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RESEARCH

Earnings inequality patterns: A comparative analysis of France, Italy, Portugal and Spain

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Abstract

In recent decades, inequality has become a central concern in both academic research and policy debate. This paper examines gross individual earnings inequality among employed workers in four European countries – France, Italy, Portugal, and Spain – using EU-SILC microdata for 2010, 2014, and 2019. Rather than relying on a single indicator of inequality or a narrow set of explanatory variables, we adopt a multidimensional empirical framework that considers multiple inequality measures and integrates a broad range of hypothesized correlates within a unified analytical setting. Methodologically, we combine Recentered Influence Function (RIF) regressions with a RIF-based Oaxaca–Blinder decomposition in order to analyse both the cross-sectional correlates of inequality and the role of compositional changes over time. The results show substantial cross-country heterogeneity. Variables associated with Skill-Biased Technological Change and broader processes of structural transformation emerge as important correlates of earnings inequality, but their relevance and configuration vary markedly across national contexts. By contrast, labour-market fragmentation appears as a more general pattern: atypical employment arrangements, especially temporary and part-time work, are consistently associated with higher levels of earnings inequality in all four countries. Overall, the findings suggest that earnings inequality is shaped by multiple, overlapping, and country-specific processes, rather than by common and homogeneous mechanisms. The analysis identifies statistical associations rather than causal effects, but it offers a comparative account of the institutional and structural correlates of inequality across the four economies examined.

Keywords Earnings inequality · Recentered Influence Function (RIF) regression · EU-SILC microdata · Southern and Western Europe · Technological, structural and institutional drivers of inequality

JEL Classification C21 · D33 · D63 · J31 · O57

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1 Introduction

In recent decades, the issue of income inequality in advanced capitalist countries has gained significant prominence in both scholarly research and political discourse. One notable factor contributing to this growing attention is the widespread dissemination and impact of Piketty's work (2014, 2015, 2022). The renewed focus on inequality is well justified: in the so-called "advanced economies", income and wealth inequality – after peaking during the early decades of the twentieth century – experienced a substantial decline, only to begin rising again from the 1980s and 1990s onwards (Alfani 2025). This historical parallel with a period marked by the emergence of totalitarian regimes and global conflict is particularly concerning, especially given that rising inequality and economic polarisation are increasingly viewed as key contributors to social unrest, declining social cohesion, and growing political polarisation (Duca and Saving 2016; Polacko 2021; Stiglitz 2012; Turchin 2023).

The body of research on inequality has expanded exponentially, encompassing diverse strands that range from measurement methodologies to the analysis of its consequences, the identification of its causes, and the evaluation of potential policy responses (when considered necessary). Navigating this vast and multifaceted literature presents a significant challenge in itself.

The aim of our research is to embrace – rather than reduce – the inherent complexity of this topic. We begin by recognising that the choice of inequality measurement has profound implications, as different metrics often yield markedly different results. Likewise, we avoid deterministic or overly simplistic interpretations of causality. Our analytical strategy seeks to incorporate, within a single empirical framework, as many of the features associated with inequality discussed in the literature as possible. Few empirical studies attempt to simultaneously account for multiple aspects of income inequality (a notable exception is Lazović Vuković and Damijan 2025), and to the best of our knowledge, there are virtually no studies that analyse these aspects jointly across multiple measures of inequality and across multiple countries.

At the core of our analysis is an examination of the key correlates of earnings inequality in four European countries – France, Italy, Portugal, and Spain (the rationale behind this selection is discussed later in the paper). To this end, we employ a micro-econometric strategy based on EU-SILC data that combines Recentered Influence Function (RIF) regression (Firpo et al. 2009, 2018; Firpo and Pinto 2016) and a RIF-based Oaxaca-Blinder decomposition to compare distributional outcomes across survey years (2010, 2014, 2019).

We explicitly sidestep the broader normative debate on the "inequality of what?" (Sen 1980), which would lead us into yet more complex terrain, and instead focus on inequality of outcomes (Ferreira and Peragine 2016). More specifically, we examine earnings from labour, a key component of income. We do not analyse wealth, consumption, or pay in a broader sense. Moreover, our unit of analysis is the individual rather than the household.

Before proceeding, we wish to highlight a fundamental complexity that arises at the very outset of any inquiry into income inequality: the question of measurement. How inequality is defined and quantified significantly affects both the diagnosis and the interpretation of its underlying patterns. As Trapeznikova (2019) notes, each measure captures different aspects of the distribution. For example, the Gini coefficient is more sensitive to changes in the middle of the distribution, the Coefficient of Variation (CV) places greater emphasis on the upper tail, while the variance of log income is more responsive to changes at the bottom. Measures based on quantile ratios (e.g., income share ratios) offer the advantage of focusing on specific points in the distribution, allowing for a more nuanced understanding of distributional dynamics.

In this paper, we deliberately employ multiple measures of inequality to underscore an essential point: different measures capture distinct distributional features depending on how inequality is conceptualised and measured. Including multiple indicators allows us to capture distinct distributional mechanisms and helps avoid potentially misleading generalisations based on a single metric.

The remainder of the paper is structured as follows. Section 2 presents a concise review of the literature on factors associated with income inequality. Section 3 illustrates recent trends in income inequality across the four countries under study, alongside descriptive statistics (at country level) on the variables considered in the analysis. Section 4 outlines the methodological approach employed in our analysis and describes the data, while Section 5 presents the empirical results. Section 6 concludes with broader reflections and final remarks.

2 Income inequality drivers in developed countries: a short literature review

As noted in the Introduction, the literature on income inequality and its determinants (or correlates, depending on the analysis) is both vast and rapidly expanding, making any comprehensive synthesis inherently difficult. In this section, we highlight the concepts most relevant to our analysis, which provide the theoretical foundation for our investigation and inform the interpretation of our empirical findings.

Technological progress is widely recognised as a potential driver of income inequality, primarily discussed in relation to two interrelated channels linked to labour earnings differentials. First, it is often characterised as skill-biased, a pattern reflected in higher productivity and remuneration levels among skilled workers relative to unskilled ones. Second, certain occupations or tasks, depending on their sectoral or functional characteristics, are more frequently described in the literature as more exposed to automation and to technological substitution processes, including robotics and artificial intelligence (Lazović Vuković and Damijan 2025). This line of inquiry, rooted in the seminal works of Kuznets (1955) and Tinbergen (1975), has since evolved substantially (Acemoglu 1998, 2002a,b; Acemoglu and Autor 2010; Katz and Autor 1999).

The central tenet of the Skill-Biased Technological Change (SBTC) framework is that technological innovation increases the demand for skilled labour, thereby widening wage disparities between skilled and unskilled workers. A substantial body of empirical research supports this hypothesis (Acemoglu 1998; Autor et al. 1998; Bresnahan 2021; Goos and Manning 2007; Goos et al. 2009; Katz and Murphy 1992; OECD 2011). However, this view is not uncontested. Roser and Cuaresma (2016), for instance, find no significant link between technological progress and rising inequality, while Rossvoll and Sparrman (2015) describe evidence aligned with more equal earnings distributions in certain contexts.

A more recent strand of the literature focuses on specific forms of technological transformation, such as automation, robotisation, and the application of artificial intelligence in production processes (Acemoglu and Restrepo 2019, 2020a; Felten et al. 2021; Graetz and Michaels 2018). Some studies have also highlighted the possibility of a non-linear relationship between technological change and income inequality (Card and DiNardo, 2002;

Goldin and Katz 1998), suggesting that the direction and intensity of the effect may depend on threshold effects or stages of technological adoption.

Overall, while a relationship between technological progress and income inequality is broadly acknowledged in the literature, its magnitude and nature appear to be context-dependent. Institutional configurations, labour market structures, and broader socio-economic factors mediate this relationship, leading to cross-national variation. This consideration is particularly relevant for the subsequent empirical analysis presented in this paper.

In parallel to the literature on automation and robot adoption, a broader strand of research has analysed digitalisation through a task-based and ICT-oriented perspective. This approach focuses on changes in the composition of tasks within occupations and sectors, rather than simply describing labour replacement through automation. Seminal contributions highlight that information and communication technologies tend to substitute for routine tasks while complementing non-routine cognitive activities, thereby reshaping occupational structures and corresponding to changes in the wage distribution (Autor et al. 2003). Cross-country evidence further suggests that ICT diffusion has been associated with job and wage polarisation in several advanced economies, with heterogeneous effects across skill groups and sectors (Michaels et al. 2014). More recent conceptual work stresses that technological change simultaneously destroys and creates tasks, implying that its distributive consequences are contingent on how labour markets and institutions absorb and reallocate workers across occupations and industries (Acemoglu and Restrepo 2019). Within this framework, indicators related to occupations, sectors, and educational attainment can be interpreted as reflecting channels through which digitalisation and task reallocation are associated with earnings inequality, without implying a direct causal link.

The third major driver identified in the literature as contributing to the dynamics of income inequality is ‘globalisation’, understood in its various manifestations: increased capital flows, foreign trade, and labour migration. In this context, our focus will be on the latter two dimensions – international trade and labour mobility – as these are the aspects examined in our analysis.

According to the Stolper-Samuelson theorem, the gains from trade liberalisation accrue to a country’s relatively abundant factors of production, while its scarce factors incur losses. Consequently, in advanced economies where capital and skilled labour are relatively abundant, trade openness is expected to benefit these factors, thereby exacerbating income inequality. However, this standard model presents significant limitations, and alternative mechanisms may come into play. In fact, empirical evidence concerning the distributive effects of trade openness remains inconclusive. Some studies find that international trade has contributed to rising income inequality (Autor et al. 2014; Barusman and Barusman 2017; Borjas and Ramey 1995; De Lyon and Pessoa 2020; Roser and Quaresma 2016). Others, however, question the strength of this relationship (Krugman 1995, 2008), with some even suggesting that trade may mitigate inequality (Asteriou et al. 2014). Helpman (2016), in his review of the literature, acknowledges that while trade may indeed contribute to wage inequality, its overall explanatory power regarding the rise in inequality in advanced economies appears to be limited. Of particular interest to our study is the observation that the distributive consequences of trade tend to be country-specific (Autor et al. 2021; Dustmann 2021).

Turning to international labour mobility, particularly the immigration of low-skilled workers into high-income countries, this phenomenon has the potential to affect income distribution by exerting downward pressure on the wages of the lowest-paid native workers, and by weakening their bargaining power. Nonetheless, the empirical literature suggests that such effects are generally small or even negligible (Card 2009; Di Pasquale 2022;

Kierzenkowski and Koske 2012). The debate remains open, however, with some studies continuing to question this benign interpretation (Rossvoll and Sparrman 2015; Xu et al. 2016). As with trade, the relationship between labour mobility and income inequality appear to be highly context-dependent and vary significantly across countries.

Another potential driver of income inequality is structural change – namely, the transformation in the sectoral composition of output and employment. In the context of advanced economies, particular attention is paid to the shift in employment from manufacturing to services. Structural change may influence income inequality due to the fact that wage levels typically differ across sectors, reflecting variations in productivity and the labour share associated with each sector. In addition, wage dispersion can also vary within sectors. As a result, the reallocation of labour towards service sectors – some characterised by high wages and others by low wages – or towards sectors exhibiting greater internal wage variability, may contribute to rising inequality.

Rohrbach (2009), analysing a panel of 19 OECD countries from 1970 to 1999, finds that 'sector dualism' – the wage differential between the knowledge sector and other sectors – does not significantly impact the Gini coefficient. In contrast, 'sector bias,' defined as income disparity within the knowledge sector, does appear to have an effect. Similarly, Antonelli and Tubiana (2020) investigate the implications of the shift to a knowledge-based economy in 20 OECD countries over the period 1990–2016. Their findings suggest that this transition contributes to wage polarisation, particularly between creative professionals and standard labour.

Overall, empirical findings in this domain remain inconclusive (Cosentino de la Vega 2023; Förster and Tóth 2015). Crucially for our analysis, existing evidence underscores that the effects of structural change on income distribution are complex and context-dependent. They vary significantly according to institutional frameworks and the prevailing policy environment (Ghosh et al. 2023).

For the sake of analytical clarity, we attempt to construct a taxonomy of the potential determinants of income inequality. However, it is evident that these determinants frequently interact in complex and overlapping ways. For example, structural change is significantly shaped by both technological progress and exposure to international trade – particularly when the latter is associated with processes of de-industrialisation. Indeed, structural change can be understood as the channel through which technological advancement and global trade exert their influence on income distribution. Furthermore, both globalisation and technological change interact with specific national contexts and institutional frameworks, often producing markedly different outcomes across countries (Nolan et al. 2019). The significance of this interaction is further underscored by the observation that discrepancies in empirical findings on the trade–inequality nexus may stem from the omission of key explanatory variables – such as technological progress or structural change – in econometric models (Lazović Vuković and Damijan 2025).

From this perspective, accounting for the level of education becomes crucial. Furthermore, the skill premium may represent one of the channels through which the effects of technological progress are transmitted. However, the long-term dynamics remain potentially ambiguous. In the short run, an increased demand for skilled labour can stimulate its supply via greater educational attainment, which may, in turn, dampen the skill premium. At the same time, this process may also reinforce the development of skill-biased technological change. The empirical literature reflects this complexity: Dabla-Norris et al. (2015) find a positive correlation between education and inequality, whereas Roser and Cuaresma (2016) report the opposite. Nonetheless, the equalising effect of education appears to weaken when considered in interaction with technological progress.

The final driver of inequality we wish to consider is labour market regulation. Beginning in the early 1990s, a series of structural reforms were implemented across European countries with the objective of introducing greater flexibility into their labour markets. A prominent aspect of these reforms was the liberalisation of fixed-term contracts. Temporary workers generally possess weaker bargaining power compared to their permanent counterparts, a disparity that may have contributed to the emergence of a dual labour market and a widening gap between different categories of workers, thereby exacerbating inequality (Berton et al. 2012).

Weisstanner (2017), in an analysis of 22 OECD countries spanning the period 1995 to 2014, finds that deregulation in temporary employment correlates with a decline in the income shares of the middle and lower-middle income quintiles. Similarly, Tridico (2018), examining 25 OECD countries from 1990 to 2013, provides evidence supporting the hypothesis that rising inequality over this period was driven by increased labour market flexibility, the weakening of trade unions, growing financialisation, and the retrenchment of the welfare state. Consistent with these findings, Rossvoll and Sparrman (2015) show that less stringent regulations concerning temporary employment are associated with higher levels of income inequality. Murray et al. (2012) likewise underscore that the growing prevalence of part-time and temporary contracts contributes to wage dispersion, thereby intensifying inequality in labour earnings.

Hacker (2008) argues that greater labour market flexibility shifts economic risks from firms to workers, thereby altering the functional distribution of income in a way that favours capital owners over more vulnerable labour suppliers. Labour market flexibilisation is commonly associated with a reduction in workers' bargaining power – often linked to the erosion of trade union strength – which in turn shapes the capital-labour relationship. In this regard, the theoretical and empirical contribution of Coveri and Pianta (2022) is particularly illuminating: they demonstrate how structural change and capital-labour conflict interact to influence the evolution of profits and wages, and consequently, the broader distribution of income.

This perspective reinforces our overarching argument that labour market regulation does not operate in isolation. Rather, it interacts dynamically with structural change and other institutional and macroeconomic factors, illustrating the difficulty of isolating individual drivers of income inequality.

