could nonetheless argue that the RBTC approach is about the price schedule of workers' individual characteristics, and that the polarization of the wage structure can be counteracted by some changes in the composition of the workforce. Using the semi-parametric procedure central to this paper[3], we decompose, for each economy, the change in wages into a structure and a composition effect. Results are graphically represented in Figure 2.1 (dashed lines). It clearly appears that only the UK, the Netherlands[4], Luxembourg[5] and to some extent Finland exhibit a U-shaped growth in wage structure quantiles. Note that other papers, such as Naticchioni, Ragusa and Massari (2014), Naticchioni and Ragusa (2014) and Antonczyk, DeLeire and Fitzenberger (2018) (focusing on Germany), already emphasized, for some European countries, the absence or scantiness of wage polarization.[6]. While Figure 2.1 confirms these claims, it also shows that amongst the countries whose patterns of change are not polarized, there are still important cross-country differences in the evolution of the wage structure.

Institutions, and more particularly labor market institutions (LMI), have been introduced as a key explanatory factor of the differentiated impact of technology on the distribution of wages.[7] Even for the US, which actually exhibit wage polariza-

[3]This methodology, introduced by DiNardo, Fortin and Lemieux (1996) and refined by Firpo, Fortin and Lemieux (2018), is extensively described in the next section.

[4]Ignoring what happens at the very top end of the distribution.

[5]Same remark as for the Netherlands.

[6]This however does not mean that wage inequality, measured with one-dimensional metrics such as wage percentile ratios, has not been increasing in European countries, nor that inequality has remained constant in every part of the distribution. For example, Dustmann, Ludsteck and Schönberg (2009) highlight the fact that while "the United States and Germany experienced similar changes at the top of the distribution" during the 1990s, only Germany witnessed a "rise in lower tail inequality" during this period. This explains the absence of wage polarization in this country between 1990 and today.

[7]See notably Antonczyk, DeLeire and Fitzenberger (2018), who argue that "if institutional differences matter, one would not necessarily expect to see similar patterns in wage growth and polar-

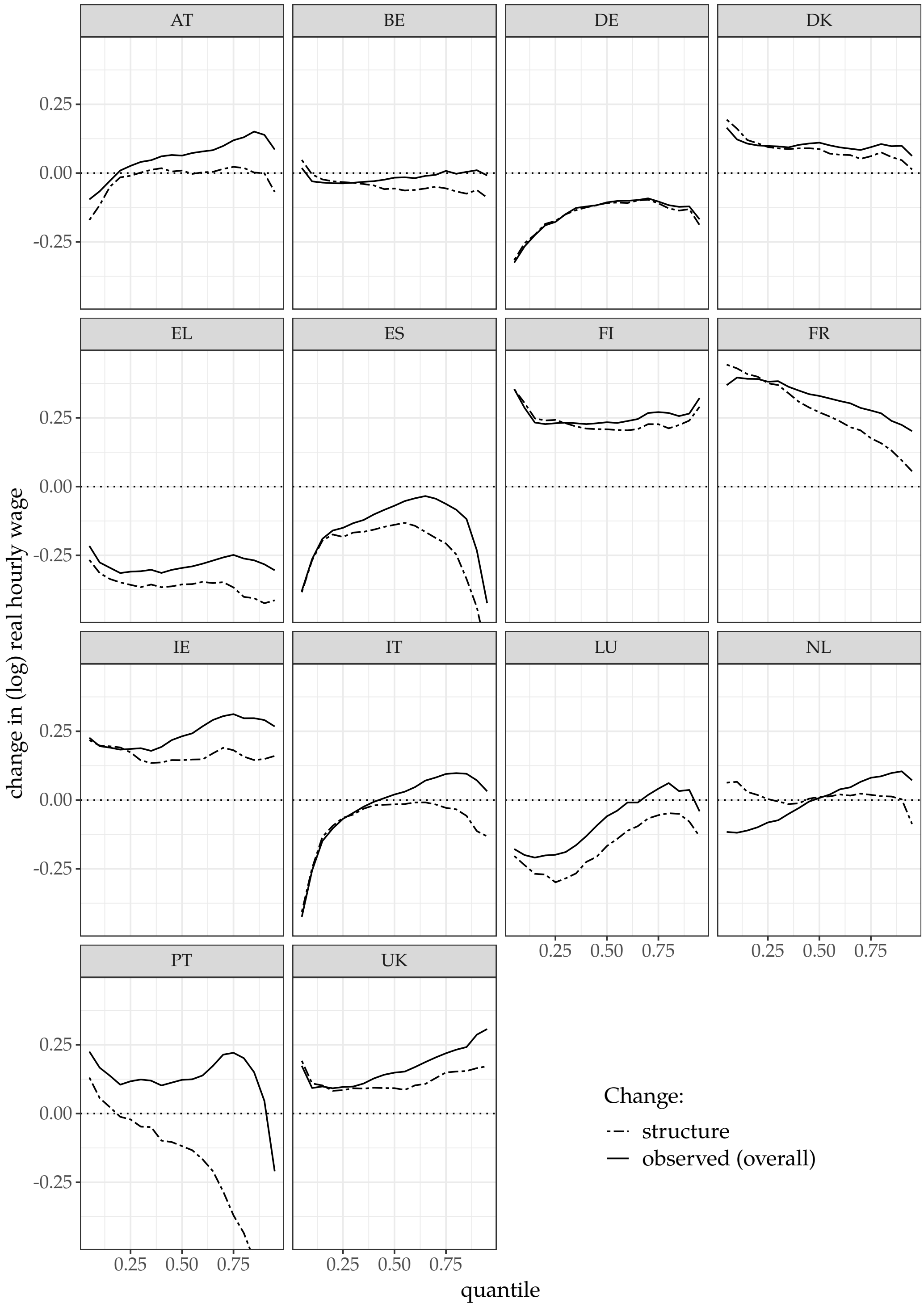

Figure 2.1: Change in wage ventiles, 1995-2016: observed change and wage structure effect

tion, institutional changes have been considered as alternatives to SBTC-based explanations. DiNardo, Fortin and Lemieux (1996) (DFL hereafter) claim that falling minimum wage and deunionization explain a substantial part of the evolution of the distribution of wages during the 1980s, while Firpo, Fortin and Lemieux (2018) (FFL hereafter) argue that deunionization (leading, in the US case, to a decrease in coverage) led to a polarized change of the wage distribution between 1988/90 and 2014/16.

In this paper, we endorse the idea that "the effects of national economies of changing technology, increasing globalization, and intensifying competition are filtered through institutional structures" (Gautié and Schmitt, 2010) and, by extension, that institutions can (partially) explain cross-country differences in wage polarization. More precisely, we adopt the *Varieties of Capitalism* (*VoC* hereafter) approach, according to which institutional *complementarities* — and not only institutional characteristics considered in isolation — are the key determinants of a nation's "comparative advantage"[8], itself impacting the occupational and wage structure of this nation's economy.

In line with these ideas, we estimate the cross-country differentiated effect of institutional forces[9] on the change in the structure of earnings by comparing, for several countries, the evolution of the wage structure in the private sector with the one in the public sector. In other words, we treat the wage-setting process of the public sector as an archetypal combination of a country-specific set of institutional forces[10]. We then use the difference in the change in wage structure between the two sectors to assess the degree to which the previously mentioned institutional forces counteract their market counterpart(s), including SBTC/RBTC. Our strategy is based on two core assumptions: the first is that wages in the public sector are generally more prone to be set institutionally than in the private sector, and the second is that institutions do have an impact on wages. These assumptions are documented in Section 2.2.

For each country and sector, we estimate the wage structure and its evolution using the semi-parametric decomposition technique introduced by DFL and refined by FFL. Our findings indicate that the public sector wage-setting process, when highly institutionalized with respect to the private sector and not subject to major 'market-oriented' institutional changes (including politically-induced reforms), leads to a different pattern of evolution of the wage structure than what is observed in the private sector. In some cases, such as Germany and the Nether-

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ization for different countries."

[8] See notably Hancké, Rhodes and Thatcher (2007)

[9] Following North (1990), Hall and Soskice (2001) define institutions as "a set of rules, formal or informal, that actors generally follow, whether for normative, cognitive or material reasons." The authors also emphasize the fact that, from this perspective, markets are a specific type of institutions, which are "marked by arm's length relations and high levels of competition" and embedded in a "legal system that supports formal contracting and encourages relatively complete contracts." In the context of this paper, we define institutions as institutions — in the sense of Hall and Soskice (2001) — which are not of the 'market' type. They thus include standard labor market institutions such as collective bargaining and employment protection legislation, but are not limited to these.

[10] Such a strategy therefore allows us to avoid the problem of disentangling the different impacts of the different institutional forces. As pointed out by Kahn (2000), "certain policies form a package; it may therefore be difficult to pinpoint the impact of a particular one."

lands, this pattern can even be labeled as 'anti-polarizing' since wage structure quantiles in the public sector are characterized by an inverse U-shaped growth.

We then implement, for each sector and country, an augmented version of the detailed decomposition method introduced by FFL. This procedure allows us to isolate the contribution to the wage structure effect of educational attainment, one of the main sources of a worker's skills, and therefore to test whether institutional forces actually mute the channel through which the RBTC approach claims that technical change operates. As shown and discussed in sections 2.4 and 2.5, this is the case for some countries, as expected, but not for all.

Our contribution is threefold. First, and as already emphasized, we capture the effect of institutions on the wage structure by assessing the impact of belonging to the public sector, rather than by focusing on the impact of narrowly-defined institutional features (such as union membership and legally set or collectively bargained minimum wages). While the latter strategy has been extensively used in the literature[11], it has two major disadvantages regarding the paradigmatic stance we adopt.

Its first disadvantage comes from the rather restrictive definition of institutions that it implies. To capture a (country-specific) institutional profile, such a strategy requires the inclusion, in the model specification, of a comprehensive set of institutional covariates and interaction terms between them. Aside from a potential dimensionality issue, implementing a decomposition procedure in this context is problematic since some core institutional features are not located at the individual level, but rather at the sectoral or national level. By considering the impact of the public sector, we capture not only the influence of a generally high collective bargaining coverage and union membership rate (in comparison with the private sector), but also of other institutional features, such as centralized bargaining[12] and the prevalence of a specific status,[13] as well as their interactions.

The other disadvantage of the 'standard' strategy is related to the comparative perspective we adopt. Since institutional variables such as union coverage are only available for a limited number of countries and a limited number of years, they are usually not included in harmonized survey data (such as ECHP and EU-SILC, which provide the earnings information required for our analysis). Even when such a variable is available in a national survey, harmonization with other surveys is not guaranteed. The possibility of cross-country comparison is thus drastically limited.

The second part of our contribution is related to the method used to assess the impact of the public sector on the structure of wages. We estimate this impact by decomposing (and comparing) the change in wages in both sectors rather

[11] For the US, DFL estimate the impact of the change in the real minimum wage and in union membership on the overall distribution of wages, while FFL estimate the contribution of the change in union coverage to composition and wage structure effects at different quantiles of the distribution of wages.

[12] For example, Zagelmeyer (2007) finds a positive association between public sector affiliation and collective bargaining centralization.

[13] This status has notably been designed such as to shelter civil servants from market forces. In Sweden, the government even explicitly pursued a policy of wage egalitarianism for the civil servants. See e.g. Zetterberg (1994).

than by estimating the contribution to the wage structure effect of a covariate indicating whether or not a worker belongs to the public sector. This latter strategy, which implies operating a detailed — as opposed to aggregate — decomposition, has notably been implemented by Bárcena-Martin and Silber (2018), who find that "gender and working in the public sector are important determinants of bipolarization".[14]

A paper using such a strategy in another context than the one of a decomposition procedure is Fournier and Koske (2013). Examining how public employment affects the distribution of wages, these authors show that "a fall in public employment may raise or reduce earnings inequality, depending on country specificities".

This latter approach implicitly assumes that belonging to the public sector is an individual characteristic priced on a market and that the pricing of other characteristics is the same across sectors. Our strategy has the advantage of relaxing these assumptions which are, in our view, rather unrealistic. Our approach allows to capture the impact of institutions *on the change in the pricing of the workers' individual characteristics*, change which notably follows SBTC/RBTC. Since we assume that this is the actual channel through which institutions have an impact on wages, this is also what we are ultimately interested in estimating.

This impact on the price of the workers' *overall* characteristics can then be apportioned amongst the different characteristics considered individually. In order to do so, we use the FFL detailed decomposition method based on the Firpo, Fortin and Lemieux (2009) RIF-regression procedure. Focusing on the pricing of education, a core source of a worker's skills, we apply this method for both sectors and compare the results. This comparison should tell us whether the impact of institutions operate through the same channel as technical change does, according to the RBTC theory .

Our third and final contribution consists in modifying the recentered influence function regression method — itself used in the FFL detailed decomposition method — in such a way as to smooth the coefficient estimates along the different quantiles. This limits the variability of these estimates, which can be abnormally high in small samples, leading to ill-shaped partial effect curves. This modification consists in applying the Barnichon and Brownlees (2019) smooth local projections (SLP) method — originally a time series methodology — to quantiles instead of time. We also modify this estimator such that it takes into account the sample weights.

The remainder of the paper is structured as follows. We start the next section by documenting the two fundamental assumptions underlying our strategy. The first assumption states that the wage-setting process is (generally) more institutionalized in the public than in the private sector. The second assumption, which is actually a necessary (but not sufficient) condition for the validity of our thesis, states that institutions *do* have an impact[15] on the distribution of wages. Next, we detail the aggregate and detailed decomposition methods used to answer our research question. We then present the results — which include some preliminary

[14]Note that in their paper, the dependent variable is not a quantile but a summary index of *bipolarization* of the distribution. In that case, "polarization" has a slightly different meaning from the one introduced by Autor, Katz and Kearney (2006), which is used in this paper.

[15]To be distinguished from the nature/the shape of this impact, which is the object of this paper.

analysis based on RIF-regressions — and discuss their interpretation. We finally conclude.

2.2 Methodology

2.2.1 First core assumption: public sector wage-setting process as highly 'institutionalized'

Central to our identification strategy is the assumption that wages in the public sector are generally more prone to be set institutionally than in the private sector. Core evidences supporting this claim are the higher rates of bargaining coverage and union membership in the former relative to the latter. Figure 2.2 reveals that in all the European countries considered (and the US), union density is higher in the public than in the private sector. The same holds for the coverage rate, which represents the proportion of workers whose wages are set in the context of a collectively bargained agreement. The difference between the two sectors is even more striking in that case: in almost all the European countries for which we have data, the coverage rate in the public sector was of one hundred percent thirty years ago and remained constant until today. A notable exception is the UK, which witnesses a sharp decrease in the coverage rate since 1985 in both the public and the private sectors, thereby converging towards the rates observed in the US.

An indirect evidence of the difference in the prevalence of institutional forces between the two sectors can be obtained by implementing a between-sector aggregate decomposition exercise. Figure 2.3 shows the evolution, between the two periods considered in this paper, of the contribution of the pricing of individual characteristics to the public-private wage gap. While in every country workers at the top-end of the wage structure (and, supposedly, of the distribution of skills) seem penalized for belonging to the public sector, the reverse happens for workers at the bottom-end. In some countries such as Portugal, Belgium and somehow Luxembourg and Ireland, the difference in wage structure between the two sectors exhibits an inverse U-shaped pattern, revealing a *potential* anti-polarizing impact of the public sector. Since this wage structure effect has a similar shape as the impact of union membership or bargaining coverage[16], what can be observed in Figure 2.3 is typically what we expect from a highly 'institutionalized' sector. It is important to emphasize that this rough aggregate decomposition exercise, implemented at two different points in time, can *not* be used as a proper evidence of the anti-polarizing or downgrading[17] impact of institutional clusters on the wage structure. The reason is that the *ignorability* assumption — required to identify the wage structure effect — is not likely to hold in this case since the two groups used to build the counterfactual distribution correspond to the two sectors. The presumed violation of the *ignorability* assumption is due to the highly likely self-selection of workers into the sectors considered.

Additional insights suggesting that the wage-setting process is more 'institutionalized' in the public than in the private sector can be found in the literature.

[16]See notably Firpo, Fortin and Lemieux (2009) and FFL.

[17]In the sense that the higher the wage, the higher the penalty of belonging to the public sector.

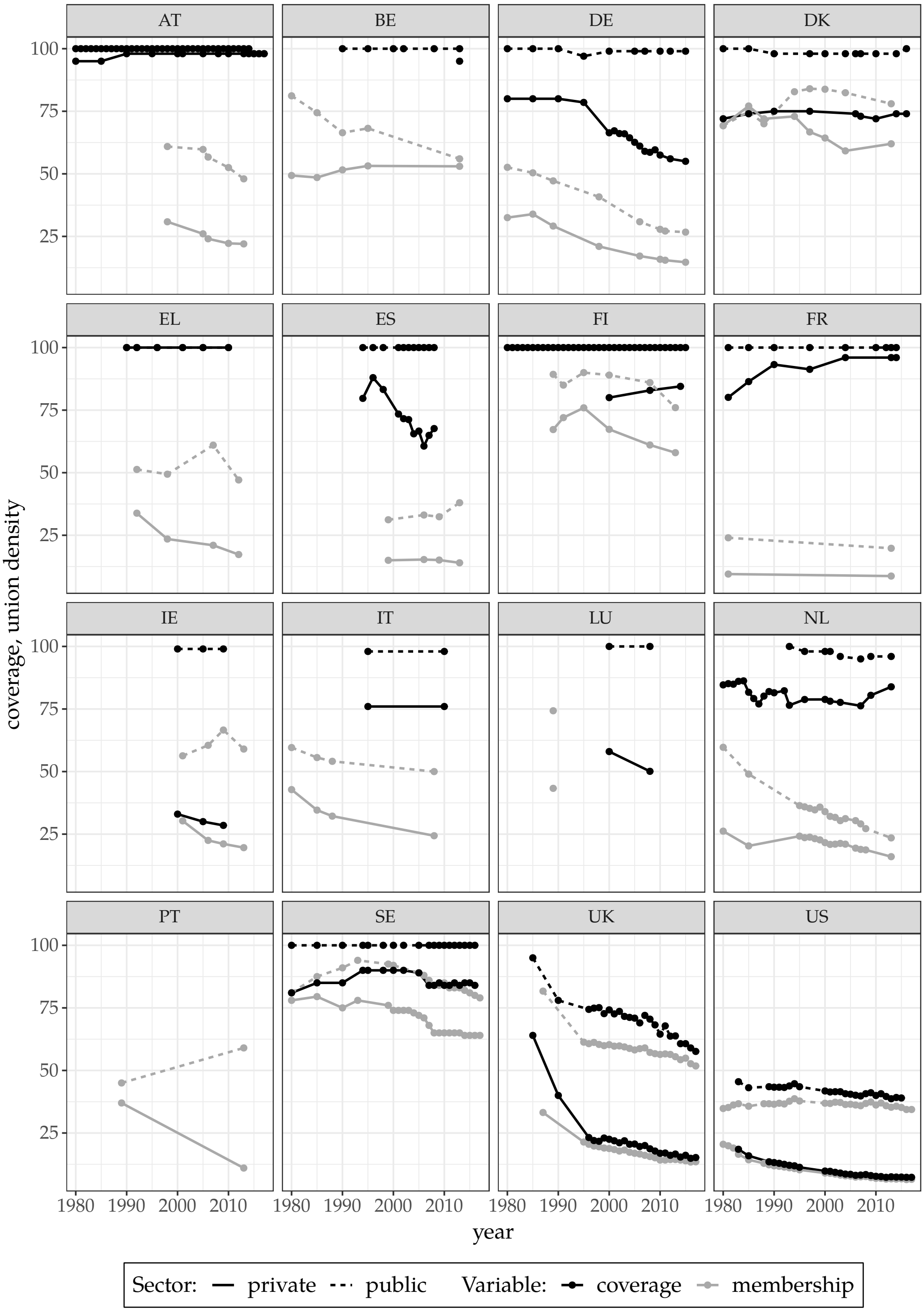

Figure 2.2: Sector-specific bargaining coverage and union membership rate, 1980-2017

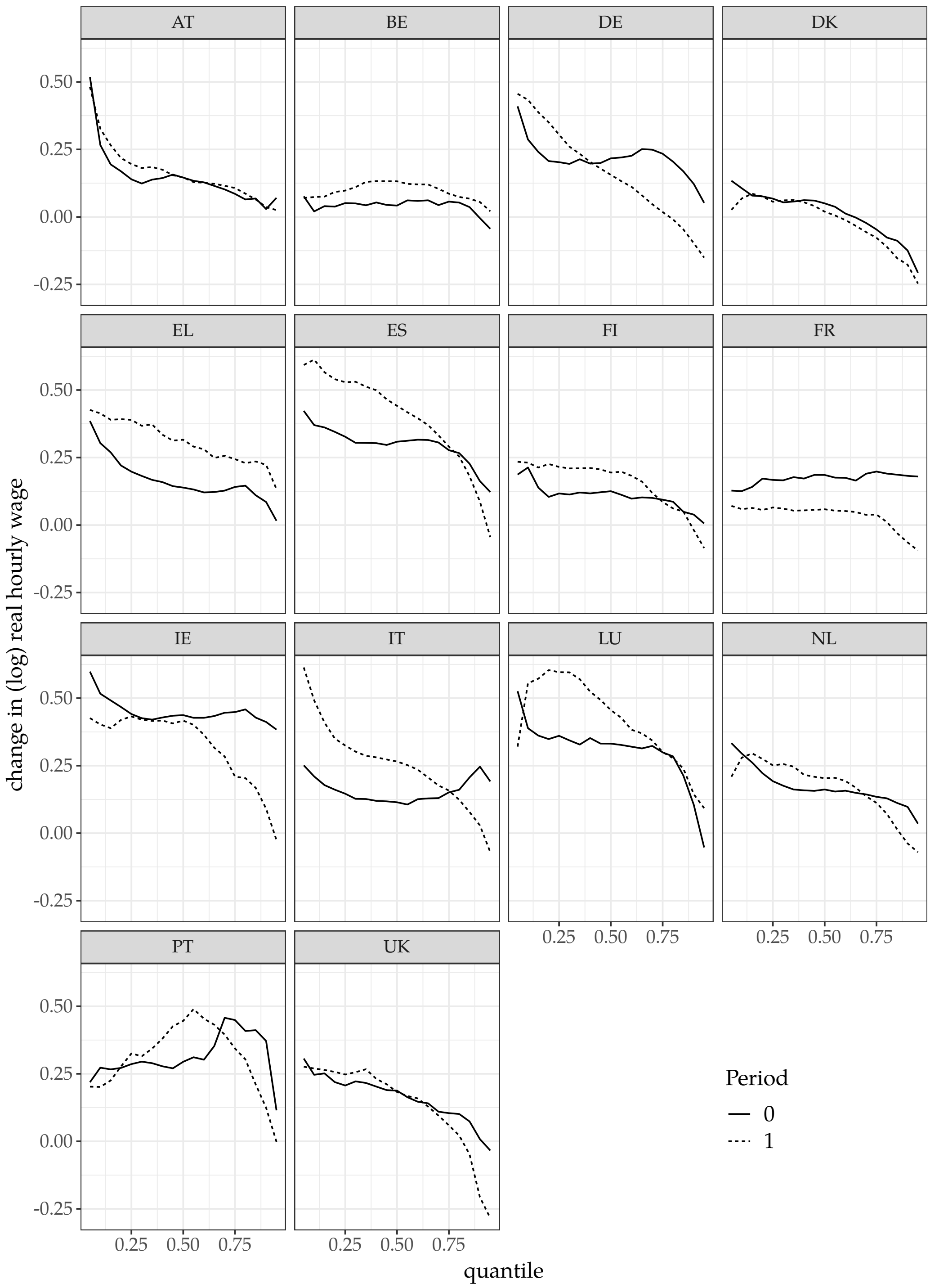

Figure 2.3: Decomposition of the difference between sectors: wage structure effect, t_0 (1995) v. t_1 (2016)

Focusing on the US, Kim and Sakamoto (2010) claim that unionized public workers are the workers who benefit from the highest institutional protection from market forces. According to Holmlund (1997), the public sector wage premium would be partly due to the difference in bargaining power between public and private sector unions. The high power he attributes to the public sector unions leads him to model wage-setting in this sector in such a way that "the government adjusts employment and the tax rate after the wage has been set by the public-sector union" (Holmlund, 1993). In line with the idea that the bargaining power of unions is higher in the public sector, Card, Lemieux and Riddell (2020) argue that, in this sector, unions' impacts on wage inequality are "much larger". Campos et al. (2017) recall that other explanations of the public wage premium "are linked to the degree of public wage-setting centralization", which is itself linked to reduced pay dispersion.[18] Reviewing studies which examine the extent of spatial wage variation in the public sector of several European countries, Elliott, Mavromaras and Meurs (2007) note that spatial compression of public earnings is associated with centralization of the wage-setting process. The fact that "in many countries (...) public sector wages are very similar in nominal terms for employees of regions with different private sector productivities and costs of living" (Cardullo, 2017) thus suggests a relatively high level of centralization of the wage-setting process in the public sector relative to the private sector. It is therefore not surprising that Elliott, Mavromaras and Meurs (2007) use as a benchmark the archetypal case where "pay setting in the private sector is flexible" while in the public sector it is "institutionalized and inflexible".

2.2.2 Second core assumption: impact of institutions on wages

A second implicit but nonetheless crucial assumption underlying our strategy is that institutional forces do have an impact on wages. An extended literature provides empirical evidence of the effect of LMIs. In this section we present a review of this literature, organized along the type of LMI considered.

2.2.2.1 Unionization and union coverage

Examining the association between union density and cross-industry wage dispersion, Freeman (1988) finds that "some countries have moved to near-universal unionization with narrow wage differentials, others to weak unions and wider differentials". Katz, Loveman and Blanchflower (1995) go further by highlighting the ability of powerful unions to resist the impact of SBTC. According to them, the "earlier appearance of rising overall wage inequality in the US than in Britain may reflect the power of British unions to oppose the apparently market-driven forces that contributed to rising overall wage inequality among males in the United States in the 1970s." They then argue that "similar changes in relative skill demands are

[18] Cf. infra. See also Wallerstein (1990), Moene and Wallerstein (1997) and Wallerstein (1999). Falch and Strøm (2006) confirmed this link for the public sector in Norway, that they considered — as the other Scandinavian countries — as a "prominent example of centralized-wage setting systems". Studying the impact of increased local flexibility in Norway's public sector wage-setting, they observed a widening of the wage dispersion across local governments following this reform.

likely to have occurred in France, but the effect of such changes on wages has been somewhat offset by a high minimum wage and the ability of French unions to extend contracts even in the face of declining membership", a claim concurring with the idea that unions do not only derive their power from the union membership rate. Applying a two-step strategy to longitudinal data in order to correct for selection and misclassification biases, Card (1996) finds that union wage effect in the US is larger for less-skilled workers, which leads to a compression of the wage structure. Using microdata aggregated at the country level, Kahn (2000) reaches a similar conclusion. His results indeed show that "greater union density, collective bargaining coverage, or coordination of wage-setting lowers the wage differential between those with middle- and those with low-skill levels for both men and women".[19] Such claims are however partly contested by DiNardo, Fortin and Lemieux (1996): developing and implementing a semi-parametric decomposition procedure, the authors find that the sharp decrease in the unionization rate during the 1980s "played a significant role in explaining the clear collapse of the middle of the distribution" of wages. These findings are indirectly confirmed by Firpo, Fortin and Lemieux (2009), who build and implement a regression method capturing unconditional (partial) quantile effects. They show that the effect of union status on US wages is higher around the middle of the distribution than at its bottom and top ends.[20] Combining the reweighting approach of DFL and the RIF-regressions of Firpo, Fortin and Lemieux (2009), FFL shows that the decrease in union coverage participated to the polarization of the US wage *structure* between 1990 and 2016.

While the studies previously mentioned focus on the *direct* impact of unionization, one should keep in mind that even in the US, union membership may impact (and have impacted) the distribution of wages through other channels. These alternative channels are summarized by Collins and Niemesh (2019). First, unions may have influenced wage levels of non-unions firms. Second, "union pressures also could have caused endogenous relocation of firms and skilled workers", which in turn impacted the distribution of wages. Finally, the 'great compression' of the middle of the twentieth century may be subject to hysteresis effects: in the words of Collins and Niemesh (2019), "even as unions faded from the private sector after the 1970s in the US, traces of the differential compression of the 1940s remained visible at the end of the century".

High union membership rates are important sources from which unions derive their power to shape the distribution of wages. However, other features of the collective bargaining framework determine the ability of unions to influence the wage-setting process.

2.2.2.2 Centralization and coordination of collective bargaining

While union density and coverage rates are important indicators of unions' power in the bargaining game, other dimensions of the bargaining regime have an impact on the outcome of the wage-setting process. Amongst these dimensions are the

[19] It should be noted that depending on the country considered, earnings can be either net, either gross which — in our view — weakens the conclusion reached by the author.

[20] This effect is even negative for the highest wage earners, who correspond to the mostly skilled workers.

degrees of centralization and coordination of pay-setting. While the former refers to "the level(s) at which wages are bargained or set", the latter gives "the degree of intentional harmony in the wage-setting process — or, put another way, the degree to which minor players deliberately follow along with what the major players decide." (Kenworthy, 2001). While the former concept is defined both *de jure* (on the basis of the bargaining authority of each level) and *de facto* (on the basis of the actual level(s) at which bargaining takes place), the latter is, in the words of Kenworthy (2001), a "fundamentally (...) behavioral concept", which implies that it is only characterized by the actual behavior of the agents. An extremely centralized and coordinated bargaining regime would therefore be a regime in which the vast majority of unions deliberately follow the stance of a peak-level structure which negotiates wage agreements applied nationwide. Such a regime is expected to lead to a heavily compressed distribution of wages. In the words of Calmfors et al. (2001), "one should expect the scope for pay compression to be larger when bargaining is more centralized and coordinated". They argue that such expectations are backed by a "robust empirical finding", of which we give an overview in the remainder of this section.

According to Freeman (1988), "wage dispersion reflects the overall wage-setting system in a country": while countries with highly centralized bargaining exhibit very low wage dispersion, highly decentralized bargaining regimes lead to very high dispersion. This (seemingly linear) relationship is also highlighted by Rowthorn (1992), who claim that "casual observation of the data (...) suggests that wage dispersion is related to bargaining structure", and that "overall dispersion is normally higher where bargaining is decentralised". Restricting their sample to male workers, Blau and Kahn (1996) investigate this claim by regressing different measures of wage dispersion on a measure of centralization. They find a positive association between decentralization of the bargaining process and dispersion of wages. They then focus on wage differentials between skill groups and find that the more coordinated the wage-setting process, the narrower the wage gap between middle- and high-skill workers. Studying a sample including both men and women and focusing on low- and middle-skill workers, Kahn (2000) reaches similar conclusions. Working with wage decile ratios and implementing an error-correction model on cross-country panels of data, Wallerstein (1999) finds that the more coordinated (notably through centralization) the wage-setting, "the more egalitarian the distribution of pay". While obtained from another methodological approach, Canal Dominguez and Gutierrez (2004) results are in the same spirit: using the Oaxaca-Blinder decomposition method, they find that sector level agreements lead to lesser wage dispersion than agreements signed at the firm level. Decomposing the dispersion of log wages and comparing the components across wage-setting regimes, Gerlach and Stephan (2006) find that firms applying higher-level collective contracts exhibit lower wage dispersion.

2.2.2.3 Minimum wage

Depending on the country considered, minimum wage can be of two types: either statutory, either collectively bargained and agreed. A statutory minimum wage is determined by legislation. It generally applies to all adult members of the workforce. A collectively agreed minimum wage — a mechanism of great importance in the Nordic countries — is bargained between the parties, i.e. unions and employers, and can be "supplemented with local rates". (Eldring and Alsos, 2012). Such a minimum wage can be extended to "an entire region, industry/or profession, irrespective of whether the employer and/or the employee is organised." This is notably the case in Finland, Iceland and Norway (Eldring and Alsos, 2012). Before the introduction of a federal statutory minimum wage in 2015, it has also been the case in Germany for some construction industries such as the roofing sector (Gregory and Zierahn, 2020). It is important to emphasize that the ability and the will of generalizing a local rate to a whole region or industry depends on the power and the coordination of unions, and on the centralization of the bargaining regime. It thus depends on the other institutions and their mutual linkages, in line with the *VoC* approach. Note that a system of institutions where the benefits of employees with high bargaining power extend to workers with little bargaining power has been labeled as "inclusive" by Bosch, Mayhew and Gautié (2010).

Studies assessing the impact of minimum wage on the distribution of wages usually distinguishes between two types of effect. The first is "to truncate or thin out the lower tail of the wage distribution (below the minimum) and to create a spike at minimum" (Neumark and Wascher, 2008). This spike was particularly pronounced in the US, as notably shown by DFL who implement a non-parametric estimation of the probability density function of US hourly wages. This phenomenon can simply be explained by the fact that employed workers whose productivity is below the minimum wage rate[21] 'concentrate' at this level (Neumark and Wascher, 2008).

The second type consists in spillover effects, which can be either positive or negative, depending on the segment of the distribution that is considered. Positive spillovers are found at the bottom-end of the distribution. Lee (1999) even finds a positive effect of the minimum wage until the median of the distribution. Neumark and Wascher (2008), Stewart (2012*a*), Stewart (2012*b*) and Gregory and Zierahn (2020) review potential explanations of these positive spillovers. We refer to these papers for further details. Negative spillovers, on the other hand, impact earners located (way) higher in the distribution. Neumark, Schweitzer and Wascher (2004) find that an increase in the US minimum wage has a slightly negative effect on high wage earners, while Gregory and Zierahn (2020) find that a minimum wage with large bite can induce negative spillovers for top earners, at least in the German industry they study. We refer the reader to Gregory and Zierahn (2020) for a (theoretical) explanation of such effects.

2.2.3 Aggregate decomposition to assess the impact of institutions on the wage structure effect

Our thesis is that institutions have an anti-polarizing impact on the way changing technology affects the price of workers' characteristics. This can be shown by com-

[21] Note that to explain this phenomenon in a neoclassical setting, Pettengill (1981) suggests that workers just below the minimum wage actually adjust their effort in order to slightly raise their productivity so that they are not driven out of the market.

paring the evolution of the wage structure in a highly institutionalized sector to the change in wage structure in a sector characterized by a less institutionalized wage-setting process. Our strategy consists in making use of the distinction between the private and the public sector, the former exhibiting more signs of institutionalization than the latter (as shown at the beginning of this section).

To distinguish the part of the overall change in wage due to a change in the distribution of the workforce characteristics from the part due to a change in the pricing of these characteristics, we adopt the decomposition framework as formalized by Fortin, Lemieux and Firpo (2011). For the remainder of this section, we adopt a notation similar to theirs.

Consider two groups of workers (in our case, two time periods), denoted by $t \in \{0,1\}$. The wage of individual i in time t (denoted by y_{ti}) is determined by observable (X_i) and unobservable (ϵ_i) attributes through a wage structure function g_t:

$$y_{ti} = g_t(X_i, \epsilon_i).$$

The observed change in a distributional statistic ν between t_0 and t_1 can be written as

$$\Delta_O^\nu = \nu(F_1) - \nu(F_0) = \nu_1 - \nu_0,$$

where F_1 and F_0 are the cumulative density functions of wages in $t = 0$ and $t = 1$, respectively. These observed distributions can be rewritten in conditional forms, $F(y; T_y = 0, T_x = 0) \equiv F_0$ and $F(y; T_y = 1, T_x = 1) \equiv F_1$, where $T_y = t$ is the pay schedule prevailing in time t while $T_X = t$ refers to the prevailing characteristics of the workforce in time t.