A substantial body of comparative research has documented the role of industrial relations institutions in relation to the level and dispersion of earnings across countries. Early cross-country contributions emphasised how differences in wage-setting institutions, collective bargaining coverage, and coordination mechanisms are associated with persistent international variation in wage inequality (Blau and Kahn 1996; Card et al. 1999). Subsequent studies have shown that collective bargaining institutions are linked not only to average wage levels but also the structure of the wage distribution, often compressing dispersion, particularly at the lower end. Evidence from European countries highlights that the relationship between these institutions is highly context-specific and depends on the degree of bargaining centralisation and coverage. For instance, research on Italy and Spain shows that collective bargaining arrangements are closely associated with lower wage dispersion within and across sectors, even in the presence of structural and compositional changes in labour markets (Devicienti et al. 2018; Ramos et al. 2022). Beyond their direct associations, industrial relations institutions have also been discussed as potential moderators of other inequality-generating forces, such as technological change and labour market dualisation, by shaping wage norms and limiting the transmission of shocks into earnings dispersion (Western and Rosenfeld 2011). This literature suggests that institutional configurations constitute an important contextual layer for interpreting observed cross-country differences in earnings inequality. At the same time, it should be noted that many of these institutional features operate primarily at the national level, whereas the empirical strategy adopted in this paper focuses on cross-country comparisons combined with regional (NUTS-2) variation within countries. Given that collective bargaining frameworks, minimum wage regulations, and union structures are largely defined at the national level in the countries considered, they are not explicitly modelled in the regional decomposition analysis. Rather, they constitute part of the broader institutional context within which regional differences in earnings inequality are observed and interpreted. Despite the considerable body of empirical and theoretical research produced over the past decades, our understanding of the underlying drivers of income inequality remains limited. Even the most widely accepted explanatory factors – such as technological change and international trade – fall short in accounting for developments observed at both the top and bottom of the income distribution (Chancel 2021). Moreover, potential drivers often interact in complex ways, making it exceedingly difficult to disentangle their individual effects. Compounding this challenge, countries that experience similar levels of exposure to specific drivers nonetheless exhibit markedly different inequality outcomes (Blanchet et al. 2019; Lazović Vuković and Damijan 2025).

3 Countries trajectories

Before proceeding with the micro-level analysis, this section offers a brief overview of the evolution of inequality and, in broad terms, the main factors associated with it in the countries under examination.

3.1 France

Figure 1 presents data for France, the country exhibiting the lowest level of income inequality among those considered in the analysis. Both inequality indices shown in Fig. 1 are fairly stable over time.

France also records the lowest incidence of self-employment among the four countries examined, and this share remains stable over time. In contrast, the incidence of part-time contracts is relatively high, though also stable. The share of temporary contracts, while low in absolute terms, has been increasing in recent years.

International trade exhibits a clear long-term upward trend. In addition to total trade, the figure reports the share of exports in GDP, which will serve as the key trade-related variable in the subsequent micro-level analysis.

A long-term structural shift towards the service sector is evident, consistent with established literature. However, for the purposes of the micro analysis, it will be necessary to disaggregate this transformation by examining the various sub-sectors within services.

Tertiary education attainment is increasing rapidly. Meanwhile, the share of migrants in the population is already substantial, though it has not grown significantly in recent years.

France's relatively low levels of inequality are often associated with substantial social spending and a comparatively high minimum wage (Garbinti et al. 2018). Conversely, regarding the sources of existing inequality, capital income emerges as a key driver. It is notably concentrated among the wealthiest segments of the population and has been increasing relative to labour income (Garbinti and Goupille-Lebret 2019). Within our

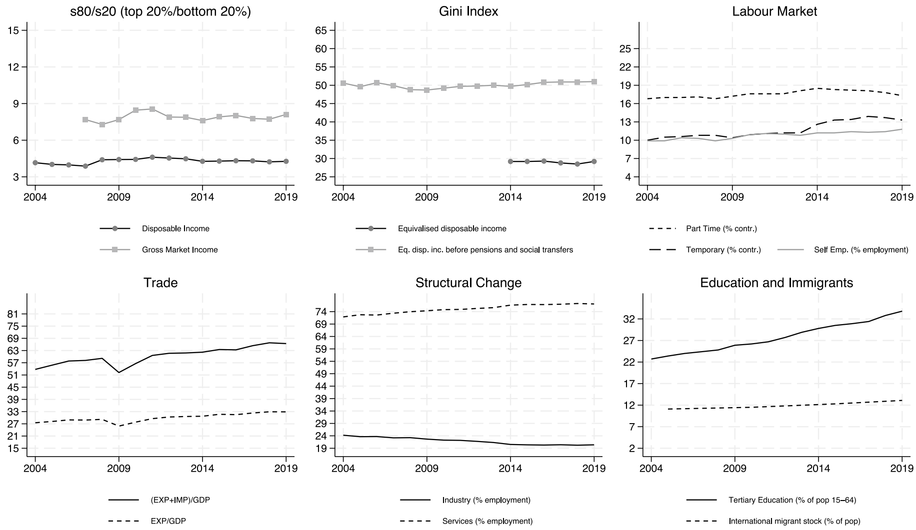

Fig. 1 Trends of income inequality and potential correlates, France (2004–2019)

analytical framework, this phenomenon may be partially attributed to the declining bargaining power of workers, a trend that appears to coincide with the expansion of temporary employment contracts in France in recent years, as illustrated in Fig. 1. This development is observed alongside a rise in inequality, suggesting a possible interrelation.

3.2 Italy

Figure 2 presents data pertaining to Italy. The evidence suggests that inequality has increased since the 2008 crisis, particularly with regard to the S80/S20 ratio, and therefore in terms of polarisation. While the figure refers to individual income, the inequality trend aligns with the findings of Brandolini et al. (2018), who report a sharp rise in household income inequality during the currency crisis of the early 1990s, followed by a more gradual increase during the recession spanning 2008 to 2013. Similarly, the evidence on polarisation shown in the figure is consistent with Clementi and Fabiani (2025), who document a rise in household income polarisation in Italy between 1990 and 2020, driven by a shrinking middle and increased concentration in the top and bottom deciles.

The proportion of self-employed individuals remains notably high, although it exhibits a slight downward trend over time. In contrast, the use of temporary and part-time contracts shows a consistent and substantial increase throughout the entire period under consideration. Since the early 2000s, the share of immigrants in the population has grown significantly, as has the proportion of individuals with tertiary education. Nevertheless, Italy continues to record the lowest share of tertiary-educated citizens among the countries included in the analysis.

Territorial disparities play a substantial role in shaping income distribution in Italy. Briskar et al. (2022) emphasize the significant regional heterogeneity, with higher levels of inequality observed in the South relative to the Centre and North, a finding corroborated by Güell et al. (2018). According to Briskar et al. (2022), sectoral composition is a key factor in explaining the evolution of earnings variance. Naticchioni et al. (2016) draw attention to

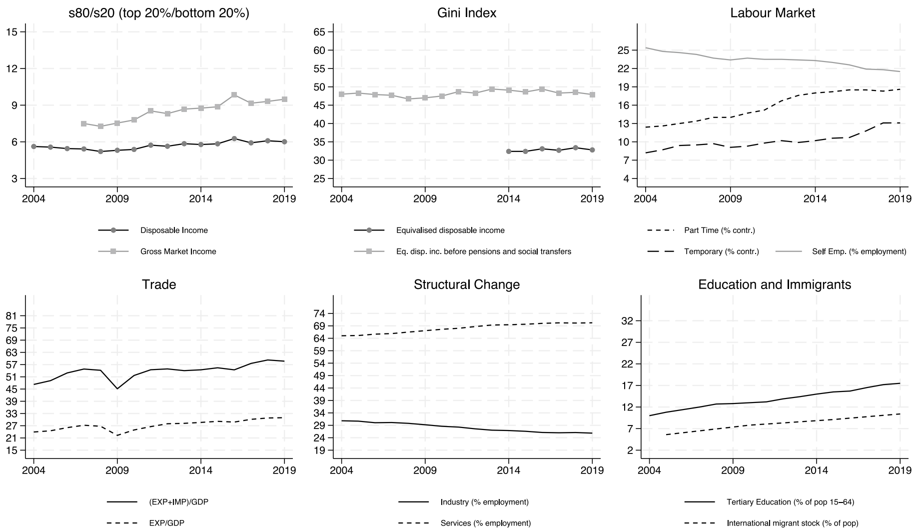

Fig. 2 Trends of income inequality and potential correlates, Italy (2004–2019)

the persistent and substantial earnings penalty experienced by younger cohorts when compared to older ones.

Hoffman et al. (2022) and Depalo and Lattanzio (2023) attribute a significant portion of the increase in earnings volatility to the growing prevalence of atypical employment contracts, specifically temporary and part-time arrangements. Guzzardi et al. (2024) further document that younger individuals, women, and residents of Southern regions are disproportionately exposed to rising inequality. Additionally, their analysis highlights that the Italian tax system exhibits only limited progressivity and becomes regressive for the top 5% of the income distribution.

3.3 Portugal

Figure 3 presents data from Portugal. In the initial years represented by the graph (2004–2008), there seems to be a modest decline in inequality, which started from a very high level. This was followed by a period of growth until 2014, after which a fairly rapid decline has been observed in recent years. The S80/S20 ratio shows these trends clearly. During this phase of inequality reduction, several notable labour market dynamics emerge: the share of self-employed workers declined rapidly; the share of workers on fixed-term contracts stabilised after a period of substantial growth; and the incidence of part-time employment remained relatively low.

Among the countries considered in this analysis, Portugal appears to be the most exposed to international trade, particularly in terms of imports. Although the magnitude of immigration flows is comparable to that observed in Italy, migrants in Portugal tend to exhibit higher levels of education than the native population (Olivera et al. 2023). With respect to tertiary education, Portugal displays a dynamic more akin to that of France.

The high levels of inequality observed at the beginning of the 2000s have been attributed to Skill-Biased Technological Change (SBTC), occurring in a context characterised by a shortage of skilled labour (Cardoso 1998; Centeno and Novo 2014). During this period,

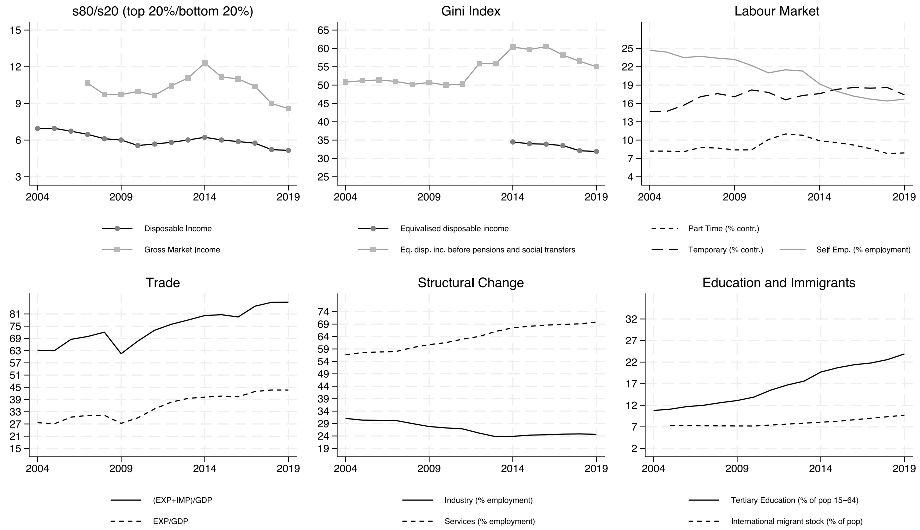

Fig. 3 Trends of income inequality and potential correlates, Portugal (2004–2019)

the skill premium in Portugal ranked among the highest in developed economies (Machado and Mata 2005; Martins and Pereira 2004). This trend was subsequently mitigated by a phase of educational expansion and democratisation, driven by large-scale public investment in education. These policies effectively rebalanced the supply and demand for skills, leading to a reduction in the education wage premium (Cardoso et al. 2008; Olivera 2024). This evolution is clearly reflected in the steep rise in tertiary education attainment shown in Fig. 3.

The decline in inequality from 2014 onward is also attributable to additional factors. Focusing on earnings, Olivera et al. (2023, p. 2) identify a compression at the lower end of the income distribution as a key driver: “individuals in the bottom decile enjoyed income growth of the order of 5% a year, while those at the top of the distribution actually saw their earnings decrease”. This process coincided with a substantial increase in the minimum wage, which by 2019 exceeded 60% of the median wage. Olivera (2023) provides quantitative evidence demonstrating that the compression of the wage distribution and the accompanying reduction in inequality can largely be attributed to the upward trajectory of the minimum wage.

3.4 Spain

In the case of Spain (Fig. 4), two periods can be clearly identified: the first, beginning with the 2008 crisis, is characterised by an increase in inequality; in the second period, beginning in 2014, there is a reduction in inequality.

The incidence of temporary contracts in Spain is particularly high and, from the mid-2000s onwards, appears to closely mirror the dynamics of income inequality – rising and falling in tandem. Part-time employment has experienced substantial growth, although it has shown a tendency to decline in the most recent period. Conversely, the share of self-employed workers has been on a downward trajectory. Spain’s exposure to foreign trade is broadly comparable to that of France and Italy. Structural change within the economy

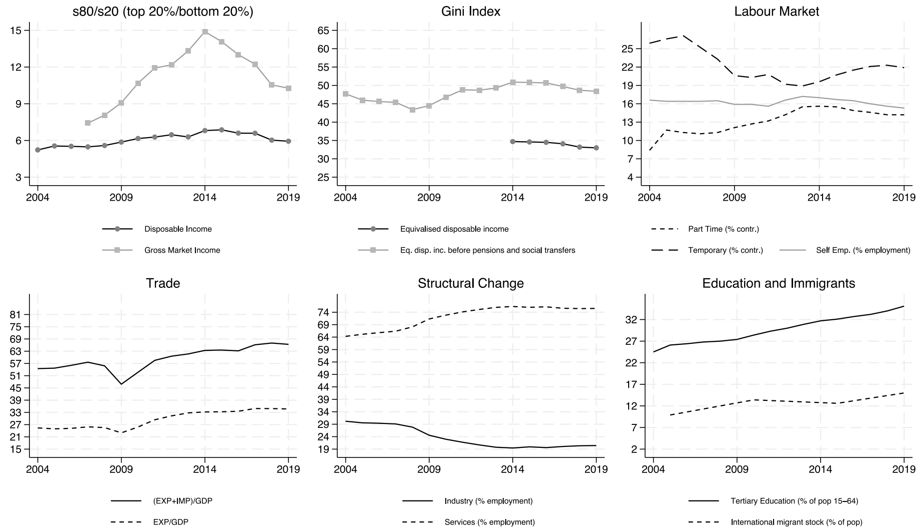

Fig. 4 Trends of income inequality and potential correlates, Spain (2004–2019)

accelerated notably in response to the 2008 financial crisis. The proportion of individuals attaining tertiary education is both high and increasing rapidly. Migration has shown a long-term upward trend, with Spain registering the highest share of migrants among the countries considered. Similar to the case of Italy, Spain also exhibits significant regional disparities in economic and labour market outcomes (Apergis et al. 2025).

Income inequality in Spain appears to be strongly correlated with the business cycle, particularly through its impact on the (persistently high) unemployment rate (Bonhomme and Hospido 2013). Severance payments for permanent workers are relatively high, whereas those for temporary contracts are significantly lower. The widespread use of temporary contracts, as illustrated in Fig. 4, is thus partly attributable to this cost differential. The high level of employment protection afforded to permanent workers, contrasted with the minimal protection for temporary employees, creates incentives for employers to adjust to economic fluctuations by not renewing temporary contracts. This dynamic contributes to the persistence of a dual labour market characterised by substantial wage inequality, which is further exacerbated during periods of crisis by job losses concentrated among temporary workers (Anghel et al. 2023).

García-Louzao et al. (2023) document that young workers initially employed on fixed-term contracts experience, on average, wage growth that is 16 percentage points lower over a 15-year period compared to their peers with open-ended contracts. The 2021 labour market reform, which aimed to discourage the use of temporary contracts (Rodríguez and Izquierdo 2022), is expected to contribute to a reduction in labour market dualism – though such effects are not yet observable in the data analysed here.

The decline in inequality observed around the turn of the century (which can be observed in the initial trend of the Gini index) has been attributed to a combination of falling unemployment – reaffirming the cyclical nature of inequality in Spain – and a reduction in the tertiary education wage premium. The latter resulted from a rapid expansion in the number of graduates, thereby increasing the supply of skilled labour (Izquierdo and Laquesta 2007; Pijoan-Mas and Sánchez-Marcos 2010). As for the more recent reduction in inequality, two policy interventions may have played a significant role: in 2015, a reform enhanced benefits for the long-term unemployed, and beginning in 2018, the minimum wage was substantially increased (Anghel et al. 2023).

4 Microdata analysis

4.1 Methodology

4.1.1 RIF regression

As previously mentioned, we analyse distributional patterns in earnings across the four selected countries – France, Italy, Portugal, and Spain – using the regression method based on the notion of Recentered Influence Function (RIF). The influence function, introduced by Cowell and Victoria-Feser (1996), quantifies how a single observation affects a chosen distributional statistic – such as a specific quantile or the Gini coefficient. By recentering this function, it can be integrated into a regression framework, allowing for the estimation of how explanatory variables affect the distributional statistic of interest.

To illustrate this point, consider the widely used Gini coefficient of income inequality (Gini 1914). Let $\mu_Y = \int_{-\infty}^{\infty} yf(y)dy$ denote the mean of the income distribution Y, and let F_Y be the corresponding cumulative distribution function. The Gini coefficient can then be expressed as (see e.g. Firpo et al. 2018):

$$\nu^G(F_Y) = 1 - 2\mu_Y^{-1}R(F_Y), \tag{1}$$

where $R(F_Y) = \int_0^1 GL(p;F_Y)dp$, with $p = F_Y(y)$, and where $GL_Y(p)$ denotes the generalized Lorenz ordinate defined as $GL(p;F_Y) = \int_{-\infty}^{F_Y^{-1}(p)} zdF_Y(z)$. The generalized Lorenz curve plots the cumulated income of a given share of the population (normalized by population size) against the cumulative population proportion.

Monti (1991) derives the influence function of the Gini coefficient as follows:

$$IF(y;\nu^G, F_Y) = A(F_Y) + B(F_Y)y + C(y;F_Y), \tag{2}$$

where $A(F_Y) = 2\mu_Y^{-1}R(F_Y)$, $B(F_Y) = 2\mu_Y^{-2}R(F_Y)$, and $C(y;F_Y) = -2\mu_Y^{-1}y[1-p] + GL(p;F_Y)$, with $R(F_Y)$ and $GL(p;F_Y)$ as defined in Eq. (1). Although the function in Eq. (2) is theoretically unbounded from above, it typically reaches its maximum at the upper bound of the empirical support of the income distribution. As a result, the Gini coefficient is highly sensitive to measurement errors in the top tail of the income distribution – a point emphasized by Cowell and Victoria-Feser (1996).

A key property of influence functions is that their expectation is equal to zero by definition:

$$\mathbb{E}[IF(y;\nu^G, F_Y)] = 0. \tag{3}$$

Firpo et al. (2009) propose a simple but powerful transformation in which the distributional statistic of interest is added back to the influence function. This yields what they define as the Recentered Influence Function (RIF). In the case of the Gini coefficient, recentering produces the following expression:

$$RIF\left(y;\nu^G,F_Y\right) = \nu^G + IF\left(y;\nu^G,F_Y\right) = 1 + B\left(F_Y\right)y + C\left(y;F_Y\right). \tag{4}$$

The implication of this transformation lies in the fact that the expectation of the RIF equals the original distributional statistic:

$$\mathbb{E}\left[RIF\left(y;\nu^G,F_Y\right)\right] = \nu^G. \tag{5}$$

Building on this result, Firpo et al. (2009) show that the conditional expectation of the Gini's RIF can be expressed as a linear function of the explanatory variables:

$$\mathbb{E}\left[RIF\left(y;\nu^G,F_Y\right)\middle|X=x\right] = X' \cdot \beta. \tag{6}$$

By applying the law of iterated expectations to Eq. (6), one obtains an expression that links the Gini coefficient directly to the mean values of the covariates:

$$\nu^G = \mathbb{E}\left[RIF\left(y;\nu^G,F_Y\right)\right] = \mathbb{E}\left[\mathbb{E}\left[RIF\left(y;\nu^G,F_Y\right)\middle|X=x\right]\right] = \mathbb{E}(X)\cdot\beta. \tag{7}$$

In practice, following Firpo et al. (2009), our analysis proceeds by first computing the RIF for the Gini coefficient for each individual income observation using Eq. (4). Then, the coefficient vector β is estimated by Ordinary Least Squares (OLS) using the following regression model, applied to the survey income data available for each of the selected countries:

$$RIF\left(y_{i,g};\nu^G,F_Y\right) = \alpha + \sum\nolimits_{j=1}^{J}\beta^j \cdot x_{i,g}^j + \gamma_g + \varepsilon_{i,g}, \quad i=1,2,\ldots,N, \quad g=1,2,\ldots,G, \tag{8}$$

where α is a constant term, $x_{i,g}^j$ represents the j-th explanatory variable for individual i residing in territorial unit g, β^j is the corresponding regression coefficient, γ_g captures region-specific (but unit-invariant) unobserved heterogeneity, and $\varepsilon_{i,g}$ is the error term.[1]

The estimated parameter $\widehat{\beta^j}$ can be interpreted as the marginal effect of a small shift in the distribution of X^j on the Gini coefficient ν^G, assuming other covariates are held constant. It also serves as a linear approximation of the effect of larger changes in X^j on ν^G (see Firpo et al. 2018).

The RIF-OLS regression method can be extended to analyze the impact of a set of covariates on a wide range of distributional functionals, as analytical expressions for (recentered) influence functions have been derived for many distributional statistics (see, for example, Essama-Nssah and Lambert 2012, and Rios-Avila 2020, for comprehensive lists of formulas).

In addition to the Gini coefficient, our analysis considers several other distributional statistics: the mean, the median, the income quintile share ratio (S80/S20), and the Palma

[1] As will be explained in Sect. 4.2, for each of the countries analysed, an alternative version of model (8) will also be estimated, in which regional fixed effects are replaced by three region-specific variables assigned to individuals based on their region of residence. In this case, the model reads as follows:

$$RIF\left(y_{i,g};\nu^G,F_Y\right) = \alpha + \sum\nolimits_{j=1}^{J}\beta^j \cdot x_{i,g}^j + \sum_{k=1}^{3}\gamma^k \bullet z_g^k + \varepsilon_{i,g}, \quad i=1,2,\ldots,N, \quad g=1,2,\ldots,G,$$

where $${z}_{g}^{k}$$ represents the $$k$$-th region-specific variable and $${\gamma }^{k}$$ is the corresponding regression coefficient. The interpretation of all other terms remains unchanged.

ratio of income concentration (Cobham and Sumner 2013). The RIFs corresponding to these measures are summarized in Table 1.

From a practical standpoint, all the RIF-OLS regressions are estimated using the rifhdreg command (Rios-Avila 2020), available within the Stata econometric software. The regressions are weighted using the individual-level cross-sectional weights provided by the database employed in the analysis, in order to ensure the representativeness of the target population.

It is important to emphasize that the econometric analysis is strictly limited to estimating statistical associations between the variables considered and does not seek to establish causal relationships. Therefore, the results should be interpreted as correlations rather than as evidence of causality.

4.1.2 RIF decomposition

Once the RIF estimates for each statistic are obtained, we decompose the changes in distributional measures over time following the framework of the Blinder-Oaxaca decomposition for mean differentials (Blinder 1973; Oaxaca 1973). This approach allows the overall difference in a given distributional measure between two groups (or time periods) to be expressed as the sum of distinct components attributable to: (i) differences in observable characteristics (endowment effect), and (ii) differences in the returns to these characteristics (coefficient effect). An interaction component, together with the constant term, is included to ensure that the decomposition exactly reproduces the total observed difference.

Formally, let $\widehat{\Delta}^{\nu} = \nu_1 - \nu_0$ denote the total difference in a given distributional statistic between period 1 and period 0. The aggregate decomposition can be written as:

$$\widehat{\Delta}^{\nu} = \widehat{\Delta}^{\nu}_X + \widehat{\Delta}^{\nu}_{\beta} + \widehat{\Delta}^{\nu}_I, \tag{9}$$

where $\widehat{\Delta}^{\nu}_X$, $\widehat{\Delta}^{\nu}_{\beta}$ and $\widehat{\Delta}^{\nu}_I$ denote the endowment, coefficient, and interaction effects, respectively. Although the interaction term does not admit a straightforward economic interpretation, it is required to guarantee the completeness of the decomposition.

A more granular decomposition can be derived by allocating the overall difference in the distributional statistic to individual covariates. Relying on the estimated coefficients from the RIF regressions, the decomposition can be expressed in general form as follows:

$$\widehat{\Delta}^{\nu} = \underbrace{\sum_{k=1}^{K}\left(\bar{x}_k^1 - \bar{x}_k^0\right)\widehat{\beta}_k^0}_{\widehat{\Delta}^{\nu}_X} + \underbrace{\left(\widehat{\alpha}^1 - \widehat{\alpha}^0\right) + \sum_{k=1}^{K}\left(\widehat{\beta}_k^1 - \widehat{\beta}_k^0\right)\bar{x}_k^0}_{\widehat{\Delta}^{\nu}_{\beta}} + \underbrace{\sum_{k=1}^{K}\left(\bar{x}_k^1 - \bar{x}_k^0\right)\left(\widehat{\beta}_k^1 - \widehat{\beta}_k^0\right)}_{\widehat{\Delta}^{\nu}_I}, \tag{10}$$

Table 1 Definitions of Recentered Influence Functions (RIFs) for the distributional statistics considered in this study

Statistics	*Definition*	*RIF*	*Source*
Mean	$\mu_Y = \int_{-\infty}^{\infty} yf(y)dy$	$RIF\left(y;\mu_Y, F_Y\right) = y$	Essama-Nssah and Lambert, (2012); Firpo et al. (2018); Rios-Avila (2020)
Median	$q_Y(0.5) = F_Y^{-1}(0.5)$	$RIF\left(y;q_Y(0.5), F_Y\right) = \begin{cases} q_Y(0.5) + \frac{0.5}{f(q_Y(0.5))}, y > q_Y(0.5) \\ q_Y(0.5) - \frac{0.5}{f(q_Y(0.5))}, y < q_Y(0.5) \end{cases}$	Essama-Nssah and Lambert, (2012); Firpo et al. (2018); Rios-Avila (2020)
Gini	$G_Y = 1 - 2\mu_Y^{-1}R\left(F_Y\right)$ $R\left(F_Y\right) = \int_0^1 GL\left(p;F_Y\right)dp$ $GL\left(p;F_Y\right) = \int_{-\infty}^{q_Y(p)} zdF_Y(z)$	$RIF\left(y;G_Y, F_Y\right) = 1 + 2\mu_Y^{-2}R\left(F_Y\right) - 2\mu_Y^{-1}y\left[1-p\right] + GL\left(p;F_Y\right)$	Essama-Nssah and Lambert, (2012); Firpo et al. (2018); Rios-Avila (2020)
Income quintile share ratio S80/S20[a]	$Iqsr_Y = \frac{1-L_Y(0.8)}{L_Y(0.2)}$	$RIF\left(y;Iqsr_Y, F_Y\right) = Iqsr_Y + \frac{1}{L_Y(0.2)}\left[-IF\left(y;L_Y(0.8), F_Y\right) - Iqsr_Y IF\left(y;L_Y(0.2), F_Y\right)\right]$	Rios-Avila (2020)
	$L_Y(0.2) = \mu_Y^{-1}GL\left(0.2;F_Y\right)$	$IF\left(y;L_Y(0.2), F_Y\right) = -\frac{y}{\mu_Y}L_Y(0.2) + \frac{0.2q_Y(0.2)}{\mu_Y} + \left(\frac{y-q_Y(0.2)}{\mu_Y}\right)\mathbb{I}\left\{y < q_Y(0.2)\right\}$	
	$L_Y(0.8) = \mu_Y^{-1}GL\left(0.8;F_Y\right)$	$IF\left(y;L_Y(0.8), F_Y\right) = -\frac{y}{\mu_Y}L_Y(0.8) + \frac{0.2q_Y(0.8)}{\mu_Y} + \left(\frac{y-q_Y(0.8)}{\mu_Y}\right)\mathbb{I}\left\{y < q_Y(0.8)\right\}$	
Palma ratio[a]	$Iqsr_Y = \frac{1-L_Y(0.9)}{L_Y(0.4)}$	$RIF\left(y;Iqsr_Y, F_Y\right) = Iqsr_Y + \frac{1}{L_Y(0.4)}\left[-IF\left(y;L_Y(0.9), F_Y\right) - Iqsr_Y IF\left(y;L_Y(0.4), F_Y\right)\right]$	Rios-Avila (2020)
	$L_Y(0.4) = \mu_Y^{-1}GL\left(0.4;F_Y\right)$	$IF\left(y;L_Y(0.4), F_Y\right) = -\frac{y}{\mu_Y}L_Y(0.4) + \frac{0.2q_Y(0.4)}{\mu_Y} + \left(\frac{y-q_Y(0.4)}{\mu_Y}\right)\mathbb{I}\left\{y < q_Y(0.4)\right\}$	
	$L_Y(0.9) = \mu_Y^{-1}GL\left(0.9;F_Y\right)$	$IF\left(y;L_Y(0.9), F_Y\right) = -\frac{y}{\mu_Y}L_Y(0.9) + \frac{0.2q_Y(0.9)}{\mu_Y} + \left(\frac{y-q_Y(0.9)}{\mu_Y}\right)\mathbb{I}\left\{y < q_Y(0.9)\right\}$	

[a] The indicator function $\mathbb{I}\{\bullet\}$ takes the value of 1 when the statement in brackets is true and 0 when the statement is false

where x_k represents the k-th covariate, and $\widehat{\beta}_k^0$ and $\widehat{\beta}_k^1$ are the estimated coefficients for period 0 and period 1, respectively.[2] This detailed decomposition enables an in-depth analysis of the extent to which the observed difference in the distributional statistic of interest is accounted for by each covariate.[3]

In the empirical analysis that follows, the RIF decomposition is implemented over the entire 2010–2019 period for France and Italy. By contrast, for Portugal and Spain the analysis is conducted separately for two subperiods, 2010–2014 and 2014–2019. As further highlighted in Sect. 4.2, this distinction is motivated by the markedly different dynamics of inequality observed across countries. In Portugal and Spain, the main inequality indicators display a non-monotonic pattern, increasing up to a peak around 2014 and subsequently declining. In France and Italy, instead, the evolution of inequality over the same period appears either mildly monotonically increasing or broadly stable, depending on the specific measure considered. Splitting the sample for Portugal and Spain therefore allows us to account for the structural break implied by the post-2014 reversal in inequality trends and to provide a more accurate decomposition of distributional changes across distinct phases.