Consider now a counterfactual distribution defined as $F_C \equiv F(y; T_y = 0, T_X = 1)$, which represents what would have been the distribution of wages if $t = 1$ workers — that is, workers characterized by the distribution of characteristics prevailing in $t = 1$ — had been paid according the pricing of these characteristics prevailing in $t = 0$. This counterfactual thus combines the wage structure of $t = 0$ and the composition of the workforce prevailing in $t = 1$. Using this counterfactual, it is possible to decompose Δ_O^ν in two parts,

$$\Delta_O^\nu = (\nu_1 - \nu_C) + (\nu_C - \nu_0) = \Delta_S^\nu + \Delta_X^\nu,$$

where $\Delta_S^\nu \equiv \nu_1 - \nu_C = \nu\big(F(y; T_y = 1, T_X = 1)\big) - \nu\big(F(y; T_y = 0, T_X = 1)\big)$, the *wage structure effect*, is the part due to the change in the pricing of workers' characteristics, while $\Delta_X^\nu \equiv \nu_C - \nu_0 = \nu\big(F(y; T_y = 0, T_X = 1)\big) - \nu\big(F(y; T_y = 0, T_X = 0)\big)$, the *composition effect*, is the part due to the change in the distribution of these characteristics.

At the core of our decomposition exercise is the estimation of Δ_S^ν for both the public and the private sectors, itself requiring the estimation of the counterfactual distributional statistic $\nu(F_C)$. To operate the latter estimation, we implement the procedure introduced by DFL and refined by FFL. DFL show that the counterfactual distribution F_C can be obtained by applying a special kind of *inverse probability weighting* procedure on the $t = 0$ workers . More precisely, this method consists in applying to these workers an appropriate reweighting function so that the distribution of their characteristics mimics the one prevailing in $t = 1$. On the basis of these results, FFL generalize the procedure by defining three (re)weighting functions[22] to be (directly) applied on the 'pooled' ($t = 0$ and $t = 1$) sample,

$$\omega_0(T) = \frac{1-T}{\Pr(T=0)}, \omega_1(T) = \frac{T}{\Pr(T=1)} \text{ and } \omega_C(T,X) \equiv \frac{\Pr(T=1|X)}{\Pr(T=0|X)} \frac{1-T}{\Pr(T=1)},$$

where $\Pr(T=0) = 1 - \Pr(T=1)$, $\Pr(T=0|X) = 1 - \Pr(T=1|X)$, and T takes the value 0 if the worker belongs to the period $t = 0$ and 1 if she belongs to the period $t = 1$. The two first reweighting functions simply reweight the workers to make the two groups (i.e. periods) comparable, while the third is used to build the counterfactual. While the estimation of $\Pr(T = 0)$ and $\Pr(T = 1)$ is trivial, the conditional probability $\Pr(T = 0|X)$ can be estimated by implementing a *logit* model, using notably demographic and employment variables as predictors. Note that our specification of this model is further detailed in Section 2.3.

Once these reweighting functions have been separately estimated for both sectors, they can be used to compute the sector-specific estimates of the wage structure effect. These estimates can then be compared to assess the difference in the evolution of the pricing of workers' characteristics between the two sectors. In this paper, we follow FFL and focus on the change in wage quantiles. First, this allows to decompose the change in wages along the whole support of their distribution, thus capturing potential (and expected) heterogeneity in this change, including polarization. Second, this facilitates the implementation of the detailed decomposition procedure described in the following section.

2.2.4 Detailed decomposition to isolate the contribution of key characteristics

While a between-sector comparison of the wage structure effect gives a broad picture of the impact of institutions on the evolution of the pricing of workers' characteristics, we also aim at testing the idea that institutions mitigate the impact of technical change on wages through the pricing of skills. This requires apportioning, for each sector, the wage structure effect between the different contributions of the different characteristics — including the level of skills — of the workers. This can be done by implementing the *detailed* decomposition method proposed by FFL and based on the *recentered influence function* (RIF) regressions introduced by Firpo, Fortin and Lemieux (2009) in their seminal paper on unconditional quantile regressions. For a comprehensive exposition of the detailed decomposition method based on RIF regressions, we refer the reader to FFL. For a deeper understanding of the theory and practice of RIF regressions, we refer the reader to Firpo, Fortin and Lemieux (2009). Here we briefly summarize the method, using the same notation as FFL.

Not surprisingly, RIF regressions take their name from the use of recentered influence functions as dependent variables. An influence function, denoted by $IF(y;\nu,F)$, "describes the effect of an infinitesimal contamination at the point [y]

[22]Note that these (re)weighting functions have already been introduced by Firpo and Pinto (2016), on the basis of DFL. For a derivation of the original ω_C reweighting function, see DFL.

on the estimate [of ν], standardized by the mass of the contamination" (Hampel et al., 1986).[23] Since $\mathbb{E}\big[IF(y;\nu,F)\big] = 0$ (by definition), the expectation of the recentered influence function $RIF(y;\nu,F)$ is imply equal to the distributional statistic ν and, by the law of iterated expectations, ν can thus be rewritten as:

$$\nu(F) = \mathbb{E}\Big[\mathbb{E}\big[RIF(y;\nu,F)|X=x\big]\Big], \tag{2.1}$$

which is true for every distribution considered so far, i.e. the observed distribution F_t for $t \in \{0,1\}$ and the counterfactual distribution F_C.

For obvious reasons, the conditional expectation in (2.1) is called by Firpo, Fortin and Lemieux (2009) a RIF-regression. Depending on the distribution considered ($t=0$, $t=1$ or the counterfactual), FFL denote RIF-regressions by $m_t^{\nu}(x) \equiv \mathbb{E}[RIF(y_t;\nu_t,F_t)|X,T=t]$, for $t \in \{0,1\}$, and $m_C^{\nu}(x) \equiv \mathbb{E}[RIF(y_0;\nu_C,F_C)|X,T=1]$. From (2.1), Δ_S^{ν} and Δ_X^{ν} can thus be rewritten in terms of these regressions:

$$\begin{aligned}
\Delta_S^{\nu} &= \nu_1 - \nu_C = \mathbb{E}[m_1^{\nu}(X)|T=1] - \mathbb{E}[m_C^{\nu}(X)|T=1], \\
\Delta_X^{\nu} &= \nu_C - \nu_0 = \mathbb{E}[m_C^{\nu}(X)|T=1] - \mathbb{E}[m_0^{\nu}(X)|T=0].
\end{aligned}$$

The previously characterized conditional expectations can be approximated with linear projections, $m_{t,L}^{\nu} = x'\gamma_t^{\nu}$, for $t \in \{0,1\}$, and $m_{C,L}^{\nu} = x'\gamma_C^{\nu}$, where the γ coefficients can simply be estimated by OLS.[24] Since the expectation of the approximation error is zero, FFL can in fine rewrite the structure and composition effects as:

$$\begin{aligned}
\Delta_S^{\nu} &= \mathbb{E}[X|T=1]'(\gamma_1^{\nu} - \gamma_C^{\nu}), \\
\Delta_X^{\nu} &= \mathbb{E}[X|T=1]'\gamma_C^{\nu} - \mathbb{E}[X|T=0]'\gamma_0^{\nu}.
\end{aligned} \tag{2.2}$$

With (2.2), FFL provide an elegant and computationally easy way to estimate the contribution to the wage structure and composition effects of each individual covariate. Since we are working with quantiles — more precisely, ventiles — as distributional statistics, the functional form of the related RIFs is well-known and pretty straightforward to estimate. These RIFs are then used as dependent variables in the RIF-regressions, from which we obtain estimates of the γ coefficients.

2.2.4.1 Smoothing the unconditional quantile effect estimates and, by extension, the wage structure effect

One of the drawbacks of the FFL decomposition approach is linked to the use of the RIF-regression method in small samples such as the ones available for the public sector. We are not specifically interested in the unconditional quantile partial effect — approximated by the coefficients of the RIF-regression — at each quantile considered separately. We are rather interested in the global shape taken by these

[23] In the words of FFL, this influence function can be understood as a "measure of robustness of ν to outlier data when F is replaced by the empirical distribution."

[24] The vectors of coefficients γ_0^{ν} and γ_1^{ν} are estimated by regressing $RIF(y;\nu,F)$ on Mincerian regressors, using observations from the $t=0$ and $t=1$ sample, respectively. The vector of coefficients γ_0^{ν} is estimated on the basis of the *reweighted* version of the t_0 sample, previously used to build the counterfactual distribution.

effects when considered all along the quantiles, and in small samples this curve can be ill-shaped. The fact that these coefficients are used to compute the contribution of each covariate to the wage structure effect extends the problem to our final estimates.

To remedy to this problem, we apply the smooth local projections (SLP) method of Barnichon and Brownlees (2019), originally designed for time series analysis, to the estimation of the RIF-regression coefficients. We simply replace the time dimension by the different quantiles, and include the sample weights in the estimation. In the remainder of this section we briefly present the estimator and the underlying model, following closely Barnichon and Brownlees (2019) but adjusting the notation for our specific case, which implies quantiles.

Denote by rif_τ the recentered influence function corresponding to the quantile τ. Consider the RIF-regression model

$$rif_{\tau,i} = \sum_{k=1}^{K} \gamma_{\tau,k} x_{k,i} + u_{\tau,i}, \tag{2.3}$$

where we omit the intercept for notational convenience.

In the same spirit as Barnichon and Brownlees (2019), we approximate the $\gamma_{\tau,k}$ coefficients using a linear B-splines basis function expansion in the quantile τ:

$$\gamma_{\tau,k} \approx \sum_{p=1}^{P} B_p b_p(\tau)$$

where $b_p : \mathbf{R} \to \mathbf{R}$ for $p = 1, \ldots, P$ is a set of B-spline basis functions and B_p for $p = 1, \ldots, P$ is a set of scalar parameters.

Equation (2.3) can thus be approximated as

$$rif_{\tau,i} = \sum_{k=1}^{K} \sum_{p=1}^{P} B_p b_p(\tau) x_{k,i} + u_{\tau,i}, \tag{2.4}$$

As pointed out by Barnichon and Brownlees (2019), a model such as the one in (2.4) is linear in the parameters and can be represented as a linear regression. Since we are working with ventiles, let R_i denote the vector $(rif_{0.05,i}, \ldots rif_{0.95,i})'$ and let l denote its size. X_i is a $l \times KP$ matrix of which the different $b_p(\tau)x_k$ are the elements. Define B as the vector of B-splines parameters $(B_1, \ldots, B_p)'$. Equation (2.4) can then be represented as a linear model

$$R_i = X_i B + U_i, \tag{2.5}$$

where U_i is the $l \times 1$ vector of the regression errors.

Denote by R, X and U the vertically stacked versions of R_i, X_i and U_i. Following Barnichon and Brownlees (2019), we estimate the stacked model by *generalized ridge estimation*. The estimator $\hat{B}$ of the vector of B-splines parameters B is thus

$$\begin{aligned} \hat{B} &= \arg\min_B \{ \|R - XB\|^2 + \lambda B' \mathbf{P} B \} \\ &= (X'X + \lambda \mathbf{P})^{-1} X'R, \end{aligned} \tag{2.6}$$

where **P** is a symmetric positive semidefinite penalty matrix and λ is a positive shrinkage parameter which determine the bias/variance trade-off of the estimator. In the context of B-splines, the penalty matrix **P** is defined such as to shrink the estimated RIF-regression coefficients toward a polynomial of an arbitrary order. We refer to Barnichon and Brownlees (2019) for further details.

We complement the Barnichon and Brownlees (2019) estimator by including the sample population weights in the estimation process. Our final estimator thus takes the form:

$$\hat{B} = (X'WX + \lambda\mathbf{P})^{-1}X'WR,$$

where W is a block-diagonal matrix, each block on the diagonal containing the sample weights. This estimator allows to compute a smoothed version of the RIF-regression coefficients, which are in turn used in the FFL detailed composition method. In this paper, we make use of this (modified) method to specifically capture the effect of education and potential experience, which are two of the main observable sources of an individual's skills.

Concerning the choice of the shrinkage parameter λ, two methods can be used. As highlighted by Silverman (1986) in the case of bandwidth selection in kernel density estimation, such a parameter can be selected "by eye", i.e. subjectively and thus according to what one wants to see, or by using an automatic method. Automatic methods are data-driven selection methods, which Racine (2008) regroups into four categories. One of these categories is cross-validation, which is the method used by Barnichon and Brownlees (2019). More precisely, they use the k-fold cross-validation technique, which consists in selecting the value of λ which minimizes the prediction errors when the sample is repeatedly divided into a training set and a validation set.

Such cross-validation methods, especially the leave-one-out cross-validation technique, are notably used to select the bandwidth parameter in kernel density estimation (see e.g. Jones, Marron and Sheather, 1996, and Li and Racine, 2007). However, as discussed by Groß and Rendtel (2016), wage data reported by survey participants are often rounded. This phenomenon, called "heaping", can induce standard cross-validation techniques to select values of bandwidth which introduces "spurious spikes and bumps" (Groß and Rendtel, 2016) in the estimated density function. While several techniques could be used to handle this problem, their appropriateness is evaluated in a subjective manner, i.e. "by eye". Since we are working with recentered influence functions which are estimated on the basis of wage data, we choose to directly use the subjective method for the choice of the shrinkage parameter λ.

In the next section, we describe the data, including the covariates used — notably as determinants of wages — in the aggregate and detailed decomposition procedures.

2.3 Data

2.3.1 Harmonization of the data

Contrary to the US for which a single data source — such as the CPS-MORG — can be used, assessing *and* comparing the evolution of the wage structure for different European countries requires the use of two distinct survey datasets.

For the 1990s workers, who correspond to the first group of workers in our decomposition exercise, we use the personal data files of the European Community Household Panel (ECHP), a longitudinal survey that has been implemented between 1994 and 2001 in the (at the time) twelve and then fifteen member states of the European Union. Micro-data on the second group of workers — workers from the second half of the 2010s — come from the European Union Statistics on Income and Living Conditions (EU-SILC), which provides both longitudinal and cross-sectional (we use the latter) annual data on income, employment and other living conditions. EU-SILC started in 2004, year of entry of several new member states. It thus covers a more important number of countries than ECHP. The latter however limits our analysis to a set of fourteen countries: Belgium, Denmark, Germany, Greece, Spain, France, Ireland, Italy, Luxembourg, Netherlands, Austria, Portugal, Finland and the United Kingdom.

EU-SILC is the successor of ECHP. In the same spirit as the latter, it has been designed so as to be the "EU reference source for comparative statistics on income distribution and social inclusion at the European level."[25] Cross-country harmonization efforts thus have been made under the supervision of the European statistical office. However, despite these efforts, all variables (including some of our variables of interest) are not available across all countries and for all years. Moreover, the transition between ECHP and EU-SILC has been accompanied by an "unavoidable disruption in the time series of indicators produced" (Eurostat, 2005). Merging these data sources in order to operate a between-period decomposition analysis thus requires us to properly harmonize our variables of interest.

2.3.2 Public v. private sector workers

Since our strategy consists in estimating and comparing the change in the wage structure for the private and the public sector, we need to distinguish between these two types of workers. While ECHP contains a binary variable indicating whether the respondent works in the public sector, there is no such variable in EU-SILC. We thus use an alternative (and somehow more restrictive) definition of a public worker, based on the main activity of the local unit in which the worker is employed. The related variable — available in both ECHP and EU-SILC — indicates in which category of the statistical classification of economic activities (NACE, from the French *Nomenclature statistique des Activités économiques dans la Communauté Européenne*) the worker is employed. As shown in Table 2.1[26], three of these economic activities (industries) were typically handled by the public sector in the early 1990s

[25]Source: `https://ec.europa.eu/eurostat/web/income-and-living-conditions`

[26]We build this table using the NACE categorical/nominal variable and the variable indicating whether or not a worker belongs to the public sector, both available in ECHP.

Table 2.1: Percentage of public workers by economic activity (NACE) in the early 1990s

	1	2	3	4	5	6	7	8	**9**	**10**	**11**	12
All	13.7	8.8	5.3	2.7	49.8	5	15.3	13.9	97.2	89.8	77.4	45.6
AT	24.1	9.1	3.1	1.2	65.9	5.6	5.2	23.7	98	96.4	67.5	50.7
BE	23.3	5.3	6.8	7.1	65.4	18.6	10.5	11.3	94.3	89.3	47.7	64.9
DE	39.8	6.7	5.9	3.3	47.4	9.5	37.9	21.2	97.6	90.7	62.1	52.6
DK	9.7	4.4	7	0.5	46.6	7.5	1.2	16.5	94.5	91.6	90.1	43.2
EL	22.8	20.5	2.3	2.4	59.2	3.6	55.3	22.5	98.8	88	85.8	45.3
ES	6.8	8.7	3.8	2.9	47	4.6	6	4.1	99.9	83.3	81.9	32.9
FI	30	16.3	18	4.2	38.9	0	6.9	35.9	100	90.9	81.9	57.9
FR	15.6	7.9	1.5	2.7	57.9	6.9	12.8	15.2	96.8	87.9	67.1	35.9
IE	11	9.4	26.5	1.7	76.2	3.5	16.3	12	99.1	96.1	80.3	33.5
IT	19.2	8.2	2.1	2.6	57.3	1.4	13.8	11.9	98.5	96.8	88.3	50.4
LU	43.6	3.5	0	2.7	59.9	12.5	16.5	10.7	100	90.5	40	62
NL	1	10.5	0	0.6	11.4	2.3	5.7	6.6	93.1	90.9	64.9	31.9
PT	3.8	7.5	4.1	4	38.4	3.7	24	6.6	95.1	81.5	90	29.8
UK	7.5	7.8	11	4.4	33.6	8.8	3.9	11.2	97.3	80.4	84.6	32.4

Notes: 9: public administration and defence, compulsory social security; 10: education; 11: health and social work.
Source: ECHP, our calculations.

in Europe: "public administration and defence, compulsory social security", "education" and "health and social work". While authors such as Campos et al. (2017) — who claim to follow the extant literature on the public sector pay gap — define public workers as those employed in the three previously mentioned categories, we prefer to exclude health and social workers from our baseline public sector definition. Indeed, while it is true that the *European* share of these employees working in the public sector in the early 1990s is quite substantial (77.4 percent), it is also rather heterogeneous across countries. For Belgium, France, Luxembourg, Germany and the Netherlands, this share is lower than 70 percent. For Belgium and Luxembourg, it is even lower than 50 percent. We thus decide to restrict the definition of public workers to employees of the "public administration and defence, compulsory social security" and "education" sectors.

2.3.3 Earnings data

A variable central to our analysis is the gross wage earned by our population of interest, which is composed of currently working male employees aged between 16 and 65 years. In both surveys, two monetary earnings variables are available: one gives workers' current monthly earnings, the other gives their annual earnings during an income reference period prior to the time of the interview. While both variables have a net and a gross version in EU-SILC, in ECHP only *net* annual earnings are provided. Following Naticchioni, Ragusa and Massari (2014), we create a *gross* annual earnings variable by dividing *net* earnings by the net/gross ratio, which is provided by the household data files. The main flaw of this approach is that this ratio is the same for all members of a given household, which potentially induces approximation errors. However, the monthly wage variable in EU-SILC is only available for a limited number of countries since, according to the documentation, member states are required to provide such information only when they have no other source to calculate the gender pay gap. We thus face a trade-off between introducing a potential source of approximation error and limiting our comparative analysis to a restricted set of countries, which does not include major European countries such as Germany and France.

Since we aim at conducting the most extended comparative analysis possible, we choose to use annual wage and salary earnings as our wage variable. This allows us to operate our analysis on fourteen European countries: Austria, Belgium, Germany, Denmark, Greece, Spain, Finland, France, Ireland, Italy, Luxembourg, the Netherlands, Portugal and the United Kingdom.

An important challenge linked to the use of this variable in a labor market analysis arises from the fact that the period to which it refers is not the same as the time of the interview. Almost all employment and demographic variables used as predictors in our analysis describe the *current* situation of the worker, which may be different from the situation of the same worker during the income reference period. Her situation may also have changed *during* the reference period. For example, an individual may have been employed during the first half of the period, but unemployed during the second half. It may also be that this worker has been employed during the whole period, but changed his number of hours worked per week in the middle of it, e.g. starting working full-time and ending up as part-time worker. This is problematic since we do not want to exclude part-time workers from our sample: jobs newly created may actually take the form of part-time jobs. We however need a measure of hours worked for the income reference period.

To handle these temporality issues, we use survey-provided calendar information, exclude some observations from our data and impose specific assumptions. This notably allows us to derive hourly earnings from their annual counterpart according to a procedure derived/adapted from Engel and Schaffner (2012) and described in Appendix 2.A. Earnings then have to be made comparable between periods. In ECHP, they are expressed in national currencies, and thus need to be converted to ECU/euros using the exchange rate tables provided in the data files. We finally adjust nominal values to real values for both surveys using consumer price index data.

Figure 2.4 presents kernel density estimates of the probability density functions of (log) real hourly wages for both periods and both base measures of earnings, *before trimming*. Summary statistics of these distributions are presented graphically, in the form of boxplots, in Appendix 2.A.

Given that our *hourly* wage measure is obtained from *annual* earnings information, it is hardly surprising to find outliers in our derived wage data, as shown in Appendix 2.A. Especially striking is the heavy presence of data points at the very bottom tail of the distribution for some countries. This is even more striking given that some of these countries actually have a rather stringent minimum wage legislation. In the US empirical literature on wage polarization, outliers are usually

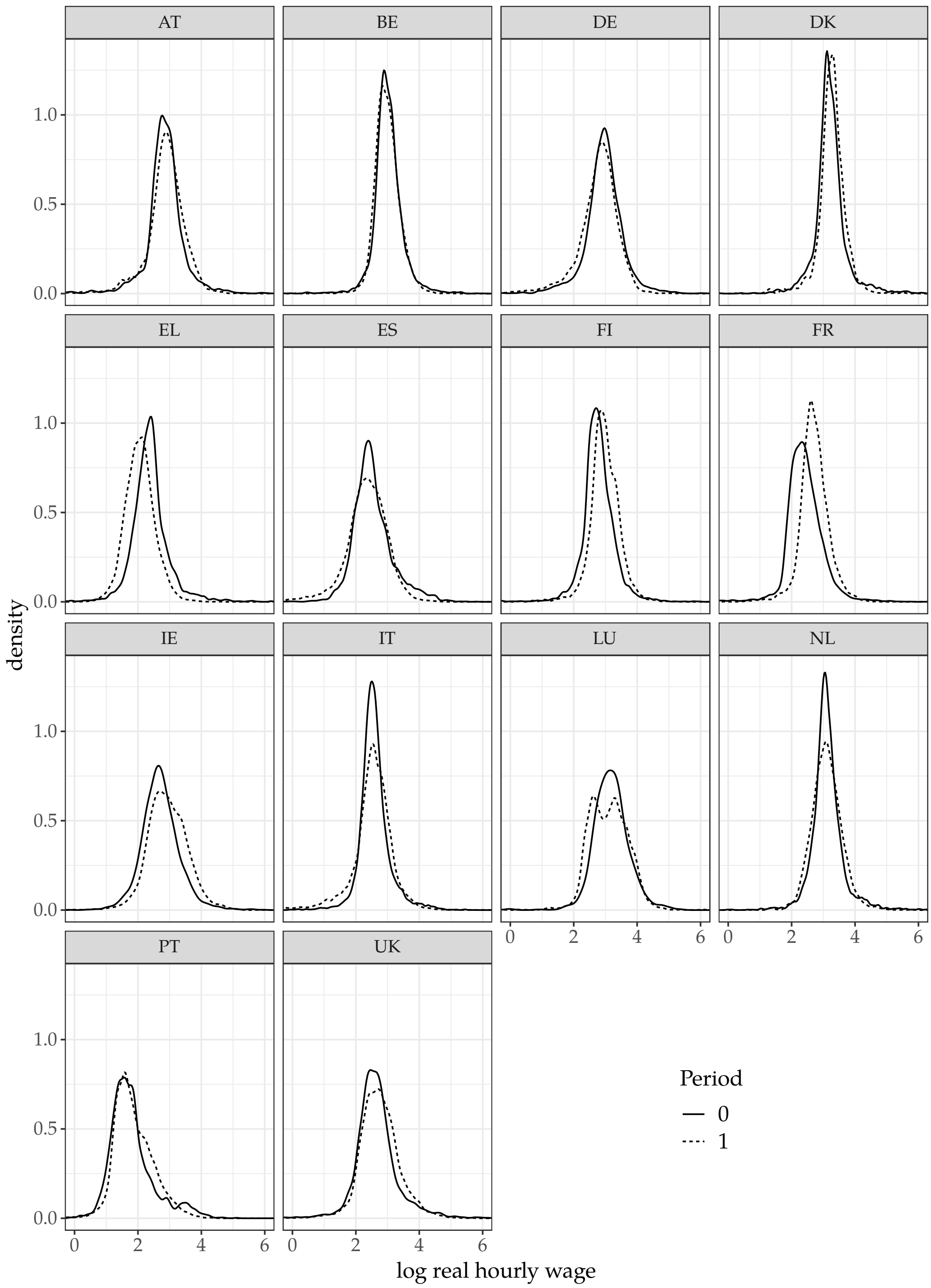

Figure 2.4: Estimated probability density function of log real hourly wage

handled by trimming wages above and below arbitrary thresholds (see e.g. Autor, Katz and Kearney, 2006; Lemieux, 2006). We choose to let the data speak, and trim wages according to the country-specific fence[27] of the adjusted boxplot for skewed distributions introduced by Hubert and Vandervieren (2008).

2.3.4 Explanatory variables

Recall that during the first stage of our decomposition exercise, we estimate reweighting functions that are used to build counterfactual wage quantiles for each sector. The second stage consists in estimating the contribution of the change in the pricing of skills to the change in the sector-specific wage structure.

2.3.4.1 Variables used in the aggregate decomposition (first stage)

The reweighting functions of the first stage are estimated using predicted probabilities of belonging to the second period, which are themselves computed on the basis of a logit model. Since the goal of this model is to yield the most accurate predicted probabilities, we are not limited by structural interpretation constraints in the choice of the predictors (explanatory variables and some of their interaction terms). The main constraint we face is linked to the limited number of observations for the public sector, which can easily lead to an estimation problem if we are working with a too important number of dummy variables and terms resulting from their interaction.

In our baseline logit model, predictors include *marital status*, *education*, *potential experience*, *industry* and *occupation*, as well as interaction terms between some of these variables. Coding of education and potential experience groups is described in the next (sub)section.

2.3.4.2 Variables used in the detailed decomposition (second stage)

We adopt the view that institutions mitigate the impact of SBTC on the (relative) pricing of skills. For the second step of our decomposition exercise, we thus rely on the Mincer equation, according to which core predictors of wages are educational attainment and potential experience.

We use these core predictors converted to ordered categorical variables, along with occupational categories and categories of economic activity (industry). We then include these categorical variables as binary variables in the RIF-regressions. This allows to study the impact of a change in the representation of a given category in the workforce, but also the contribution of this category to the wage structure effect.

Note that since the coding of these variables differs between the ECHP and EU-SILC datasets, an harmonization effort is required. For example, educational attainment in ECHP includes only three categories, which roughly correspond to low-, middle- and high-skill workers. While the EU-SILC version of this variable is more detailed, for the sake of comparability we aggregate these detailed categories

[27] This fence is a function of the first and third quartiles of the distribution, but also of the medcouple, a robust measure of skewness introduced by Brys, Hubert and Struyf (2004).

such as to make them correspond to the ECHP ones. The different variables and the required harmonization procedures are described in Appendix 2.A.

2.4 Results

2.4.1 Aggregate decomposition: the impact of institutionalization of the wage-setting process on wage polarization

In this section, we examine the results of the country-specific aggregate decomposition exercise. To facilitate their exposition, we present them graphically in Figure 2.5 and describe these results by groups of countries.

2.4.1.1 Polarizing private sector and mitigation of polarization in the public sector

From Figure 2.5, it is easy to see that polarization of the wage structure only occurs in the private sector of a limited number of European countries (dark blue frames). In our sample, only five countries exhibit a wage structure effect that can actually be characterized as 'polarized/polarizing': the United Kingdom, Ireland, the Netherlands, Luxembourg and Finland. The clearest polarized pattern is observed in the United-Kingdom, which is not really surprising since this is the country we expect the most to follow the US path, due to their institutional proximity. The Netherlands and Luxembourg also exhibit a polarized pattern of change in private sector wages: if we ignore what happens at the extreme top-end of the distribution, this pattern is U-shaped. Finally, Finland and Ireland face a similar pattern, but less pronounced. At different degrees, these five countries all exhibit the two components of wage polarization: a decrease in the wages in the middle of the distribution relative to the ones at the bottom (second component), and an increase in the wages at the top relative to the ones in the middle (first component).

As expected, change in wages in the public sector — the most institutionalized of the two sectors, as shown in the introduction — follows a different pattern. At least one of the two components of polarization observed in the private sector is partially counteracted in the public sector. In the United-Kingdom and Finland, wages at the top of the public sector distribution decreased relative to those in the middle. In Luxembourg, the second component is clearly counteracted in the most institutionalized sector, while the first component is present but to a lesser degree, thus implying a mitigation of the overall phenomenon in the country. Finally, if we ignore the extreme bottom-end of the wage distribution in the Netherlands, change in the public sector wage structure is actually anti-polarizing: being inverse U-shaped, its pattern of change goes against the one prevailing in the private sector. The same holds for Ireland.

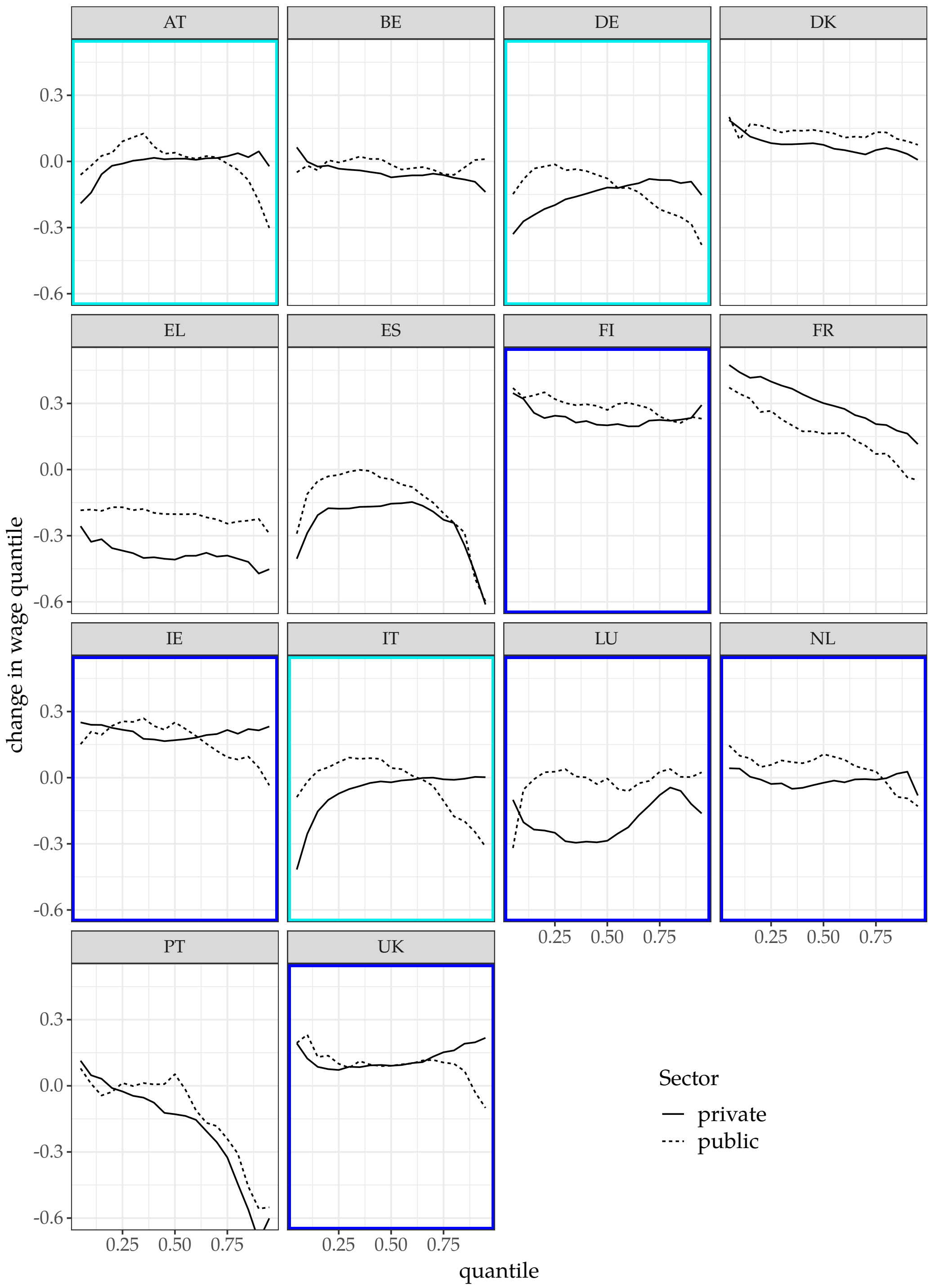

Figure 2.5: Change in wage structure: between-sector comparison across several European countries

2.4.1.2 Anti-polarized pattern of change in the public sector, one-sided polarization in the private sector

Some other countries only face one component of wage polarization in their private sector, while their public sector exhibits an anti-polarized pattern of change in the wage structure. Austrian, German and Italian (light blue frames) private sectors are all subject to what can be called an "upgrading" pattern of change in the wage structure: the higher the rank in the original ($t = 0$) distribution, the higher the wage increase. This implies that only the first component of wage polarization is observed in these countries' private sector. In contrast, the wage structure of their public sector is subject to an anti-polarized pattern of change.[28] In Portugal and Greece, only the second component of wage polarization takes place in the private sector. In the public sector, however, the pattern of change is again anti-polarized[29]. While the Spanish public sector is also a clear case of U-shaped change in the wage structure, the characterization of the private sector is less straightforward. Ignoring the last quarter of the distribution, the pattern of change could eventually be labeled as 'upgrading'. However, more consistent with the overall picture drawn by Figure 2.5 would be to characterize it as anti-polarized.[30]

2.4.1.3 Downgrading pattern of change in the public sector

The private sector of the remaining countries — Belgium, Denmark and France — only face the second component of wage polarization. While this phenomenon is not observed in the Belgian and Danish public sectors, in France the pattern of change is exactly the same in the public and the private sector.

2.4.1.4 Intermediate conclusion

From these results we can already conclude that institutionalization of the wage-setting process, when not leading to an anti-polarized change in wages, mitigates at least one of the two components of wage polarization.

2.4.2 How institutions mediate the impact of SBTC: smoothed RIF-regressions and detailed decomposition

In the previous section, we estimated the impact of institutionalization of the wage-setting process on the evolution of wage structure. According to the SBTC/RBTC approach, wage polarization is due to the change in the price of skills following technical progress. In this section, we examine how institutions shaped the change

[28]As shown by Figure 2.5, this pattern is U-shaped, but in a skewed way: its maximum is rather reached at the middle of the second quarter of the distribution than at its median. However, this is also the shape that polarization takes in the US when it is evaluated on the basis of the wage ventiles.

[29]Note that for Portugal this is the case only if we ignore the extreme bottom-end of the distribution.

[30]This can nonetheless be debated given that the maximum of this inverse U-shaped pattern is reached in the second half of the distribution of wages, departing from the implicit definition of polarization that has been derived from the US case.

in the pricing of skills. As previously explained, our strategy is to compare, between sectors, how the change in pricing of education contributed to the overall wage structure effect. We do so by implementing the detailed decomposition method presented in Section 2.2.

We first focus on the impact of the change (*de facto*, an increase) in the share of employed high-skill workers, one of the predicted impact of RBTC. Note that aggregating the effects of the different educational categories to obtain the overall contribution of education to the wage structure effect does not fundamentally change the results. To facilitate the exposition of the results of our detailed decomposition exercise, we present them graphically, for different groups of countries.