The procedure described above is implemented using the oaxaca_rif command in Stata developed by Rios-Avila (2020). In the empirical application, we adopt the normalization proposed by Yun (2005a,b), which ensures that the results of the detailed decomposition are invariant to the choice of the base group. This adjustment prevents the allocation of effects across covariates from being mechanically driven by the reference-category definition and enhances the interpretability and robustness of the decomposition results.

4.2 Data and variables

This study draws on microdata from the European Union Statistics on Income and Living Conditions (EU-SILC), a harmonized survey designed to collect detailed information at both the individual and household levels on income, employment, education, and living conditions across EU member states. For the purposes of the empirical analysis, we restrict attention to the 2010, 2014 and 2019 waves. Consequently, the RIF regression analysis outlined in Section 4.1.1 will be conducted separately for each country in three different years (2010, 2014, 2019) to evaluate both constant results and those that demonstrate variability over time.

The decision to select a minimum of three years is rooted in the aspiration to leverage the opportunities presented by the EU-SILC surveys for dynamic analysis of inequality.

[2] Equation (10) presents a "threefold" decomposition framework in which a common reference distribution is adopted for the identification of both $\widehat{\Delta}_X^\nu$ and $\widehat{\Delta}_\beta^\nu$, while an additional interaction component, $\widehat{\Delta}_I^\nu$, is explicitly included (see, for example, Jones and Kelley 1984). Equations (9) and (10) may equivalently be reformulated by interchanging the roles of the two periods in the estimation of $\widehat{\Delta}_X^\nu$ and $\widehat{\Delta}_\beta^\nu$. Furthermore, the interaction component $\widehat{\Delta}_I^\nu$ can be reassigned to either the endowment effect or the coefficient effect, thereby yielding a corresponding "twofold" decomposition. Although these alternative formulations are widely used in the literature, the selection among them does not entail substantive estimation difficulties (Fortin et al. 2011).

[3] It is worth noting that, in order to decompose the total difference according to Eq. (9), the estimation of two counterfactual distributions is required. The first counterfactual is constructed by combining the distribution of observable characteristics from period 1 with the estimated returns to those characteristics from period 0, $\overline{X}^{1\prime}\widehat{\beta}^0$. The second counterfactual is obtained by pairing the distribution of characteristics from period 0 with the corresponding returns estimated for period 1, $\overline{X}^{0\prime}\widehat{\beta}^1$. In this context, $\overline{X}\prime$ denotes the vector of mean covariate values.

The overall period to be covered relates to the dynamics and last years highlighted in Figs. 1, 2, 3, and 4.

The decision to stop at 2019 and not go beyond that year is dictated by the desire to analyse the covariates of inequality without the disturbance (or interference) of the pandemic period.

The selection of the intermediate year (2014) is once more informed by the data emphasised in Figs. 1, 2, 3, and 4. For two countries (France and Italy), the trend in inequality appears to be consistent over time, thus enabling the decomposition analysis discussed in Section 4.1.2 to be reasonably carried out between the first and last years (2010 and 2019). However, a discernible shift in trend is evident for two countries (Spain and Portugal) in 2014. Consequently, for these two countries it is deemed pertinent to undertake decomposition analysis across two distinct periods: 2010–2014 and 2014–2019.

The analysis is restricted to individuals who were employed at the time of the survey. By focusing exclusively on the employed population, we intentionally exclude both the unemployed and the economically inactive. This decision reflects the study's focus on labour earnings, as distinct from broader measures of income that include social transfers, pensions, or capital income. The dependent variable is annual gross labour earnings, which is subject to a trimming procedure to mitigate the influence of outliers. Specifically, observations with annual earnings below €100 or exceeding €1,000,000 are excluded from the sample.[4]

The countries included in the analysis – France, Italy, Spain, and Portugal – were selected based on shared institutional features characteristic of Southern and Western Europe, notably high levels of labour market segmentation. These countries also exhibit variation in industrial composition and exposure to automation, making them particularly suitable for comparative analysis. An additional selection criterion was the availability of the variable on individuals' region of residence (NUTS-2), which is critical for the use of regional variables within the empirical model.[5] This approach enables robust cross-country comparisons while accounting for subnational heterogeneity.

The covariates employed in the empirical analysis are derived from the individual-level modules of EU-SILC and encompass key socio-demographic and labour market characteristics. Age is measured in completed years at the end of the income reference period and is constructed using the respondent's year of birth in conjunction with a flag indicating whether their birthday had occurred during the calendar year. Gender is recorded as a binary biological characteristic, while citizenship captures legal nationality, distinguishing between nationals and foreign citizens, including both EU and non-EU nationals.

Occupational structure is identified using the International Standard Classification of Occupations (ISCO), which codes individuals' main occupations according to the tasks they perform. This classification facilitates the integration of measures related to skill content and exposure to automation at the occupational level. Education is captured using the International Standard Classification of Education (ISCED) framework, which specifies both the highest completed level of education and the educational track – general or

[4] The earnings variable used is derived from EU-SILC variables PY010G (for employees) and PY050G (for self-employment), which reports the respondent's annual gross cash income, before taxes and social contributions.

[5] While EU-SILC aims for wide coverage, NUTS (Nomenclature of Territorial Units for Statistics) classifications are not provided for all participating countries or regions due to several factors, including sample size limitations and the specific design of national data collection.

vocational. Sectoral affiliation is determined based on the statistical classification of economic activities in the European Community (NACE, Nomenclature statistique des Activités économiques dans la Communauté Européenne), allowing for the linkage of individuals to external, sector-specific indicators of robotization.

Employment status is constructed from detailed survey questions regarding contract type and self-employment. This information is recoded into a categorical variable distinguishing between permanent and temporary employees, full-time and part-time contracts, and self-employed individuals with or without employees. This typology captures important dimensions of labour market segmentation and employment stability, which are central to our investigation of earnings differentials and susceptibility to technological displacement.

In addition to the individual variables from the EU-SILC database, we include three variables at regional level. In the EU-SILC dataset, regional identifiers for individuals correspond to the NUTS-2 level for France (22 regions), Spain (19 regions), and Portugal (7 regions), and to the NUTS-1 level for Italy (5 regions). For Portugal, the variable indicating individuals' region of residence is only available for 2019 in EU-SILC, meaning that, in the case of Portugal, regional variables can only be used in the 2019 RIF analysis and cannot be used in decomposition analysis.

The first regional variable included is the unemployment rate (source: Eurostat). The rationale for including this variable is twofold. First, the baseline estimate employs average wage as the dependent variable, and the inclusion of the unemployment rate formalises a standard "wage equation". Second, in some countries, unemployment has been identified as a potential driver of income inequality. Indeed, the typical mechanisms through which unemployment can affect earnings – particularly wages – such as those described in "efficiency wage" theory, may operate differently across various segments of the income distribution. It should be noted that unemployed individuals are excluded from the micro-data analysis due to the lack of available data on key variables such as sector of employment and ISCO classification. Therefore, the correlation between unemployment and inequality can only be explored in terms of its impact on the earnings of employed individuals.

The second regional variable is the share of regional exports in regional GDP (source: OECD Regional Database), intended to capture the region's exposure to international trade. It is important to note that this variable refers exclusively to exported goods and excludes services. Imports are not considered, as regional-level import data are ambiguous: goods imported into a given region are not necessarily consumed there. Consequently, the region in which an import is recorded may be relevant only in a formal sense, rather than a substantive one.

The third regional variable is regional exposure to robotization, built in accordance with the methodology established in the existing literature on technological change. The variable was created by combining data from various databases. Data on robot installations at the sector and country levels comes from the database of the International Federation of Robotics (IFR). These data were combined with the OECD's "Structural Analysis Database" (STAN), from which data on employed persons (both employees and the self-employed) were taken at the sector/country level.[6] In this way, it was possible to obtain a

[6] The partitioning of the sectors that could be used for merging the two databases is as follows (following Klump et al. 2021): Agriculture, forestry and fishing; Mining and quarrying; Food and Beverages; Textiles; Paper products – Recorded media; Plastic and chemical products; Glass, ceramics, stone, mineral products; Metal; Electrical/Electronics; Manufacture of motor vehicles; Manufacture of other vehicles; Wood, furniture, all other manufacturing; Electricity, gas, water supply; Construction; Services.

robotisation "density" variable at country and sector level, defined as the number of robots installed per thousand engaged. To quantify the "average" and generic "density" of robotisation for each sector, the mean value of this variable was calculated for each sector by taking its mean among the available Eurozone countries in the two databases.[7]

Following Acemoglu and Restrepo (2020b) and Valentini et al. (2023) the values of the "density" of robotization for each sector are combined with sectoral employment shares within each region to compute a regional-level proxy for exposure to robotization. The variable is thus a weighted average of sectoral "density" of robots (over engaged), where each sector's weight corresponds to its employment share in the respective region. To calculate regional employment shares by sector, we first utilized the Eurostat Labour Force Survey to determine the shares of macro sectors, that are agriculture, construction, "industry" (manufacturing, mining, utilities) and services. Subsequently, we reconstructed the distribution of employment across the various "industry" sub-sectors using data from Eurostat's Structural Business Statistics (SBS) database (Valentini et al. 2023).[8] For both databases, some interpolation was necessary to fill in the missing years.

The inclusion of the regional exposure to robotization (which uses "robots per thousand engaged" as its unit of measurement) is intended to capture the potential impact of a specific and recent form of technological change – robotization – as discussed in the literature review in Section 2.

It was deemed appropriate to limit the analysis to three regional variables, given that the smallest number of regions across the four countries is five (Italy, at the NUTS-1 level). Descriptive statistics for both the EU-SILC microdata and the regional-level variables are provided in Appendix A.

Consistent with the conceptual framework outlined in Sect. 2, the covariates used in the empirical analysis are grouped into four broad interpretative dimensions, which are also reflected in the presentation of the results. First, globalisation-related mechanisms are proxied by citizenship and by regional exports of goods as a share of GDP. Citizenship is used as an individual-level indicator related to migration status, while regional exports capture the degree of exposure of local labour markets to international trade. Second, labour-market regulation and segmentation are captured by the type of employment, which distinguishes between permanent and temporary employees, full-time and part-time arrangements, and self-employment. These categories reflect the contractual heterogeneity and labour-market dualism discussed in Section 2. Third, variables related to SBTC include ISCO occupational categories, ISCED educational attainment, and regional exposure to robotisation. Occupational categories capture differences in task and occupational profiles, educational attainment reflects differences in formal skills and the potential role of the skill premium, while robot exposure provides a regional proxy for automation-related technological change. Finally, structural change is proxied, in a narrower sense, by NACE sectoral affiliation. This choice follows the definition adopted in Section 2, where structural change is understood as a transformation in the sectoral composition of output and employment, especially the shift from manufacturing to service activities. Accordingly, the sectoral dummies should be interpreted as observable manifestations of workers' position

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[7] Austria, Belgium, Germany, France, Netherlands, Denmark, Finland, Lithuania, Latvia, Slovenia, Slovacchia, Spain, Italy, Portugal, Greece, Ireland.

[8] While LFS covers all workers, SBS only covers the private sector. However, it remains the best proxy available for the composition of employment at regional level. Moreover, the presence of public employment within the manufacturing sector should not be very significant.

within the changing sectoral structure of each economy, rather than as direct measures of structural change itself.

Age, gender and regional unemployment are included as additional controls for demographic composition and local labour-market conditions.

5 Results

Prior to the presentation and interpretation of the results of the two analyses, it is imperative to emphasise that the methodologies employed do not permit the identification of causal relationships between variables. Nevertheless, the correlation analysis provides a valuable source of insight, particularly with regard to comparisons between the four countries under consideration.

5.1 RIF regression evidence

Table 2 presents the results of the RIF regressions for France, while Table 3 reports the corresponding results for Italy. These are followed by Table 4 for Portugal and Table 5 for Spain. The estimates refer to the three benchmark years considered in the analysis, namely 2010, 2014, and 2019.

Since the core focus of the paper is on earnings inequality, the discussion below concentrates primarily on the inequality-related indicators. Results for mean and median earnings are reported in the tables and are mentioned only when they provide useful descriptive context for interpreting the distributional patterns.

Across all four countries, the estimated coefficients are, in most cases, fairly similar across the different years considered. Although some variation naturally emerges, the overall patterns remain stable over time, which facilitates the interpretation of the findings. To enhance clarity in the presentation and interpretation of the results, we will adopt a thematic – rather than country-by-country – approach in the discussion that follows.

Age and gender display the expected associations with earnings levels, but their relationship with inequality is more country-specific. Workforce ageing is associated with a modest rise in income concentration among higher-income groups, although the relationship is weak or not statistically significant in France and Italy in 2019. Female employment is associated with lower earnings inequality in France, Italy and Portugal, whereas no clear pattern emerges for Spain.

Citizenship, used as a proxy for migration-related mechanisms, shows only limited and country-specific associations with earnings inequality. Although foreign citizens generally display lower earnings levels in several countries, the relationship with the inequality indicators is modest in France and Italy and not statistically robust in Spain and Portugal.

Findings related to the export variable differ substantially across countries. It is important to underline that, as highlighted in the literature, international trade exposure may operate indirectly through various channels, such as structural change or SBTC. Given that our analysis controls for these factors, the estimated effect pertains specifically to the role of exports of goods (excluding services). The results confirm marked cross-country heterogeneity. In France and Portugal, no robust relationship with the inequality indicators emerges. In Italy, export intensity is positively associated with several inequality measures, especially those capturing polarisation (such as the S80/S20 ratio and the Palma ratio), suggesting that the upper part of the distribution benefits more from export-oriented regional

Table 2 RIF analysis results, France, by year

		2010					2014					2019				
		mean	**median**	**gini**	**s80s20**	**palma**	**mean**	**median**	**gini**	**s80s20**	**palma**	**mean**	**median**	**gini**	**s80s20**	**palma**
	Age	368.77***	215.55***	0.00***	−0.00	0.01***	328.72***	184.98***	0.00***	0.01	0.01***	367.39***	216.57***	0.00	−0.02	0.00
		(19.32)	(12.74)	(0.00)	(0.02)	(0.00)	(24.09)	(14.57)	(0.00)	(0.02)	(0.00)	(25.79)	(17.09)	(0.00)	(0.02)	(0.00)
	Male	base	base	base	base	base	base	base	base	base	base	base	base	base	base	base
	Female	−3714.67***	−2307.76***	−0.03***	−1.19***	−0.23***	−5747.32***	−2676.32***	−0.04***	−0.66	−0.34***	−5188.38***	−3296.47***	−0.03***	−0.90*	−0.20**
		(449.75)	(305.52)	(0.01)	(0.43)	(0.07)	(511.17)	(344.82)	(0.01)	(0.49)	(0.07)	(627.94)	(433.24)	(0.01)	(0.46)	(0.08)
Citizenship (globalization—migration)	Native	base	base	base	base	base	base	base	base	base	base	base	base	base	base	base
	EU	−316.76	247.82	0.00	0.58	−0.00	−2379.45	−3154.34***	0.00	−0.03	−0.02	−3313.09***	−1032.57	0.05*	4.45**	0.33*
		(883.64)	(710.21)	(0.02)	(1.02)	(0.11)	(1531.20)	(969.71)	(0.03)	(1.73)	(0.19)	(1214.44)	(1243.18)	(0.03)	(1.96)	(0.19)
	NON-EU	−1455.62*	−1239.63**	0.03	1.69*	0.18	−1493.08	−1218.76*	0.01	0.83	0.08	−677.41	−1670.97**	0.04**	1.99**	0.30**
		(746.46)	(569.12)	(0.02)	(0.93)	(0.12)	(909.96)	(647.24)	(0.02)	(0.99)	(0.14)	(1150.62)	(733.43)	(0.02)	(0.87)	(0.14)

Table 2 (continued)

		2010					2014					2019				
		mean	**median**	**gini**	**s80s20**	**palma**	**mean**	**median**	**gini**	**s80s20**	**palma**	**mean**	**median**	**gini**	**s80s20**	**palma**
Type of employment (labour market regulation)	Employee, permanent, full time	base	base	base	base	base	base	base	base	base	base	base	base	base	base	base
	Employee, permanent, part time	−8163.86*** (379.33)	−6786.78*** (386.84)	0.13*** (0.01)	7.74*** (0.60)	0.92*** (0.06)	−7759.06*** (539.25)	−6941.18*** (487.34)	0.12*** (0.01)	7.13*** (0.76)	0.89*** (0.08)	−8756.07*** (570.88)	−7744.33*** (522.74)	0.12*** (0.01)	6.76*** (0.65)	0.85*** (0.07)
	Employee, temporary, full time	−7992.56*** (504.84)	−8506.47*** (483.03)	0.18*** (0.01)	9.63*** (0.82)	1.19*** (0.09)	−7465.39*** (618.33)	−8950.88*** (549.17)	0.13*** (0.01)	6.43*** (0.82)	0.89*** (0.08)	−7118.17*** (700.19)	−8941.14*** (638.63)	0.13*** (0.01)	7.09*** (0.85)	0.90*** (0.09)
	Employee, temporary, part time	−11893.75*** (648.90)	−9839.16*** (493.32)	0.34*** (0.01)	21.57*** (1.18)	2.28*** (0.09)	−13478.14*** (733.88)	−11,291.74*** (583.09)	0.33*** (0.02)	22.03*** (1.45)	2.23*** (0.12)	−13999.84*** (1044.83)	−11136.28*** (742.56)	0.35*** (0.02)	22.97*** (1.62)	2.38*** (0.12)
	Self-employed with employees	5221.55* (3010.57)	−2844.76*** (987.81)	0.37*** (0.06)	16.46*** (2.11)	2.71*** (0.45)	3746.85 (4967.65)	−1762.63 (2452.44)	0.27*** (0.08)	14.12*** (4.23)	1.92*** (0.62)	5407.23 (3945.82)	−3580.74** (1589.93)	0.29*** (0.06)	12.95*** (2.13)	2.13*** (0.47)
	Self-employed without employees	−10753.49*** (1578.04)	−9411.44*** (752.82)	0.22*** (0.03)	14.56*** (1.49)	1.52*** (0.24)	−7859.11*** (1463.29)	−8802.73*** (673.17)	0.28*** (0.03)	17.94*** (1.45)	1.96*** (0.21)	−11212.23*** (1230.40)	−8110.22*** (824.73)	0.23*** (0.02)	15.97*** (1.21)	1.49*** (0.13)
ISCO classification (SBTC)	Managers	18259.33*** (1336.68)	11010.82*** (575.74)	0.12*** (0.03)	3.17*** (1.12)	0.86*** (0.23)	21043.92*** (1191.24)	12319.15*** (669.60)	0.12*** (0.02)	4.08*** (1.12)	0.81*** (0.18)	30727.54*** (2198.49)	14540.56*** (788.88)	0.23*** (0.04)	6.92*** (1.42)	1.59*** (0.32)
	Professionals	15693.20*** (835.57)	11336.90*** (570.28)	0.05*** (0.02)	0.71 (0.87)	0.32** (0.13)	14518.24*** (975.78)	10790.58*** (655.82)	0.04** (0.02)	0.40 (1.03)	0.33** (0.14)	17245.30*** (1112.01)	13765.80*** (756.86)	0.01 (0.02)	−0.47 (1.06)	0.05 (0.15)

Table 2 (continued)

		2010					2014					2019				
		mean	**median**	**gini**	**s80s20**	**palma**	**mean**	**median**	**gini**	**s80s20**	**palma**	**mean**	**median**	**gini**	**s80s20**	**palma**
	Technicians and ass. profes-sionals	5298.20*** (517.23)	9014.65*** (507.85)	−0.13*** (0.01)	−5.40*** (0.72)	−0.88*** (0.08)	5022.33*** (590.82)	8610.46*** (605.45)	−0.11*** (0.01)	−4.74*** (0.85)	−0.76*** (0.08)	7202.75*** (740.52)	10845.95*** (707.66)	−0.11*** (0.01)	−4.82*** (0.88)	−0.75*** (0.09)
	Clerical support workers	1239.89*** (447.07)	2858.87*** (532.75)	−0.09*** (0.01)	−4.33*** (0.74)	−0.62*** (0.07)	1137.61* (588.40)	2005.79*** (651.62)	−0.09*** (0.01)	−4.89*** (0.89)	−0.58*** (0.08)	571.42 (747.66)	3115.32*** (804.01)	−0.11*** (0.01)	−5.60*** (0.92)	−0.72*** (0.10)
	Service and sales workers	1055.91** (467.40)	1668.79*** (477.57)	−0.02* (0.01)	−0.36 (0.85)	−0.15** (0.08)	2039.66*** (566.73)	2404.88*** (557.88)	−0.02* (0.01)	−0.90 (0.97)	−0.16* (0.09)	2380.49*** (623.46)	2765.68*** (633.90)	−0.00 (0.01)	0.47 (0.95)	−0.03 (0.09)
	Skilled agricul-ture, for-estry—fishery	1338.26 (1600.99)	4853.73*** (1691.66)	−0.05** (0.02)	−1.31 (1.53)	−0.31** (0.15)	1378.40 (2100.96)	3730.85*** (1442.64)	−0.08*** (0.03)	−3.99** (1.72)	−0.57*** (0.19)	−1671.01 (2428.30)	2568.17 (2408.59)	−0.05* (0.03)	−1.39 (2.03)	−0.32* (0.19)
	Craft and related trades workers	366.86 (586.59)	4420.90*** (622.06)	−0.13*** (0.01)	−4.99*** (0.88)	−0.89*** (0.09)	127.16 (810.92)	3196.70*** (858.12)	−0.09*** (0.02)	−3.40*** (1.21)	−0.59*** (0.12)	−446.63 (887.96)	3149.80*** (936.24)	−0.09*** (0.02)	−3.16*** (1.09)	−0.56*** (0.11)
	Plant/machine opera-tors/assemb	−224.15 (557.61)	3170.82*** (635.44)	−0.12*** (0.01)	−5.22*** (0.83)	−0.80*** (0.09)	−1936.86** (783.28)	3472.10*** (826.67)	−0.11*** (0.02)	−3.89*** (1.21)	−0.71*** (0.11)	−1238.65 (830.27)	3236.07*** (864.39)	−0.10*** (0.02)	−3.81*** (0.96)	−0.63*** (0.10)
	Elementary occupa-tions	base	base	base	base	base	base	base	base	base	base	base	base	base	base	base
ISCED – Education (SBTC)	Primary	base	base	base	base	base	base	base	base	base	base	base	base	base	base	base
	Secondary	4487.19*** (438.40)	3791.28*** (459.07)	−0.01 (0.01)	−1.43** (0.69)	−0.07 (0.07)	4341.80*** (885.34)	2877.49*** (748.62)	−0.02 (0.02)	−2.98** (1.39)	−0.14 (0.12)	91.54 (1097.38)	−596.01 (1076.87)	0.00 (0.02)	−0.47 (0.98)	0.03 (0.10)
	Tertiary	9639.13*** (652.19)	5895.22*** (548.86)	0.04*** (0.01)	0.01 (0.84)	0.31*** (0.10)	9430.84*** (1020.62)	5865.10*** (824.76)	−0.01 (0.02)	−3.26** (1.47)	−0.01 (0.14)	6080.83*** (1236.69)	2687.45** (1158.29)	0.03 (0.02)	0.15 (1.09)	0.20* (0.12)

Table 2 (continued)

		2010					2014					2019				
		mean	median	gini	s80s20	palma	mean	median	gini	s80s20	palma	mean	median	gini	s80s20	palma
NACE—sector (structural change)	Agriculture, forestry and fishing	−6173.94***	−4622.07***	−0.02	0.24	−0.17	−4766.50***	−1848.13	−0.07**	−1.95	−0.52***	−4968.56**	−4179.37**	−0.03	−1.35	−0.29
		(1752.46)	(1729.18)	(0.02)	(1.62)	(0.17)	(1672.05)	(1173.45)	(0.03)	(1.45)	(0.20)	(2148.67)	(2049.73)	(0.03)	(1.89)	(0.19)
	Mining; manufacturing; utilities	base	base	base	base	base	base	base	base	base	base	base	base	base	base	base
	Construction	−1633.53**	−1469.67**	0.03*	1.28*	0.20**	−1422.66	1784.83**	−0.08***	−3.04***	−0.60***	−2767.28***	−1762.01*	−0.02	−0.43	−0.11
		(662.50)	(587.04)	(0.01)	(0.74)	(0.10)	(948.42)	(833.68)	(0.02)	(0.99)	(0.14)	(941.47)	(950.66)	(0.02)	(0.87)	(0.11)
	Wholesale, retail trade; repair of motor vehicles	−4372.85***	−4868.71***	0.02	0.50	0.14	−3173.06***	−2358.67***	−0.05***	−2.79***	−0.36***	−4315.61***	−3664.65***	0.01	0.16	0.08
		(731.10)	(495.04)	(0.02)	(0.70)	(0.12)	(897.43)	(704.30)	(0.02)	(0.92)	(0.14)	(1095.96)	(721.32)	(0.02)	(0.87)	(0.15)
	Transportation and storage	−1153.07*	393.76	−0.01	−0.46	−0.07	547.77	2166.49***	−0.08***	−3.77***	−0.59***	3247.16**	1511.36*	0.05*	1.60*	0.36*
		(690.13)	(611.40)	(0.01)	(0.69)	(0.11)	(964.05)	(784.97)	(0.02)	(0.91)	(0.14)	(1553.38)	(876.18)	(0.03)	(0.95)	(0.21)
	Accommodation and food services	−5930.95***	−4743.89***	−0.04*	−1.42	−0.26*	−6024.99***	−3653.00***	−0.03	−0.45	−0.17	−7900.19***	−4232.92***	−0.04**	−2.19*	−0.21
		(905.29)	(713.70)	(0.02)	(1.26)	(0.14)	(1331.61)	(907.36)	(0.03)	(1.64)	(0.21)	(1257.64)	(1020.23)	(0.02)	(1.14)	(0.14)
	Information and communication	−730.52	−870.39	0.03	1.01	0.22	−2259.54	−1070.76	−0.05*	−1.77	−0.42*	−4415.89***	−2889.89***	−0.03	−1.13	−0.27
		(1465.22)	(770.91)	(0.03)	(1.16)	(0.24)	(1455.06)	(863.27)	(0.03)	(1.43)	(0.22)	(1616.35)	(962.20)	(0.03)	(0.98)	(0.20)
	Financial and insurance services	1594.98	1521.22**	−0.00	−0.11	0.01	3160.55*	1986.42**	0.00	−0.36	0.01	5569.96**	911.89	0.09*	2.97*	0.70
		(1164.67)	(735.00)	(0.03)	(0.92)	(0.19)	(1801.55)	(990.17)	(0.04)	(1.37)	(0.30)	(2736.92)	(932.52)	(0.05)	(1.64)	(0.43)

Table 2 (continued)

	Real estate, professional, scientific, technical, administrative act.;	−3355.09*** (973.05)	−2210.36*** (590.75)	−0.00 (0.02)	0.01 (0.85)	0.01 (0.17)	−2349.65* (1200.79)	−1561.81** (710.41)	−0.02 (0.02)	−0.96 (1.07)	−0.13 (0.19)	−3968.97*** (1416.01)	−4312.64*** (836.80)	0.02 (0.02)	0.71 (1.01)	0.23 (0.18)
	Public administration	−4482.30*** (552.33)	−1447.23*** (528.34)	−0.08*** (0.01)	−3.39*** (0.56)	−0.56*** (0.08)	−3338.63*** (932.41)	296.52 (720.92)	−0.11*** (0.02)	−4.71*** (0.85)	−0.79*** (0.14)	−3216.95*** (818.78)	−1093.24 (786.36)	−0.07*** (0.01)	−2.93*** (0.57)	−0.42*** (0.09)
	Education	−11121.20*** (745.55)	−3585.43*** (530.18)	−0.14*** (0.02)	−4.54*** (0.79)	−0.98*** (0.12)	−8120.68*** (1024.00)	−2070.01*** (698.97)	−0.14*** (0.02)	−4.66*** (0.94)	−1.00*** (0.15)	−11066.51*** (949.13)	−4325.97*** (765.17)	−0.10*** (0.02)	−2.90*** (0.72)	−0.63*** (0.11)
	Human health and social work	−3121.79*** (654.54)	−2122.56*** (498.96)	0.02 (0.01)	1.54** (0.68)	0.16 (0.10)	−4118.22*** (1001.73)	−1756.72*** (681.67)	−0.01 (0.02)	0.70 (0.99)	−0.08 (0.15)	−6258.30*** (821.15)	−4347.29*** (713.43)	−0.00 (0.01)	0.59 (0.68)	0.04 (0.10)
	Arts, Entertainment and recreation; other services activities	−1633.53** (662.50)	−1469.67** (587.04)	0.03* (0.01)	1.28* (0.74)	0.20** (0.10)	−6165.95*** (1339.28)	−3849.36*** (942.17)	−0.03 (0.03)	−0.05 (1.52)	−0.23 (0.19)	−4738.50*** (1541.09)	−3751.36*** (1030.83)	−0.01 (0.02)	−0.79 (1.19)	−0.07 (0.16)
	Regional Unemployment Rate	44.90 (85.34)	49.61 (90.48)	0.00* (0.00)	0.21** (0.11)	0.02 (0.01)	−198.94* (113.78)	−63.56 (93.33)	0.01** (0.00)	0.49*** (0.15)	0.04** (0.02)	−198.84 (166.00)	169.86 (136.92)	−0.01*** (0.00)	−0.30** (0.15)	−0.05** (0.02)
Robots (SBTC)	Regional Exposure to Robotization	1429.60*** (478.97)	991.45** (395.56)	0.00 (0.01)	−0.32 (0.55)	0.03 (0.08)	249.25 (430.89)	444.27 (337.60)	−0.01 (0.01)	−0.58 (0.50)	−0.06 (0.06)	−1527.13*** (433.18)	−1011.27*** (342.88)	−0.02*** (0.01)	−1.00*** (0.37)	−0.12** (0.05)