Prior to this detailed decomposition analysis, we use the RIF-regression technique to assess the *potential* power of institutions to impact the channel through which technical change is supposed to lead to polarization. For each sector, we examine the impact of increasing the share of workers with the highest level of education on wage ventiles. We then compare these results.

2.4.2.1 A RIF-regression preliminary analysis

Before examining the cross-sector difference in the contribution of education to the change in the wage structure, we assess the impact of increasing the proportion of tertiary-educated workers on the different ventiles of the unconditional distribution of wages. We consider this RIF-regression analysis as *preliminary* — and thus inconclusive — since it ignores not only the time dimension[31], central to the polarization phenomenon, but also the difference between the wage structure and the composition effects. It can still provide a taste of how institutions can mediate the impact of SBTC/RBTC on the distribution of wages, while requiring a less restrictive set of identification assumptions than the detailed decomposition method implemented later.

The principle is the following. According to the RBTC approach, technical change makes the substitution of middle- with high-skill workers in performing routine tasks more and more profitable, leading to an increase in the wage of the latter type of workers relative to the former. Middle-skill workers are then redirected towards tasks with lower requirements in terms of skills, and the wages prevailing for such tasks are supposed to increase.[32] Both phenomenons constitute the polarization of wages. If this theory holds for a given country and if institutions actually mitigate or counteract these phenomenons, increasing the share of high-skill workers in the private sector should have a polarized impact on the wage quantiles while this impact should be limited in the public sector. We estimate such impacts, which have been labeled *unconditional quantile partial effects* by Firpo, Fortin and Lemieux (2009), using their RIF-regression procedure, which we augment with the built-in smoothing estimator described earlier. The results of this preliminary analysis are presented in Figure 2.6.

For each country and for each period (with the notable exceptions of Finland and Belgium in t_0), an increase in the share of high-skill workers leads to the first

[31]However, we indirectly take the time dimension into account by operating our RIF-regression analysis for each of the two periods.

[32]See notably Acemoglu and Autor (2011).

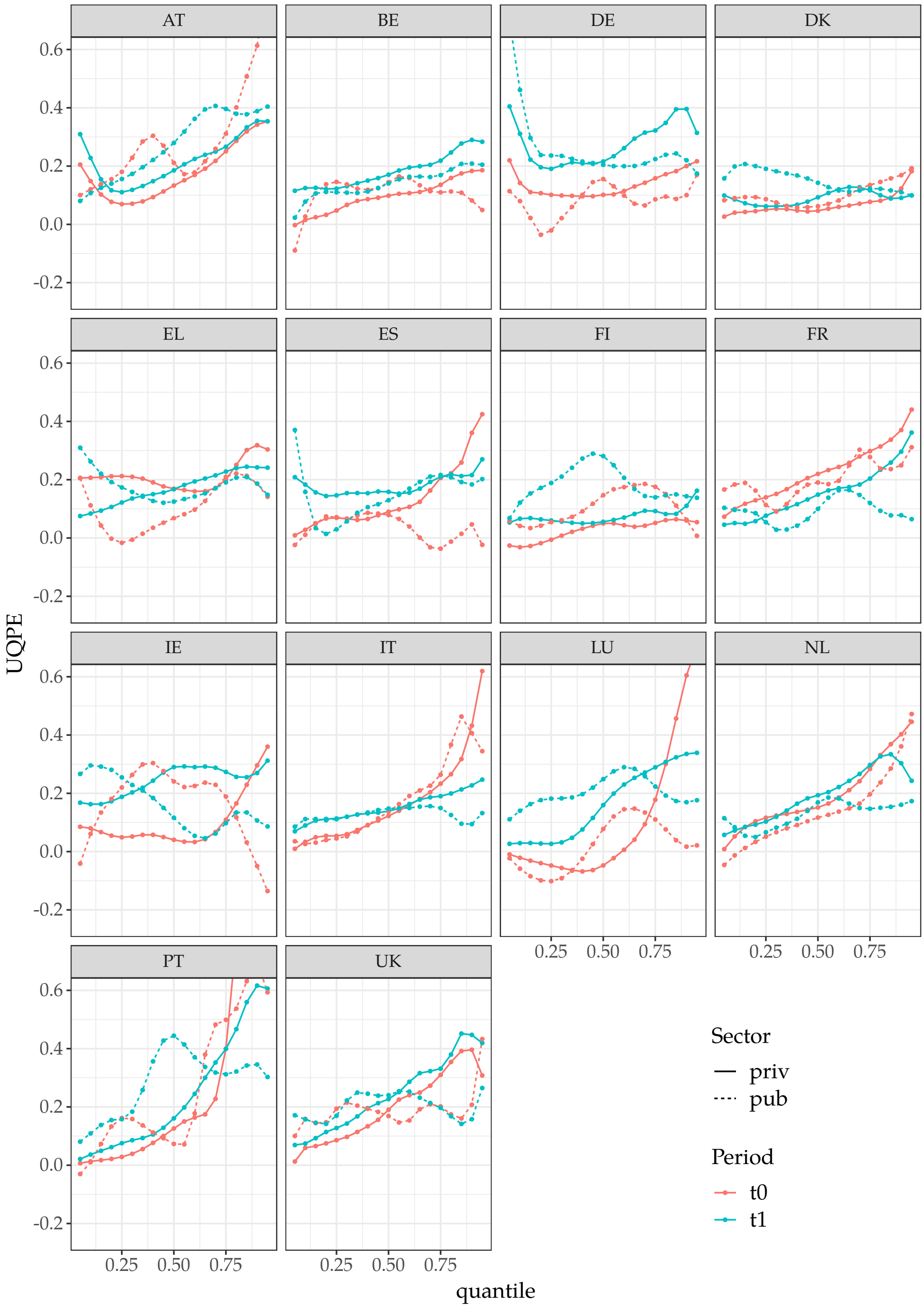

Figure 2.6: Smoothed unconditional quantile partial effects (UQPE) of an increase in the proportion of tertiary-educated workers: a between-sector comparison across several European countries

component of wage polarization — i.e. the increase of high-skill relative to middle-skill wages — in the private sector. This is hardly surprising: high-skill workers are expected to be more present at the top than at the middle of the distribution, and the RIF-regression method does not distinguish between composition and structure effects.

In a more limited number of countries, the second component — i.e. the increase of low-skill relative to middle-skill wages — is also observed. This is less intuitive since high-skill workers are more likely to end up at the top and at the middle than at the bottom of the distribution of wages.[33]. When both components are present, the estimated unconditional partial effects (UQPE) are in line with the predictions of the RBTC approach. This is the case for Austria and Germany in both periods, and for Ireland, Greece and Luxembourg in t_0.

The impact along the wage quantiles of an increase in the share of tertiary-educated workers is almost always less polarized in the public sector than in the private sector. In some countries and for some periods, such as Ireland, Finland, Spain, Luxembourg and Germany in t_0, and Portugal, Finland, France and Luxembourg in t_1, this pattern is even inverse U-shaped, indicating a strong potential anti-polarizing impact of institutionalization. Notable exceptions are Greece and Spain in t_1, for which the public sector's UQPE pattern is polarized. While these exceptions mitigate the results of our preliminary analysis, the overall picture indicates that institutions have the potential to mute the channel through which technical change leads to polarization according to the RBTC approach.

2.4.2.2 Detailed decomposition results

We now turn to the detailed decomposition of the change in wages, focusing on the (unconditional) impact of the actual change in the price associated with tertiary education. We assume that the impact of RBTC on the wage structure in our framework can be captured through its supposed impact on the tertiary education premium: if it has not been muted by institutional forces, RBTC is supposed to increase this premium, which in turn is expected to contribute to the aggregate polarization of the wage structure.

We thus expect polarization of the private sector's aggregate wage structure[34] to be (at least) partially due to the RBTC/SBTC-induced increase in the price of high skills. As shown in Figure 2.7, this is what we observe for the United-Kingdom, the Netherlands and Finland. This is however not the case in Luxembourg, whose private sector exhibits an anti-polarizing pattern of change in the return to education when the latter is measured by three educational groups. Concerning the public sector, we expect the contribution of tertiary education to have a somehow anti-polarized impact on the aggregate wage structure. This is clearly what we observe for Finland, Luxembourg, and the United-Kingdom. For the Netherlands, the pattern could rather be labeled as 'downgrading' (as opposed to 'upgrading') if

[33]Capturing this *unconditional* quantile effect is made possible by the use of the RIF-regression method. The latter contrasts with the 'standard' quantile regression approach, introduced by Koenker and Bassett (1978), which can only capture quantile effects *conditional* on the distribution of the workers' characteristics.

[34]Recall that it is the case for the United-Kingdom, the Netherlands, Finland and Luxembourg.

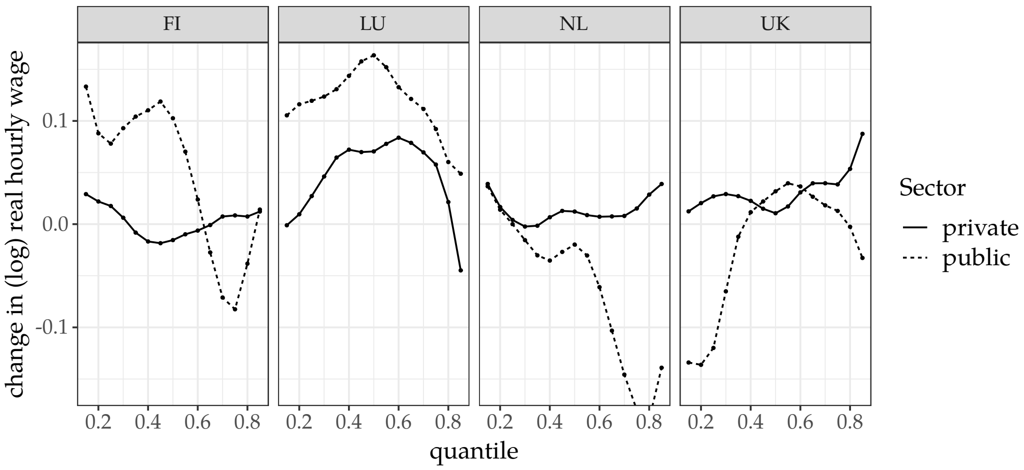

Figure 2.7: Countries exhibiting a polarized aggregate wage structure effect for the private sector: contribution of tertiary education, public v. private sector

we ignore the extreme top-end of the distribution. In this country, return to tertiary education in the most institutionalized sector seems to counteract the first component of wage polarization while contributing to the second, thus participating to a compression of the wage structure. Note that while the French private sector does not exhibit a polarized aggregate wage structure effect, the change in the pricing of tertiary education actually contributed to it in a polarized way. Figure 2.8 gather all the countries for which the change in the price of tertiary education contributed in a polarized way to the wage structure effect for the private sector. For all these countries, the part of the first component of wage polarization due to the change in the pricing of tertiary education is mitigated by institutionalization. For France and the UK, the pattern is anti-polarizing.

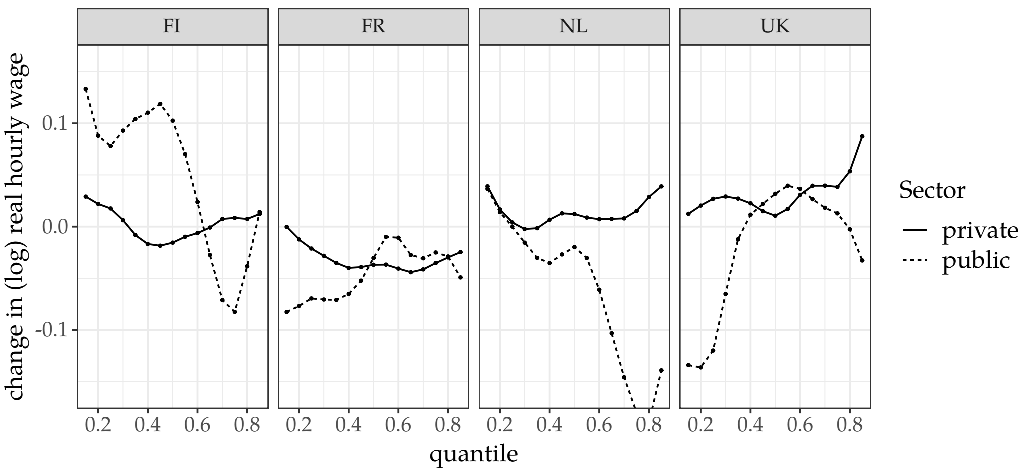

Figure 2.8: Countries for which tertiary education contributes in a polarized way to the aggregate wage structure effect: contribution in the public v. private sector

For the rest of the countries, the contribution of tertiary education to the private sector's wage structure effect cannot be considered as polarizing. In some cases, it cannot even be considered as upgrading (e.g. Austria, Belgium, Denmark and

Portugal). In Ireland, it is even strongly anti-polarizing for the private sector while clearly polarizing for the public sector. There are several potential explanations for that, including a high level of institutionalization of the private sector and the impact of financial crises. We discuss these potential explanations in the next sections. Another explanation could be that for some countries, the level of skills is not captured adequately by educational attainment: due to the use of ECHP, this variable is indeed coded into only three ordered categories. We thus complement educational attainment with another observable source of skills: potential experience. We aggregate the contribution of the former and the contributions of the highest levels of the latter. The results of the detailed decomposition are presented in Figure 2.9.

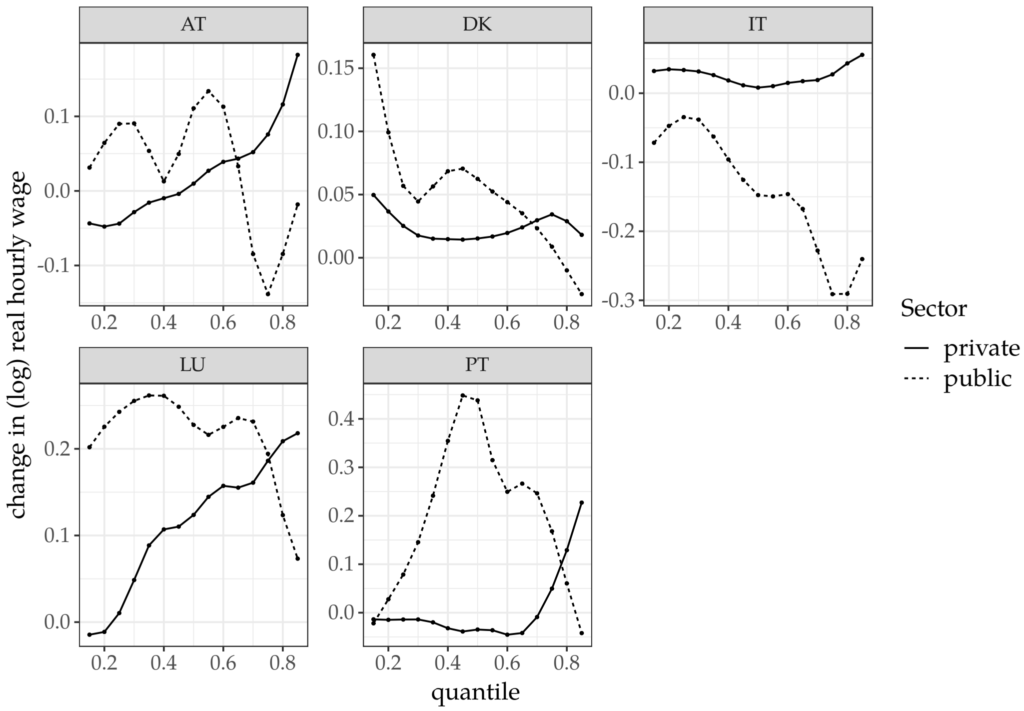

Figure 2.9: Aggregated contribution to the wage structure effect of different sources of skills: results for selected countries

For Denmark, Italy and Portugal, the aggregated contribution to the private sector's wage structure effect of the previously mentioned sources of skills is polarizing. This is in line with the predictions of the RBTC theory. For these three countries, institutions counteract at least one component of wage polarization. For Portugal, the impact of institutional forces is clearly anti-polarizing. In the Austrian and Luxembourg private sectors, the aggregated contribution is clearly upgrading, while the institutional impact can be considered as anti-polarizing. This is in line with the idea that the impact of technical change is mediated by institutions, which are able to attenuate and even counteract its polarizing effect on the structure of wages.

2.5 Interpretation and discussion

2.5.1 Aggregate decomposition

2.5.1.1 On the non-generalized polarization of the private sector wage structure

Results from the aggregate decomposition exercise confirm the anti-polarizing effect of institutions on the structure of wages. However, polarization of the private sector wage structure is only observed in a limited number of countries.

There are four potential explanations for that. First, while the public sector wage-setting process is generally more institutionalized than the one of the private sector, the latter is still heavily impacted by institutional forces. While reforms of labor market institutions have been undertaken during the period studied in this paper, Figure 2.2 clearly shows that institutional determinants of wages are still present in continental European countries. In the US, for which the phenomenon of wage polarization has been originally observed, the private sector wage-setting process is clearly less influenced by institutional forces than its continental European counterpart.

Second, Europe has been hit two times by financial crises during this period: the first time by the global financial crisis of 2007/2008, and the second by the 2010 debt crisis. While the impact of these two major events are not studied in this paper, it may have mitigated the relative wage increase in the top-half of the distribution. It may also be that employment, not wages, has been the channel of adjustment to the new macroeconomic conditions. This would be a particularly interesting starting point for further research.

Third, both institutional forces and financial crises may have influenced the type of technology implemented as well as the extent of this implementation. In this paper, we follow an important share of the literature empirically characterizing the determinants of wage polarization (and, more generally, wage dynamics) by implicitly modeling technical change as exogenous. However, it may be that institutional forces affect the cost of adopting technology, leading to a differentiated implementation of technical progress, which would reinforce the impact of institutions on private sector wages, as previously described. A similar reasoning applies for financial crises, notably through their impact on the price of capital.

Finally, it may be that other factors and mechanisms limit the polarizing impact of RBTC. Concerning other factors, one could think of skill supplies and their evolution, which may hamper the expected impact of technical change on the distribution of wages in the private sector. For example, the supply of high skills and its evolution may have been so important that they actually counteracted the polarizing impact of a RBTC-induced shift in demand towards nonroutine cognitive tasks. An example of a mechanism which could mitigate this impact is the "employment growth-selection effect" highlighted by Böhm, von Gaudecker and Schran (2019). According to these authors, skills deteriorate in growing occupational categories but improve in shrinking ones. In the framework they adopt, such a phenomenon is more particularly due to the fact that, in any occupation, "both entrants and leavers [possess] lower skills than stayers." While technical change exerts a polarizing pressure on skill prices, the previously mentioned selection effect can partly inhibit their impact on wages. This effect has been captured by Böhm, von Gaudecker and Schran (2019) in a sample of German workers from which civil servants have been excluded, and the possibility that other European countries have been subjected to it should be considered. Another example of a mechanism potentially limiting the impact of technical change in the private sector is the effect of public sector wages on their private counterparts. According to the results of Afonso and Gomes (2014), a 1 percent increase in real public sector wage growth leads to a 0.3 percent increase in the growth rate of private sector wages. On the other hand, a 1 percent increase in real private sector wage growth increases public sector wage growth by 0.6 or 0.7 percent, depending on the specification of the empirical model. It is nonetheless conceivable that the respective magnitudes of these effects are heterogeneous across countries, and that in some cases the net effect actually contributed to attenuating the polarizing impact of technical change on private sector wages.

2.5.1.2 Institutional impact: anti-polarized v. downgrading wage structure effect

While institutional forces generally counteract the first component of wage polarization, this is not always the case for the second component, i.e. the increase of low-skill relative to middle-skill wages.

There are two possible interrelated explanations for that. The first comes from the representation of the different skill groups, both in electoral and union membership terms: where public unions and voters are mostly composed of middle-skill workers, one can expect the institutionalized wage-setting process to favor this category of workers. The second comes from the unions and/or government's ideological orientation. From an egalitarian institution, one can expect a compression of the overall wage distribution.

2.5.2 Detailed decomposition

2.5.2.1 Aggregated impact on the pricing of educational categories

Interpreting the results of our detailed decomposition exercise is less straightforward. We expect the contribution of the return to education to the public sector wage structure effect to be either downgrading or anti-polarized[35]. In other words, we expect institutional determinants to be biased towards low- and/or middle-skill workers, and thus to (relatively) penalize high-skill workers in terms of change in wages. For most of the countries, results corroborate our intuition. However, this is not the case for all countries. In the Irish public sector, both low- and high-skill workers have been favored in comparison with middle-skill workers. This is particularly puzzling given that, in this country, the public sector has an overall anti-polarizing effect on the wage structure. There are four potential and non-mutually

[35] We expect a downgrading impact when institutional agents (e.g. unions and/or the government) explicitly pursue an egalitarian policy, i.e. a compression of the wage distribution. An anti-polarized impact is expected when the bias is less 'ideological' than directed at the most politically represented (high union membership, largest share of voters) group of workers.

exclusive explanations for the fact that the public sector faces the first component of wage polarization. First, it may be that high-skill workers are over-represented in this sector in comparison with other countries.

Second, it is possible that — at least for these countries — the three educational categories of the ECHP variable for educational attainment[36] do not exactly correspond to the 'low-', 'middle-' and 'high-skill' categories used by e.g. Acemoglu and Autor (2011). For example, it may be that an important share of individuals with a recognized third level of education (the most educated category) can actually be considered as middle-skill workers in some countries. This could also explain both the absence of anti-polarized change in the public sector wage structure and the absence of the first component of wage polarization in the private sector.

Third, it may be that institutional reforms, especially the ones for which there no sector-specific data such as the degree of centralization of the wage-setting process, have been more important in the public than in the private sector. This would not be surprising for Ireland, whose public sector has been substantially reformed following the public debt crisis (see e.g. MacCarthaigh, 2017).

Finally, and as highlighted earlier in this section, public and private sector wages are not independent. As emphasized by Afonso and Gomes (2014), the former impact the latter, but the reverse is also true. According to their results, the impact is even greater in the second case. This would lead the effect of RBTC in the private sector to spill over into the public sector, potentially exerting polarizing pressures on the distribution of public sector wages. Note that we expect this spillover effect to be particularly acute in countries where the public sector applies a systematic comparison with its private counterpart when determining wage levels. Interestingly, only Ireland has been characterized by such a mechanism (Giordano et al., 2015).

2.5.3 On the potential limitations of our strategy

Before concluding, we discuss four apparent limitations of our strategy, and their (potential) impact on our estimates. Discussing the first three limitations, we show that our strategy is rather conservative and should not lead to an overestimation of the anti-polarizing impact of institutions. The four and final limitation is related to the cross-country heterogeneity in the public sector institutional setting and working conditions.

While we assume that distributional differences between public and private wages come from the cross-sector difference in institutionalization of the wage-setting process, one could argue that the adoption of technical change, and thus the evolution of the demand for skills, differs between sectors. This first limitation is thus linked to the more general and previously mentioned issue of endogenous technical change, which here takes the form of a cross-sectoral diversity in its implementation.

[36]These categories are constituted of workers with less than the second stage of secondary education, workers who actually attained this stage and workers with a recognized third level of education. While the coding of this variable is more fine-grained in the EU-SILC data than in the ECHP, for obvious reasons of comparability we have to adopt the less detailed version of the latter.

Our response to such a claim depends on the origin of this potential differentiated adoption of technology. Would it be due to the cross-sector difference in institutional characteristics, then our strategy remains valid since it is *in fine* this difference which leads to a difference in the evolution of the demand for skills and thus to a differentiated change in the distribution of wages.

It could then be argued that this cross-sector difference rather comes from difference in the objective function of the sector-specific units/agents. Since the public sector does not aim at "maximizing profits", it could end up implementing different technologies and hiring in a different way than the private sector. However, given the rather extended definition of institutions presented in the introduction, this specificity would be considered as a departure from the market logic in the Hall and Soskice (2001) sense, and thus as a difference in institutionalization compared to the private sector. To this argument could also be opposed that in a context of public finance management being reformed, the objective function of the public sector has become more and more "cost-minimizing".

It could finally be argued that this difference in adoption of new technologies, and thus in the hiring of high-skill workers, comes from short/middle-term funding limits[37] leading to a public strategy of sticking with existing technologies, and this despite the fact that it may not be a good strategy for long-run cost reduction. However, such financial pressures also lead to reforms of public sector labor markets, including their institutional characteristics (see e.g. Elliott, Mavromaras and Meurs, 2007). It is thus likely that if there has been a differentiated increase in technology adoption, it has been accompanied by a decrease in institutionalization of the public sector's pay-setting. This leads us to the second potential limitation of our strategy.

The second limitation comes from the potential differentiated evolution of the bargaining regime in the two sectors between t_0 and t_1. Our strategy ignores the potential reforms of the wage-setting system, and the estimated cross-sector difference in the evolution of the wage structure could actually come from two different sector-specific reform paths. However, this limitation more precisely concerns the identification of the public sector wage gap, which is not what we are ultimately interested in. If the difference in change in the wage structure comes partly from the fact that de-institutionalization of the wage-setting process has been more important in the private than in the public sector, it ends up incorporated in the institutional impact estimated from the between-sector comparison. If de-institutionalization[38] has been more important in the public than in the private sector, then we underestimate the impact of institutions and our estimates can be seen as lower bounds of the actual effect. We can thus characterize our strategy as

[37]Especially when pressures exerted on government to limit spending are high.

[38]We ignore the case of 're-institutionalization', which is highly unlikely, notably because of the creation of the European single market. According to Elliott, Mavromaras and Meurs (2007), the single market "has the effect of decentralizing bargaining" since it "encourages the transformation of previously single-national, centralized, systems of wage setting into competing systems of wage-setting". According to the same authors, "pressures for reform of labour market institutions as a result of the creation of a single market will bear most heavily on the private sector which operates in competitive product markets", competition that is magnified by the forces of globalization. In the public sector, such pressures mainly arise from pressures on its finances, which can be considered as *indirect* consequences of the creation of the single market.

conservative.

The third limitation stems from the fact that public and private sector wages have an impact on each other, as shown by Afonso and Gomes (2014). Our strategy ignores such interdependence, which could reduce the difference in wage structure between the two sectors. This would in turn lead our strategy to underestimate the impact of institutions. In order to properly characterize the effect of the private-public spillover[39] on our estimates, the impact of each sector on the other would have to be estimated at different points of the distribution. This is undoubtedly an interesting path for further research.

The fourth and final potential limitation is related to the way we capture the concept of institutions in a cross-country framework. While it is safe to assume that the wage-setting process is more institutionalized in the public than in the private sector[40], by no means does this assumption imply cross-country homogeneity in terms of public sector characteristics. As emphasized by Checchi, Fenizia and Lucifora (2021), the institutional setting and working conditions prevailing in the public sector depend on the country considered. By operating our decomposition analysis on each country separately, we allow for such heterogeneity. The downside of our strategy is related to the generalization of our results. Since the concept of institutions we consider is de facto country-specific, these results cannot be used to draw conclusions about the impact of precise institutional configurations. It would however be possible to analyze the results by groups of countries whose public sectors share some common institutional characteristics. An alternative strategy, in the spirit of Checchi, Fenizia and Lucifora (2021), would be to pool the data according to these different groups and to operate the analysis on each of them separately. Checchi, Fenizia and Lucifora (2021) group the countries according to an extended version of the welfare state regimes defined by Esping-Andersen (1990, 1999), but other documented categorizations could be considered.

2.6 Conclusion

Under the documented assumption that wage-setting is more institutionalized in the public than in the private sector, we compared the evolution of the wage structure effect between these two sectors in order to identify the impact of institutions on the pricing of workers' characteristics. We did so by implementing the reweighing approach to counterfactual introduced by DiNardo, Fortin and Lemieux (1996) and refined by Firpo and Pinto (2016) and Firpo, Fortin and Lemieux (2018). As expected, institutions in Europe have been able to mitigate wage polarization, a phenomenon which has been originally observed in the US between the 1980s and the 2010s. In some countries, the price schedule of the highly institutionalized sector has even been subject to an anti-polarized pattern of change. While this could be expected from a sector (or an industry) in which middle-skill workers are heavily represented, further research would be required in order to confirm (or infirm) this intuition.

[39] See Section 2.5.

[40] See Section 2.2.

Our strategy allowed us to test whether institutions affect the wage structure through the same channel as technical change does according to the RBTC theory, i.e. the pricing of workers' skills. We isolated the contribution of education to the sector-specific wage structure effect by implementing the Firpo, Fortin and Lemieux (2018) detailed decomposition method based on RIF-regressions, that we complemented with a built-in smoothing mechanism based on the Barnichon and Brownlees (2019) smooth local projection estimator. In some countries, the impact of institutions on the pricing of educational attainment clearly contributed to their overall anti-polarizing effect. For some other countries, we captured the impact of the change in the pricing of skills by considering not only education, but also potential experience. For these countries, institutions mitigated the contribution of skills to wage polarization — at least for one of its component, if not both.

In a limited number of countries, this impact actually contributed to the polarization of hourly earnings. Further research is required to investigate this unexpected phenomenon and the potential explanations suggested in Section 2.5.

Note that this paper remains silent about job polarization. This latter phenomenon is nonetheless likely to be affected by the presence of institutional forces, notably as an indirect consequence of these forces impacting the wage structure. This impact on the wage structure can therefore be used as a 'starting point' to model the effect of institutions on the evolution of employment.

Appendix 2.A Data

2.A.1 Presentation of the data sources

Micro-data used in this paper comes from two sources: the European Community Household Panel (ECHP) and the European Union Statistics on Income and Living Conditions (EU-SILC). Data on the 1990s workers, who correspond to the first group of workers in our decomposition exercise, comes from the personal data files of the ECHP. This longitudinal survey has been implemented between 1994 and 2001 in the twelve (in 1994) and then fifteen (in 1995, following the entry of Austria, Finland and Sweden) member states of the European Union. Micro-data on the second group of workers — workers from the second half of the 2010s — come from the EU-SILC, which provides both longitudinal and cross-sectional annual data on income, employment and other living conditions. Since our decomposition exercise implies distributional characteristics measured at two distant points in time, it does not require the use of panel data. We therefore use the cross-sectional files of the EU-SILC.

EU-SILC started in 2004, year of entry of several new member states. It thus covers a more important number of countries than ECHP. The latter however limits our analysis to a set of fourteen countries: Belgium, Denmark, Germany, Greece, Spain, France, Ireland, Italy, Luxembourg, Netherlands, Austria, Portugal, Finland and the United Kingdom. Sweden is not included since gross earnings data are missing for this country in ECHP. This can be explained by the fact that Sweden was not participating in the project: comparable national source have thus been included (Eurostat, 2005), but without the guarantee that all variables were available.

While cross-country harmonization efforts have been made[41] under the supervision of the European statistical office, all variables are not available across all countries and for all years. Moreover, the transition between ECHP and EU-SILC has been accompanied by an "unavoidable disruption in the time series of indicators produced" (Eurostat, 2005). Merging these data sources in order to operate a between-period decomposition analysis thus requires us to properly harmonize our variables of interest. In this Data Appendix, we especially focus on the additional harmonization effort required to obtain comparable measures of hourly earnings.

2.A.2 Population of interest and restriction of the sample

In our analysis, we focus on currently working male employees aged between 16 and 65 years. The main reason we focus on males is that males and females are considered as impacted differently by the same structural explanatory factors. For example, Fortin and Lemieux (2016) claim that offshoring and technical change have more direct effects on male than on female workers. Since the same could be assumed for institutional factors, we choose to restrict our sample to male workers.

[41]For ECHP, see notably `https://ec.europa.eu/eurostat/ramon/statmanuals/files/transition_echp_eu-silc.pdf`: "Statisticians and users alike agree that the European Community Household Panel (ECHP) survey has offered a unique information source with a large range of topics, standardised methodology and procedures and a pure longitudinal panel design."

2.A.3 Earnings data

We are interested in the gross hourly earnings of our population of interest. In both surveys, two monetary earnings variables are available: one gives workers' current monthly earnings, the other gives their annual earnings during an income reference period prior to the time of the interview. In ECHP, the two variables are respectively labeled "current wage and salary earnings - gross (monthly)" and "wage and salary earnings (net, NC, total year prior to the survey)", where NC stands for national currency. In EU-SILC, their respective labels are "gross monthly earnings for employees" and "employee cash or near cash income". Despite the difference in label between the two surveys, we can conclude from the documentation that both annual earnings variables refer to the same definition of earnings. While both variables have a net and a gross version in EU-SILC, in ECHP only *net* annual earnings are provided (except for Finland and France, for which the gross value is given). Following Naticchioni, Ragusa and Massari (2014), we create a gross annual earnings variable by dividing net earnings by the net/gross ratio, which is provided by the household data files. The main flaw of this approach is that this ratio is the same for all members of a given household, which potentially induces approximation errors. However, the monthly wage variable in EU-SILC is only available for a limited number of countries since, according to the documentation, member states are required to provide such information only when they have no other source to calculate the gender pay gap. We thus face a trade-off between introducing a potential source of approximation error and limiting our comparative analysis to a restricted set of countries, which does not include major European countries such as Germany and France. Countries for which the monthly wage variable is available in EU-SILC for our period of interest are Luxembourg, the United Kingdom, Ireland, Italy, Greece, Portugal and Austria. In contrast, the annual gross earnings variable is available for all the fourteen countries we focus on. Since we aim at conducting the most extended comparative analysis possible, we choose to use annual wage and salary earnings as our wage variable. This allows us to operate our analysis on fourteen European countries: Austria, Belgium, Germany, Denmark, Greece, Spain, Finland, France, Ireland, Italy, Luxembourg, the Netherlands, Portugal and the United Kingdom. Note that combining both variables (using one when the other is missing for an individual, after having converted both into hourly earnings) cannot be considered as a valid alternative since our exploratory analysis indicates that they do not exactly measure the same concept of income. This seems to be confirmed by the ECHP documentation on imputation, where one can find — to the best of our knowledge — the most precise definition of the 'wage and salary' variable. According to this definition, monthly wage is only one component, amongst others, of regular wage and salary earnings. Moreover, since the annual earnings are measured for a different period than the one of the interview, combining both variables would require to use the EU-SILC panel (as opposed to the cross-sectional) datasets/files, which entails some limitations, notably in terms of available variables.

A important challenge linked to the use of this variable in a labor market analysis arises from the fact that the period to which it refers is not the same as the time of the interview. Almost all employment and demographic variables used as predictors in our analysis describe the current situation of the worker, which may be different from the situation of the same worker during the income reference period. His situation may also have changed during the reference period. For example, an individual may have been employed during the first half of the period, but unemployed during the second half. It may also be that this worker has been employed during the whole period, but changed his number of hours worked per week in the middle of it, e.g. starting working full-time and ending up as part-time worker. This is problematic since we do not want to exclude part-time workers from our sample: jobs newly created may actually take the form of part-time jobs. We however need a measure of hours worked for the income reference period. To handle these temporality issues, we use survey-provided calendar information, exclude some observations from our data and impose specific assumptions. This notably allows us to derive hourly earnings from their annual counterpart according to a procedure derived/adapted from Engel and Schaffner (2012). Since this procedure was originally targeted to EU-SILC, we had to adjust it before applying it to ECHP.

We now give a brief description of the procedure we apply. Note that calendar information is crucial to this procedure and that the information provided varies according to the survey considered. First, we compute for how long the different workers had their current job, and remove from the sample workers who got their current job the same year as the interview. For workers who started their job during the income reference period (the year before the interview), we compute the number of months which have been worked during this period. We exclude from our sample workers who started their job during the income reference period but for whom there is no information about the number of months worked during this period. We then build a monthly wage measure from annual earnings, dividing the latter by the number of months worked. We finally compute the hourly wage by multiplying the monthly wage by 12 and by dividing this product by the number of hours worked weekly multiplied by 52. We winsorize the number of hours worked in order to avoid the use of implausible values.

Since our hourly wage measure is obtained from annual earnings and annual hours worked (themselves derived from other variables), it is not surprising to find outliers in our derived hourly wage data. Figure 2.A.1 shows scatterplots (with jittered points) and kernel density estimates of the probability density function of (log) real hourly wages, for the different countries of our sample.