Table 2 (continued)

International competition (globalisation—trade)	Regional Export of goods (% on gdp)	−41.74*** (13.88)	−40.38*** (11.20)	0.00 (0.00)	0.01 (0.02)	0.00 (0.00)	−23.00 (20.70)	−23.93* (12.52)	−0.00 (0.00)	−0.03* (0.02)	−0.00 (0.00)	23.42 (22.55)	30.56* (16.22)	−0.00 (0.00)	0.00 (0.02)	−0.00 (0.00)
	Constant	6474.74*** (1632.56)	9150.06*** (1216.22)	0.25*** (0.04)	5.44*** (1.75)	0.65** (0.26)	13118.92*** (2002.47)	12768.83*** (1553.54)	0.30*** (0.04)	6.36** (2.51)	0.97*** (0.29)	18725.01*** (2273.75)	16544.68*** (1962.75)	0.38*** (0.04)	10.62*** (2.14)	1.58*** (0.25)
	N	9646	9646	9646	9646	9646	8916	8916	8916	8916	8916	9581	9581	9581	9581	9581
	r2	0.35	0.37	0.15	0.19	0.13	0.36	0.36	0.16	0.18	0.14	0.40	0.37	0.17	0.20	0.15

Robust standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; s80s20 = top 20%/bottom 20%; palma = palma ratio (top 10%/bottom 40%)

Table 3 RIF analysis results, Italy, by year

		2010					2014					2019				
		mean	**median**	**gini**	**s80s20**	**palma**	**mean**	**median**	**gini**	**s80s20**	**palma**	**mean**	**median**	**gini**	**s80s20**	**palma**
	Age	410.83*** (24.52)	232.16*** (11.21)	0.00*** (0.00)	0.03** (0.02)	0.02*** (0.00)	339.38*** (17.42)	215.08*** (12.12)	0.00*** (0.00)	0.02 (0.02)	0.01*** (0.00)	328.63*** (16.29)	210.22*** (12.40)	0.00 (0.00)	−0.03 (0.02)	0.00* (0.00)
	Male	base	base	base	base	base	base	base	base	base	base	base	base	base	base	base
	Female	−6824.42*** (513.24)	−3983.28*** (242.65)	−0.03*** (0.01)	−0.95*** (0.34)	−0.26*** (0.09)	−6112.88*** (349.79)	−3910.49*** (271.02)	−0.02*** (0.01)	−0.64* (0.33)	−0.18*** (0.06)	−7086.15*** (435.88)	−4103.63*** (304.08)	−0.03*** (0.01)	−0.48 (0.42)	−0.23*** (0.07)
Citizenship (globalization—migration)	Native	base	base	base	base	base	base	base	base	base	base	base	base	base	base	base
	EU	−1781.23* (958.65)	−2487.20*** (745.90)	0.03 (0.02)	0.75 (1.04)	0.20 (0.15)	−2291.74*** (685.75)	−2283.18*** (690.12)	0.03* (0.01)	1.32 (0.90)	0.22* (0.11)	−299.45 (1603.67)	−3796.74*** (636.93)	0.06* (0.04)	1.98 (1.37)	0.56* (0.33)
	NON-EU	−3524.39*** (649.23)	−4502.79*** (554.60)	0.03*** (0.01)	1.16* (0.64)	0.25** (0.10)	−4292.45*** (436.83)	−4114.55*** (524.56)	0.01 (0.01)	−0.67 (0.56)	0.11 (0.08)	−3051.03*** (522.06)	−4246.42*** (486.05)	0.02** (0.01)	0.24 (0.66)	0.22** (0.09)
Type of employment (labour market regulation)	Employee, permanent, full time	base	base	base	base	base	base	base	base	base	base	base	base	base	base	base
	Employee, permanent, part time	−9780.04*** (403.78)	−10468.86*** (353.03)	0.19*** (0.01)	7.67*** (0.55)	1.43*** (0.07)	−9133.78*** (353.84)	−11447.90*** (357.86)	0.17*** (0.01)	5.51*** (0.53)	1.44*** (0.06)	−9117.77*** (430.07)	−11862.23*** (428.79)	0.11*** (0.01)	3.15*** (0.59)	1.02*** (0.08)
	Employee, temporary, full time	−6070.66*** (502.18)	−7953.51*** (347.42)	0.16*** (0.01)	6.86*** (0.54)	1.20*** (0.09)	−8175.46*** (434.38)	−9148.50*** (475.86)	0.15*** (0.01)	7.41*** (0.68)	1.29*** (0.08)	−8336.36*** (438.88)	−9885.47*** (477.82)	0.11*** (0.01)	6.01*** (0.72)	1.00*** (0.09)
	Employee, temporary, part time	−10882.93*** (552.20)	−10259.03*** (404.20)	0.35*** (0.01)	18.69*** (1.01)	2.56*** (0.10)	−10444.47*** (668.73)	−11701.05*** (542.71)	0.31*** (0.01)	17.11*** (1.22)	2.56*** (0.12)	−9348.71*** (572.12)	−10859.40*** (541.22)	0.23*** (0.01)	12.92*** (1.16)	2.08*** (0.12)
	Self-employed with employees	11159.18*** (1627.90)	1283.63** (509.07)	0.24*** (0.03)	7.39*** (0.96)	1.95*** (0.28)	5647.91*** (1627.60)	−291.17 (624.73)	0.16*** (0.03)	6.13*** (1.09)	1.35*** (0.29)	1412.38 (1460.45)	−3293.94*** (638.74)	0.12*** (0.03)	5.64*** (1.07)	1.06*** (0.26)
	Self-employed without employees	−1149.93 (769.10)	−3160.89*** (363.09)	0.10*** (0.02)	3.63*** (0.49)	0.74*** (0.13)	−5222.26*** (568.23)	−6439.20*** (388.17)	0.13*** (0.01)	6.39*** (0.49)	1.11*** (0.09)	−4758.59*** (749.90)	−6301.23*** (478.62)	0.12*** (0.01)	7.40*** (0.73)	1.06*** (0.12)

Table 3 (continued)

		2010					2014					2019				
		mean	median	gini	s80s20	palma	mean	median	gini	s80s20	palma	mean	median	gini	s80s20	palma
ISCO classification (SBTC)	Managers	10482.51*** (1211.38)	5719.08*** (580.39)	0.01 (0.03)	−0.91 (0.84)	0.10 (0.20)	15992.30*** (1879.95)	5765.01*** (751.96)	0.17*** (0.04)	5.26*** (1.36)	1.41*** (0.34)	19596.84*** (2531.32)	7751.26*** (841.52)	0.18*** (0.05)	5.78*** (1.93)	1.62*** (0.48)
	Professionals	16161.24*** (1237.81)	9361.67*** (540.79)	0.07*** (0.03)	0.98 (0.83)	0.57*** (0.21)	13545.10*** (806.23)	9823.00*** (571.01)	0.04** (0.02)	1.58** (0.74)	0.27** (0.14)	13304.44*** (811.54)	9672.48*** (597.74)	0.01 (0.01)	−0.66 (0.86)	0.08 (0.14)
	Technicians and ass. professionals	6933.83*** (582.68)	7522.41*** (449.89)	−0.08*** (0.01)	−3.12*** (0.55)	−0.58*** (0.09)	6556.21*** (544.00)	8402.37*** (521.54)	−0.08*** (0.01)	−2.44*** (0.62)	−0.69*** (0.09)	7213.74*** (656.79)	7565.46*** (561.55)	−0.09*** (0.01)	−4.74*** (0.78)	−0.82*** (0.11)
	Clerical support workers	4727.42*** (516.90)	5779.68*** (481.78)	−0.09*** (0.01)	−4.08*** (0.54)	−0.68*** (0.08)	3518.37*** (489.93)	5745.44*** (534.16)	−0.10*** (0.01)	−3.88*** (0.61)	−0.82*** (0.08)	4828.28*** (596.09)	5916.75*** (604.34)	−0.09*** (0.01)	−4.47*** (0.79)	−0.78*** (0.10)
	Service and sales workers	4023.70*** (560.15)	3046.56*** (483.46)	−0.01 (0.01)	−1.00 (0.61)	−0.09 (0.09)	2357.02*** (458.12)	2091.62*** (499.69)	−0.03*** (0.01)	−1.54** (0.65)	−0.22*** (0.08)	4334.80*** (575.95)	3694.61*** (537.79)	−0.05*** (0.01)	−4.15*** (0.83)	−0.42*** (0.10)
	Skilled agriculture, forestry—fishery	−2507.99** (1156.42)	−1286.09 (894.82)	−0.04* (0.02)	−1.93* (1.16)	−0.27 (0.17)	−3440.12*** (1163.29)	−2402.57** (989.01)	−0.02 (0.02)	−0.91 (1.56)	−0.21 (0.19)	−2985.21** (1259.98)	−1537.77 (1290.36)	−0.01 (0.03)	−0.01 (1.88)	−0.06 (0.23)
	Craft and related trades workers	11.77 (552.98)	2181.46*** (495.18)	−0.09*** (0.01)	−3.66*** (0.58)	−0.69*** (0.09)	−246.86 (533.58)	2545.04*** (562.01)	−0.09*** (0.01)	−3.58*** (0.66)	−0.74*** (0.09)	1206.30** (605.41)	2823.02*** (656.08)	−0.09*** (0.01)	−4.84*** (0.83)	−0.79*** (0.10)
	Plant/machine operators/assemb	819.63 (589.16)	2578.90*** (575.31)	−0.08*** (0.01)	−3.28*** (0.62)	−0.61*** (0.09)	9.57 (613.52)	4272.81*** (742.80)	−0.13*** (0.01)	−5.22*** (0.68)	−1.07*** (0.10)	2940.65*** (716.60)	5479.92*** (771.13)	−0.10*** (0.01)	−5.31*** (0.87)	−0.90*** (0.12)
	Elementary occupations	base	base	base	base	base	base	base	base	base	base	base	base	base	base	base

Table 3 (continued)

		2010					2014					2019				
		mean	**median**	**gini**	**s80s20**	**palma**	**mean**	**median**	**gini**	**s80s20**	**palma**	**mean**	**median**	**gini**	**s80s20**	**palma**
ISCED – Education (SBTC)	Primary	base	base	base	base	base	base	base	base	base	base	base	base	base	base	base
	Secondary	4379.76*** (789.52)	2817.82*** (507.88)	−0.01 (0.02)	−1.20* (0.65)	−0.04 (0.13)	5895.21*** (730.76)	4127.48*** (681.27)	−0.01 (0.01)	−2.39*** (0.91)	−0.07 (0.11)	4068.76*** (762.46)	3126.00*** (890.64)	−0.03* (0.02)	−3.36** (1.43)	−0.24 (0.15)
	Tertiary	12007.58*** (1288.84)	5351.10*** (593.76)	0.09*** (0.03)	2.18** (0.89)	0.75*** (0.22)	12161.74*** (984.71)	6852.23*** (747.39)	0.06*** (0.02)	0.05 (1.03)	0.51*** (0.16)	10722.71*** (1021.16)	5949.29*** (942.28)	0.04* (0.02)	−0.77 (1.52)	0.35* (0.19)
		2010					**2014**					**2019**				
		mean	**median**	**gini**	**s80s20**	**palma**	**mean**	**median**	**gini**	**s80s20**	**palma**	**mean**	**median**	**gini**	**s80s20**	**palma**
NACE—sector (structural change)	Agriculture, forestry and fishing	−5117.74*** (1090.27)	−2228.54*** (768.67)	0.02 (0.02)	2.49** (0.99)	0.12 (0.16)	−7472.03*** (1125.78)	−4262.69*** (865.32)	0.06*** (0.02)	5.93*** (1.46)	0.52*** (0.18)	−4716.59*** (1158.20)	−2470.15*** (939.48)	0.01 (0.02)	1.89 (1.30)	0.13 (0.19)
	Mining; manufacturing; utilities	base	base	base	base	base	base	base	base	base	base	base	base	base	base	base
	Construction	−1601.31** (650.07)	−723.73 (485.81)	−0.01 (0.01)	−0.01 (0.49)	−0.09 (0.10)	−1235.13 (948.12)	−1625.87*** (623.69)	0.01 (0.02)	0.14 (0.75)	0.03 (0.17)	−2968.92*** (796.08)	−1999.04*** (690.65)	−0.03** (0.01)	−1.64** (0.72)	−0.29** (0.13)
	Wholesale, retail trade; repair of motor vehicles	−2536.83*** (792.37)	−1461.97*** (405.85)	−0.02 (0.02)	−0.54 (0.53)	−0.15 (0.13)	−3253.15*** (576.84)	−2474.77*** (476.86)	−0.04*** (0.01)	−2.02*** (0.50)	−0.35*** (0.09)	−2576.14*** (736.53)	−2939.25*** (520.85)	0.01 (0.01)	−0.00 (0.68)	0.04 (0.13)
	Transportation and storage	50.38 (706.28)	2833.38*** (601.25)	−0.06*** (0.01)	−1.54*** (0.52)	−0.42*** (0.10)	−654.83 (1003.98)	428.95 (691.66)	−0.01 (0.02)	0.21 (0.78)	−0.07 (0.17)	−1297.15 (793.37)	486.21 (741.05)	−0.03** (0.01)	−1.42* (0.73)	−0.21* (0.13)
	Accommodation and food services	−6032.98*** (977.16)	−3188.93*** (572.26)	0.01 (0.02)	1.70** (0.79)	0.01 (0.17)	−7628.73*** (743.23)	−4625.75*** (633.32)	−0.01 (0.01)	1.02 (0.85)	−0.06 (0.13)	−7331.34*** (976.12)	−5917.39*** (650.97)	0.04** (0.02)	3.88*** (1.15)	0.35** (0.17)

Table 3 (continued)

Information and communication	481.23 (1301.72)	1708.11** (717.67)	−0.01 (0.02)	0.27 (0.78)	−0.13 (0.19)	679.98 (1196.14)	600.13 (771.74)	−0.01 (0.02)	−0.04 (0.83)	−0.15 (0.18)	−1595.28 (1474.53)	−1950.00** (880.26)	0.00 (0.03)	−0.02 (1.19)	−0.02 (0.24)
Financial and insurance services	10127.92*** (1490.08)	4420.21*** (572.37)	0.11*** (0.03)	3.92*** (0.93)	0.74*** (0.25)	7557.17*** (1116.39)	4084.59*** (624.03)	0.06** (0.02)	2.75*** (0.83)	0.37* (0.19)	10888.59*** (1641.09)	3439.18*** (731.74)	0.12*** (0.03)	4.48*** (1.21)	0.94*** (0.30)
Real estate, professional, scientific, technical, administrative act.;	1596.57 (1352.53)	−1172.96*** (442.85)	0.10*** (0.03)	3.31*** (0.86)	0.78*** (0.24)	−1864.14*** (720.65)	−2691.28*** (498.02)	0.02 (0.01)	0.52 (0.60)	0.16 (0.12)	−1452.40* (861.60)	−2861.18*** (539.00)	0.04** (0.02)	1.40* (0.75)	0.33** (0.15)
Public administration	59.09 (780.65)	4755.55*** (452.32)	−0.08*** (0.02)	−1.72*** (0.51)	−0.57*** (0.13)	−710.00 (685.32)	4096.55*** (498.55)	−0.10*** (0.01)	−3.19*** (0.52)	−0.81*** (0.11)	890.38 (916.35)	3557.25*** (531.99)	−0.05*** (0.02)	−1.12 (0.72)	−0.51*** (0.16)
Education	−7030.15*** (834.40)	−129.34 (495.25)	−0.14*** (0.02)	−4.13*** (0.58)	−1.01*** (0.14)	−10936.28*** (799.79)	−3034.88*** (599.91)	−0.17*** (0.02)	−6.29*** (0.66)	−1.40*** (0.13)	−8741.62*** (906.35)	−2386.81*** (646.98)	−0.12*** (0.02)	−4.47*** (0.79)	−1.01*** (0.15)
Human health and social work	877.97 (865.32)	346.70 (478.92)	0.01 (0.02)	0.14 (0.58)	0.14 (0.14)	−1909.70** (744.84)	−1247.51** (534.07)	−0.00 (0.01)	−0.12 (0.62)	0.02 (0.13)	298.07 (971.68)	−1367.42** (588.41)	0.04** (0.02)	1.19 (0.81)	0.41** (0.17)
Arts, Entertainment and recreation; other services activities	−5215.82*** (919.13)	−2920.64*** (537.31)	0.03 (0.02)	2.34*** (0.72)	0.18 (0.15)	−6575.27*** (677.68)	−4723.75*** (534.88)	0.04*** (0.01)	2.30*** (0.71)	0.38*** (0.11)	−6948.76*** (814.50)	−5868.33*** (596.65)	0.06*** (0.02)	3.92*** (0.98)	0.53*** (0.16)