In Figure 2.A.1 are also represented the Hubert and Vandervieren (2008) adjusted boxplots for skewed distributions. These boxplots clearly show the presence of outliers in our wage data. We remove these outliers by trimming wages on the basis of the fence (and thus the whiskers) of the adjusted boxplots. This fence is a function of the medcouple, a robust measure of skewness introduced by Brys, Hubert and Struyf (2004). Note that in order to remain conservative in our trimming strategy, we set the degree to which the whiskers extend out from the box (of the boxplot) to a value slightly larger than the standard.

2.A.4 Other variables

For variables other than earnings we simply use the information available at the time of the interview. Since we restrict our sample to workers who started their

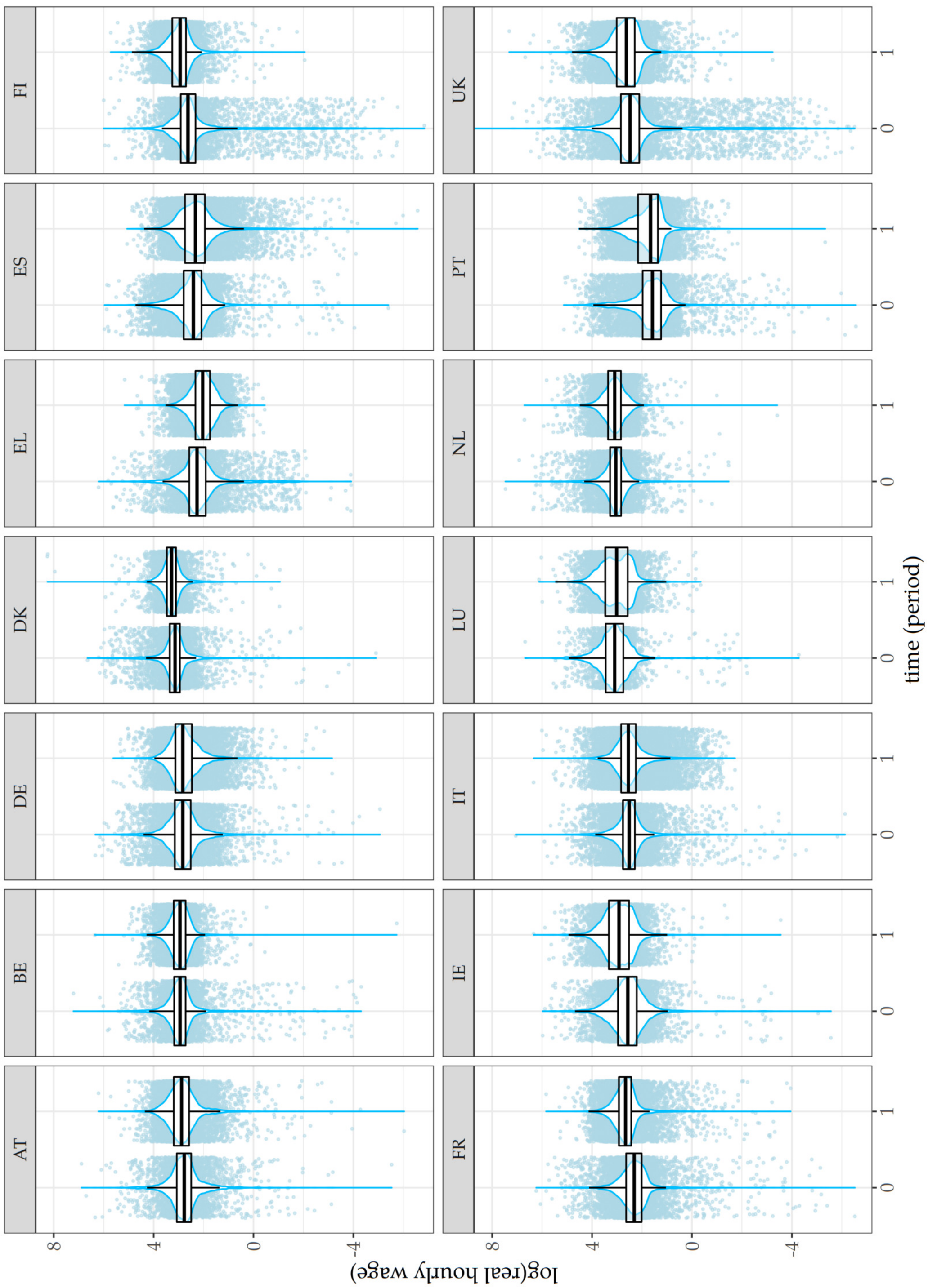

Figure 2.A.1: Scatterplots, adjusted boxplots and kernel density estimates of probability density function for (log) real hourly wages

current job before or during the income reference period, this strategy is completely safe for variables directly linked to the job, such as the occupational category or the economic activity/industry. For other variables, such as marital status, it amounts to assume that their value did not change between the income reference period and the year of the interview. Since the income reference period is the year preceding the year of interview, the probability that such a change happened between the two periods is relatively limited. In our analysis, we use the following variables:

- ***educational attainment***: Due to the coding used in ECHP datafiles, we recode the EU-SILC version of this variable into 3 categories: *less than the second stage of secondary education*, *second stage of secondary education* and *recognized third level of education*.

- ***potential experience***: Difference between the year of the interview and the year when the highest level of education was attained. When one of these variables are missing, we use the variable indicating the number of years spent in paid work. When the previously mentioned variables are missing and when the worker has no (formal) education, we subtract 14 from his age, thereby assuming that individuals do not start working earlier than 14. This variable is finally recoded into an ordered categorical variable with 7 categories.

- ***occupational category***: The original variable is based on ISCO 2-digit categories. To guarantee comparability between surveys and countries and to ensure appropriate representation of the different categories in our sample, we aggregate these categories into 6 groups.

- ***economic activity*** (industry): The original variable is based on aggregates of NACE 2-digit categories. To guarantee comparability between surveys and countries and to ensure appropriate representation of the economic sectors in our sample, we aggregate these categories into 12 groups.

- ***full-time v. part-time work***: When the original binary variable is missing, we assign a value on the basis of the number of hours usually worked per week.

- ***marital status***: Recoded into a binary variable.

Chapter 3

Centralized Collective Bargaining and Cross-Country Differences in Labor Market Polarization

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3.1 Introduction

Labor market polarization is a twofold concept, potentially characterizing the evolution of both employment and wages during the last thirty or forty years. Job polarization[1] can be defined as a phenomenon implying "relative employment declines in the middle of the distribution [of skills] and relative gains at the tails" (Autor and Dorn, 2013). A now common explanation of this phenomenon is the "routinization hypothesis" introduced by Autor, Levy and Murnane (2003). It roughly states that skill-biased technical change leads to a computerization of routine tasks which implies the substitution of middle-skill workers with machines, more precisely computers, to which high-skill workers are complement. Part of the middle-skill workers are consequently redirected towards some non-routine manual tasks previously performed by low-skill workers, and for which the demand increases. When it concerns wages, polarization refers to a simultaneous growth of earnings at both ends of the wage distribution relative to the middle. Both low- and high-wage (corresponding to low and high-skill) workers see their earnings increasing relatively to middle-wage (corresponding to middle-skill) workers.

Employment and wage polarization having been observed concomitantly in the US, a link between the two has naturally been established. Acemoglu and Autor

[1]Note that while this term has been consecrated by Autor, Katz and Kearney (2006), they attribute it to Goos and Manning (2003), later published as Goos and Manning (2007). It however appears that this phenomenon has been concomitantly highlighted by Wright and Dwyer (2003), who labeled it in the same way.

(2011) explain both with skill-biased technical change (SBTC hereafter), making use of the routinization hypothesis. Their Ricardian model of the labor market, in which the two polarization phenomena are interdependent, adequately fits US stylized facts in terms of labor market polarization. Unfortunately, and for several reasons, applying their approach to European data is not straightforward. First, both the role and the importance of labor market institutions differ between the US and Europe, but also between European countries. There is an extensive literature on the impact of these institutions, and an important part of this literature argue that they actually have an impact on labor market outcomes. Second, there is no clear consensus on the pervasiveness of job polarization in Europe. Moreover, when job polarization has been attested for an European country, part of the literature linked it with episodes of deregulation and de-standardization of the labor market (Dwyer and Wright, 2012). Finally, there are only limited signs of wage polarization in Europe, compared to the US.

This paper extents the Acemoglu and Autor (2011) (AA2011 hereafter) model — which, as already mentioned, is able to capture polarization — to institutional contexts in which unions can impose wage premiums for all workers, including non-union members. The way we model unions and the bargaining process, that we assume centralized and in which unions' role can be guaranteed by the law, allows us to capture cross-country differences in terms of wage polarization. The model predicts that unions' action on wages is accompanied by a mitigation of employment polarization. The presence of highly coordinated unions operating in a highly centralized wage-setting regime limits the substitution of middle-skill workers with high-skill workers. By extension, less middle-skill workers are redirected towards "low-skill" tasks.

While there is a relative consensus that the US have faced job polarization, the European case is more controversial. Some authors claim that job polarization has been pervasive in Europe (see e.g. Goos, Manning and Salomons, 2009, 2014), but others argue that only a few European countries have been subject to polarization of employment (see e.g. Oesch and Rodriguez Menes, 2011; Fernández-Macías, 2012; Fernández-Macías and Hurley, 2017; Oesch and Piccitto, 2019). However, it appears that clear signs of wage polarization have only been observed in the US and in some other Anglo-Saxon countries. We can notably mention Antonczyk, DeLeire and Fitzenberger (2018) who, comparing Germany and the US, find no evidence of wage polarization in the former after 1985. Focusing on the period 1995-2007 and examining several European countries, Naticchioni and Ragusa (2014) conclude that their wage structure shows only scant signs of polarization. In continental European and Nordic countries, it seems that if there was job polarization, it has been accompanied by at most weak wage polarization.[2] The question of how to reconcile these European stylized facts and the SBTC/routinization approach thus naturally arises.

A substantial body of literature justifies the use of institutions — especially unions[3] — to explain the differentiated impact of SBTC on the wage distribution.

[2] Which does not mean that they do not exhibit increases in other inequality measures, such as the Gini coefficient.

[3] As pointed out by Calmfors et al. (2001), "evidence that unions compress pay is common."

Focusing on US male workers, DiNardo, Fortin and Lemieux (1996) develop a semi-parametric procedure to evaluate the contribution of deunionization to the change of the wage distribution between 1979 and 1988. They argue that the decline in unionization rate has substantially contributed to the "collapse" of the middle of the wage distribution during that period. Firpo, Fortin and Lemieux (2018) combine the reweighting method of DiNardo, Fortin and Lemieux (1996) with the unconditional quantile regression of Firpo, Fortin and Lemieux (2009) in order to decompose the contribution of deunionization into a price and a composition effect. Examining the period between 1988 and 2016, they conclude that unions — more precisely, the change in unionization rate — explain an important part of the changes in the US males' wage distribution, including wage polarization.

While the previous papers examine the impact of unions on the entire distribution of wages, other studies confirm the impact of wage-setting institutions on wages by focusing on measures of position and/or dispersion. Some of these studies insist on the specific role of the unionization rate, also called union density. Focusing on the US, the UK and Canada, Card, Lemieux and Riddell (2004) show that union membership "systematically reduce(s) the variance of wages for men."[4] Koeniger, Leonardi and Nunziata (2007) show that the impact of union density on male wage inequality remains negative and significant when using data from eleven countries, including some Western European countries. Other studies highlight the importance of the wage-setting regime to explain the ability of unions to limit wage dispersion. Freeman (1988) already points out that wage dispersion is lower in Scandinavian countries, where pay is centrally determined, than in countries where wage setting is way more decentralized, such as Japan and the US. Rowthorn (1992) insists on this apparent relationship between wage dispersion and the bargaining structure, precising that the "overall dispersion is normally higher where bargaining is decentralized." Similarly, Freeman and Katz (1995) emphasize the fact that the greater importance of institutions in the wage-setting process in Europe is accompanied by a lower dispersion of wages than in the US.[5] Using international data, Blau and Kahn (1996) reach similar conclusions, confirmed by Blau and Kahn (2005) who use an alternative dataset. Wallerstein (1999) goes further: according to him, "in comparing wage inequality across countries, the share of the work force covered by collective bargaining is less important than cross-national differences in bargaining institutions, in particular, cross-national differences in the centralization of wage-setting and the concentration of unions." Moreover, he claims that "the more the wage schedule is determined collectively, whether the coordination is achieved by the explicit centralization of wage-setting or through the implicit cooperation of a small number of actors, the more egalitarian the distribution of pay." In other words, the more centralized the wage-setting process and the more coordinated the unions, the more important is the institutionally-induced compression of the wage distribution. In this paper we extend the previously described "'wage-compression paradigm" (Brugiavini et al., 2001) to wage polarization, a phenomenon that is linked to, but nonetheless different from wage

[4]Card (2001) insists on the fact that in the US, shifts in unionization explain part of the change in wage inequality for men, but not for women

[5]Katz, Loveman and Blanchflower (1995) notably mention the case of French unions, which have been able "to extend contracts even in the face of declining membership."

inequality.

Acemoglu, Aghion and Violante (2001) propose a model in which deunionization is the consequence of SBTC rather than the direct cause of the increase in wage inequality. While their conclusion may be particularly relevant for the US where unions' influence heavily depends on union membership, European trade unions "do not rely so heavily on membership as the basis for their financial survival and political influence"(Bryson, Ebbinghaus and Visser, 2011). According to the same authors, European trade unions are "strongly embedded in social, political and economic structures which help sustain them and provide a strong foundation for their influence in society." In other words, the wage-setting regime in which unions operate can dissociate unions' influence from the unionization rate.[6] This is why the unions we model operate in a specific wage-setting context, impeding SBTC from removing their bargaining power.

Before describing the model, let us insist on the fact that while there is a rather large body of empirical evidence that institutions — especially unions — have a significant impact on the evolution of wage inequality, one should stay cautious concerning the nature and the magnitude of this effect. As notably highlighted by Bryson (2007), it is particularly difficult to identify what wages would have been in absence of unions, and thus the causal impact of the latter: their presence can actually impact the overall distribution of wages through general equilibrium effects. However, this word of caution does not annihilate the whole body of evidence that wage-setting institutions are a key explanatory factor of international differences in wage inequality.

3.2 The model

To capture stylized cross-country differences in terms of wage polarization, we introduce unions in a Ricardian model of the labor market *à la* Acemoglu and Autor (2011). While our model is static, we solve it and characterize the equilibrium in two steps, which roughly mimic what happens in the real world.

The first step follows the AA2011 baseline framework, where firms operate in a free-market context, i.e. without being constrained by centralized institutions. Firms can employ three skill-types of workers whose wages are competitively set. This notably implies that a worker's wage is equal to his marginal productivity. In the second step, unions observe the outcome of the first step. They aim at maximizing the wage bill, and thus bargain with firms in order to make wages deviate from the workers' marginal productivity. The ability of unions to impose a markup over marginal productivity — that we also call wage premium — depends on their bargaining power. In the case they have no bargaining power, the model boils down to AA2011. If unions actually have the power to impose wage premiums, they then negotiate wages with the firms for each possible allocation of workers. We consider more specifically the case where unions have full bargaining power and decide of the markups. In all cases, firms choose the optimal allocation of workers given the wage setting that has been implemented.

[6]Unions' power is thus better proxied by union coverage than by union membership.

3.2.1 First step: competitive wages and allocation of skills to tasks

This first step is entirely described by the baseline model of AA2011. We quickly present this model and characterize its outcome.

3.2.1.1 Final good

The final good is produced by combining tasks coming from a continuum located on the unit interval. These tasks are combined according to a Cobb-Douglas technology of the form

$$Y = \exp\left[\int_0^1 \ln y(i)\,\mathrm{d}i\right],$$

where $y(i)$ is the amount of task i, with $i \in [0,1]$. From the first order condition of the final good producer's profit-maximization problem and denoting the price of task i as $p(i)$,

$$p(i)y(i) = p(i')y(i') \quad \forall i, i' \in [0,1], \tag{3.1}$$

which implies that expenditure are the same across all tasks.

3.2.1.2 Intermediate tasks

Tasks are performed by three types of workers, namely *low-*, *medium-* and *high-*skill workers. The exogenous supplies of skill-specific labor are respectively denoted by H, M and L. Tasks are produced by combining these workers, and this process is characterized by a linear production function of the parametric form

$$y(i) = A_L\alpha_L(i)l(i) + A_M\alpha_M(i)m(i) + A_H\alpha_L(i)h(i),$$

where A_L, A_M and A_H are factor-augmenting technologies respectively biased toward low-, medium- and high-skill workers, while $\alpha_L(i)$, $\alpha_M(i)$ and $\alpha_H(i)$ are task-specific productivities of respectively low, medium and high skills in producing task i. The numbers of low-, medium- and high-skill workers performing task i are respectively denoted by $l(i)$, $m(i)$ and $h(i)$ and must be such that

$$\int_0^1 l(i)\,\mathrm{d}i \le L, \quad \int_0^1 m(i)\,\mathrm{d}i \le M \quad \textit{and} \quad \int_0^1 h(i)\,\mathrm{d}i \le H.$$

The linear specification of the production function implies that each task i is produced using one type of skills. Since tasks are competitively produced, workers are paid at their marginal productivity and we can thus write that

$$w_s(i) = p(i)A_s\alpha_s(i) \quad ; \quad s \in \{L, M, H\},$$

where w_s is the wage that a type s worker obtains by performing task i.

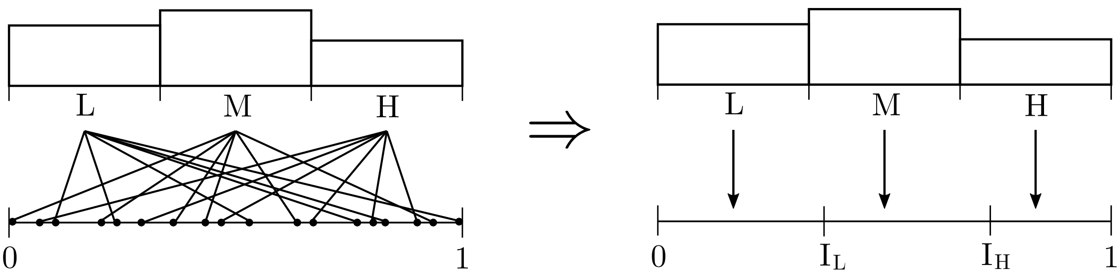

Figure 3.1: Impact of the task-specific relative productivity assumption on the allocation of skills to tasks

3.2.1.3 Law of one price for skills

The law of one price applies for skills, in the sense that workers of the same skill group must receive the same wage whatever the task they perform. Intuitively, the reason is simple: if one task is less rewarding than the others, workers stop performing this task. However, the functional form of the final good production does not allow for such a situation: each task must be produced.

This implies that wages do not *directly* depend on tasks anymore. Formally,

$$w_s = p(i)A_s\alpha_s(i) \quad \forall i \in [0,1] \quad ; \quad s \in \{L, M, H\}.$$

3.2.1.4 Allocation of skills to tasks

Recall that due to the linear production function of tasks, each task is performed by one type of worker. Now, following AA2011, we further assume that $\alpha_L(i)/\alpha_M(i)$ *and* $\alpha_M(i)/\alpha_H(i)$ *are continuously differentiable and strictly decreasing.* This assumption is central since it characterizes the structure of comparative advantage in the model. Basically, it says that the higher the task index, the more high-skill workers outperform middle-skill workers and the more middle-skill workers outperform low-skill workers. This assumption thus ranks tasks according to their complexity in terms of skills.

The allocation of skills to task derives from this assumption. It is such that each skill-group of workers performs tasks from one and only one convex subset of the continuum of tasks. These subsets are delimited by two *endogenous* thresholds, I_L and I_H. At the equilibrium, low-skill workers only perform tasks $i < I_L$, middle-skill workers only produce tasks $I_L < i < I_H$ and high-skill workers only perform tasks $i > I_H$. This is illustrated in Figure 3.1.

3.2.1.5 Impact of the structure of comparative advantage

Because of (3.1) and the allocation of skills to tasks, we can write that

$$\begin{aligned}
p(i)\alpha_L(i)l(i) = &\quad p(i')\alpha_L(i')l(i') \quad \forall\, i, i' < I_L \\
p(i)\alpha_M(i)m(i) = &\quad p(i')\alpha_M(i')m(i') \quad \forall\, I_L < i, i' < I_H \\
p(i)\alpha_H(i)h(i) = &\quad p(i')\alpha_H(i')h(i') \quad \forall\, i, i' > I_H.
\end{aligned}$$

Now, by the *law of one price for skills*, we have that

$$\begin{aligned} l(i) &= l(i') \quad \forall\, i, i' < I_L \\ m(i) &= m(i') \quad \forall\, I_L < i, i' < I_H \\ h(i) &= h(i') \quad \forall\, i, i' > I_H, \end{aligned}$$

which basically means that for each subset of tasks and thus each skill group, each task is produced using the same quantity of workers. Using the market clearing conditions, we finally have that

$$\begin{aligned} l(i) &= \frac{L}{I_L} \quad \forall\, i < I_L \\ m(i) &= \frac{M}{I_H - I_L} \quad \forall\, I_L < i < I_H \\ h(i) &= \frac{H}{1 - I_H} \quad \forall\, i > I_H, \end{aligned}$$

which implies that the quantity of labor used to produce a task is simply the supply of this type of labor divided by the "amount" (more precisely, the range) of tasks to which it is assigned.

3.2.2 Second step: unions and wage premiums

Unions observe the market wages set during the first step and start bargaining with firms. As previously explained, they can impact wages by negotiating a markup over the marginal productivity of each type of worker. Each markup, or wage premium, is a share of this marginal productivity and the wages resulting from the bargain can thus be expressed as

$$w_s^u = (1 + c_s)p(i)A_s\alpha_s(i) \quad ; \quad s \in \{L, M, H\}, \tag{3.2}$$

where c_s — that we call the *premium factor* for the type s — determines the share of the marginal productivity of the type $s \in \{L, M, H\}$ that constitutes the wage premium for this type. These premium factors are choice variables and thus endogenously determined. For tractability, we assume that the premium factor is the same for both low- and middle-skill workers. Equation (3.2) can thus be rewritten as

$$\begin{aligned} w_L^u &= (1 + c_{LM})p(i)A_L\alpha_L(i) \\ w_M^u &= (1 + c_{LM})p(i)A_M\alpha_M(i) \\ w_H^u &= (1 + c_H)p(i)A_H\alpha_H(i). \end{aligned} \tag{3.3}$$

where $c_{LM} \equiv c_L = c_M$. While this assumption is somehow strong, it is appealing for several reasons. First, it makes the model tractable. Second, since middle-skill workers are typically more productive than low-skill workers, it implies that unions are positively biased towards the former in absolute terms. This is in line with the idea that middle-skill workers, including production and clerical workers, constitute the historical "core business" of unions. Finally, this assumption is conservative. One could claim that low-skill individuals nowadays mainly work in service jobs for which the unionization rate is typically low, that unions do not pursue egalitarian goals and by extension that they do not care — or at least do not care anymore — about low-skill wages. If it was true, the union-induced mitigation of wage polarization would be even more important than what our model predicts. In other words, this assumption is more likely to lead to an underestimation of the impact of unions on polarization rather than to an overestimation of this impact.

3.2.2.1 Unions' preferences and utility function

Following Moene and Wallerstein (1997), we assume that unions maximize the wage bill while preserving full employment.[7] We moreover assume that they are positively and originally biased towards low- and middle-skill workers: as long as unions perceive these workers as more 'important' than high-skill workers, they prefer to increase the wages of the former rather than the latter.

Unions exhibit a quasilinear utility function of the following form:

$$U'(c_{LM}, c_H) \quad = \alpha_{LM} \ln(c_{LM}) + \alpha_H c_H$$

where $\alpha_{LM} > 0$ and $\alpha_H > 0$ can be thought of as some kind of "political weights" *à la* Wallerstein (1990). Normalizing the weight attached to the high-skill premium factor to one and defining $k \equiv \alpha_{LM}/\alpha_H$, we can represent the preferences of the unions by the utility function

$$U(c_{LM}, c_H) \quad = k \ln(c_{LM}) + c_H,$$

where, by definition, $k > 0$. The parameter k can be thought of as the relative bias of unions towards the group of low- and middle-skill workers.

Apart from the full-employment consideration, that we introduce later as a constraint, this utility function features the previously requested characteristics. First, it is increasing in both c_{LM} and c_H, which implies that unions aim at maximizing wages. Second, unions are at first positively biased towards c_{LM}, i.e. towards low- and middle-skill workers. This can be seen by comparing the marginal utility of c_{LM} and c_H, which is decreasing in the first and constant in the second. We actually have that

$$MU_{c_{LM}} \equiv \frac{\partial U(c_{LM}, c_H)}{\partial c_{LM}} = k \frac{1}{c_{LM}}$$

$$MU_{c_H} \equiv \frac{\partial U(c_{LM}, c_H)}{\partial c_H} = 1,$$

which implies that when c_{LM} is close to zero, increasing it yields more additional utility than increasing c_H. Moreover, unions have some kind of permanent bias towards low- and middle- workers: while it is possible for them to set $c_H < 0$, the unions we examine here always set $c_{LM} > 0$.[8]

[7] The literature on unions (cf. infra) has emphasized the ability of highly coordinated unions to adjust their wage demands to employment considerations. We consider an extreme version of these unions.

[8] We insist on the fact that middle-skill workers are historically the core business of unions.

In a previous section, we assumed that unions were biased towards low- and middle-skill workers *at least up to a certain point*, corresponding to a situation where unions consider high-skill workers as equally "important" as the other workers. Let us now first identify this point in order to interpret it later. Using the marginal utilities of c_{LM} and c_H, we can see that unions are indifferent between increasing c_{LM} and increasing c_H when

$$MU_{c_{LM}} = MU_{c_H} \Leftrightarrow k\frac{1}{c_{LM}} = 1 \Leftrightarrow c_{LM} = k. \tag{3.4}$$

We can thus conclude that unions remain positively biased towards low- and middle-skill workers as long as $c_{LM} < k \Leftrightarrow MU_{c_{LM}} > MU_{c_H}$. There is nonetheless a reversal of this bias when $c_{LM} > k \Leftrightarrow MU_{c_{LM}} < MU_{c_H}$. The question is how to interpret this reversal of unions' bias at $c_{LM} = k$.

When characterizing the equilibrium in the case where unions have full bargaining power, we will see that for all $k > 0$, it intuitively makes sense that unions start to perceive high-skill workers as more "important" than low- and middle-skill workers when $c_{LM} = k$.

3.2.2.2 Embedding employment consideration

We embed the assumption that unions preserve full-employment in the following constraint:

$$\begin{aligned} \mathbb{W} \equiv \quad & c_{LM}\int_0^1 p(i)A_L\alpha_L(i)l(i)\,\mathrm{d}i + c_{LM}\int_0^1 p(i)A_M\alpha_M(i)m(i)\,\mathrm{d}i \\ & \qquad\qquad\qquad\qquad + c_H\int_0^1 p(i)A_H\alpha_H(i)h(i)\,\mathrm{d}i \\ = 0, \end{aligned} \tag{3.5}$$

where $\mathbb{W}$ is the (total, or net) rent extracted by unions when they impose markups over workers' marginal productivity. In other words, it is the cost surplus faced by firms when wage premiums are set. This cost surplus is the sum of the aggregated wage premium for all tasks performed by low- and middle-skill workers and the aggregated wage premium for all tasks performed by high-skill workers. For any given allocation of skills to tasks, the constraint (3.5) becomes

$$c_{LM}\int_0^{I_L} p(i)y(i)\,\mathrm{d}i + c_{LM}\int_{I_L}^{I_H} p(i)y(i)\,\mathrm{d}i + c_H\int_{I_H}^1 p(i)y(i)\,\mathrm{d}i = 0$$

and, by (3.1), can be simplified as

$$I_Hc_{LM} + (1-I_H)c_H = 0 \quad \Leftrightarrow \quad c_H = -\frac{I_H}{1-I_H}c_{LM}. \tag{3.6}$$

The constraint (3.5) can be interpreted as the standard trade-off between wage and employment faced by the unions, as presented in the literature. By increasing wages relative to a no-unions/free-market framework, unions increase the costs faced by firms. However, they do not want firms to leave the market: this would lead to unemployment. Unions thus have to compensate firms by redistributing the extracted rent: higher wages for a group of workers have to be compensated with lower wages for the other. While the constraint faced by unions of imposing no cost surplus on firms is rather strong, it is however in line with the general idea that strongly coordinated unions take the potential adverse effect of their action on employment into account and moderate accordingly the cost surplus they impose (see notably Koeniger, Leonardi and Nunziata, 2007). In our model, if unions set $c_{LM} > 0$, by (3.5) they have to set $c_H < 0$. In that case setting $\mathbb{W} = 0$ implies compressing the distribution of wages. This is in line with the conclusion of Vandekerckove, Van Gyes and Goos (2018), who study the employment and distributional effects of minimum wages in Belgium. They argue that employment effects of minimum wages are negligible, due to Belgian unions operating in a highly institutionalized labor market in which they are able to compress the upper tail of the wage distribution. They thus compensate firms for the additional costs they impose on them when they increase the wages of the less-skilled workers (the low- and middle-skill workers in our case).

It is also particularly interesting to see that we can actually interpret (3.6),

$$I_H c_{LM} + (1 - I_H) c_H = 0,$$

as the unions' equivalent of a consumer's budget constraint. $\mathbb{W}$ (that we assume here equal to zero) would be the budget endowment of unions, i.e. what they can afford in terms of cost surplus to be imposed on firms. The premium factors c_{LM} and c_H are the "goods" unions derive utility from, and I_H and $1 - I_H$ can be thought as their respective prices: the higher I_H, the larger the amount of tasks performed by low- and medium-skill workers, and thus the higher the additional cost imposed on firms implied by an increase in c_{LM}. The same reasoning holds for $1 - I_H$ and c_H.

3.2.3 The bargaining game between unions and firms

Unions' ability to set wages according to (3.3) depends on their bargaining power, denoted by $\lambda \in \{0, 1\}$.[9] The Nash bargaining solution of the unions-firms bargaining problem solves the following optimization problem:

$$\max_{c_{LM}, c_H} \left[U(c_{LM}, c_H) - U_T \right]^{\lambda} \left[V(c_{LM}, c_H) - V_T \right]^{1-\lambda} \quad \text{s.t.} \quad \mathbb{W} = 0 \tag{3.7}$$

where $V(c_{LM}, c_H)$ is the objective function of firms in the bargaining process. U_T and V_T are the utilities derived from the threat points, respectively by unions and firms. These are the utilities unions and firms get if they refuse to bargain or fail to reach an agreement. They are assumed to be such that $U(c_{LM}, c_H) \geq U_T$ and $V(c_{LM}, c_H) \geq V_T$. As previously mentioned, the constraint $\mathbb{W} = 0$ states that

[9] In this paper we consider only two extreme cases: unions with full bargaining power, for which $\lambda = 1$, and unions with no bargaining power at all, for which $\lambda = 0$. Future work might investigate what happens in intermediary cases, i.e. when λ belongs to $]0, 1[$.

in order for firms not to leave the market, they have to be compensated for the additional costs they face if c_{LM} or c_H is strictly greater than zero.

Note that we assume that the firms — the tasks producers — are represented in the bargaining process by some kind of employers' organization, a confederation of firms which aggregates their interests. It makes plausible the idea that unions and firms bargain over both c_{LM} and c_H, even if each task is produced using one type of labor and firms are not explicitly modeled as multitasking.

3.2.3.1 Back to AA2011: the second step when unions have no bargaining power

In the case where unions have no bargaining power at all ($\lambda = 0$), only firms set the wages and the problem (3.7) reduces to

$$\max_{c_{LM},c_H} V(c_{LM}, c_H) - V_T \quad \text{s.t.} \quad \mathbb{W} = 0. \tag{3.8}$$

In the bargaining game, firms want to set c_{LM} and c_H such as to maximize their profits. They could try to extract a rent by setting c_{LM} and/or c_H less than zero. However, because of the free-entry condition of the perfectly competitive framework, outsiders would enter the market and offer workers a wage closer to their marginal productivity. This would drive insider firms out of the market: knowing that, these firms dislike any departure from the competitive equilibrium. An objective function that captures this feature is

$$V(c_{LM}, c_H) = -(0 - c_{LM})^2(0 - c_H)^2.$$

This function is such that when firms can decide alone (i.e. when $\lambda = 0$), they choose not to depart from the competitive-equilibrium outcome of the first step.[10] The first order condition of (3.8) indeed yields

$$-4\Big(\frac{I_H}{1-I_H}\Big)^2 c_{LM}^3 = 0 \qquad \Leftrightarrow \qquad c_{LM} = c_H = 0,$$

and our model boils down to AA2011.

3.2.3.2 Maximizing the wage bill: the second step when unions have "full" bargaining power

Unions we consider operate in a specific institutional framework, in the sense that their characteristics and their environment give them a full bargaining power (corresponding to $\lambda = 1$). More particularly, we assume an economy in which unions are highly coordinated and centralized and in which the law is such that their role in the wage setting process is guaranteed. In this kind of economy, unions have an important impact on the wage setting process and union coverage is typically high.[11] They have the power of making wages differ from the workers' marginal

[10] The "departure terms" are squared since firms dislike any departure — negative or positive — from the free-market outcome of the first step.

[11] Even if the union membership rate is relatively low. An extreme example is France, where unionization rate is low while union coverage rate is particularly high. This limited relationship between unionization and unions' power is due to the specific institutional context previously described. This context allows us to ignore the potential impact of SBTC on unionization rate and thus unions' power, as highlighted by Acemoglu, Aghion and Violante (2001).

productivity and, additionally, their impact on wages generalizes to the whole economy, independently of the union membership status of the workers. This type of unions and wage setting process roughly correspond to some continental European and Nordic economies.

When $\lambda = 1$, the bargaining problem reduces to the unions' optimization problem which takes the form

$$\max_{c_{LM}, c_H} k \ln(c_{LM}) + c_H - U_T \quad \text{s.t.} \quad c_H = -\frac{I_H}{1 - I_H} c_{LM}.$$

The first order condition is

$$c_{LM} = k \frac{1 - I_H}{I_H}. \tag{3.9}$$

Substituting (3.9) into (3.6), we get $c_H = -k$. The unions we consider thus compensate[12] the positive wage premium granted to low- and middle-skill workers by setting high-skill workers' wages lower than their marginal productivity. This implies that they actually compress the wage distribution, reducing wage inequality.

Since k can be thought of as the relative bias of unions towards low- and middle-skill workers, $c_H = -k$ implies that the penalty imposed to high-skill workers[13] in the wage-compression process is directly and exactly proportional to this (relative) bias.

Back to unions' bias Substituting (3.4) into (3.9), we can now see that unions are indifferent between increasing c_{LM} and c_H when

$$I_H = 1 - I_H \Leftrightarrow I_H = \frac{1}{2}. \tag{3.10}$$

In other words, they are indifferent between increasing c_{LM} and c_H when their "prices" are equal. Since each of these prices is actually the size of the set of tasks performed by each group[14], (3.10) implies that unions equally value c_{LM} and c_H when the set of task performed by high-skill workers is as large as the one performed by low- and middle-skill workers.

How to intuitively interpret this kind of preferences-reversal threshold? While I_H, the proportion of tasks performed by low- and middle-skill workers, can be thought as the price (i.e. the cost) of c_{LM}, it can also be interpreted as the relative[15] importance of low- and middle-skill workers in the labor market and hence their influence. Since the same reasoning holds for $1 - I_H$ and high-skill workers, the latter are perceived by unions as more important than their low- and middle-skill

[12]Which is in line with the argument of Vandekerckove, Van Gyes and Goos (2018) mentioned earlier.

[13]This penalty is expressed here in terms of the premium factor, i.e. as a share of the high-skill workers productivity.