Table 3 (continued)

	Regional Unemployment Rate	−587.99*** (101.99)	−309.00*** (64.33)	−0.00 (0.00)	−0.00 (0.08)	−0.02 (0.02)	−316.14*** (83.88)	−169.30*** (63.04)	0.00* (0.00)	0.19** (0.08)	0.02* (0.01)	−561.22*** (100.32)	−291.64*** (77.20)	0.00 (0.00)	0.14 (0.10)	0.00 (0.02)
Robots (SBTC)	Regional Exposure to Robotization	1092.55 (686.82)	192.54 (382.73)	0.03** (0.01)	1.23** (0.49)	0.25** (0.12)	459.43 (424.88)	544.74* (319.03)	0.00 (0.01)	0.47 (0.39)	0.02 (0.07)	757.20** (347.77)	357.22 (246.04)	0.01 (0.01)	0.37 (0.34)	0.09 (0.06)
International competition (globalisation—trade)	Regional Export of goods (% on gdp)	7.07 (42.61)	64.77** (30.21)	−0.00*** (0.00)	−0.09** (0.03)	−0.02*** (0.01)	79.23 (54.71)	75.93* (41.42)	0.00 (0.00)	−0.00 (0.05)	0.00 (0.01)	−70.35 (56.68)	43.11 (44.28)	−0.00** (0.00)	−0.07 (0.06)	−0.02** (0.01)
	Constant	6747.88*** (2531.74)	9981.86*** (1382.61)	0.26*** (0.05)	5.61*** (1.79)	0.73* (0.42)	8730.21*** (2327.29)	10133.26*** (1874.62)	0.23*** (0.04)	4.35** (2.20)	0.38 (0.38)	13984.41*** (2523.03)	13114.88*** (2035.90)	0.38*** (0.05)	11.70*** (2.75)	1.68*** (0.42)
	N	16412	16412	16412	16412	16412	16589	16589	16589	16589	16589	16222	16222	16222	16222	16222
	r2	0.23	0.31	0.09	0.11	0.08	0.29	0.36	0.13	0.13	0.12	0.27	0.32	0.10	0.10	0.10

Robust standard errors in parentheses; * $p<0.1$, ** $p<0.05$, *** $p<0.01$; s80s20 = top 20%/bottom 20%; palma = palma ratio (top 10%/bottom 40%)

contexts. In Spain, by contrast, higher export intensity is associated in several cases with lower inequality.

In Spain, average earnings tend to be lower in the regions with the highest export activity, a pattern consistent with competitive pressures linked to international markets. At the same time, several indicators are associated with a reduction in inequality in contexts characterised by greater export capacity.

Structural change can be analysed by considering the sectoral dummies, with manufacturing serving as the reference category. This allows for a convenient interpretation in terms of "de-industrialisation". In France, the transition towards service-based sectors is associated with lower inequality – particularly in sectors such as Accommodation and Food Services and Information and Communication Technologies (ICT) – with an especially prominent role played by public services, namely Public Administration and Education. In Italy, the shift away from manufacturing towards Construction and selected services sectors – such as Transportation and Storage – is likewise associated with lower inequality, whereas others – such as Accommodation and Food Services, Financial and Insurance Activities, and Recreation – are linked to higher levels of polarisation. Additionally, in Italy, public sector employment (Public Administration and Education) is related to comparatively lower inequality levels (this point will be revisited shortly). As observed in France, several service sectors in Portugal – such as Wholesale and Retail Trade, Accommodation and Food Services, Real Estate and Professional Services, Education, and Recreation – are associated with lower inequality compared to manufacturing. Lastly, in Spain, some service sectors – particularly Financial and Insurance Activities and Recreation – correlate with higher inequality, whereas predominantly public sectors such as Public Administration, Education, and Human Health correspond to lower inequality.

The manner in which the structural transition towards services is associated with inequality appears to be significantly shaped by the extent of public employment, a factor that warrants further investigation. The share of government employment as a percentage of total employment in the four countries under consideration is as follows: France, 22.35% in 2007 and 21.31% in 2019 (−1.04 percentage points); Italy, 14.53% in 2007 and 13.35% in 2019 (−1.19 percentage points); Portugal, 14.49% in 2007 and 14.19% in 2019 (−0.30 percentage points); and Spain, 13.43% in 2007 and 15.38% in 2019 (+1.95 percentage points). The year 2007 is selected as the starting point due to data availability (OECD), while 2019 is chosen as the reference year for our micro-level analysis. These figures indicate that France maintains the highest level of public employment, Italy records both the lowest level and the most pronounced decline, and Spain is the only country among the four in which the share of public employment has increased over the period.

The results concerning the "education" variable point to a possible role for the skill premium associated with tertiary education – and, by extension, the relevance of SBTC – in the observed patterns of earnings inequality in France and in Italy (as evidenced by a positive correlation with the Gini coefficient and Palma ratio). These findings suggest that the distributive effect of education may primarily reflect a disproportionate advantage accruing to the top 10% of earners. Portugal emerges as the country where educational attainment, at both the secondary and tertiary levels, exerts the most consistent and substantial influence on income distribution across nearly all inequality metrics. In contrast, Spain appears to be a partial outlier within this group, as the relationship between educational attainment and inequality indicators is generally weak and limited – emerging only for tertiary education in 2010 and 2014.

However, patterns consistent with SBTC may also manifest through variations across occupational categories, as classified by the International Standard Classification of

Table 4 RIF analysis results, Portugal, by year

		2010					2014					2019				
		mean	**median**	**gini**	**s80s20**	**palma**	**mean**	**median**	**gini**	**s80s20**	**palma**	**mean**	**median**	**gini**	**s80s20**	**palma**
	Age	226.61*** (21.07)	68.87*** (11.25)	0.00*** (0.00)	0.13*** (0.02)	0.03*** (0.01)	287.24*** (20.95)	99.79*** (11.16)	0.00*** (0.00)	0.16*** (0.02)	0.04*** (0.01)	247.41*** (17.04)	101.90*** (7.58)	0.00*** (0.00)	0.06*** (0.02)	0.02*** (0.00)
	Male	base	base	base	base	base	base	base	base	base	base	base	base	base	base	base
	Female	−3941.48*** (577.13)	−2482.04*** (256.28)	−0.03* (0.02)	−1.40** (0.55)	−0.31* (0.17)	−3755.03*** (416.19)	−2829.12*** (230.56)	−0.01 (0.01)	−0.54 (0.47)	−0.18 (0.12)	−4002.72*** (386.52)	−2366.35*** (166.84)	−0.02** (0.01)	−0.59 (0.37)	−0.24** (0.11)
Citizenship (globalization—migration)	Native	base	base	base	base	base	base	base	base	base	base	base	base	base	base	base
	EU	−1886.18* (1040.41)	−229.50 (878.80)	−0.08*** (0.03)	−2.75** (1.11)	−0.67*** (0.23)	1403.91 (1834.03)	−92.85 (625.93)	0.05 (0.06)	1.62 (1.97)	0.47 (0.61)	396.18 (989.71)	747.21 (473.01)	−0.01 (0.03)	−0.40 (0.86)	−0.04 (0.22)
	NON-EU	−138.28 (756.14)	−732.31 (456.79)	0.01 (0.03)	0.30 (0.80)	0.10 (0.23)	304.95 (726.70)	−100.53 (415.55)	−0.00 (0.02)	−0.14 (0.78)	−0.05 (0.21)	398.36 (607.35)	−113.41 (291.55)	0.00 (0.02)	−0.12 (0.61)	0.02 (0.16)
Type of employment (labour market regulation)	Employee, permanent, full time	base	base	base	base	base	base	base	base	base	base	base	base	base	base	base
	Employee, permanent, part time	−5812.79*** (637.14)	−4215.61*** (458.32)	0.19*** (0.03)	11.32*** (1.43)	1.48*** (0.22)	−4738.17*** (609.46)	−3428.36*** (510.10)	0.21*** (0.02)	14.63*** (1.57)	1.86*** (0.20)	−5838.60*** (679.16)	−4291.28*** (412.36)	0.19*** (0.02)	11.54*** (1.24)	1.54*** (0.16)
	Employee, temporary, full time	−4471.27*** (421.19)	−3002.83*** (350.22)	0.04*** (0.01)	2.76*** (0.62)	0.34*** (0.11)	−4269.48*** (396.48)	−3495.50*** (315.83)	0.12*** (0.01)	8.09*** (0.75)	1.09*** (0.11)	−3671.38*** (337.87)	−2397.11*** (243.00)	0.08*** (0.01)	4.56*** (0.46)	0.65*** (0.09)
	Employee, temporary, part time	−4760.38 (4832.72)	−4653.52*** (1337.37)	0.32*** (0.10)	16.21*** (3.40)	2.67*** (0.94)	−8758.55*** (945.95)	−6669.32*** (795.70)	0.32*** (0.04)	22.32*** (2.60)	2.81*** (0.31)	−7990.64*** (752.56)	−5230.89*** (561.12)	0.26*** (0.03)	15.35*** (1.72)	2.07*** (0.21)
	Self-employed with employees	−4937.24*** (1369.84)	−1353.87* (692.29)	−0.04 (0.04)	−0.09 (1.22)	−0.37 (0.33)	4395.44 (3509.54)	−1320.98 (809.84)	0.28** (0.11)	10.34*** (3.32)	2.69** (1.12)	9058.49*** (2899.79)	−325.38 (640.74)	0.36*** (0.09)	10.90*** (2.39)	3.17*** (0.82)
	Self-employed without employees	−4309.60*** (1301.45)	−2711.91*** (476.95)	0.08** (0.04)	4.61*** (1.17)	0.67* (0.37)	−4656.82*** (1031.13)	−4189.47*** (546.08)	0.11*** (0.03)	7.13*** (1.10)	1.00*** (0.26)	−5690.85*** (949.45)	−4595.92*** (331.42)	0.18*** (0.03)	10.01*** (0.96)	1.45*** (0.25)

Table 4 (continued)

		2010					2014					2019				
		mean	median	gini	s80s20	palma	mean	median	gini	s80s20	palma	mean	median	gini	s80s20	palma
ISCO classification (SBTC)	Managers	9708.75*** (1370.58)	4073.30*** (645.35)	0.14*** (0.04)	3.38*** (1.28)	1.27*** (0.39)	11174.63*** (1737.49)	6357.36*** (607.18)	0.13** (0.05)	4.95*** (1.69)	1.36*** (0.53)	12792.07*** (1475.17)	5473.54*** (425.49)	0.17*** (0.05)	4.60*** (1.29)	1.50*** (0.41)
	Professionals	14507.37*** (1453.59)	7318.37*** (578.20)	0.14*** (0.05)	4.54*** (1.38)	0.99** (0.42)	10061.06*** (998.24)	8383.83*** (518.62)	0.01 (0.03)	1.72 (1.14)	0.17 (0.29)	10500.14*** (833.48)	7082.24*** (381.90)	0.02 (0.03)	0.61 (0.86)	0.23 (0.22)
	Technicians and ass. professionals	7794.59*** (1673.96)	5732.45*** (523.52)	0.02 (0.06)	1.59 (1.50)	0.07 (0.51)	3801.23*** (626.13)	6337.85*** (451.64)	−0.11*** (0.02)	−2.64*** (0.78)	−0.98*** (0.17)	4474.50*** (508.46)	5416.45*** (337.58)	−0.07*** (0.01)	−2.24*** (0.62)	−0.53*** (0.12)
	Clerical support workers	3068.56*** (811.86)	3633.58*** (525.43)	−0.04* (0.03)	−1.27 (0.84)	−0.31 (0.23)	966.27** (488.56)	4572.16*** (503.89)	−0.12*** (0.01)	−3.58*** (0.75)	−0.96*** (0.14)	536.72 (384.28)	3301.00*** (364.41)	−0.10*** (0.01)	−3.44*** (0.61)	−0.74*** (0.10)
	Service and sales workers	2300.85*** (615.59)	1363.52*** (460.36)	0.00 (0.02)	−0.32 (0.69)	−0.00 (0.15)	1997.27*** (364.03)	2219.33*** (393.63)	−0.04*** (0.01)	−1.50** (0.60)	−0.39*** (0.10)	1650.80*** (354.98)	1619.78*** (280.15)	−0.05*** (0.01)	−2.12*** (0.56)	−0.35*** (0.09)
	Skilled agriculture, forestry—fishery	83.53 (1168.67)	−950.58 (885.09)	0.03 (0.03)	0.84 (1.22)	0.25 (0.24)	1629.02 (1601.55)	1559.24 (982.37)	0.03 (0.04)	2.10 (1.93)	0.21 (0.37)	223.29 (1367.65)	2071.59*** (675.85)	−0.07* (0.04)	−1.72 (1.45)	−0.67* (0.36)
	Craft and related trades workers	1985.58*** (625.89)	2328.39*** (486.02)	−0.01 (0.02)	−0.32 (0.71)	−0.04 (0.16)	1000.37* (520.25)	2856.16*** (478.62)	−0.08*** (0.01)	−2.36*** (0.72)	−0.72*** (0.14)	40.82 (441.57)	2253.03*** (350.81)	−0.11*** (0.01)	−4.06*** (0.61)	−0.83*** (0.11)
	Plant/machine operators/assemb	1640.33** (792.77)	2931.92*** (553.33)	−0.05** (0.02)	−1.22 (0.89)	−0.38* (0.21)	−378.79 (532.18)	1592.02*** (486.96)	−0.07*** (0.02)	−2.43*** (0.76)	−0.69*** (0.15)	159.38 (458.43)	2581.21*** (381.22)	−0.11*** (0.01)	−4.23*** (0.62)	−0.89*** (0.11)
	Elementary occupations	base	base	base	base	base	base	base	base	base	base	base	base	base	base	base

Table 4 (continued)