[14]The groups we consider here are the two groups linked to c_{LM} and c_H, i.e. the group composed of low- and middle-skill workers and the group composed of high-skill workers.

[15]Since the continuum of tasks is located on the unit interval, $I_H/1$ is also the *proportion* of tasks performed by low- and high-skill workers.

counterparts when $1 - I_H > I_H$. When this is the case[16], unions *aim*[17] at relieving pressure from the group of high-skill workers.

While this holds for every $k > 0$, the existence and the uniqueness of the equilibrium is guaranteed only for $k = 1/2$. We thus assume that $k = 1/2$, acknowledging that the price to pay to guarantee the existence and uniqueness of the equilibrium is a loss of generality. In the following paragraphs, we nonetheless provide some justification for assuming such a value for k.

The unions' utility function: last remarks As previously mentioned, our specification of the unions' utility function features some desirable characteristics. First, the natural logarithm embeds some kind of permanent positive bias towards low- and middle-skill workers. If unions have to set a negative premium for one group to compensate the positive premium for the other[18], they always impose the negative premium on high-skill workers. Since unionized workers are typically from the middle of the skill distribution, we consider this as a desirable property.

Second, the quasilinearity of their utility function originally makes these unions extremely biased towards low- and middle-skill workers, which is in line with the industrial history of these institutions. This specification nonetheless allows for a reversal of preferences (in marginal terms) when high-skill workers perform more[19] tasks than low- and middle-skill workers. When unions perceive high-skill workers as more important — for the labor market and the economy in general — than the group composed of low- and middle-skill workers, they prefer to increase c_H rather than further increasing c_{LM}.[20]

Finally, this specification — in combination with Assumption 1 — conveniently guarantees the existence and the uniqueness of the equilibrium. It thus makes the model tractable and allows us to derive interesting analytical results.

However, assuming a specification which has the previous desirable property comes at a cost, which consists in having an *a priori* counterintuitive term $1/2$ weighting the c_{LM} contribution to unions' utility. We however claim that it can be justified by somehow thinking backward: since the existence of unions only makes sense because workers actually work, their utility function must have been tailored and adjusted such that relatively stable matching between workers and jobs are actually realized. In other words, we assume that unions' founders and managers adjusted the rule underlying unions' behavior such that workers find at least minimally stable jobs.

3.2.4 Final adjustment of the allocation of skills to tasks

We now close the model by imposing no-arbitrage conditions, according to which marginal task I_L is equally profitably produced using either low- or middle-skill

[16]This notably happens for relatively high values of A_H/A_M and/or H/M.

[17]We insist on "aim" since this is not what they actually do. Unions' problem specification in our model is such that *in fine* they set $c_H = -k$, independently of the value taken by I_H.

[18]As previously highlighted, they are actually constrained to do so.

[19]Formally, when $1 - I_H > I_H$.

[20]This does not mean that they necessarily do so, since an increase in $1 - I_H$ makes more costly an increase in c_H.

workers, and marginal task I_H is produced equally profitably using either middle- or high-skill workers. In other words, these no-arbitrage conditions state that the cost of producing I_L (I_H) with low- or middle- (middle- or high-) skill workers must be the same:

$$w_M^u m(I_H) = w_H^u h(I_H)$$
$$\Leftrightarrow \quad (1 + c_{LM})^{-1} (1 + c_H) \frac{A_H \alpha_H(I_H)}{A_M \alpha_M(I_H)} = \frac{1 - I_H}{I_H - I_L} \frac{M}{H} \tag{3.11}$$

$$w_L^u l(I_L) = w_M^u m(I_L)$$
$$\Leftrightarrow \quad \frac{A_M \alpha_M(I_L)}{A_L \alpha_L(I_L)} = \frac{I_H - I_L}{I_L} \frac{L}{M} \tag{3.12}$$

For the sake of tractability, we assume from now on a specific functional form for the relative task-specific productivities. Note that we also impose this assumption on the AA2011 baseline model when we compare our model's results with theirs.

Assumption 1. *The relative task-specific productivities are linear in the task index and take the following form:*

$$\frac{\alpha_H(i)}{\alpha_M(i)} = \frac{\alpha_M(i)}{\alpha_L(i)} = i. \tag{3.13}$$

The no-arbitrage conditions (3.11) and (3.12) determine the values finally taken by the task-allocation thresholds — i.e. the adjustment variables for firms in this second step — in response to the adjustment of wages operated by unions. The equilibrium is now completely characterized.

Case where unions have no bargaining power In that case $c_{LM} = c_H = 0$, and (3.11) boils down to the relevant no-arbitrage condition of the AA2011 baseline model.

3.3 Results: comparative statics and numerical simulations

We can now characterize the impact of SBTC on the task allocation thresholds I_L and I_H and, by extension, on the relative wages.

We first define the core concepts studied in this paper, in the specific terms of the task-based framework. We then provide the intuition underlying the mechanics of polarization in the context of this framework. Next, we use the model developed in this paper to analytically assess the impact of SBTC on job and wage polarization. Finally, we numerically compare the predictions of our model — which includes the impact of unions operating in a centralized bargaining process — with the predictions of the AA2011 baseline model (to which our model's first step corresponds) considered under Assumption 1.

3.3.1 Polarization in the task-based framework: definitions and underlying mechanics

3.3.1.1 Definitions

SBTC is defined as an increase in A_H, which is the factor-augmenting technology biased towards high-skill workers:

Definition 1. *Skill-Biased Technical Change (SBTC) is an increase in the skill-specific (as opposed to task-specific) average productivity of high-skill workers, A_H. It can be expressed as a positive infinitesimal change in A_H ($\ln A_H$), respectively denoted by $\mathrm{d}A_H > 0$ ($\mathrm{d}\ln(A_H) > 0$).*

In the AA2011 framework with three categories of skills, wage polarization has two components: an increase in the wage of high-skill workers relative to the wage of middle-skill workers and a decrease in the wage of middle-skill workers relative to the wage of low-skill workers.

Definition 2. *Wage polarization is the combination of an increase in w_H/w_M and a decrease in w_M/w_L following the occurrence of SBTC. It can thus be expressed as the combination of the two following inequalities:*

$$\frac{\mathrm{d}(w_H/w_M)}{\mathrm{d}A_H} > 0 \ \textit{and thus} \ \frac{\mathrm{d}\ln(w_H/w_M)}{\mathrm{d}\ln(A_H)} > 0,$$

and

$$\frac{\mathrm{d}(w_M/w_L)}{\mathrm{d}A_H} < 0 \ \textit{and thus} \ \frac{\mathrm{d}\ln(w_M/w_L)}{\mathrm{d}\ln(A_H)} < 0.$$

In the AA2011 task-based framework, SBTC-induced job polarization is made of three components. First, it requires a substitution of high-skill workers for middle-skill workers in performing tasks previously executed by the latter. Second, it implies a redirection of these middle-skill workers towards tasks previously performed by low-skill workers. Finally, it implies a reduction in the set of tasks performed by middle-skill workers.

Definition 3. *Job (employment) polarization implies*

$$\frac{\mathrm{d}I_H}{\mathrm{d}A_H} < 0 \ \textit{and thus} \ \frac{\mathrm{d}I_H}{\mathrm{d}\ln(A_H)} < 0,$$

$$\frac{\mathrm{d}I_L}{\mathrm{d}A_H} < 0 \ \textit{and thus} \ \frac{\mathrm{d}I_L}{\mathrm{d}\ln(A_H)} < 0, \ \textit{and finally}$$

$$\frac{\mathrm{d}(I_H - I_L)}{\mathrm{d}A_H} < 0 \ \textit{and thus} \ \frac{\mathrm{d}(I_H - I_L)}{\mathrm{d}\ln(A_H)} < 0.$$

which is equivalent to state that job polarization is defined as the inequality $\frac{\mathrm{d}I_H}{\mathrm{d}\ln(A_H)} < \frac{\mathrm{d}I_L}{\mathrm{d}\ln(A_H)} < 0$.

Before deriving the comparative statics and interpreting the results in terms of job and wage polarization, we first introduce an intuitive explanation of this phenomenon in the AA2011 framework.

3.3.1.2 Intuitive description of the underlying mechanics

The impact of SBTC on task allocation thresholds is illustrated in Figure 3.2.

a) A positive shock in A_H makes high-skill workers more productive than before. It becomes profitable for firms to substitute these workers for middle-skill workers. The I_H threshold decreases: high-skill workers now perform tasks that were previously performed by middle-skill workers. Think about a software developer developing and maintaining algorithms replacing production operators in handling precision machines involved in the production process. In terms of tasks, the tasks previously performed by middle-skill production operators are now performed by programmers. This leads to high-skill jobs creation, while jobs consisting of routine tasks disappear: it is the first component of *job* polarization.

Demand for high-skill workers increases, while demand for middle-skill workers decreases. Note that if their relative supply remains constant (which is the case in our comparative statics perspective), middle-skill wages decrease. The wage of high-skill relative to middle-skill workers increases: it is the first component of *wage* polarization.

b) The decline in middle-skill workers' wages makes them cheap enough to perform some tasks that were previously performed by low-skill workers: the I_L threshold decreases. In our software developers - production operators example, production operators now take low-skill service jobs. Note that there is no unemployment in the model. This implies that technological progress entails the creation of new jobs consisting in low-skill tasks, so that all the low- and middle-skill workers are employed. Combined with the fact that "middle-skill" jobs are destroyed, this leads to the second component of *job* polarization: the employment share of "low-skill" jobs increases in detriment of "middle-skill" jobs.

Finally, note that I_L decreases less than I_H, which means that the set of tasks performed by middle-skill workers contracts due to SBTC. This ensures that SBTC unambiguously decreases w_M/w_L, which is the second component of wage polarization.

3.3.2 Impact of SBTC on relative wages and task allocation thresholds: analytical results

To derive the comparative statics of our model, we first take the logarithm of the system of no-arbitrage conditions (3.11)-(3.12) and then totally differentiate it

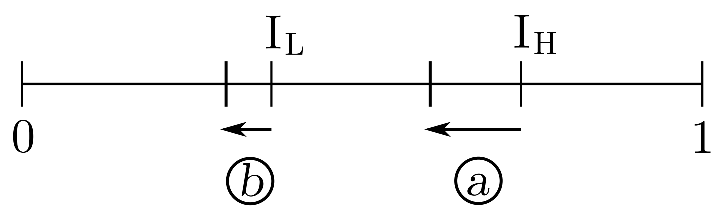

Figure 3.2: SBTC and job polarization, a graphical representation

$$\Delta I_H < \Delta I_L < 0$$

with respect to $\ln A_H$. We rearrange the output so as to get a system of equations from which we derive closed-form solutions for $\mathrm{d}I_H / \mathrm{d}\ln(A_H)$ and $\mathrm{d}I_L / \mathrm{d}\ln(A_H)$, themselves used to derive the results presented in this section. Lemma 1, which constitutes the basis for the proofs of the propositions, is presented in Appendix 3.A.

While we first need to solve for the impact of SBTC on task allocation thresholds before deriving its impact on relative wages, we present the latter first. It is intuitively appealing since it mimics the functioning of our model's unions, which bargain over wages. The impact of these unions on the allocation of skills to tasks is thus indirect.

3.3.2.1 Impact of SBTC on relative wages

From (3.11)-(3.12), relative wages can be expressed as functions of the task-allocation thresholds and the relative supplies of skills:

$$\frac{w_H^u}{w_M^u} = \frac{1 - I_H}{I_H - I_L}\frac{M}{H}, \quad \frac{w_M^u}{w_L^u} = \frac{I_H - I_L}{I_L}\frac{L}{M} \quad \text{and} \quad \frac{w_H^u}{w_L^u} = \frac{1 - I_H}{I_L}\frac{L}{H}. \tag{3.14}$$

Using (3.14) and the impact of SBTC on task allocation thresholds (see Lemma 1, in Appendix 3.A), it is straightforward to see that powerful unions operating in a centralized wage-setting system do not fully abolish the polarizing impact of SBTC on wages.

Proposition 1. *Under Assumption 1, wage polarization takes place in a centralized collective bargaining regime:*

$$\frac{\mathrm{dln}\left(\frac{w_H^u}{w_M^u}\right)}{\mathrm{dln}(A_H)} > 0, \quad \frac{\mathrm{dln}\left(\frac{w_M^u}{w_L^u}\right)}{\mathrm{dln}(A_H)} < 0.$$

Note that Proposition 1 does not provide any information on the difference between our model (with unions) and AA2011 model (without unions) in the magnitude of this effect. Whether or not unions mitigate wage polarization is assessed using numerical simulations.

3.3.2.2 Impact of SBTC on task allocation thresholds

Proposition 2. *Under Assumption 1, job polarization takes place in a centralized collective bargaining regime:*

$$\frac{\mathrm{d}I_H}{\mathrm{dln}(A_H)} < 0, \quad \frac{\mathrm{d}I_L}{\mathrm{dln}(A_H)} < 0 \;\; \textit{and} \;\; \frac{\mathrm{d}(I_H - I_L)}{\mathrm{dln}(A_H)} < 0.$$

Proposition 2 is straightforwardly derived from Lemma 1 (see Appendix 3.A). It remains silent about the difference in the magnitude of the impact between our model and the AA2011 model considered under Assumption 1. Proposition 2 only tells us that the sign of the effect is the same in both models. To assess the difference between the two, we rely on numerical simulations.

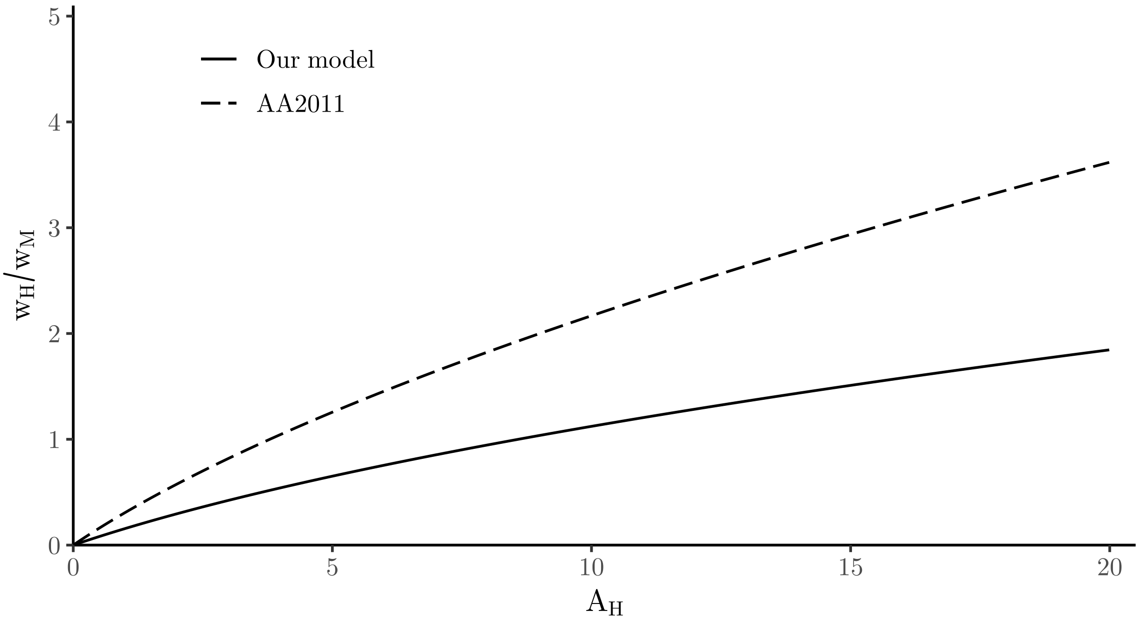

Figure 3.3: The impact of SBTC on w_H/w_M, numerical results

3.3.3 Polarization with and without unions: numerical comparisons

In order to assess the impact on polarization of centralized bargaining with powerful unions, we numerically solve the no-arbitrage conditions for both task-allocation thresholds and compare the results for both models.

For the sake of readability, in this section we only present the results for a given set of values of the parameters. While more results are presented in Appendix 3.B, this presentation cannot be exhaustive. In order for the reader to be able to visually distinguish between the two models, we have to focus on a subset of the numerical results. All results nonetheless point towards the same conclusion: powerful unions participating to a centralized bargaining process mitigate labor market polarization.

3.3.3.1 Impact of SBTC on relative wages

Impact of SBTC on w^u_H/w^u_M: From Proposition 1, SBTC widens the wage differential (more precisely, the relative wage) between high- and middle-skill workers, in both our model and AA2011. Numerical simulations, as illustrated with Figure 3.3, show that the impact of an increase in A_H is smaller in our model than in AA2011. We thus conclude that unions mitigate — we somehow modeled them to do so — this SBTC-induced wage differential: for given values of the model parameters, it is smaller with than without unions.

Impact of SBTC on w^u_M/w^u_L: The second component of wage polarization is a decrease in middle-skill wages relative to low-skill wages. It happens in both models,

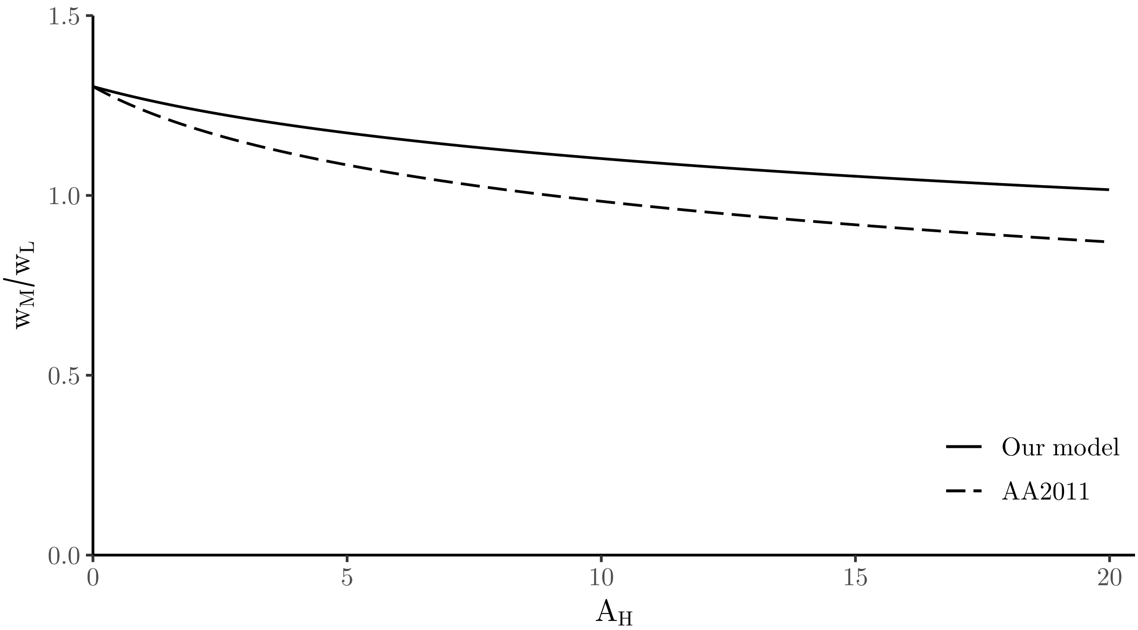

Figure 3.4: The impact of SBTC on w_M/w_L, numerical results

but again numerical simulations show that the second component of wage polarization is mitigated by unions: the decrease in wage differential between low- and middle-skill workers following SBTC is smaller in our model than in AA2011. This is illustrated with some results from these numerical simulations, presented in Figure 3.4.

We can thus conclude that the way we model unions and their action allows us to capture stylized differences in terms of wage polarization between economies with limited unions power and economies in which unions are highly centralized and coordinated.

Impact of SBTC on w_H^u/w_L^u: While wage polarization does not necessarily imply that this impact is positive, it nonetheless contributes to the dispersion of the wage distribution, understood in this case as the difference (more precisely, the ratio) between the wages of high- and low-skill workers. While both our model and AA2011 predict a widening of this wage differential following SBTC, its magnitude is again limited by unions. Results from numerical simulations are presented in Figure 3.5.

3.3.3.2 The impact of SBTC on task allocation thresholds: what is the effect of institutions on job polarization?

Now that we have the confirmation that our model captures stylized differences in terms of wage polarization, we are interested in its comparative prediction concerning job polarization. We algebraically derived the impact of SBTC on the task allocation thresholds (see Proposition 2) and we have seen that job polarization also takes place in a collective bargaining regime with powerful unions. To compare the

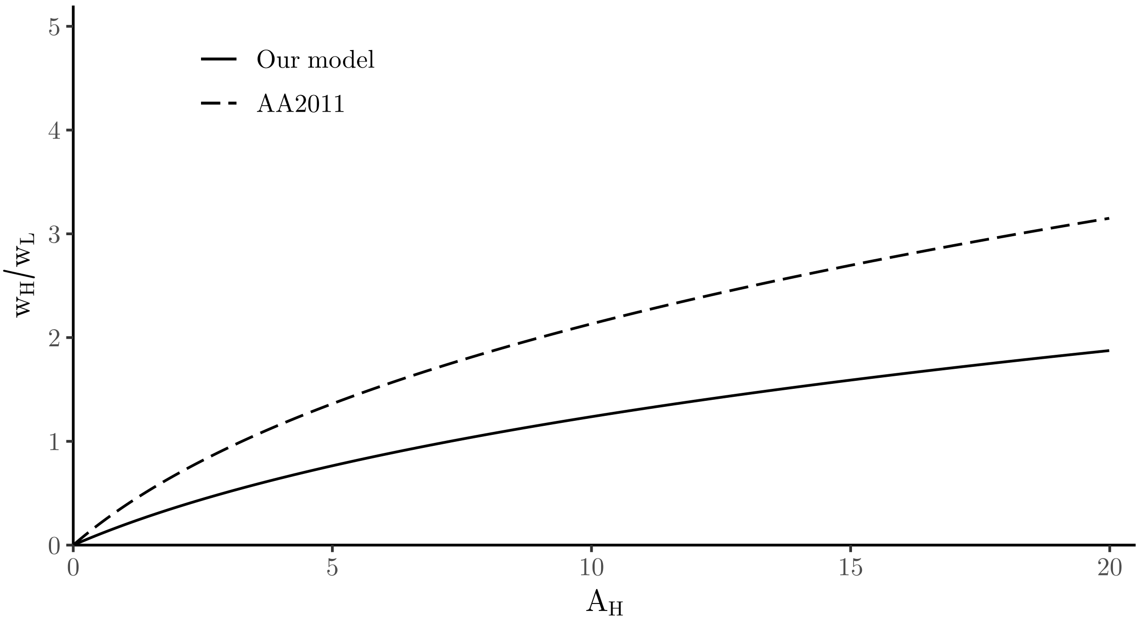

Figure 3.5: The impact of SBTC on w_H/w_L, numerical results

difference in magnitude with and without unions, we again rely on numerical simulations.

Impact of a change in A_H on I_H The two curves at the top of Figure 3.6 tell us that the decrease in I_H following SBTC is less important with than without unions. Unions thus contain the first component of job polarization; their action on wages limits the extent to which high-skill workers are substituted for middle-skill workers.

This prediction is particularly interesting, notably since it is *a priori* counterintuitive. In our setting, unions set wages of middle-skill workers higher than their marginal productivity and compensate firms by setting wages of high-skill workers lower than their marginal productivity. Intuitively, firms should become even more prone to substitute high-skill for middle-skill workers. The explanation of why it is not the case has two forms: one which is linked to the inner mechanics of the model, and another one which is more intuitive.

The mechanical explanation is twofold. First, if firms were substituting high-skill for middle-skill workers in reaction to the union wage premiums, there would be *a posteriori* a downward pressure on middle-skill wages. This would imply a downward adjustment of the wage premium previously set by the unions. However, this cannot happen since this wage premium has already been set by the unions which have, by assumption, the power to impose this deviation.[21] Second and as explained in the next paragraph, the exogenous nature of the skill/labor supply and the behavior of I_L do not allow for such additional substitution.

A more intuitive explanation is that firms adjust their allocation of skills to tasks

[21]One can also think of this premium as the output of collective bargaining, and of which unions have the power to impose the implementation.

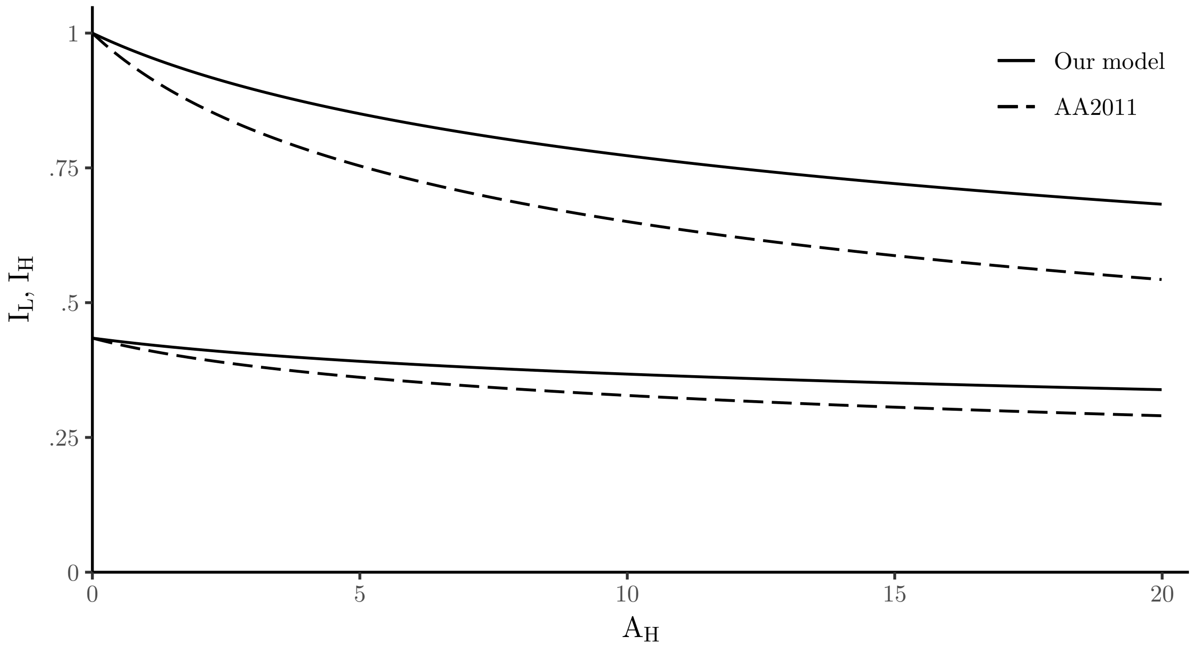

Figure 3.6: The impact of SBTC on I_H and I_L, numerical results

according to how unions make wages deviate from workers' marginal productivity. Firms (re-)allocate skills (workers) to tasks in order to realign the marginal products of the workers with the wages set in the bargaining process.[22] They thus give more "productive" tasks to low- and middle-skill workers with unions than without.

Impact of a change in A_H on I_L The two curves at the bottom of Figure 3.6 shows that unions mitigate the negative impact of A_H on I_L. It comes from the fact that both with and without unions, SBTC leads to downward pressure on middle-skill wage. It thus becomes profitable for firms to make middle-skill workers perform some[23] tasks previously performed by low-skill workers. However, since unions mitigate the impact of SBTC on wages, they also limit the substitution effect of SBTC. This explains why its impact on I_L is less negative with than without unions.

As mentioned in the previous section, this differential contributes to explaining why a lower (relative) decrease in middle-skill wage does not lead to further substitution of middle-skill with high-skill workers. Since 1) less middle-skill workers are reallocated to low-skill tasks with unions than without, 2) the supply of workers is exogenous and thus fixed and 3) all the workers are employed, it must be that middle-skill workers lose less top-tasks in our model than in AA2011.

The impact of a change in A_H on $I_H - I_L$ Following an increase in the high-skill-related factor, I_L decreases less than I_H, both in our model and in AA2011. Middle-skill workers thus lose a wider range of tasks than what they gain (which is

[22]See e.g. Betcherman (2012). A similar reasoning, applied to minimum wage and its spillover effects, can be found in Stewart (2012*a*).

[23]More precisely, the most complex tasks previously performed by low-skill workers.

nothing more than what low-skill workers lose in terms of tasks), but their net loss is mitigated by unions. Intuitively, this is consistent with the decrease in middle-skill relative to low-skill wage being less important with than without unions.

3.4 Conclusion and final remarks

In order to fit stylized differences between Anglo-Saxon and some continental European and Nordic countries in terms of wage polarization, we model the action of unions on wages in a Ricardian model of the labor market *à la* Acemoglu and Autor (2011). A final good is competitively produced using a continuum of intermediate tasks performed by three skill-types of workers. The allocation of skills to tasks is such that the continuum of tasks is divided into tree convex sets, each of these being produced using one type of workers.

We assume highly centralized and coordinated unions, operating in an institutional framework that is such that unions are able to make wages deviate from workers' marginal productivity. These unions end up setting a positive wage premium — a markup over marginal productivity — for both low- and middle-skill workers. To avoid firms leaving the market, which would lead to unemployment, unions compensate them for the additional costs they face by imposing a negative premium on high-skill workers. The way we model unions thus allows us to capture the "compensation" — which is actually a transfer from high-skill workers to low- and middle-skill workers — that can occur in highly institutionalized labor market.[24] The impact of such unions on relative wages globally fits the stylized facts we want to reproduce.

A particularly interesting implication of our model consists in its predictions about job polarization. While the wage of middle-skill relative to high-skill workers is higher with unions than without, firms nonetheless substitute less high-skill for middle-skill workers following SBTC in the presence of unions. The corollary of this result is that less middle-skill workers are reallocated to tasks previously performed by low-skill workers in an environment with unions. In other words, the type of unions we consider mitigates both wage and employment polarization.

We think that the predictions of our model in terms of job polarization are interesting not only because they are counterintuitive, but also because they lead to potential explanations which could constitute interesting paths for future research. Comparatively lower wages for high-skill workers should *a priori* give firms incentives to substitute more intensively middle-skill workers with high-skill workers in the centralized collective bargaining regime case than in the "free-market" case. As previously mentioned, one explanation is that firms allocate workers so that their wage fit their marginal productivity in the task they perform. It would be interesting to investigate whether firms actually implement such allocation rules.

Another type of explanation, which is not explicitly taken into consideration by our model, is linked to the additional training that could be provided to workers under the pressure of workers' representatives. Including the potential skill-upgrading impact of institutions would be an interesting extension of the model.

[24] See notably Vandekerckove, Van Gyes and Goos (2018)

Note that in our setting unions adjust to technical change, which is considered exogenous. Another interesting (and ambitious) extension of our model would therefore consist in endogenizing the implementation of technical change, so that it does not only shape but also respond to the action of institutions.

While the natural next move is to extensively confront the results of the model to the data, this step is not facilitated by the fact that our model only nests two extreme cases: on one hand unions so decentralized that SBTC eradicates their ability to impact wages, and on the other hand unions so highly centralized and coordinated that they are able not only to impose wage premiums, but also to do it in such a way that they completely impede firms to leave the market. Extending the model to intermediate cases would surely be an interesting path to follow for further research.

Appendix 3.A Lemma 1

Lemma 1.

$$\frac{\mathrm{d}I_H}{\mathrm{d}\ln(A_H)} = -\left(2\frac{1}{I_L} + \frac{1}{I_H - I_L}\right)\frac{1}{|J|} < 0 \ \textit{and}$$

$$\frac{\mathrm{d}I_L}{\mathrm{d}\ln(A_H)} = -\frac{1}{I_H - I_L}\frac{1}{|J|} < 0\,,$$

where $|J|$ denotes the determinant of the Jacobian matrix of the totally differentiated system of the logarithm of the no-arbitrage conditions (3.11)-(3.12).

Proof. Taking the logarithm of the system of no-arbitrage conditions (3.11)-(3.12), totally differentiating it with respect to $\ln A_H$ and rearranging the output allows to get to the following system, here in matrix form:

$$\begin{bmatrix} -\left(2\frac{1}{I_H} + \frac{1}{I_H - I_L} + 2I_H\frac{1}{1 - I_H^2}\right) & \frac{1}{I_H - I_L} \\ \frac{1}{I_H - I_L} & -\left(2\frac{1}{I_L} + \frac{1}{I_H - I_L}\right) \end{bmatrix} \begin{bmatrix} \frac{\mathrm{d}I_H}{\mathrm{d}\ln(A_H)} \\ \frac{\mathrm{d}I_L}{\mathrm{d}\ln(A_H)} \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \end{bmatrix} \tag{3.15}$$

where the coefficient matrix is Jacobian. Its determinant $|\mathbf{J}|$ exists as long as $I_H \neq I_L$.

Because of the allocation of skills to tasks and the structure of comparative advantage in the model, we necessarily have that $I_H > I_L$. $|\mathbf{J}|$ therefore always exist and is positive. One can thus solve (3.15) for $\mathrm{d}I_H/\mathrm{d}\ln(A_H)$ and $\mathrm{d}I_L/\mathrm{d}\ln(A_H)$ to get:

$$\frac{\mathrm{d}I_H}{\mathrm{d}\ln(A_H)} = -\left(2\frac{1}{I_L} + \frac{1}{I_H - I_L}\right)\frac{1}{|J|} < 0 \ \text{and}$$

$$\frac{\mathrm{d}I_L}{\mathrm{d}\ln(A_H)} = -\frac{1}{I_H - I_L}\frac{1}{|J|} < 0\,.$$

□

Appendix 3.B Numerical simulations: extended results

This appendix presents a subset of the numerical results used to assess the impact of unions on wage and job polarization. Results for wage polarization are presented in figures 3.B.1 and 3.B.2, while results for job polarization are presented in Figure 3.B.3. As highlighted in Section 3.3.3, we only present some of the results for the sake of readability. All results nonetheless point towards the same conclusion: powerful unions participating to a centralized bargaining process mitigate labor market polarization.

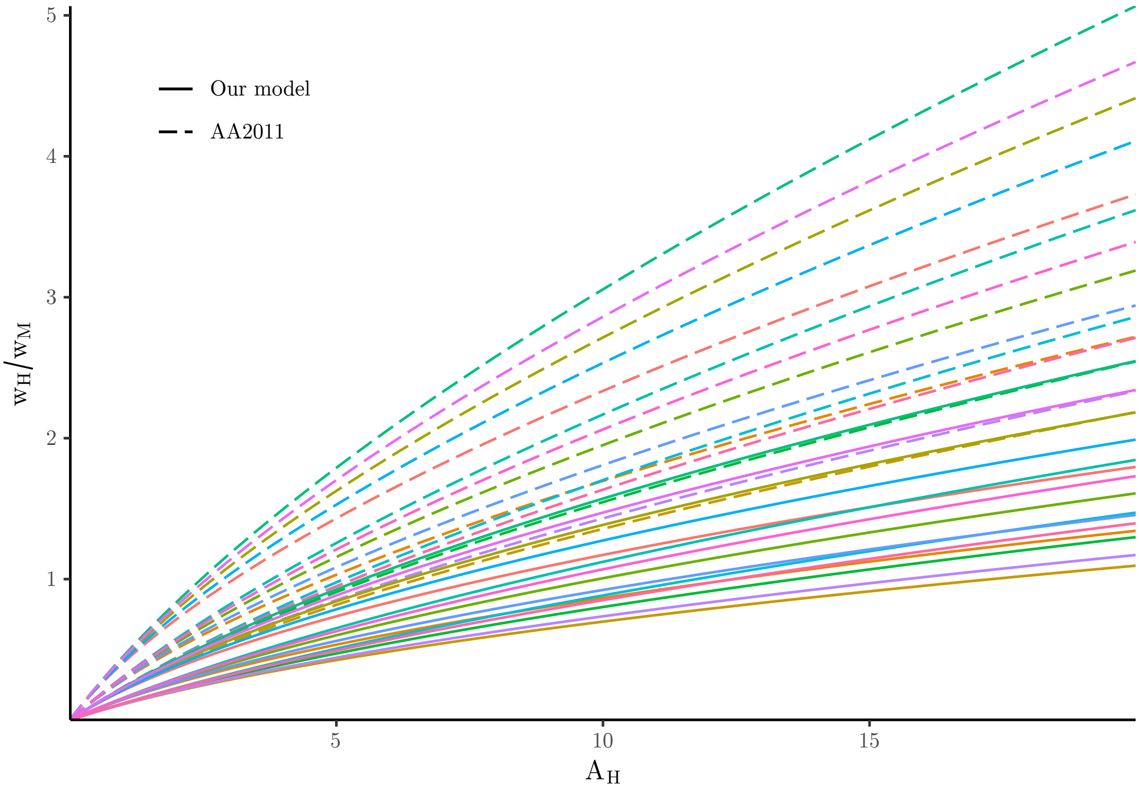

Figure 3.B.1: The impact of SBTC on w_H/w_M, numerical results (extended)

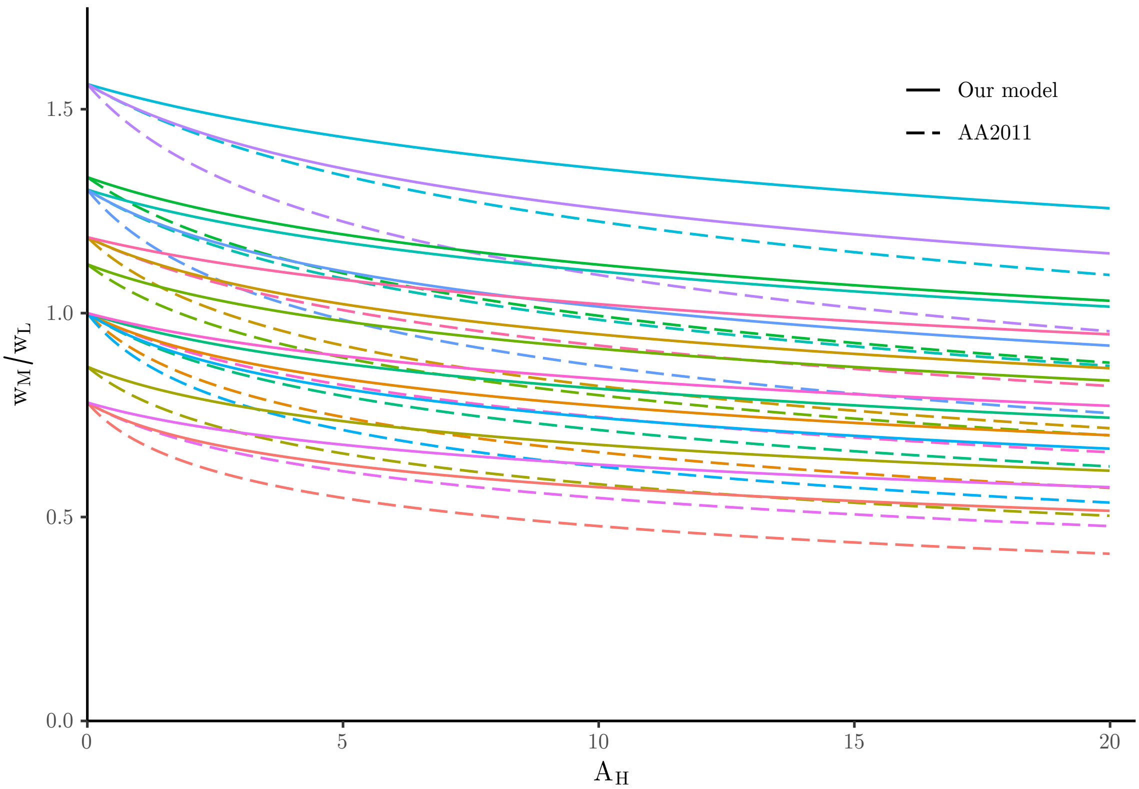

Figure 3.B.2: The impact of SBTC on w_M/w_L, numerical results (extended)

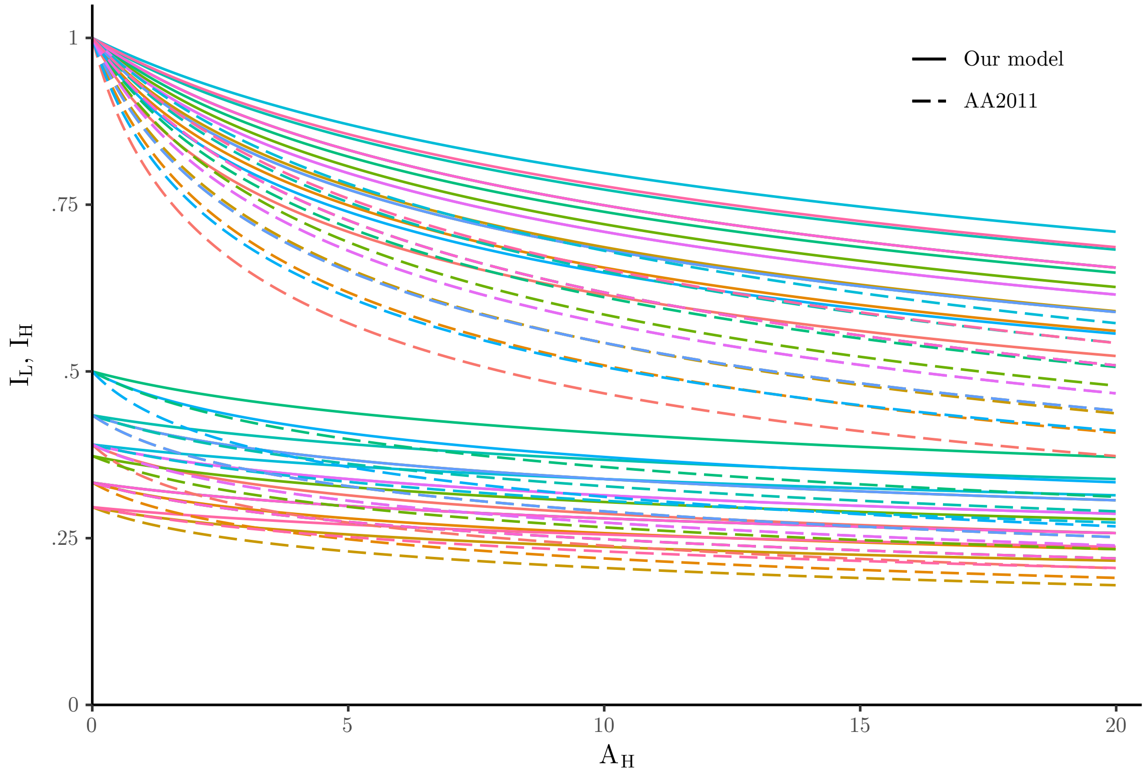

Figure 3.B.3: The impact of SBTC on I_H and I_L, numerical results (extended)

Chapter 4

The Impact of Institutions on Job Polarization: a Panel Cointegration Analysis

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4.1 Introduction

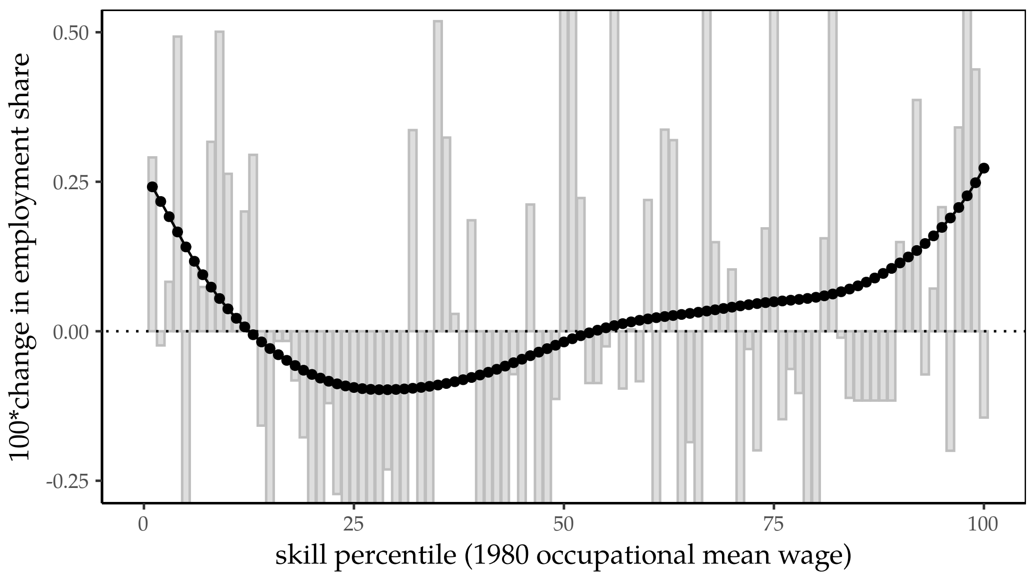
4.1.1 TC and Job polarization in (some) developed economies

Job polarization can be defined as the simultaneous increase in the employment share of low- and high-skill jobs relative to middle-skill jobs. Depending on the way these job categories are defined and measured, different conclusions can be drawn about the extent and the causes of polarization across developed economies. Three main types of non-mutually exclusive causes have been put forward by the literature: routine-biased technical change (RBTC), offshoring and institutions. In this paper, we use panel cointegration techniques to empirically characterize the impact of institutions on polarization of the labor market. More precisely, we test the predictions of the model developed by Dupuy and Pettinger (2021) (DP2021 hereafter).[1] According to this model, institutions are able to mitigate the RBTC-induced polarization of employment. Since estimating panel cointegrating vectors does not allow *per se* to assess the direction of causality, we test for the latter using panel vector autoregression (PVAR) and impulse response function (IRF) analysis. Before detailing our strategy and methodology, we review the literature in order to present the different measures of job polarization and to introduce the potential causes of this phenomenon.

[1]This paper, still unpublished, constitutes the third chapter of this dissertation. We however refer to it as DP2021, for convenience.

Focusing on the US, Wright and Dwyer (2003) define job categories as the cells of a matrix of occupational categories by economic sectors. They order these categories according to their median hourly earnings and aggregate them into quintiles. They then study the net change in the number of jobs in each quintile between 1992 and 2000, and observe that job growth has been strong in both the bottom and the top quintiles (especially in the latter) but particularly low in the middle quintile.

Ranking US occupational categories by their 1980 average years of schooling (used as a proxy for skills requirement[2]), Autor, Katz and Kearney (2006) observe that the smoothed change in occupational employment share between 1990 and 2000 takes the form a skewed U-shaped curve, confirming the findings of Wright and Dwyer (2003) that employment growth has been polarized during the period studied. Autor and Dorn (2013) confirm this pattern for the period 1980-2005, as shown in Figure 4.1. This pattern is also observed by Autor, Katz and Kearney (2006) when occupations are ranked according to their task content: while employment growth increased for occupations intensive in nonroutine cognitive tasks, it remained stable for jobs intensive in nonroutine manual tasks and decreased for occupations intensive in routine cognitive and manual tasks. The fact that the first tasks are the "most complementary with computerization" and the last the "most substitutable for computers" leads Autor, Katz and Kearney (2006) to adopt the *routine-biased technical change* (RBTC) explanation of job polarization, an approach based on the Autor, Levy and Murnane (2003) "computerization" and "routinization" explanation of the increase in US wage inequality. Before reviewing the literature on the evolution of employment in European countries, we provide a brief summary of the RBTC approach.



(Data Source: Autor and Dorn, 2013)

Figure 4.1: Job polarization in the US: change and smoothed change in occupational employment share, 1980-2005

According to this approach, skill-biased technical change increases the produc-

[2]Their findings are robust to the use of median hourly wage as an alternative skill definition.

tivity of technological capital (i.e. computers), to which high-skill workers are complement. Jobs implying routine tasks, which are typically performed by middle-skill workers, are also the most codified and codifiable, and can thus be performed by capital, i.e. by machines and more specifically computers. Technical change thus makes the substitution of computers and high-skill workers — and their jobs intensive in nonroutine cognitive tasks — for middle-skill workers materially possible, and more and more profitable (see notably Acemoglu and Autor, 2011). This leads to a downward pressure on the wages of the latter, who can thus be redirected towards jobs intensive in nonroutine manual tasks (typically low-skill interpersonal services) and previously performed almost exclusively by low-skill workers. On the other hand, the increasing demand for high-skill workers leads to an upward pressure on their wages, itself leading to an increase in demand for these services[3] now performed by both low- and middle-skill workers. Note that the fact that routine cognitive and manual (middle-skill) tasks are highly codified and codifiable make them particularly prone to offshoring, which can magnify the decline in the employment share of the related jobs.

As emphasized by DP2021 (amongst others), the RBTC explanation must be complemented by other factors and mechanisms in order to capture cross-country differences in labor market polarization. Pettinger (2021)[4] shows that this is the case for wage polarization, even when the change in wages is decomposed into a structure and a composition effect. We now review the literature focusing on the evolution of the employment structure in Europe.

Ranking occupations according to their median wage, Goos and Manning (2007) observe job polarization in Britain between 1979 and 1999. Spitz-Oener (2006) shows that the same holds for West Germany between 1979 and 1999, when occupations are ranked according to an occupational skill index. Examining the change in the share of hours worked for high-, middling, and low-paying occupations in 16 European countries over 1993-2006, Goos, Manning and Salomons (2009) find that polarization is pervasive across these countries. However, for middling occupations the magnitude of this change depends on the country considered. For low-paying occupations, both the sign and the magnitude of this change differ according to the country studied. The same holds for Goos, Manning and Salomons (2014), in which the period studied is extended to 2010.

Applying the Wright and Dwyer (2003) ranking and aggregation method on 15 European countries for the period 1995-2007, Fernández-Macías (2012) identifies three distinct types of employment dynamics: polarization, upgrading and mid-upgrading, each of them characterizing a group of four countries. Upgrading implies a somehow monotone increase of the change in employment share along the different quintiles[5], while mid-upgrading consists in a somehow inverse U-shaped pattern, which implies that the growth in employment share is higher for the third and fourth quintiles than for the top and bottom quintiles. These findings suggest that the evolution of jobs — in terms of occupational employment share

[3]See e.g. Manning (2004), who argues that “the demand in [these] least-skilled jobs may be growing” following technical change.

[4]Same remark as for DP2021. Note that this paper constitutes the second chapter of the present dissertation.

[5]In other words, the higher the quintile, the higher the increase in employment share.

— is far from being homogeneous across European countries. Studying Germany, Spain, Sweden and the UK during the period 1992-2014 and using a set of four job ranking criteria[6], Oesch and Piccitto (2019) claim that the polarization thesis only holds for the UK, and only when the earnings criterion is used. Fernández-Macías and Hurley (2017) go further in the characterization of such stylized facts and their interpretation: "using our own operationalization of tasks, we argue that routine tasks are not associated with skills in the non-linear polarized way predicted by the [hypothesis linking RBTC and job polarization], nor to the observed cases of job polarization in Europe in 1995-2007." They even conclude that "the phenomenon of job polarization observed in some European countries is not primarily the result of technological factors." These results are particularly striking since they seem to contradict the observations of Goos, Manning and Salomons (2009, 2014) while using the same data. Fernández-Macías, Hurley and Storrie (2012) claim that this discrepancy in results mainly comes from three differences in their analytic strategy and emphasis in interpretation. We refer to Fernández-Macías, Hurley and Storrie (2012) for further details.

While Fernández-Macías (2012) does not reject the RBTC-induced polarization hypothesis, he claims that there must be other factors, especially institutions, which "neutralize such effect in most countries". He argues that the role of institutions is supported by the association between "patterns of employment growth and European institutional families". Fernández-Macías and Hurley (2017) and Oesch (2013) make a similar argument, placing institutions at the core of cross-country differences in job polarization.

4.1.2 On the potential role of institutions: predictions and empirical assessment

Based on the Acemoglu and Autor (2011) Ricardian model of the labor market, DP2021 develop a model — solved in two steps — predicting the impact of technical change in two different institutional regimes. In the first step, depending on their power, institutional devices (such as unions) contribute to set wages above or below the marginal productivity of the workers, depending on their type. Workers can be of three types: low-, middle- or high-skill. In the second step, firms adjust the allocation of workers — i.e. skills — to tasks according to the output of the first step's bargaining game. The two different institutional regimes considered are two extreme cases: in the first case, unions have full bargaining power, while in the second case, they have none. While in both cases technical change leads to both wage and job polarization, in the first case the polarization phenomenon is mitigated, indicating a potential causal relationship between the degree of institutionalization of the labor market and polarization of employment, as notably suggested by Fernández-Macías (2012), Fernández-Macías and Hurley (2017) and Oesch (2013). Before describing our strategy to empirically asses this relationship, we review some studies which implement empirical models in order to capture the impact of institutions on SBTC-induced job polarization.

While Goos, Manning and Salomons (2009) do not explicitly take into account

[6]Earnings, education, prestige and job satisfaction.

institutional variables, they emphasize the weakness of the link between wage inequality and change in low-skill employment. Since the former is usually assumed to be impacted by labor market institutions, one could *a priori* conclude that the link between institutions and the degree of employment polarization must be limited. However, it should be noted that Goos, Manning and Salomons (2009) only study the cross-sectional link between the share of low-skill employment and some measures of income inequality for a given year. They thus ignore all the other channels through which institutions could have an impact on the employment structure.

In an earlier version (2011, unpublished) of Goos, Manning and Salomons (2014), the authors explicitly mention the possibility of using their model to assess the role of institutions in polarization. While they still do not explicitly include institutional variables in their model, they again consider their role in the wage-setting process by assuming occupational relative wages as exogenous. They justify this assumption by the weakness of link between relative occupational wage movements and technical change (and offshoring), that they attribute to institutional forces "muting or stopping the wage response". However, they find no strong evidence that "changes in aggregate income or income dispersion (...) play an important part in explaining changes in relative employment". Moreover, their model based on routinization and offshoring is able to "explain the bulk — though not all — of the observed polarization". These two previous points lead the authors to the conclusion that "changes in wage-setting institutions play little role in explaining job polarization in Europe."

Goos, Manning and Salomons (2014) do not even mention institutions anymore, which they choose to leave aside from the analysis. The most likely explanation is that they were previously accounting for their impact through income inequality, which they also rule out from their analysis through the assumption of consumers having homothetic preferences. This assumption is not innocuous: it implies that "changes in both the level and the distribution of aggregate income have no effect on the distribution of demand across industries." (Goos, Manning and Salomons, 2014). As emphasized by the authors themselves, "this might be thought unduly restrictive because it has been argued (...) that job polarization might be caused by increasing inequality leading to increased demand for low-skill service sector jobs from high-wage workers to free up more of their time for market work." While their semi-empirical/theoretical model does a great job in explaining job polarization and confirms the crucial role played by technical change, it still cannot rule out the impact of institutions on RBTC-induced technical change.

4.1.3 Our strategy

A substantial part of institutional characteristics is located at the national level. While some sector-specific data are available for unionization and union coverage, these two variables fail to capture important dimensions of institutional regimes. For example, the degree of centralization and/or coordination of the bargaining process may have a considerable impact on the power of unions and on their reaction to overall macroeconomic conditions.

We assume it is one of the reasons which led Goos, Manning and Salomons (2009) and Goos, Manning and Salomons (2014) not to *directly* consider institutional variables in their analysis, for which they use country-year-occupation units of observation. Fernández-Macías and Hurley (2017) explicitly mention this problem, which leads them to "only discuss the institutional arguments indirectly, by inference from cross-country variation." One of our contribution consists in directly assessing the impact of institutional variables on employment polarization. We adopt a panel setting, which allows to exploit both time and cross-sectional variability while allowing to control for country-specific effects.

While adopting a panel setting allows to obtain a relatively decent sample size, the need to control for other variables can quickly induce a dimensionality problem if too many institutional variables are used in the model. To circumvent this problem, we build a composite indicator of institutionalization where the weights of institutional variables are determined using principal component analysis, in the spirit of Baccaro and Howell (2017). This procedure is described in details in Section 4.3. Note that the other explanatory variables used in our analysis are described in the same section.

We divide job polarization into two components. The first component takes the form of an increase in the ratio of the employment share in high-skill jobs[7] to the employment share in middle-skill jobs. The second component consists in the ratio of the employment share in middle-skill jobs to the employment share in low-skill jobs. The ranking of occupations used to categorize them into skill categories is based on the European Socio-economic Groups Classification (ESeG), which "distinguishes between jobs according to the level of skill and sector of activity" (Peugny, 2019). Our analysis is operated separately on the two components of job polarization. More details about the construction of these two variables are given in Section 4.3.

The first part of our analysis consists in "naively" testing the extrapolated/extended predictions of DP2021, according to which an increase in the degree of institutionalization of the labor market limits job polarization. Rather than testing for proper causality, we estimate the long-run (LR) relationship between job polarization and institutions, which is particularly relevant given that DP2021 is a static model which remains silent about the short-run (SR) relationship between the two variables. Since our variables of interest are non-stationary, we adopt the (panel) cointegration analysis framework in order to avoid the spurious regression problem.

The second part of our analysis is a tentative to interpret structurally the empirically assessed relationship between institutionalization and polarization. While (panel) cointegration estimators are typically robust to the presence of full endogeneity, implementing such techniques does not permit *per se* to establish a particular direction of causality (Pedroni, 2019). Causal interpretation requires further assumptions, generally imposed in the form of identification restrictions. In order to give a structural interpretation to the response of the occupational/employment structure to a change in institutionalization, we impose such restrictions on the impulse responses of a panel vector autoregressive (PVAR) model.

[7] In this paper, a job is an occupational category.

4.1.4 Structure of the remainder of the paper

In the next section, we describe the methodology used to characterize the relationship between employment polarization and institutions. We first introduce the notion of cointegration, and how it characterizes the LR relationships between our variables of interest. We then present how structural analysis of impulse response functions of a PVAR model can be used to identify causal relationships between these variables.

We then introduce the data, and describe the procedures according to which we build our measure of the two components of job polarization and the composite index capturing the degree of institutionalization of the labor market. We also describe the other explanatory variables, and the theoretical concepts they are assumed to capture.

We discuss the implementation of the chosen methodology, and present the results. We interpret these results and their implications, and finally conclude.

4.2 Methodology

4.2.1 Integrated variables, spurious regression, cointegration and long-run relationships

4.2.1.1 Cointegrating vectors and long-run, equilibrium relationships

For the of sake of simplicity, we start this section by introducing the topic of cointegration in the case of a single cross-section unit. We then present the specific panel cointegration techniques we use for our analysis.

A time series y_t exhibiting a trend is said to be non-stationary, in the sense that its mean, variance, and autocovariance $Cov(y_t, y_{t-s})$, where $t \neq s$, change over time. Since the seminal work of Granger and Newbold (1974), it is well known that regressing two non-stationary but yet completely unrelated series can lead to the *spurious regression* problem: even when these series are completely independent, the regression model is likely to reveal a significant relationship.

However, and as highlighted by Banerjee et al. (1993), "variables hypothesized to be linked by some theoretical economic relationship should not diverge from each other in the long run". The concept of co-integration allows to distinguish between unrelated integrated[8] series and series which move together across time due to their equilibrium relationship.[9] Note that a necessary (but not sufficient) condition for series to be cointegrated is to be integrated of the same order. Series are said to be $I(r)$, i.e. integrated of order r, if they must be differenced r times to reach stationarity, and thus to become $I(0)$.

[8] In the words of Banerjee et al. (1993), "a series is said to be integrated if it accumulates some past effects; such a series is non-stationary because its future path depends upon all such past influences (...)."

[9] Again in the words of Banerjee et al. (1993), the concept of cointegration allows to "describe the existence of an equilibrium, or stationary, relationship among two or more time-series, each of which is individually non-stationary".

What formally distinguishes cointegrated series $\mathbf{y}_t$ from unrelated integrated series is the fact that, for the former, there exist linear combinations of the variables such that

$$\mathbf{u}_t = \boldsymbol{\alpha}_r \mathbf{y}_t \sim I(0), \qquad r = 1, 2, ..., R, \tag{4.1}$$

where R is the number of cointegrating vectors $\boldsymbol{\alpha}$ and $\mathbf{y}_t = (y_{1t}, y_{2t}, \ldots, y_{nt})' \sim I(1)$ a vector time series of dimension n integrated of order 1 (and thus non-stationary). In other words, integrated series are cointegrated when there exist linear combinations of them which are stationary, thereby indicating the existence of a stable long-run (equilibrium) relationship.

For the ease of exposition, consider the bivariate case ($n = 2$), where $\mathbf{y}_t = (y_{1t}, y_{2t})'$. In that case, if there exists a cointegration vector α, it is unique[10] and can be normalized such that $\alpha = (1, -\beta)$. Equation (4.1) can thus be written as

$$u_t = y_{1t} - \beta y_{2t} \sim I(0), \tag{4.2}$$

and can be rewritten as

$$y_{1t} = \beta y_{2t} + u_t \sim I(0). \tag{4.3}$$

Equations (4.2) and (4.3) suggest that one way to test for the existence of a cointegrating relationship is to test for stationarity of u_t, which is the residual of the regression of y_{1t} on y_{2t}. This implies that estimating the cointegration vector α and testing for the existence of a cointegration relationship are two sides of the same coin.

4.2.1.2 Estimation of cointegrating vectors

It has been shown[11] that estimating cointegrating vectors in the static regression framework of Equation (4.3) can yield poor estimates. More specifically, static OLS estimates of cointegrating vectors can exhibit large finite-sample biases. Better estimates can however be obtained with systems estimation and dynamic regressions.

Stock and Watson (1993) introduce a dynamic OLS (DOLS) estimator based on the triangular representation of a cointegrated system. Consider again the n-dimensional time series $\mathbf{y}_t = (y_{1t}, y_{2t}, \ldots, y_{nt})' \sim I(1)$, which is partitioned such as $y_t = y_{1t}$ and $\mathbf{x}_t = (y_{2t}, \ldots, y_{nt})'$. In the case of a single cointegrating vector, which we assume in the first part of our analysis, the DOLS estimate of this cointegration vector can be obtained by operating an OLS estimation of the regression model

$$y_t = \mu + \beta \mathbf{x}_t + \sum_{p=-q}^{q} \zeta_q \Delta \mathbf{x}_{t+p} + u_t. \tag{4.4}$$

In plain English, estimating a single cointegrating vector $\boldsymbol{\alpha} = (1, -\beta_1, \ldots, -\beta_{n-1})$ in the $I(1)$ case with this method simply requires to regress the 'dependent' variable onto "contemporaneous levels of the remaining variables, leads and lags of their first differences, and a constant, using (...) ordinary least squares" (Stock and Watson, 1993). The estimator used in the first part of our analysis is an extension of the DOLS estimator to the panel data case.

[10] See notably Banerjee et al. (1993).

[11] See e.g. Banerjee et al. (1993).

4.2.1.3 Testing for cointegrating relationship and estimating cointegrating vectors in a panel setting

Our panel setting has two major advantages: it offers higher power for cointegration tests, and allows for more precise estimates of model coefficients when they are homogeneous across cross-section units[12] (Choi, 2015). This is especially true given the relatively short time span of our data[13]. However, these two major advantages come at a cost, which notably implies potential cross-sectional dependence and the difficult interpretation of the panel unit root and cointegration tests[14]. As emphasized by Breitung and Pesaran (2008), often with panel tests "the best that can be concluded is that a significant fraction of the cross section units is stationary or cointegrated", and these tests "do not provide explicit guidance as to the size of this fraction or the identity of the cross section units that are stationary or cointegrated."

Panel unit root tests, with and without time trend. To be cointegrated, variables have to be integrated of the same order, which necessarily implies that the time series are independent random walks[15]. While there are different panel unit root tests, they share a similar underlying principle. Assume that for each cross-section unit $i = 1, \ldots, N$, the data generating process of the time series y_{it} is a first-order autoregressive process

$$y_{it} = (1 - \gamma_i)\mu_i + \gamma_i y_{i,t-1} + e_{it},$$

which can be rewritten as the Dickey-Fuller (DF) regression

$$\Delta y_{it} = -\theta_i \mu_i + \theta_i y_{i,t-1} + e_{it},$$

where $\theta_i = \gamma_i - 1$. The null hypothesis is that all series are independent random walks (and thus nonstationary processes), i.e. $H_0 : \gamma_1 = \ldots = \gamma_N = 1$, and thus

$$H_0 : \theta_1 = \ldots = \theta_N = 0.$$

Two alternatives can be considered: the first one states that the autoregressive parameter of the DF regression is the same for all cross-section units and (strictly) less than 0 (stationarity for all panel units), while the other states that *some* of the cross-section units are stationary. However, as highlighted by Breitung and Pesaran (2008), the results of both tests can only be given a restricted interpretation, in the sense that when the null hypothesis is rejected, "one can only conclude that a significant fraction of the AR(1) processes in the panel does not contain unit roots".

We choose to use the Im, Pesaran and Shin (2003) test, which has the major advantage of allowing for unbalanced panels. Since the time span covered by our data is relatively short ($T \sim 25$) and depends both on the variable and the country

[12] Mainly for practical reasons, we assume such homogeneity in the cointegration vector estimation of the first part of our analysis.

[13] See Section 4.3.

[14] See notably Breitung and Pesaran (2008) and Choi (2015).

[15] See e.g. Breitung and Pesaran (2008).

considered, this is a particularly desirable property. Note that a deterministic time trend can be included in such panel unit root tests, thus allowing to consider trend stationarity. Whether or not to include this deterministic trend is not an innocuous question: as we will discuss later, it implies taking a stance about the nature of the trend underlying the series. In our application, we do not include any deterministic trend in the model underlying the test.

Panel cointegration tests. As shown earlier for the time series case, estimating cointegrating vectors and testing for the existence of cointegration relationships are closely linked. However, these two problems are not exactly the same: while residuals can be obtained from panel regression models assuming heterogeneous coefficients, cointegration relationships can still be assumed homogeneous in the final estimation, for theoretical and/or practical reasons. This is the case in this paper.

There are two main groups of tests: tests based on the residuals of panel regressions, and tests based on error correction methods and likelihood ratios (Breitung and Pesaran, 2008; Choi, 2015; Pedroni, 2019). The latter are specifically designed to test for multiple cointegration. When used for a single-equation and when the assumption of weak exogeneity does not hold, the test can become inconsistent (Pedroni, 2019). Since the first part of our analysis assume a single cointegrating vector and reverse causality cannot be dismissed, we choose not to consider these tests and to focus only on the residual-based ones.

For the sake of simplicity, we follow Pedroni (2019) and present these tests by considering the bivariate case. Residual-based tests always start with a simple regression of the form

$$y_{it} = \mu_i + \beta_i x_{it} + u_{it}. \tag{4.5}$$

They then test for the null hypothesis of no cointegration by testing whether the residuals are non-stationary.

The difference between the different residual-based tests comes from the way the estimated residuals $\hat{u}_{it}$ (on which the test is ultimately applied), are treated (Pedroni, 2019). On the basis of a large scale simulation study, Wagner and Hlouskova (2010) conclude that "amongst the single equation tests for the null hypothesis of no cointegration the two tests of Pedroni applying the ADF principle perform best, whereas all other tests are partly severely undersized and have very low power in many circumstances (and virtually none for $T \leq 25$)." The last part of this conclusion is crucial for our application, where $T \sim 25$. We thus choose to use the Pedroni (1999, 2004) tests based on Dickey-Fuller[16] statistics to test for the existence of a cointegration relationship between our variables of interest.

The general idea underlying such tests is to assess the non-stationarity of the

[16] As highlighted by Wagner and Hlouskova (2010), "the correction for serial correlation can be handled either nonparametrically (...) or by using ADF type regressions". Note that Pedroni (2004) focuses on the "nonparametric treatment of the nuisance parameters", and refers to Pedroni (1999) for a discussion on the parametric treatment (through ADF regressions) of these.

residuals through an Augmented Dickey-Fuller (ADF) regression,

$$\hat{u}_{it} = \rho_i \hat{u}_{it-1} + \sum_{p=1}^{q} \rho_{ip} \Delta \hat{u}_{it-p} + \epsilon_{it},$$

where $\hat{u}_{it}$ is the estimated residual from (4.5). For further details, including the derivation of the test statistics, we refer the reader to Pedroni (1999, 2004, 2019). For an overview and a categorization of the different tests, see Breitung and Pesaran (2008), Wagner and Hlouskova (2010), Choi (2015) and Pedroni (2019).

Estimation. Two main groups of estimators can be used to estimate a single cointegrating vector while controlling for endogenous feedback effects[17] and assuming homogeneous panel. The first is based on the fully-modified OLS (FMOLS) estimator originally developed in the time series framework, while the second is based on the dynamic OLS estimator (DOLS) introduced earlier in Section 4.2. Using Monte Carlo simulations, Kao and Chiang (2000) show that the panel version of DOLS outperforms the panel version of FMOLS. We consequently choose to use the former.

There are two versions of the panel DOLS (PDOLS). The one we use has been introduced by Kao and Chiang (2000) and extended by Mark and Sul (2003). The estimated regression is

$$y_{it} = \mu_i + \beta \mathbf{x}_{it} + \sum_{p=-q}^{q} \zeta_{ip} \Delta \mathbf{x}_{it+p} + u_{it}, \tag{4.6}$$

where ζ_{ip} is specific to the cross-section unit, as indicated by the i subscript. Including leads and lags of the regressors allows to control for endogeneity (Mark and Sul, 2003).

The estimation procedure proposed by Mark and Sul (2003) is based on the within-OLS estimator. Consider $\mathbf{z}_{it} = (\Delta \mathbf{x}'_{it-q}, \ldots, \Delta \mathbf{x}'_{it+q})'$. The first step consists in subtracting, for each cross-section unit, time series mean from the regressors and the regressand:

$$\tilde{y}_{it} = y_{it} - \frac{1}{T}\sum_{t=1}^{T} y_{it}, \qquad \tilde{\mathbf{x}}_{it} = \mathbf{x}_{it} - \frac{1}{T}\sum_{t=1}^{T} \mathbf{x}_{it}, \qquad \tilde{\mathbf{z}}_{it} = \mathbf{z}_{it} - \frac{1}{T}\sum_{t=1}^{T} \mathbf{z}_{it}.$$

Individual fixed-effects have now been removed, and the regression to be estimated is $\tilde{y}_{it} = \beta \tilde{\mathbf{x}}_{it} + \zeta_i \tilde{\mathbf{z}}_{it} + \tilde{u}_{it}$. Since ζ_i is cross-section specific, the estimation setup has to be adjusted accordingly. Consider the vectors

$$\begin{aligned}
\mathbf{p}_{1t} &= (\tilde{\mathbf{x}}'_{1t}, \;\; \tilde{\mathbf{z}}'_{1t}, \;\; \mathbf{0}', \;\; \cdots \;\; \mathbf{0}')' \\
\mathbf{p}_{2t} &= (\tilde{\mathbf{x}}'_{2t}, \;\; \mathbf{0}', \;\; \tilde{\mathbf{z}}'_{2t}, \;\; \cdots \;\; \mathbf{0}')' \\
&\vdots \qquad\qquad\qquad \vdots \\
\mathbf{p}_{Nt} &= (\tilde{\mathbf{x}}'_{Nt}, \;\; \mathbf{0}', \;\; \mathbf{0}', \;\; \cdots \;\; \tilde{\mathbf{z}}'_{Nt})',
\end{aligned}$$

[17]See e.g. Pedroni (2001).

which allow to create cross-section specific leads and lags variables which are set to 0 for other cross-section units than the one to which the variables are related. The regression now takes the form $\tilde{y}_{it} = B\mathbf{p}_{it} + \tilde{u}_{it}$, where $B = (\beta, \zeta_1, \ldots, \zeta_N)$. The Mark and Sul (2003) panel DOLS estimator for the fixed-effects model is

$$B_{NT} = B + \left[\sum_{i=1}^{N}\sum_{t=1}^{T} \mathbf{p}'_{it}\mathbf{p}_{it}\right]^{-1} \left[\sum_{i=1}^{N}\sum_{t=1}^{T} \mathbf{p}'_{it}\tilde{u}_{it}\right], \tag{4.7}$$

where

$$B = \left[\sum_{i=1}^{N}\sum_{t=1}^{T} \mathbf{p}'_{it}\mathbf{p}_{it}\right]^{-1} \left[\sum_{i=1}^{N}\sum_{t=1}^{T} \mathbf{p}'_{it}\tilde{y}_{it}\right]. \tag{4.8}$$

The vector of coefficients β of (4.6), and by extension the normalized cointegrating vector, can thus be obtained by estimating B using (4.8), computing the residuals, and finally using these estimated residuals to compute B_{NT}, according to (4.7).

The second version of the PDOLS estimator has been introduced by Pedroni (2001) and consists in a between-dimension, group-mean estimator. It can simply be constructed as $\hat{\beta}_{GMD} = N^{-1}\sum_{i=1}^{N}\hat{\beta}_{D,i}$, where $\hat{\beta}_{D,i}$ is the Stock and Watson (1993) DOLS estimator applied to the ith cross-section unit. The fact that this estimator implies estimating $\beta_{D,i}$ for each cross-section unit is particularly problematic in our setting, since the time dimension of the panel is relatively short ($T \sim 25$). We thus choose to use the Kao and Chiang (2000) and Mark and Sul (2003) PDOLS estimator, which allows to directly estimate the homogeneous cointegration vector on the pooled data.

Note that Mark, Ogaki and Sul (2005) developed a system estimator allowing for cross-section dependency. While it is clearly a desirable property, such estimators require cross-section specific regressions which include "leads and lags of the regressors from cross-equations[18] in addition to own equation regressors" (Mark, Ogaki and Sul, 2005). They thus require a large T (relative to N), which is clearly not the case in our application.

On the (non-)inclusion of a deterministic time trend. All the regression-based methods discussed so far (panel unit root tests, cointegration tests and cointegrating vector estimation) allow for the inclusion of a deterministic time trend. As mentioned earlier in this paper, including or omitting this deterministic term implies taking a stand on the nature of the trend underlying the integrated variables.

This question has been discussed extensively by Harvey (1997). He argues that introducing a deterministic linear trend is not generally appropriate[19] and that a stochastic trend model should be favored. In his own words, "separating out the trend from the cycle is motivated by the idea that the economic theory which is relevant to the long run is different to the theory one wishes to apply in the short run. Irrespective of whether or not one accepts this view, an arbitrary separation into trend and cycle is clearly not to be recommended. The ideal way to proceed is by constructing a multivariate model using original data."

[18]This constitutes the 'system' aspect of their estimator.

[19]Notably because he considers such deterministic trend as too restrictive.

Empirical models explaining the evolution of the skill-premium — and more generally of wage inequality — usually include a deterministic time trend to capture the impact of skill-biased technical change (see e.g. Katz and Murphy, 1992 and, more recently, Autor, Katz and Kearney, 2008). Setting aside the questionable hypothesis that technical change and its implementation are adequately captured by a linear time trend, Dupuy (2007) claims that such a trend variable "picks up the effects of all unobserved variables linearly correlated with time (capital included)", which often leads to the rejection of an alternative model[20] based on capital-skill complementarity, even when the latter has been used to generate the data. Dupuy (2007) shows this by generating skill-premium series on the basis of the capital-based model. In 30% of the cases, the error sum of squares are lower for the regression with time trend than for the regression with capital, which is nonetheless the true model. The reverse is however not true, which makes Dupuy (2007) conclude that including a deterministic time trend in the regression leads to a bias against the capital-skill complementarity hypothesis.

Since our application implies some slowly-varying variables (such as the level of institutionalization) and the time span covered is relatively short, we assume that the trend underlying the variables is stochastic. Including a deterministic trend is likely to lead to an underestimation of the impact of these variables, and we consequently choose not to include such a trend in our analysis.

4.2.2 Testing for the direction of causality: (P)VAR/VECM, exogenous shocks and structural impulse responses

As already highlighted in the introduction and in Section 4.2, (panel) cointegration estimators are typically robust to the presence of full endogeneity. While they can be used to estimate consistently long-run relationships between our variables of interest, they nonetheless do not identify the causal direction of these relationships (Pedroni, 2019).

As mentioned in the introduction, identifying structural relations requires imposing additional restrictions on the system. To give a causal interpretation to the cointegrating vector estimated using the techniques previously described, we have to assume that the long-run relationships between the variables are completely characterized by a single cointegrating vector. More importantly, we have to assume that these variables determine the two components of job polarization, while the reverse is not true[21]. A subset of these assumptions is based on the DP2021 theoretical model, and they can be empirically tested by imposing a minimal set of restrictions on the impulse responses of the system. As explained later in this section, these restrictions aim at identifying structural — and thus exogenous — shocks to this system, in which all variables are modeled as endogenous.

[20] Namely, the Krusell et al. (2000) model which "explains demand shifts by (observable) changes in the capital stock under a capital-skill complementarity technology" (Dupuy, 2007).

[21] One could for example argue that job polarization redirects workers towards sectors where unionization is weak, and union power limited. In that case, job polarization could lead to a decrease in institutionalization of the labor market

4.2.2.1 Panel VAR and VECM

We focus on two empirical approaches allowing to model dynamically a fully-endogenous system of cointegrated variables in a panel setting. For the sake of simplicity, we introduce these approaches in the time series case.

Such approaches allow for the existence of several linearly independent cointegrating vectors. Consider the K-dimensional time series $y_t = (y_{1t}, y_{2t}, \dots, y_{Kt})' \sim I(1)$. Note that for notational simplicity and since all variables are modeled as endogenous, we drop the bold notation of vectors and matrices. For the rest of this section, we follow closely the notation of Kilian and Lütkepohl (2017).

We start by presenting the vector autoregressive (VAR) framework, from which we can derive the second approach, namely the vector error correction model (VECM). The VAR framework assumes the data generating process

$$y_t = A_1 y_{t-1} + \cdots + A_p y_{t-p} + u_t, \tag{4.9}$$

where deterministic terms are ignored. An important advantage of such a model is that it does not include contemporaneous values of the endogenous variables as regressors and can thus be consistently estimated by OLS. As pointed out by Kilian and Lütkepohl (2017), subtracting y_{t-1} on both sides of (4.9) yields the VECM

$$\Delta y_t = \Pi y_{t-1} + \Gamma_1 \Delta y_{t-1} + \cdots + \Gamma_{p-1} \Delta y_{t-p+1} + u_t, \tag{4.10}$$

where $\Pi = -(I_K - A_1 - \cdots - A_p)$ and $\Gamma_i = -(A_{i+1} + \cdots + A_p)$, with $i = 1, \dots, p-1$.

Since all the variables are $I(1)$, there can be linearly independent cointegrating relationships between them. Assuming the matrix Π has rank r, this implies that there are r such relationships. We refer to Kilian and Lütkepohl (2017) for further details. What is important to emphasize is that these r cointegrating vectors can be estimated on the basis of (4.10), and that the VAR and VEC models are isomorphic to each other (Banerjee et al., 1993). The parameters of each can thus be derived from an estimator of the parameters of the other.

Since we study the long-run relationships between our variables of interest by assuming a single cointegrating vector, estimating the panel version of (4.10) rather than the panel version of (4.9) has no real advantage for our application. We are especially interested in estimating structural shocks in order to build impulse responses which are informative in terms of causality. However, as highlighted by Kilian and Lütkepohl (2017), estimating the VAR model in levels of the integrated variables facilitates the construction of impulse responses. It also avoids the estimation uncertainty associated with the estimation of the cointegrating structure. While using the VAR rather than the VEC representation precludes the use of some types of identifying schemes for structural shocks, our identification strategy does not make use of these schemes, as explained later. We thus choose to estimate a VAR in levels rather than its VECM representation. In our panel setting, we estimate the parameters of (4.9) using the within-OLS estimator.

4.2.2.2 Estimating structural shocks and impulse responses

The structural version of the reduced-form (RF) VAR in (4.9) is given by

$$B_0 y_t = B_1 y_{t-1} + \cdots + B_p y_{t-p} + e_t, \tag{4.11}$$

and (4.9) can thus be rewritten as

$$y_t = B_0^{-1}B_1 y_{t-1} + \cdots + B_0^{-1}B_p y_{t-p} + B_0^{-1}e_t, \tag{4.12}$$

where $A_1 = B_0^{-1}B_1, \ldots, A_p = B_0^{-1}B_p$ and $u_t = B_0^{-1}e_t$. The matrix B_0 contains the contemporaneous relationships between the variables and allow to express the reduced-form errors u_t as linear combinations of the mutually uncorrelated structural errors e_t. Once the parameters of the reduced-form VAR have been estimated and the structural impact multiplier matrix B_0^{-1} recovered from these estimates, it is possible to build (structural) impulse responses indicating how the different variables dynamically respond to structural shocks in the system.[22]. These structural shocks are by definition uncorrelated and exogenous, and can thus be used to assess causality.

Note that several approaches can be used (and combined) to identify the structural shocks of interest. Since they can be expressed as $e_t = B_0 u_t \Leftrightarrow u_t = B_0^{-1}e_t$, one approach is to impose (short-run) restrictions on the elements of B_0^{-1}.

Recursive identification of structural shocks. The variance-covariance matrix of the RF errors and of the structural innovations are given respectively by $\mathbb{E}(u_t u_t') \equiv \Sigma_u$ and $\mathbb{E}(e_t e_t') \equiv \Sigma_e$. Since $u_t = B_0^{-1}e_t$ and the structural innovations are by definition uncorrelated, the variance of u_t can be expressed as

$$\begin{aligned} \Sigma_u = \mathbb{E}(u_t u_t') &= B_0^{-1}\mathbb{E}(e_t e_t')B_0^{-1\prime} = B_0^{-1}\Sigma_e B_0^{-1\prime} \\ &= B_0^{-1}B_0^{-1\prime}, \end{aligned} \tag{4.13}$$

which is valid as long as $\Sigma_e = I_K$, i.e. as long as the variance of each structural error has been normalized to one.

Operating a Cholesky decomposition of Σ_u allows to obtain a lower triangular matrix T, such that $\Sigma_u = TT'$. From Equation (4.13), it is easy to see that T is a potential candidate for B_0^{-1}. However, and as highlighted by Kilian and Lütkepohl (2017), this orthogonalization of the RF residuals can be considered as appropriate only if the recursive structure implied by T can be economically justified. To see this, consider a 3-variable VAR model. In that case, using T as B_0^{-1} means assuming the following contemporaneous relationships between the RF residuals and the structural errors:

$$\begin{bmatrix} u_t^1 \\ u_t^2 \\ u_t^3 \end{bmatrix} = \begin{bmatrix} b_{11} & 0 & 0 \\ b_{21} & b_{22} & 0 \\ b_{31} & b_{31} & b_{33} \end{bmatrix} \begin{bmatrix} e_t^1 \\ e_t^2 \\ e_t^3 \end{bmatrix}. \tag{4.14}$$

The recursive structure described by Equation (4.14) implies that the first variable is not impacted contemporaneously by the two other variables, the second variable

[22]Note that impulse response functions are theoretically derived from the moving-average (MA) representation of the VAR. If the VAR is not stable, which can be the case when variables are non-stationary and non-cointegrated, the same approach to computing impulse responses will work, but they will not approach zero for $t \to \infty$ and "will no longer represent the coefficients of the structural MA representation" (Kilian and Lütkepohl, 2017). We refer to Kilian and Lütkepohl (2017) for further details.

is only impacted contemporaneously by the first variable, and the third variable is impacted contemporaneously by all variables.

In our application, such restrictions can be sustained if we consider a VAR model with a limited number of variables, more precisely a 3-variable VAR. Institutional variables are — almost by definition — sluggish: they notably imply legal measures and political decisions which can take a substantial amount of time to be decided and implemented. The same can be said about the ratio of high- to middle-skill workers[23] in the population: when unemployed individuals are also considered, we can assume that it does not directly depend on the occupational structure of the economy, but rather on slow societal evolution. By contrast, relative employment in different occupational categories can be assumed as reacting relatively quickly to changes in the relative price of skills and/or in the level of institutionalization.

Two limitations of the previous specification must be discussed. First, our composite index of institutionalization includes the coverage rate. If, for example, a middle-skill worker switches from a covered middle-skill job to a low-skill job in a sector not covered by collective agreements, this has an impact on the coverage rate and, by extension, on the level of institutionalization. However, we choose to ignore such potential impact for two reasons. First, in a relatively important number of European countries, the coverage rate is pretty high, diminishing the probability that a worker leaves a covered job for a non-covered one. Second, our index is composite, and thus includes dimensions — e.g. the level of centralization and coordination — that are not directly impacted by such a change, limiting its impact. The second limitation comes from the limited number of variables for which such a restrictive structure can be considered as plausible. While the question of the specific ordering of (the extended set of) variables is addressed in Section 4.4, we discuss here potential solutions.

Identification in the case of a partially recursive structural system. As shown by Keating (1996), there is no need for the whole structure to be recursive when the goal is to identify a subset of the structural shocks. In his own words, "a partially recursive structure will permit an appropriate Cholesky decomposition to identify structural impulse responses, but only for shocks to the block of recursively ordered structural equations" (Keating, 1996). Assuming which equations constitute such blocks is not necessarily straightforward. It is not even sure that a block of partially recursive equations exists for the system considered. Instead of imposing such restrictions, we estimate the impulse responses of interest for each permutation of the extended set of variables. If such a block exists, it will therefore be taken into account in our results. Such an approach has nonetheless a major drawback, as highlighted by Kilian and Lütkepohl (2017). Even if the impulse responses are the same for all possible orderings of the variable, it does not prove that the true structural model is actually recursive. However, we consider that results similar to the 3-variable VAR model could make us more confident about the plausibility of the latter.

[23] In our case, the ratio of tertiary- to secondary-educated individuals.

4.3 Data and variables

In this section we present the variables used in our analysis. We first describe how we build our measures of polarization and institutionalization, which are the two core variables of interested in this paper. We then present the different variables which have been used in studies testing the RBTC hypothesis in a panel framework. We discuss the feasibility of including them in our setting, which includes variables measured at the country level.

4.3.1 Measure of polarization

Polarization can be divided into two main components. The first consists in the increase in the ratio of high-skill to middle-skill jobs, while the second is a decrease in the ratio of middle-skill to low-skill jobs. As already discussed in the introduction, there are several ways to define these 'jobs' and to rank them according to their skill-requirement.

We choose to use the European Socio-economic Groups (ESeG) classification of occupational categories, which "distinguishes between jobs according to level of skill and sector of activity, thereby making it possible to better describe the types of job that are in expansion" (Peugny, 2019). This classification allows to have a job-quality ranking which is not solely based on hourly wages or educational level. Using EU-LFS data, we calculate the number of workers employed in each of the ESeG categories, and we aggregate these categories in order to capture the employment level in the three 'skill' groups. For each country and each year, we compute the ratio of these employment levels such as to capture the two previously mentioned components of the evolution of employment. The detailed procedure is described in Appendix 4.A. Note that we consider only male employed workers, aged from 16 to 64. The reason we focus on male workers is that they usually have been considered, in the literature, as the workers on which offshoring and technical change have the more direct effects.[24]

Figure 4.2 shows the evolution of the (baseline) ratio of high- to middle-skill employment for the countries included in our analysis. Note that this variable is sometimes denoted by *jobsHovM* in the remainder of this paper. Different ratios, based on different definitions of high- and middle-skill groups of occupations, are represented in Figure 4.A.1. While a generalized upward trend is observed for all ratios and all countries, the intensity of this trend is however far from being homogeneous across countries.

The evolution of the (baseline) ratio of middle- to low-skill employment is presented in Figure 4.3. Note that this variable is sometimes denoted by *jobsMovL* in the remainder of this paper. Different definitions of this variable are shown in Figure 4.A.2. As expected, a generalized downward trend is observed, for all countries. The intensity of this trend is again heterogeneous across countries.

[24]See e.g. Fortin and Lemieux (2016).

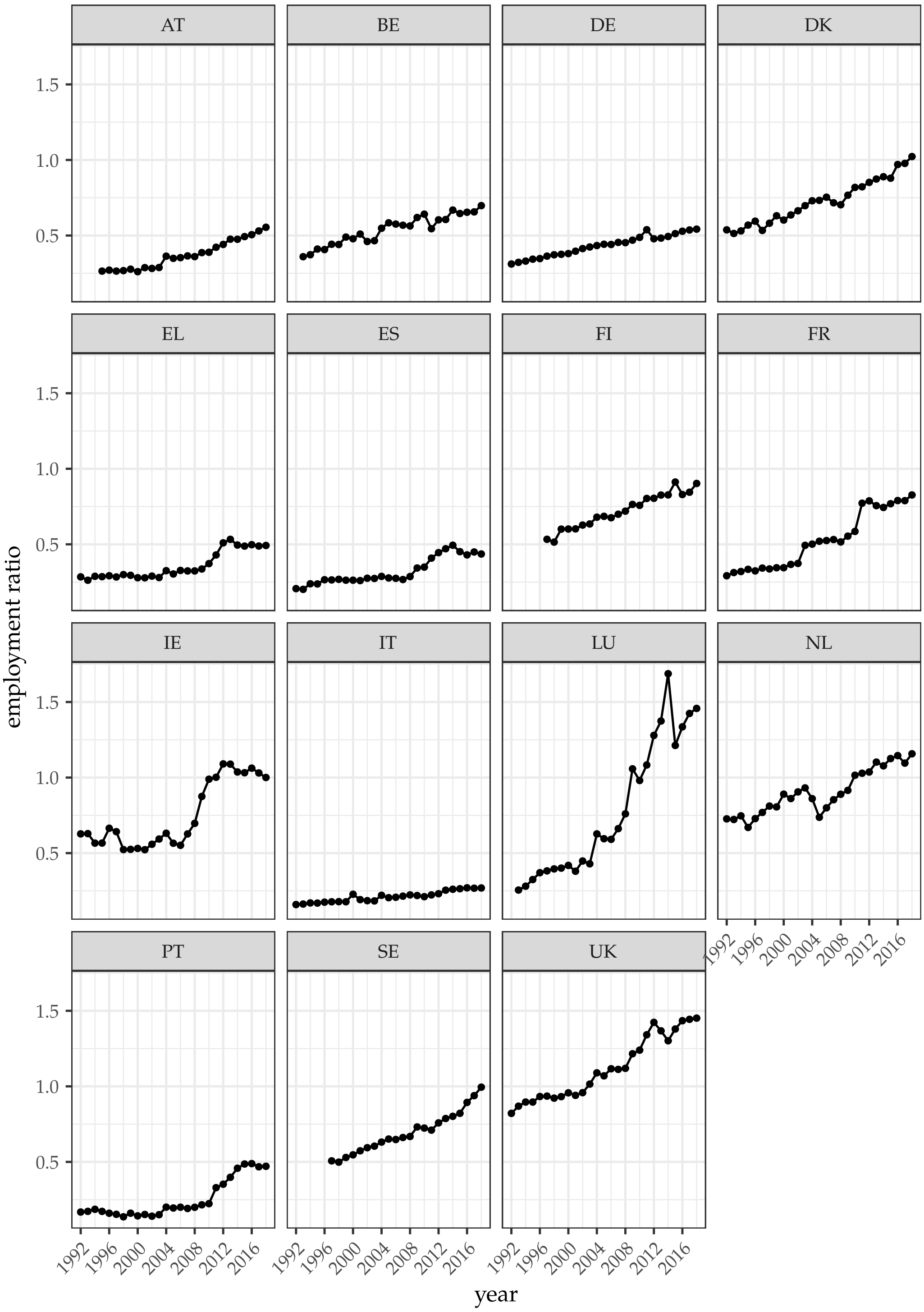


Figure 4.2: First component of job polarization captured by the ratio of high- to middle-skill employment, 1992-2018

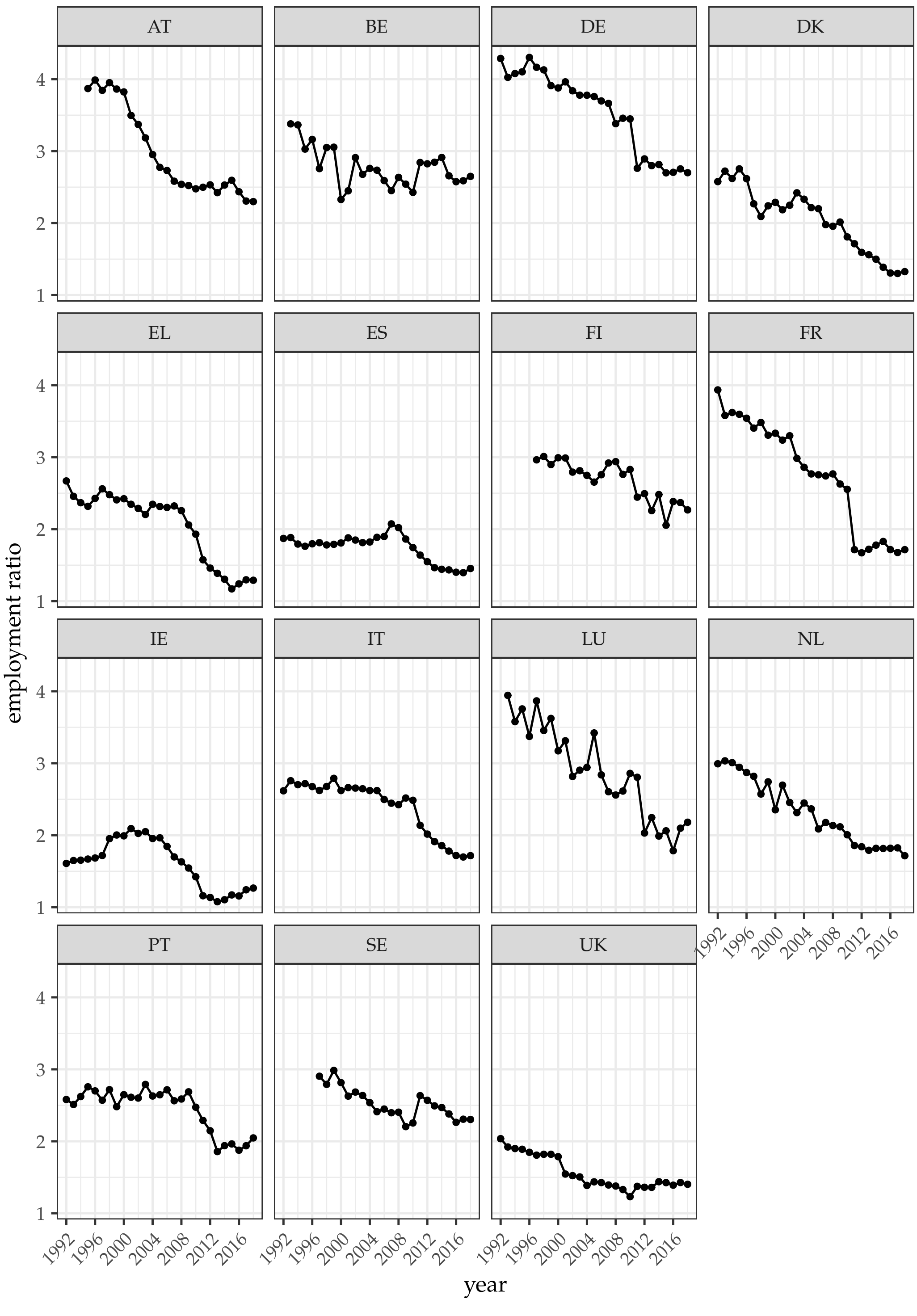


Figure 4.3: Second component of job polarization captured by the ratio of middle- to low-skill employment, 1992-2018

4.3.2 Measure of institutionalization

'Institutionalization' is a polymorphic and extended concept, and requires to be narrowed and properly defined before being quantified. Pettinger (2021) adopts a definition based on Hall and Soskice (2001), who define institutions as "a set of rules, formal or informal, that actors generally follow, whether for normative, cognitive or material reasons." Markets are therefore a specific type of institutions, which are "marked by arm's length relations and high levels of competition" and embedded in a "legal system that supports formal contracting and encourages relatively complete contracts" (Hall and Soskice, 2001). Pettinger (2021) defines institutions as institutions — in the sense of Hall and Soskice (2001) — which are not of the 'market' type. They thus include standard labor market institutions such as collective bargaining and employment protection legislation, but are not limited to these.

In this paper, we somehow narrow this definition by adopting an exhaustive version of it. We follow the AIAS ICTWSS database[25] by focusing on trade unions, wage setting, state intervention and social pacts characteristics. In an alternative version of this definition, we also include active labor market policies.

Two major problems are associated with the direct inclusion of ICTWSS variables in our panel regression setting. First, there are many variables that could have an impact on the evolution of the occupational structure, implying either a selection or a dimensionality problem. Second, some of these variables are ordered categorical variables. While they can be converted to numerical indices, some of them only vary slightly over time.

The strategy we adopt to solve the two aforementioned problems is to summarize these variables into a composite index. There are several ways of combining these variables (i.e. determining their weights), but our underlying objective of maximizing variance suggests that principal component analysis (PCA) is a good candidate. This is the strategy used by Baccaro and Howell (2017) when they quantitatively study industrial relations change in Europe. We first select a subset of variables that we consider as relevant[26] and estimate the principal components on a country basis in order to capture country-specific institutional complementarities and trends. Our baseline version[27] of the resulting composite index (that is, the first principal component) of institutionalization is presented in Figure 4.4. It is important to note that the sign of this principal component is completely arbitrary (see e.g. Jolliffe, 2002): for countries where the trend does not follow what seems to be the dominant trend for the original variables, the sign can just be reversed. Note that from visual inspection, it appears that these series are trended, a trend that we assume stochastic.

[25]Recently relabeled as the OECD/AIAS ICTWSS database. See Visser (2019).

[26]See Appendix 4.B for further details.

[27]Other versions can be obtained, depending on the variables used and the adjustment operated on some of them. See Appendix 4.B for further details.

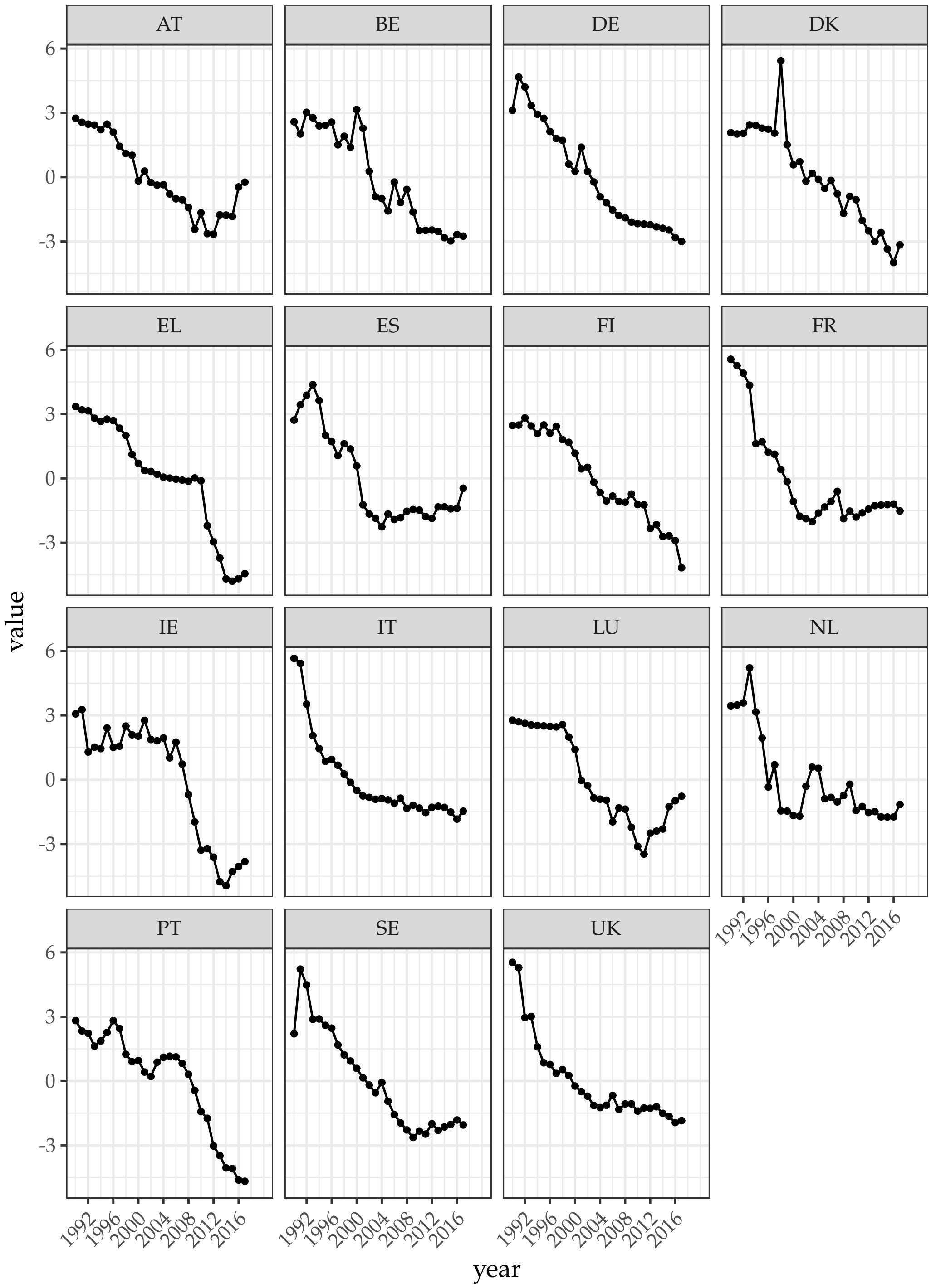


Figure 4.4: Composite index of institutionalization, 1990-2018

4.3.3 'Standard' explanatory variables of the RBTC approach and variables used in our analysis

As already mentioned in the introduction, two important papers testing for the causes of job polarization using panel data are Goos, Manning and Salomons (2009, 2014). Their strategy is to regress a country-*job*[28]-year measure of labor demand (hours worked) on several explanatory variables derived from the RBTC theory. Following notably Autor and Dorn (2013) (for the RTI) and Blinder and Krueger (2013) (for the offshorability index), they build a measure of routine task content[29] and compute the value of an offshorability index for each occupational category. Since these measures are occupation-specific, they induce time-variability by interacting them with a linear time trend. Other regressors include log-wage, which is country-occupation-year specific, and education level. They find that the Routine Task Index (RTI) has a strong negative impact on labor demand, while offshorability has a limited negative impact. Note that contrary to Goos, Manning and Salomons (2009), Goos, Manning and Salomons (2014) exclude wages from their baseline model.[30]

Since we are working with country-year units of observation, mainly because of the institutional variables, we cannot implement the same type of specification as Goos, Manning and Salomons (2009, 2014). However, we would like to somehow control for the impact of technical change, internationalization and relative wages. We describe the variables used in the rest of this section. Note that for data relative to employment and for aggregated measures based on microdata, we restrict our sample to men aged from 16 to 65, for the reasons mentioned earlier in this section.

Offshorability. The offshorability index introduced by Blinder and Krueger (2013) and implemented by Goos, Manning and Salomons (2009, 2014) is occupation-specific and requires being interacted with a deterministic trend to exhibit time variation. As an alternative, we use the country-year specific value of trade in goods and services, expressed as a percentage of GDP and provided by the OECD. The assumption underlying this choice is that the more a country is exposed to trade, the higher the incentives and the possibility to offshore occupations with a high share of routine tasks content. Note that in the remainder of this paper, this variable is denoted by *trade*.

Technical change. As already emphasized and justified in Section 4.2, we exclude linear time trend from our specification. We rather control for technical change through its assumed impact, namely the increasing demand for high-skill relative to middle-skill workers. For each country and each year, we compute the number

[28] Goos, Manning and Salomons (2009) define jobs as occupational categories, while Goos, Manning and Salomons (2014) consider jobs as occupation-industry cells and thus make use of variation by country-occupation-*industry*-year. For the sake of completeness, note that Goos, Manning and Salomons (2014) also set up a theoretical model in order to estimate structural parameters and predict employment polarization following technical change, both within and between industries.

[29] Based on the occupational content in terms of tasks.

[30] One of the reasons they give is the poor quality of wage data by country, occupation and time. The other reason is the potential endogeneity of these wages.

of employed workers with a tertiary degree and the number of workers with a secondary degree using EU-LFS microdata, and we take the ratio of the former to the latter. We also compute this ratio for all individuals, not only the currently (self-)employed workers. This is particularly useful for identifying structural shocks in the IRF analysis. Note that in the remainder of this paper, this variable is denoted either by *HovM*, either by *education ratio*.

Relative wages of the different skill groups. Individual wage data can be obtained from the ECHP and EU-SILC datasets. However, the required information to build the relative wage measures are missing for some countries and some years, leading to (strongly) unbalanced panels. Given the size of our sample and the approach we adopt, we choose to exclude relative wages from our analysis. We nonetheless capture part of the RBTC-induced downward pressure on the wage of middle-skill workers by including the ratio of employed workers with a tertiary degree to the workers with a secondary degree, as mentioned earlier. Following the RBTC rationale, the latter are also the most likely to end up unemployed, participating to the downward pressure on their wage. We thus additionally control for the unemployment rate of men aged from 15 to 64, a variable provided by the OECD. In the remainder of this paper, this variable is denoted by *UR*.

Additionally to the variables previously mentioned, we also control for GDP, which could eventually capture the increase in demand for both high- and low-skill services relative to middle-skill tasks.

4.4 Implementation and results

4.4.1 Panel unit root tests

We implement the Im, Pesaran and Shin (2003) (IPS) panel unit root test, introduced in Section 4.2, in order to verify that our variables[31] are $I(1)$, i.e. integrated of order one.

Table 4.1 shows that the null hypothesis that *all* panel contain unit roots can only be rejected for the GDP variable, and only at $p = 0.10$. This variable is however usually assumed as trended. We thus conclude that for all panels, none of these variables are stationary.

To determine the order of integration of these variables, we apply the IPS test on their first-difference (FD). We can see from Table 4.1 that for all variables and all panels, the null hypothesis can be rejected. While the alternative hypothesis is that *some* panels are stationary, we extend this conclusion to all panels. Since first-differencing our non-stationary variables makes them stationary, we conclude that these variables are $I(1)$, i.e. integrated of order one.

[31] As previously mentioned, we adopt the following notation: *jobsHovM* is the ratio of high- to middle-skill jobs, *jobsMovL* is the ratio of middle- to low-skill jobs, *institutionalization* or *instit* is our composite index of institutionalization, *HovM* is the ratio of tertiary- to secondary-educated workers, *trade* is the value of trade in goods and services expressed as a percentage of GDP, *UR* is the unemployment rate and *lgdp* is the log of GDP.

Table 4.1: Results of the IPS tests

	Original		FD	
Variable	**Statistic**	**p-value**	**Statistic**	**p-value**
jobsHovM	5.88	1.0000	-10.13	0.0000
jobsMovL	2.90	0.9981	-10.23	0.0000
institutionalization	0.74	0.7716	-10.18	0.0000
HovM	3.82	0.9999	-11.94	0.0000
trade	3.04	0.9988	-10.60	0.0000
UR	-0.25	0.3998	-6.38	0.0000
lgdp (log GDP)	-1.39	0.0824	-5.21	0.0000

4.4.2 Panel cointegration tests

For the reasons mentioned in Section 4.2, we use the Pedroni (1999, 2004) tests based on ADF regressions to see whether our variables of interest are cointegrated. The first of these tests is based on "between-dimension" (or "group-mean") statistics. These (pooled) statistics are based on estimators which "average the individually estimated coefficients for each member *i*" (Pedroni, 1999), and thus allow for panel-specific autoregressive parameters. The second, on the other hand, is based on "within-dimension" (or "panel cointegration") statistics, which are "based on estimators that effectively pool the autoregressive coefficient across different members for the unit root tests on the estimated residuals" (Pedroni, 1999).

We test two different 'specifications' for each occupational-group employment ratio (i.e. the two potential components of job polarization): one minimalist, and the other including the two additional controls mentioned in Section 4.3. The results of the tests are presented in Table 4.2.

Table 4.2: Results of the Pedroni (1999, 2004) tests based on ADF regressions

	Group mean		Panel coint.	
Specification	**Statistic**	**p-val**	**Statistic**	**p-val**
jobsHovM instit HovM trade	-3.1044	0.0010	-1.8376	0.0331
jobsHovM instit HovM trade UR lgdp	-3.5129	0.0002	-1.1409	0.1270
jobsMovL instit HovM trade	-4.2272	0.0000	-3.8026	0.0001
jobsMovL instit HovM trade UR lgdp	-3.6691	0.0001	-3.5733	0.0002

With the notable exception of the panel cointegration test for the second specification, all tests reject the null hypothesis of no cointegration, as shown in Table 4.2. It is thus safe to conclude that all panels are cointegrated, whichever the occupational-group employment ratio considered. We can now proceed to the estimation of the long-run relationship between these ratios (and by extension job polarization), assuming an homogeneous cointegrating vector and controlling for endogeneity.

4.4.3 Cointegrating vector estimation

In this section we estimate the (normalized) cointegrating vector representing the long-run relationships between our variables of interest. We use the PDOLS estimator introduced and studied by Kao and Chiang (2000) and Mark and Sul (2003). We implement the estimation procedure suggested by Mark and Sul (2003) and described in Section 4.2 of this paper. We compare these estimates with the ones obtained using the within-OLS estimator, which has a non-negligible bias in finite samples (Kao and Chiang, 2000).

Table 4.3 present the results for the first component of job polarization. Point estimates indicate that a decrease in institutionalization is accompanied by the first component of job polarization, i.e. an increase in the ratio of high- to middle-skill jobs, as predicted by DP2021. For the second (extended) specification of the model, correcting for endogeneity leads to a substantially higher estimate of this long-run equilibrium relationship. However, the PDOLS version of the Wald test fails in rejecting the null hypothesis that this relationship is different from zero. As detailed later, the bootstrapped error bands of the IRF analysis nonetheless suggest that there actually exists a structural negative reaction of the first component of job polarization to a positive shock in institutionalization.

Table 4.3: Estimation of cointegrating vectors (dependent variable: ratio of high- to middle-skill jobs)

	Within-OLS				Panel DOLS			
	(1)		(2)		(1)		(2)	
	Coef.	$P > \|t\|$	Coef.	$P > \|t\|$	Coef.	$P > \chi^2$	Coef.	$P > \chi^2$
Instit.	-0.0136	0.0000	-0.0125	0.0000	-0.0148	0.8952	-0.0195	0.9453
Edu. Ratio	0.6481	0.0000	0.6339	0.0000	0.7258	0.0000	0.7621	0.0000
Trade	0.5429	0.0000	0.5395	0.0000	0.4648	0.0000	0.5793	0.0000
UR			0.0166	0.2748			-0.0298	0.6434
log GDP			0.0197	0.7047			-0.1822	0.0000

The positive relationship between the first component of job polarization and the ratio of high- to middle-skill (employed) workers is more mechanical since we do not expect workers with a secondary degree to easily access occupations with high-skill requirements.[32] To make this relationship less trivial, we also consider the ratio of high- to middle-skill individuals, independently of their employment status. Results are presented in Table 4.4. Note that in the OLS case, changing the definition of this variable leads to a substantially higher estimated relationship between the first component of job polarization and the unemployment rate. In the PDOLS case, it changes the sign of this relationship, which becomes the same as in the OLS case. This relationship is nonetheless not significantly different from zero.

As expected, an increased exposure to trade is associated with the first component of job polarization, notably for the reasons mentioned in Section 4.3.

Results for the second component of job polarization are presented in Table 4.5. In line with the predictions of DP2021, a decrease in institutionalization of the

[32] This is especially true when educational attainment is the main recruitment criterion.

Table 4.4: Estimation of cointegrating vectors (dependent variable: ratio of high- to middle-skill jobs; education ratio independent from employment status)

	Within-OLS				Panel DOLS			
	(1)		(2)		(1)		(2)	
	Coef.	$P > \|t\|$	Coef.	$P > \|t\|$	Coef.	$P > \chi^2$	Coef.	$P > \chi^2$
Instit.	-0.0117	0.0000	-0.0095	0.0048	-0.0131	0.9425	-0.0135	0.9567
Edu. Ratio	0.6466	0.0000	0.6199	0.0000	0.8362	0.0000	0.8082	0.0000
Trade	0.6484	0.0000	0.6433	0.0000	0.5265	0.0000	0.6384	0.0000
UR			0.0547	0.0008			0.0315	0.5847
log GDP			0.0131	0.8202			-0.1245	0.0000

labor market is accompanied by the second component of job polarization, i.e. a decrease in the ratio of middle- to low-skill jobs. As for the first component of job polarization, correcting for endogeneity in the extended specification leads to an increase (in absolute value) in the point estimate of the long-run equilibrium relationship between the two variables.

The ratio of high- to middle-skill workers is supposed to capture the evolution of the equilibrium relationship between the relative supply and demand of high- and middle-skill workers, and the consequent evolution of their relative wage. An increase in this ratio is supposed to lead to a downward pressure on middle-skill wages, favoring their redirection towards low-skill jobs and thus to the second component of job polarization. The estimated cointegrating vector clearly confirms this relationship. The estimated long-run relationship between exposure to trade and the ratio of middle- to low-skill jobs is negative, which is in line with the idea that an increase in the former favors the offshoring of middle-skill jobs and/or the redirection of middle-skill workers towards low-skill interpersonal services, which are — by definition — hardly offshorable.

Table 4.5: Estimation of cointegrating vectors (dependent variable: ratio of middle- to low-skill jobs)

	Within-OLS				Panel DOLS			
	(1)		(2)		(1)		(2)	
	Coef.	$P > \|t\|$	Coef.	$P > \|t\|$	Coef.	$P > \chi^2$	Coef.	$P > \chi^2$
Instit.	0.0902	0.0000	0.0818	0.0000	0.0817	0.0704	0.1066	0.0724
Edu. Ratio	-1.0397	0.0000	-0.9073	0.0000	-1.1446	0.0000	-0.9996	0.0000
Trade	-0.7791	0.0000	-0.7586	0.0000	-0.8069	0.0000	-1.1840	0.0000
UR			-0.1508	0.0157			0.0215	0.1701
log GDP			-0.1490	0.4872			0.7209	0.0000

4.4.4 PVAR and structural IRF analysis

Our preferred specification for the 3-variable VAR is the one which assumes the following recursive structure:

$$\begin{bmatrix} u_{it}^{edu} \\ u_{it}^{instit} \\ u_{it}^{pol} \end{bmatrix} = \begin{bmatrix} b_{11} & 0 & 0 \\ b_{21} & b_{22} & 0 \\ b_{31} & b_{31} & b_{33} \end{bmatrix} \begin{bmatrix} e_{it}^{edu} \\ e_{it}^{instit} \\ e_{it}^{pol} \end{bmatrix}. \tag{4.15}$$

Since we consider the ratio of tertiary to secondary educated individuals for the whole (not just employed or self-employed workers) sample of men aged from 16 to 65, we assume that changes in this variable have deep institutional and societal roots. We consequently suppose that this variable cannot be impacted contemporaneously by unexpected changes in the others. Institutionalization of the labor market can also be considered as sluggish (for the reasons given in Section 4.2), but we assume that it will more likely be impacted directly by the educational composition of the population than the reverse. Finally, we assume that the occupational structure responds contemporaneously to the two other variables: firms adjust more quickly their occupational structure to institutional change than institutions react to such adjustments. The potential responses of the first (second) component of job polarization in the case of a (partially) recursive structure are presented in Figure 4.5 (Figure 4.6).

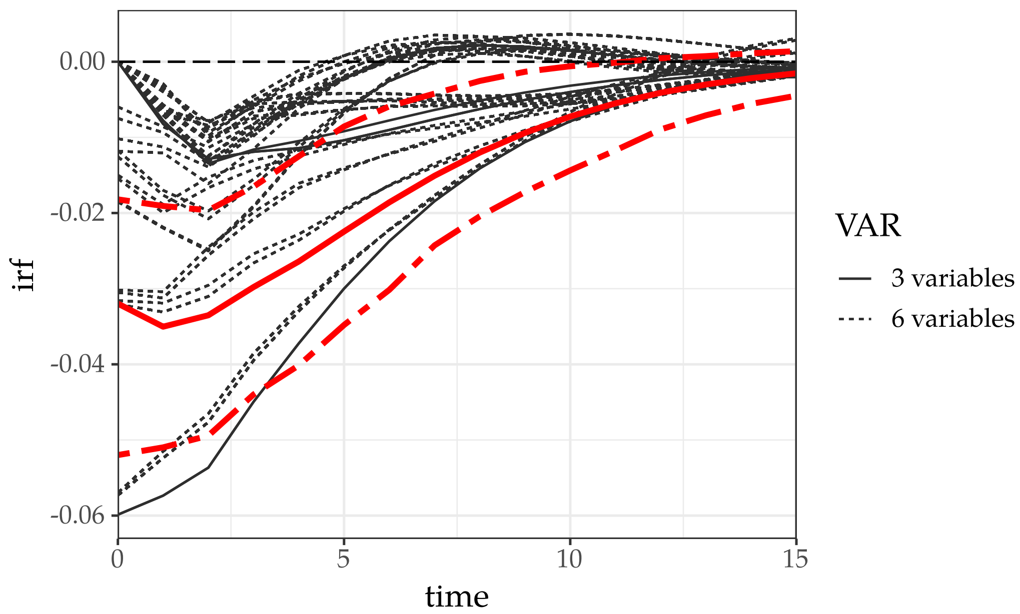


Figure 4.5: Response of the first component of job polarization to an institutional shock

The impulse response function corresponding to our preferred specification appears in red in figures 4.5 and 4.6. For this specification, we also include the upper and lower bounds (red dashed lines) of bootstrapped error bands, considered at the 0.95 confidence level. We also present the point estimates for all the other possible orderings of the three variables (solid black lines). In the same figures we include the results for all possible orderings of the 6-variable VAR (dashed black lines). Let us recall that we cannot be sure that there actually exists a relevant block of recursive equations allowing to structurally interpret one of these responses. However, since their shape is relatively similar to the one of our preferred specification,

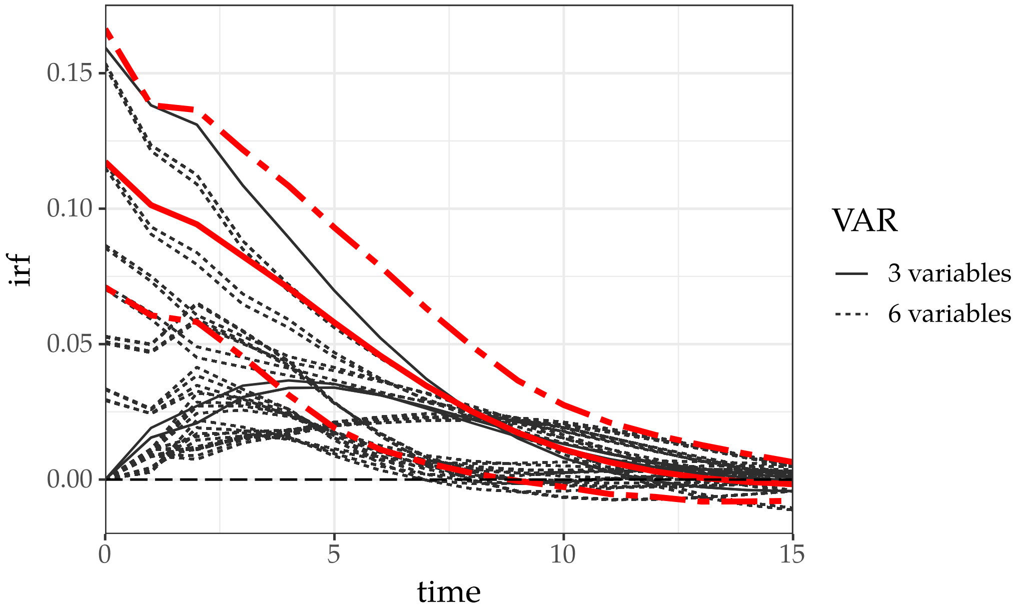


Figure 4.6: Response of the second component of job polarization to an institutional shock

which we assume structurally interpretable, this makes us more confident about its plausibility.

Figure 4.5 tells us that a positive shock in the level of institutionalization has a negative impact on the ratio of high- to middle-skill jobs, at least in the short-run if we consider the responses derived from the 6-variable VAR. Our structurally interpretable specification even reveals a non-negligible negative impact, which slowly dies out with time. In other words, de-institutionalization fosters the first component of job polarization.

The results in Figure 4.6 also confirm the predictions of DP2021: a positive shock in the level of institutionalization leads to an increase in the ratio of middle- to low-skill jobs. The impulse response function of our structurally interpretable specification indicates again a non-negligible impact, which slowly dies out with time. On the basis of our preferred specification, we can thus conclude that de-institutionalization fosters the second component of job polarization.

4.5 Concluding remarks

In this paper, we have tested the predictions of the DP2021 model, according to which institutions inhibit the SBTC-induced phenomenon of job polarization. Using a panel dynamic OLS estimator in order to correct for endogeneity, we first empirically assessed the long-run relationship between employment polarization and a composite index of institutionalization. Our results indicate that de-institutionalization is accompanied by both the first and the second component of job polarization, in line with the predictions of DP2021. While the PDOLS version of the Wald test fails to reject the null hypothesis that there is no long-run equilibrium relationship between institutionalization and the first component of job polarization, our structural impulse response analysis indicates that there exists a significant relation between the two. Using a recursive identification scheme, we isolated structurally interpretable exogenous shocks in institutionalization. We then studied the response of both components of polarization to such shocks, and found that de-institutionalization fosters polarization.

By using two linked but nonetheless distinct frameworks, we have been able to empirically document the long-run equilibrium relationship implied by DP2021 and to confirm its causal interpretation. The latter requires to impose some structure on the data generating process, which in our case took the form of recursive exclusion restrictions. While such restrictions are sustainable in the case of a 3-variables VAR, there are less plausible when a larger system is considered. A potential solution to this problem consists in set identifying the shocks by imposing a mix of sign and exclusion restrictions on the related impulse responses, at different horizons. After having built orthogonal shocks satisfying the exclusion restrictions, only the shocks leading to impulse responses satisfying the sign restrictions are kept. While this approach avoids imposing a controversial (partial) recursive structure on large systems, it certainly cannot be considered as agnostic since the aforementioned restrictions are mainly theory-driven. This approach is particularly attractive in fields where the structural interpretation of shocks has been widely discussed, such as monetary policy analysis. Implementing such set-identification strategy is less straightforward in our case, notably since the relationships between institutions, occupational structure and other key variables have not been extensively modeled. While we tried to implement such approach using a minimal set of restrictions, our results were inconclusive and we decided to stick to a more 'traditional' identification scheme. Therefore, an interesting path for further research would be to develop and test identification schemes implying a mix of sign and exclusion restriction. This would imply a more detailed modeling of the (causal) mechanisms linking institutions, occupational structure and the other key explanatory factors mentioned earlier.

Appendix 4.A Measures of the two components of job polarization

The two components of job polarization are the decrease in the employment share of middle-skill relative to low-skill jobs and the increase in the employment share of high-skill relative to middle-skill jobs. Measuring these two components thus requires to define low-, middle- and high-skill jobs and to determine the employment share of each category.

EU-LFS datasets provide information on the occupational classification of the surveyed workers. The classification used in the EU-LFS for the period covered by our analysis is the International Standard Classification of Occupations (ISCO), which does not directly provide a ranking of occupational categories. These ISCO categories can however be mapped to the socio-economic groups defined by the European Socio-economic Groups (ESeG) classification, which allows to rank jobs according to the level of skill and sector of activity (see e.g. Peugny, 2019). For the employed workers, these groups are:

1. Managers
2. Professionals
3. Technicians and associated professionals employees
5. (a). Clerks
5. (b). Skilled service employees
6. Industrial skilled employees
7. Less skilled employees

The ESeG classification can thus be used as a job quality index, that we use in turn to order occupational categories in terms of skill requirements. Our implementation of the mapping between ISCO categories and ESeG groups is based on several sources, which include the reports and the supplemental material provided by the ESSnet project, but also Peugny (2016) and the related online appendices.

We group (some of) these ESeG categories to create three skill groups. We then compute the number of employed workers in each of these groups, and take the ratio of high- to middle-skill workers and the ratio of middle- to low-skill workers. Figures 4.A.1 and 4.A.2 show the results for different definitions of these ratios. In our baseline specification, we define high-skill jobs as ESeG categories 1 and 2, middle-skill jobs as ESeG categories 5a and 6, and low-skill jobs as ESeG category 7. The resulting employment ratios are denoted by *r12ov5a6* for the ratio of high- to middle-skill jobs and *r5a6ov7* for the ratio of middle- to low-skill jobs. From visual inspection of figures 4.A.1 and 4.A.2, it clearly appears that other definitions of the skill groups lead to very similar trends as the one observed in the baseline case.

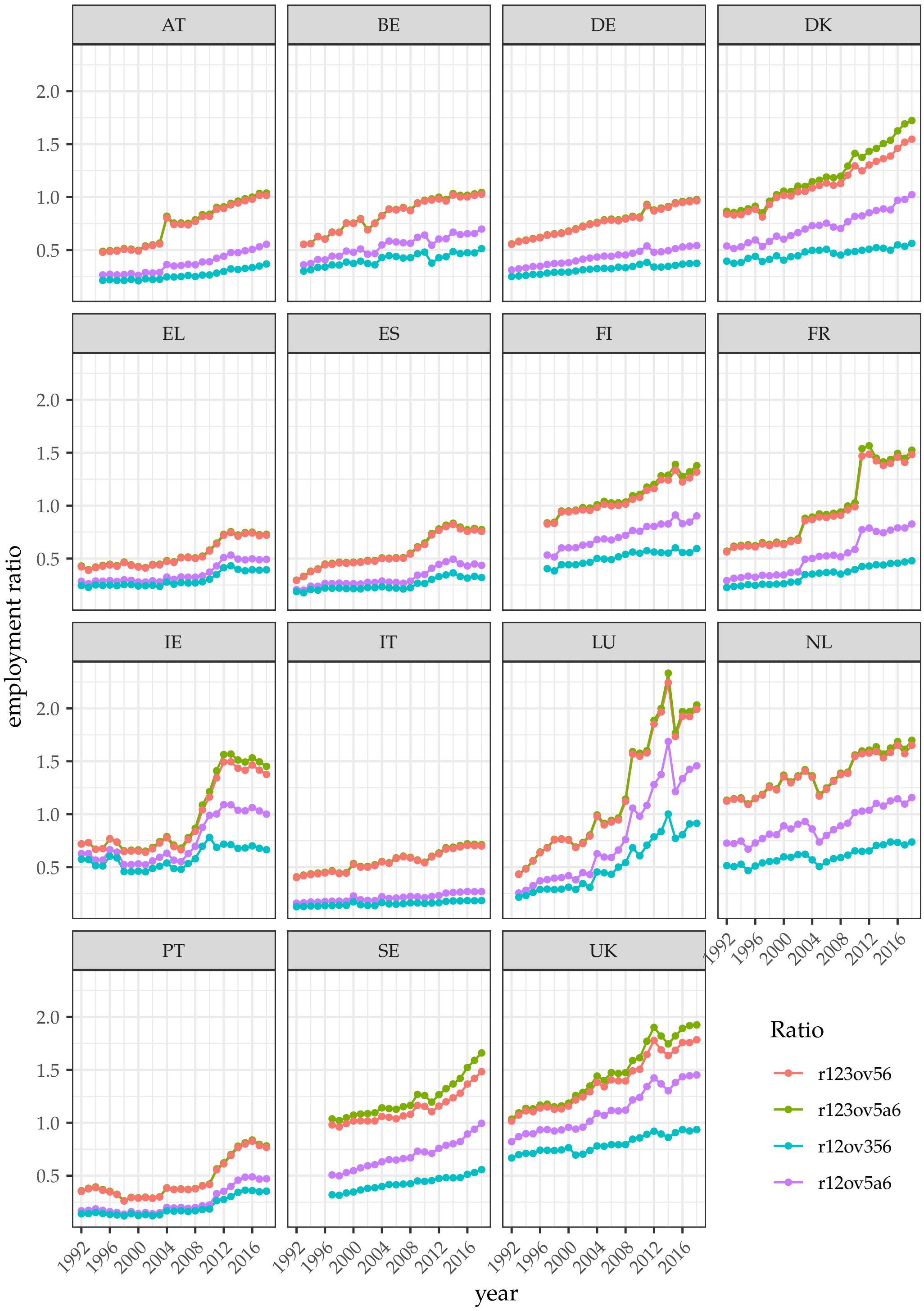


Figure 4.A.1: Different measures of the first component of job polarization, 1992-2018

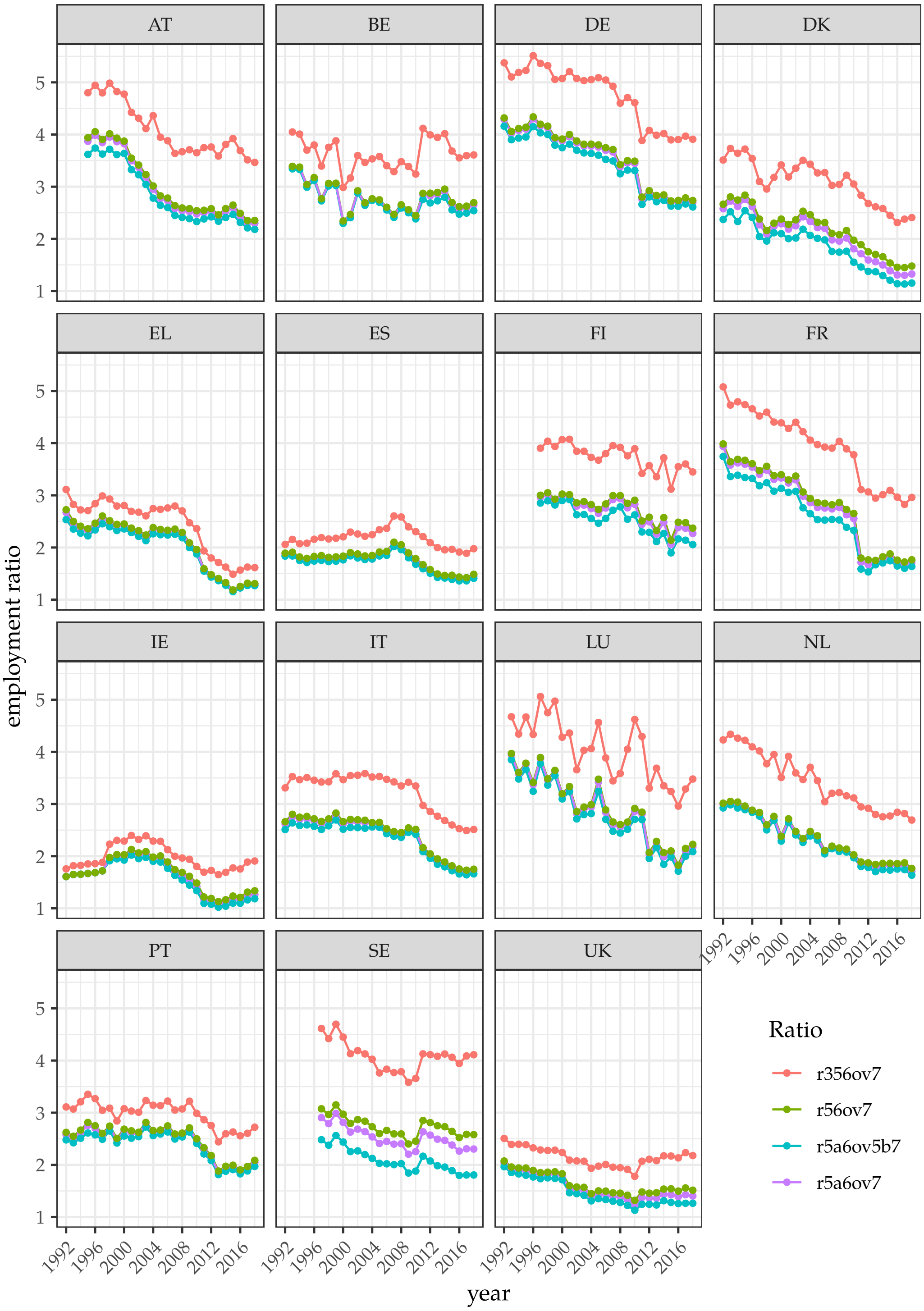


Figure 4.A.2: Different measures of the second component of job polarization, 1992-2018

Appendix 4.B Composite index of institutionalization

To build our composite index of institutionalization, we linearly combine variables from a selected set of the institutional variables available in the ICTWSS database. Our baseline set is composed of the following variables:

- *AdjCov*: Adjusted bargaining (or union) coverage rate
- *UD*: Union density rate
- *Coord*: Coordination of wage-setting
- *EXT*: Mandatory extension of collective agreements to non-organised employers
- *ETNUnions*: Effective number of unions = Effective number of union confederations × Effective number of affiliates of confederation 1
- *ShCF1*: Membership share of confederation 1
- *CENT*: Summary measure of centralization of wage bargaining
- *ALL*: All pact and (central) agreements signed in a given year
- *Govint*: Government intervention in wage bargaining
- *Level.M*: Index of multi-level bargaining (actual level of wage bargaining in a multi-level bargaining system)
- *PACTSTRUCT*: Pact or agreement is negotiated by all or some of the (possible) actors

Some of them are nominal variables. We recode them in such a way that they constitute meaningful ordered categorical variables which can be converted to numerical indices. Missing values are imputed by using a linear interpolation procedure implemented on a country basis.

The weight for each variable is determined using principal component analysis (PCA), which allows to maximize the variance of the resulting composite index. In order for the latter to reflect both the country-specific trend in the overall level of institutionalization and the country-specific complementarity of institutional characteristics, we implement PCA on a country basis.

Figure 4.B.1 shows different versions of this index, which differ according to the subset of institutional variables used in the PCA and to the adjustments made to these variables. While these versions do not completely overlap, they clearly share a similar shape. Note that we transformed some of them by reversing their sign. This allows to recover the downward trend exhibited by all the other versions of the index and by core ICTWSS institutional variables. This transformation is innocuous since, as highlighted notably by Jolliffe (2002), the sign of a principal component is completely arbitrary.

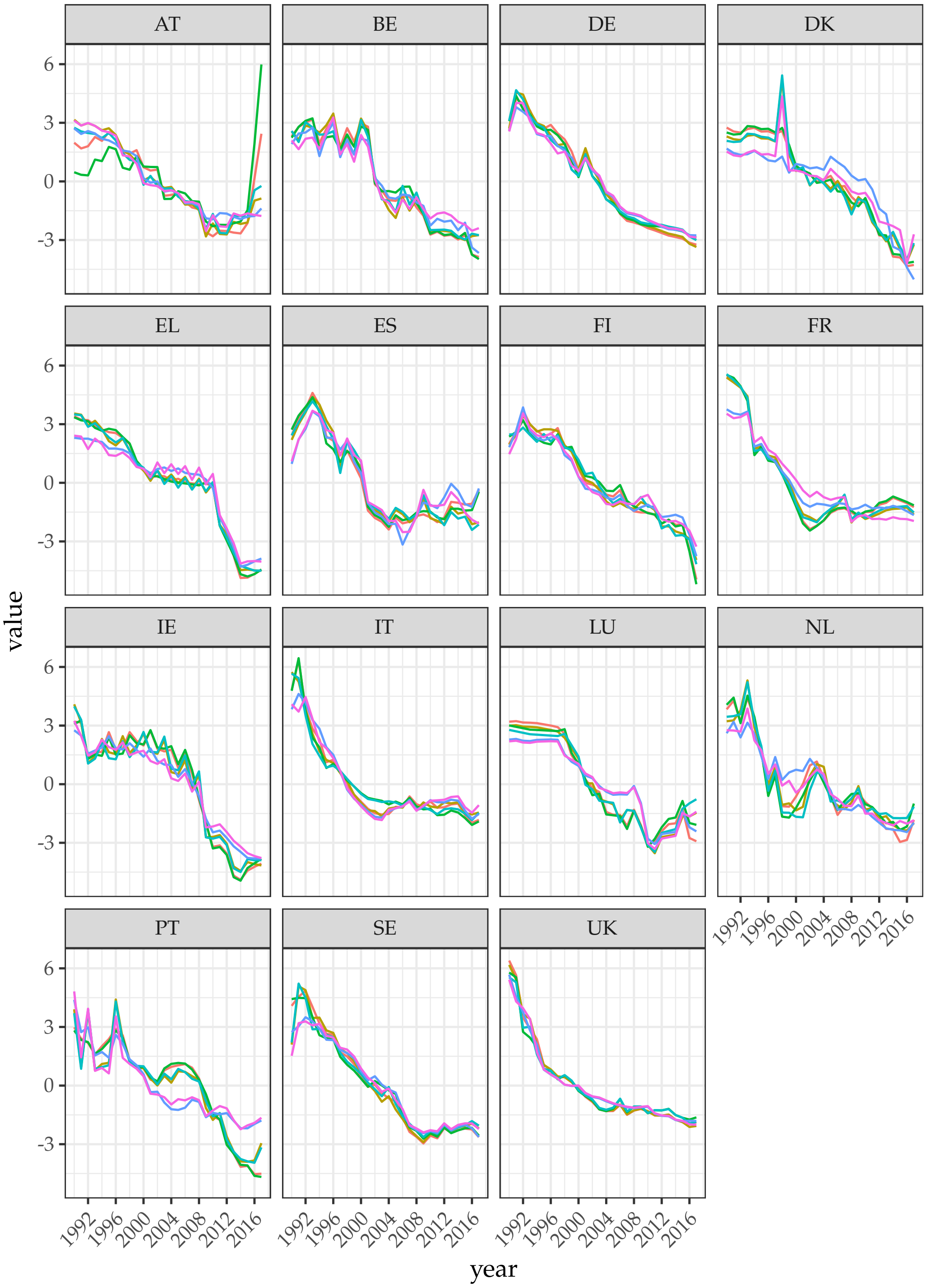


Figure 4.B.1: Different versions of our composite index of institutionalization

Chapter 5

Conclusion

This dissertation sequentially shows that the impact of technical change on the dynamics of jobs and wages is mediated by institutions. While the routine-biased technical change (RBTC) approach predicts a polarized response of the distribution of wages and jobs to technological progress, we show that this response depends on the institutional configuration considered. Since institutionalization mitigates labor market polarization, institutional differences can partially explain cross-country differences in the latter phenomenon.

In the second chapter, we use (augmented) decomposition methods and the difference in institutionalization between sectors to show that institutions can attenuate — and even counteract — the technologically-induced phenomenon of wage polarization. We isolate their impact on the aggregate wage structure effect and observe that in the majority of the countries studied, this impact mitigates at least one of the two components of wage polarization. We then use an augmented version of the Firpo, Fortin and Lemieux (2018) detailed decomposition method to show that institutional forces partially mute the impact of technical change through the channel of the pricing of skills.

In the third chapter, we make use of the previous results to include institutions in a Ricardian model of the labor market *à la* Acemoglu and Autor (2011). Institutions are modeled in such a way that the model is able to predict the mitigation of wage polarization observed in the second chapter. We then use this model to predict the impact of institutions on job polarization. According to our model, the RBTC-induced polarization of employment is less important in a highly institutionalized wage-setting process than in the case where institutions are weak.

In the fourth chapter, we test our model's prediction about the impact of institutions on job polarization. In the first part of our analysis, we use panel cointegration techniques to show that there exists a long-run equilibrium relationship between institutionalization of the labor market and job polarization. This relationship is such that a decrease in institutionalization is accompanied by an increase in employment polarization. In the second part of our analysis, we tackle the potential reverse-causality problem by adopting a system setting. More precisely, we use panel vector autoregressive modeling and structural impulse response analysis to empirically test for the causal interpretation induced by the model developed in the third chapter. We conclude from this exercise that de-institutionalization fosters employment polarization.

Our findings have non-negligible policy implications. They notably imply that a government can undertake institutional reforms in order to foster or inhibit labor market polarization. This is partly due to the fact that institutions change the skill-specific cost of labor, which in turn has an impact on the optimal allocation of skills to tasks. An example of institutional reform favoring polarization would be an extreme decentralization of the collective bargaining process. The second chapter of this dissertation even indicates that a 'simple' policy of public hiring could have an impact on the degree of wage polarization. Institutional reforms could also affect the (un)employment rate, which could in turn impact the degree of polarization of the labor market. While such a mechanism is not investigated in our analysis, it would certainly be an interesting subject of further research.

The detailed mechanisms through which institutions determine job polarization could and should be the object of further investigation. The mechanism implied by the model of the third chapter is related to the fact that low- and middle-skill workers must be paid at a level which is higher than their marginal productivity. Since the model does not allow for unemployment, firms cannot directly avoid this constraint, and they consequently choose to allocate these types of workers to jobs for which their task-specific productivity is the highest. A desirable extension of this model would be to allow for unemployment to be one of the adjustment variables. In that case, following technical change, institutional forces could potentially redirect low- and middle-skill workers towards unemployment, limiting the creation of low-skill jobs. On the other hand, it is possible that institutionalization actually increases the (unobserved) skills of these workers, notably by favoring training programs. It would be interesting to explicitly model such a behavior and its impact on the true level of the workers' skills.

Central to this thesis is the idea that institutions shape the impact of technical change on the distribution of jobs and wages. It would therefore be interesting to consider explicitly the interaction between these institutions and technical change, in the same spirit as Blanchard and Wolfers (2000) who find that the interaction between shocks and institutions is crucial to explain cross-country differences in the rise of unemployment. Another engaging exercise would be to consider the impact of institutionalization for different groups of countries, defined according to common institutional characteristics and complementarities, in the spirit of the *Varieties of Capitalism* approach. Rather than focusing exclusively on the level of institutionalization, this would allow to consider the impact of qualitatively defined institutional regimes. Note that the latter do not need to be defined — and thus postulated — prior to the econometric analysis. As pointed out by Boyer (2004), there exist methods which allow to reveal these different regimes. Such methods are based on the fuzzy-set analysis for social sciences developed by Ragin (1987, 2008). While this approach is non-standard in the field of economics, it could constitute a compelling starting point for the type of analysis previously suggested.

Taxes are institutional devices which have not been explicitly studied in this thesis. However, income taxes can lead individuals to change the type of jobs they accept (Feldstein, 1995; Dupuy et al., 2020) and can thus affect the occupational structure. They can even have an impact on pre-tax wages (Kubik, 2004; Saez, Slemrod and Giertz, 2012), and thus on the wage structure, potentially affecting wage polarization. Income taxes are not the only taxes impacting pre-tax wages. There is also evidence that corporate tax rates have an incidence on gross wages (Suárez Serrato and Zidar, 2016; Fuest, Peichl and Siegloch, 2018), thus potentially impacting the occupational structure. We are currently working on the link between taxes and labor market polarization, and we are convinced that it constitutes a promising area of research. Note that the same could be said about the different types of active labor market policies, that we only considered in terms of public expenditure, and through a composite index of institutionalization.

Finally, we follow the lead of the literature on labor market polarization by modeling technical change as exogenous. An interesting path for further research would be to study this phenomenon in the context of endogenous technological progress. While institutions mitigate its impact when it is assumed exogenous, they could also shape technical change and the way it is implemented. The basic idea would be to extend the Acemoglu (2003) model of differential technology responses to a framework allowing for polarization of jobs and wages. We strongly believe that including the impact of institutions in such models will contribute substantially to our understanding of cross-country differences in labor market polarization.

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