		2010					2014					2019				
		mean	**median**	**gini**	**s80s20**	**palma**	**mean**	**median**	**gini**	**s80s20**	**palma**	**mean**	**median**	**gini**	**s80s20**	**palma**
ISCED – Education (SBTC)	Primary	base	base	base	base	base	base	base	base	base	base	base	base	base	base	base
	Secondary	3163.74*** (442.01)	1832.20*** (312.54)	0.04*** (0.01)	1.59*** (0.45)	0.33*** (0.11)	4026.98*** (424.47)	2298.92*** (293.66)	0.05*** (0.01)	2.15*** (0.48)	0.43*** (0.12)	3688.12*** (375.56)	1975.66*** (222.71)	0.03*** (0.01)	1.20*** (0.39)	0.28*** (0.10)
	Tertiary	7378.70*** (1064.09)	2420.34*** (474.33)	0.16*** (0.03)	5.81*** (1.04)	1.31*** (0.31)	10223.68*** (957.67)	4853.21*** (462.15)	0.13*** (0.03)	5.25*** (1.04)	1.18*** (0.28)	8893.13*** (785.66)	4245.96*** (337.30)	0.09*** (0.02)	3.00*** (0.73)	0.74*** (0.21)
		2010					**2014**					**2019**				
		mean	**median**	**gini**	**s80s20**	**palma**	**mean**	**median**	**gini**	**s80s20**	**palma**	**mean**	**median**	**gini**	**s80s20**	**palma**
NACE—sector (structural change)	Agriculture, forestry and fishing	247.62 (1211.70)	1035.31 (837.07)	0.04 (0.03)	2.29** (1.13)	0.25 (0.25)	1670.22 (1713.05)	1211.67 (966.98)	0.05 (0.04)	3.24* (1.93)	0.45 (0.43)	388.87 (1724.55)	−346.06 (618.04)	0.09* (0.05)	4.25*** (1.58)	0.76 (0.48)
	Mining; manufacturing; utilities	base	base	base	base	base	base	base	base	base	base	base	base	base	base	base
	Construction	−280.40 (755.03)	700.53 (499.53)	−0.03* (0.02)	−0.83 (0.72)	−0.28 (0.17)	−1625.32** (645.43)	−683.58 (517.83)	−0.05*** (0.02)	−1.88** (0.78)	−0.47*** (0.16)	−1769.67*** (657.52)	−1165.48*** (392.44)	−0.02 (0.02)	−0.79 (0.63)	−0.17 (0.16)
	Wholesale, retail trade; repair of motor vehicles	788.32 (685.86)	988.10** (448.01)	−0.00 (0.02)	0.30 (0.70)	−0.01 (0.18)	−229.21 (721.02)	371.97 (421.81)	−0.01 (0.02)	0.03 (0.77)	−0.10 (0.20)	−1312.76** (661.34)	356.01 (312.86)	−0.04* (0.02)	−1.27** (0.60)	−0.28 (0.18)
	Transportation and storage	5739.82*** (1747.83)	2622.99*** (686.57)	0.08 (0.06)	2.56 (1.61)	0.67 (0.51)	2986.41*** (948.61)	3234.38*** (589.00)	−0.03 (0.03)	0.27 (1.02)	−0.22 (0.26)	1674.93** (757.66)	2539.93*** (433.73)	−0.03 (0.02)	−0.41 (0.69)	−0.16 (0.19)

Table 4 (continued)

Accommodation and food services	−567.27 (783.28)	−67.70 (569.08)	−0.02 (0.02)	−0.85 (0.78)	−0.18 (0.20)	−2239.28*** (760.14)	−741.60 (560.72)	−0.02 (0.02)	−0.43 (0.90)	−0.24 (0.20)	−3071.40*** (624.07)	−745.98** (376.63)	−0.05*** (0.02)	−1.23* (0.72)	−0.45*** (0.16)
Information and communication	540.04 (1405.16)	2385.89** (929.29)	−0.10*** (0.04)	−2.85** (1.27)	−0.88*** (0.33)	725.63 (1484.58)	−759.89 (707.40)	0.01 (0.04)	0.56 (1.53)	0.03 (0.41)	−153.35 (1422.87)	253.27 (477.90)	0.02 (0.04)	1.85 (1.28)	0.12 (0.37)
Financial and insurance services	13398.88*** (2607.42)	4439.15*** (799.60)	0.29*** (0.09)	9.63*** (2.59)	2.57*** (0.79)	7583.70*** (1932.77)	1361.56** (618.18)	0.16** (0.06)	5.88*** (2.02)	1.39** (0.64)	4625.46*** (1273.11)	1200.90*** (462.44)	0.06* (0.04)	2.78** (1.11)	0.39 (0.32)
Real estate, professional, scientific, technical, administrative act.;	−1686.03* (901.00)	1413.21** (623.41)	−0.09*** (0.02)	−2.58*** (0.80)	−0.69*** (0.21)	−2689.33*** (936.78)	−410.08 (486.10)	−0.03 (0.03)	−0.47 (1.05)	−0.23 (0.28)	−4066.38*** (724.72)	−860.70** (385.87)	−0.08*** (0.02)	−2.53*** (0.70)	−0.62*** (0.18)
Public administration	1814.92** (812.93)	3635.97*** (457.95)	−0.05** (0.03)	−0.60 (0.82)	−0.52** (0.23)	709.93 (727.39)	1896.39*** (440.93)	−0.06*** (0.02)	−1.09 (0.76)	−0.62*** (0.21)	858.85 (793.23)	1031.03*** (339.29)	−0.01 (0.02)	0.37 (0.72)	−0.14 (0.21)
Education	2889.82*** (912.99)	1644.85*** (487.18)	0.00 (0.03)	0.17 (0.89)	−0.07 (0.25)	−3371.99*** (804.97)	−592.81 (438.80)	−0.13*** (0.03)	−4.53*** (0.93)	−1.33*** (0.24)	−3767.81*** (690.79)	−1119.27*** (344.23)	−0.08*** (0.02)	−2.11*** (0.69)	−0.82*** (0.18)
Human health and social work	588.72 (873.15)	2025.10*** (521.71)	−0.03 (0.03)	−0.89 (0.92)	−0.16 (0.26)	−3484.64*** (741.57)	−1421.22*** (444.04)	−0.06** (0.02)	−2.45*** (0.85)	−0.52** (0.23)	−2848.99*** (653.86)	−1442.48*** (329.34)	−0.02 (0.02)	−0.89 (0.66)	−0.20 (0.17)

Table 4 (continued)

	Arts, Entertainment and recreation; other services activities	1907.10 (2441.25)	908.46 (691.76)	0.08 (0.09)	2.34 (2.19)	0.80 (0.77)	−2125.95*** (756.06)	−520.72 (552.86)	−0.03 (0.02)	−0.24 (0.94)	−0.28 (0.19)	−2760.85*** (763.70)	−461.44 (431.19)	−0.03 (0.02)	−0.59 (0.82)	−0.22 (0.19)
	Regional Unemployment Rate											11.88 (169.83)	−77.88 (91.98)	0.00 (0.00)	−0.04 (0.17)	0.02 (0.04)
Robots (SBTC)	Regional Exposure to Robotization											−2280.58*** (566.37)	−1049.41*** (261.89)	−0.01 (0.02)	−0.17 (0.53)	−0.13 (0.15)
International competition (globalisation—trade)	Regional Export of goods (% on gdp)											89.36*** (33.59)	32.50** (15.39)	0.00 (0.00)	0.00 (0.03)	0.00 (0.01)
	Constant	581.06 (1060.09)	4301.41*** (721.02)	0.15*** (0.03)	−1.66 (1.16)	−0.19 (0.28)	−1384.31 (1143.14)	2369.56*** (726.84)	0.18*** (0.03)	−2.28* (1.27)	−0.08 (0.32)	3559.78** (1746.52)	5258.50*** (884.88)	0.26*** (0.05)	3.52** (1.79)	0.55 (0.46)
	N	4453	4453	4453	4453	4453	5464	5464	5464	5464	5464	12518	12518	12518	12518	12518
	r2	0.35	0.29	0.13	0.16	0.11	0.34	0.36	0.12	0.17	0.11	0.30	0.34	0.10	0.14	0.09

Robust standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; s80s20 = top 20%/bottom 20%; palma = palma ratio (top 10%/bottom 40%)

Occupations (ISCO). Within this framework, "elementary occupations" are treated as the reference category. Across all countries and years, employment in nearly all "intermediate" ISCO categories is associated with lower levels of inequality compared to elementary occupations, whereas employment in the "managers" category, situated at the opposite end of the occupational hierarchy, tends to display a positive association with inequality. Nevertheless, cross-country differences persist. In Spain, the polarising effect of managerial positions relative to elementary occupations appears less pronounced, while the equalising effect of intermediate occupations is more robust – particularly when considering the S80/S20 ratio, which directly measures income polarisation. These findings further support the notion that SBTC is comparatively less central in the inequality patterns observed in Spain. In Portugal, the mitigating impact of intermediate occupations on inequality resembles that observed in Italy, although the inequality-enhancing pattern linked to managerial positions appears more subdued. This may suggest that, in the Portuguese context, the distributive consequences of SBTC are more strongly mediated by educational attainment, consistent with earlier findings.

Overall, the polarising effect of occupational structure as captured by the ISCO classification appears to be a significant mechanism through which SBTC may operate. This effect may complement or substitute for the role played by the education variable in accounting for inequality dynamics.

The variable measuring regional exposure to robotization offers another potential operationalisation of more recent forms of SBTC. However, interpreting its implications in this context is far from straightforward. This complexity arises, first, from its nature as a contextual (i.e., regional) variable, rather than one pertaining to individuals. Moreover, the impact of robotisation and automation on labour markets and earnings – including their distributional effects – may occur through sectoral labour reallocation (Gentili et al. 2020) and/or via differentiated impacts on skilled versus unskilled workers or across occupational groups (Acemoglu and Restrepo 2022). Notably, these dimensions are already accounted for in the analysis through the inclusion of variables capturing sectoral affiliation (NACE), occupational classification (ISCO), and educational attainment. Autor and Dorn (2013), for instance, argue that automation in goods-producing industries can drive low-skilled workers into service-sector employment, resulting in employment polarisation and wage growth concentrated at the upper and lower ends of the distribution. Similarly, Humlum (2022) finds that industrial robots have led to an average increase in real wages of 0.8 percent, while simultaneously reducing real wages among manufacturing workers by 5.4 percent. Rodrigo et al. (2024), using data from the United States, report that industrial robots have compressed within-occupation wage inequality by reducing earnings at the top of the distribution, while simultaneously exacerbating between-occupation inequality by eroding wages in the middle of the distribution.

It is therefore useful to interpret the estimates as capturing country-specific patterns associated with robotization, while also taking into account the role of NACE sectors, ISCO classifications, and educational attainment. In France and Portugal, exposure to robotization is generally associated with lower inequality, especially in 2019. This pattern may be consistent with the mechanism discussed by Rodrigo et al. (2024): since cross-sectoral and cross-occupational differences are already partly captured by other covariates, the association with robotization may reflect a compression of earnings within occupational or sectoral groups. In Italy, robotization shows little systematic association with overall earnings inequality. This suggests that the distributional channels identified in the literature may operate in opposing directions or be absorbed by the sectoral, occupational and educational variables already included in the model. In Spain, no clear correlation between

Table 5 RIF analysis results, Spain, by year

		2010					2014					2019				
		mean	**median**	**gini**	**s80s20**	**palma**	**mean**	**median**	**gini**	**s80s20**	**palma**	**mean**	**median**	**gini**	**s80s20**	**palma**
	Age	359.56*** (16.30)	207.33*** (13.39)	0.00*** (0.00)	0.12*** (0.02)	0.02*** (0.00)	341.92*** (16.80)	213.32*** (16.24)	0.00*** (0.00)	0.08*** (0.03)	0.02*** (0.00)	404.40*** (22.63)	243.04*** (14.59)	0.00** (0.00)	−0.02 (0.03)	0.01** (0.01)
	Male	base	base	base	base	base	base	base	base	base	base	base	base	base	base	base
	Female	−4749.25*** (356.18)	−3535.23*** (305.54)	−0.01 (0.01)	−0.13 (0.47)	−0.10 (0.07)	−4747.21*** (350.31)	−4140.73*** (358.09)	−0.01 (0.01)	−0.85 (0.60)	−0.13 (0.08)	−5312.61*** (521.76)	−3807.35*** (346.08)	−0.01 (0.01)	−0.66 (0.72)	−0.15 (0.13)
Citizenship (globalization—migration)	Native	base	base	base	base	base	base	base	base	base	base	base	base	base	base	base
	EU	−2535.47** (1009.30)	−2544.85*** (839.35)	0.04* (0.02)	2.42 (1.72)	0.37* (0.22)	−878.97 (945.73)	−3038.91*** (1052.28)	0.02 (0.02)	0.07 (1.88)	0.17 (0.19)	−2242.44 (1768.12)	−3658.40*** (962.01)	0.04 (0.04)	0.96 (2.20)	0.42 (0.41)
	NON-EU	−2729.15*** (537.94)	−3789.42*** (626.17)	0.01 (0.01)	−0.89 (0.89)	0.10 (0.10)	−1854.69*** (647.22)	−2261.26*** (648.57)	0.03* (0.01)	0.67 (1.35)	0.30* (0.16)	−2973.75*** (549.63)	−3451.54*** (578.51)	0.02 (0.01)	1.16 (1.10)	0.16 (0.13)
Type of employment (labour market regulation)	Employee, permanent, full time	base	base	base	base	base	base	base	base	base	base	base	base	base	base	base
	Employee, permanent, part time	−9871.38*** (409.47)	−11028.50*** (423.70)	0.20*** (0.01)	11.91*** (1.03)	1.86*** (0.11)	−10101.01*** (407.12)	−12860.61*** (545.38)	0.18*** (0.01)	7.99*** (1.02)	2.02*** (0.11)	−9439.32*** (428.41)	−10990.28*** (474.25)	0.17*** (0.01)	9.04*** (1.24)	1.90*** (0.13)
	Employee, temporary, full time	−6635.46*** (385.64)	−7242.21*** (424.98)	0.13*** (0.01)	8.52*** (0.67)	1.22*** (0.08)	−9402.18*** (389.95)	−11,475.14*** (514.14)	0.18*** (0.01)	12.49*** (1.03)	1.94*** (0.11)	−8139.09*** (401.08)	−8131.71*** (458.25)	0.14*** (0.01)	12.28*** (1.02)	1.60*** (0.11)
	Employee, temporary, part time	−12053.39*** (651.97)	−11502.01*** (564.71)	0.31*** (0.02)	24.11*** (1.77)	2.90*** (0.14)	−12187.73*** (426.13)	−14102.64*** (524.18)	0.35*** (0.01)	30.29*** (1.72)	3.87*** (0.13)	−10954.52*** (649.75)	−11266.12*** (571.01)	0.31*** (0.01)	29.16*** (1.88)	3.51*** (0.17)
	Self-employed with employees	−8328.29*** (1239.69)	−6349.18*** (863.37)	0.03 (0.02)	2.93** (1.26)	0.24 (0.24)	−7495.32*** (1263.04)	−7150.85*** (1100.80)	0.08*** (0.02)	5.38*** (1.90)	0.80*** (0.24)	1143.72 (2529.58)	−3060.46*** (990.74)	0.14** (0.06)	5.94** (2.65)	1.64** (0.66)
	Self-employed without employees	−11926.03*** (649.08)	−9577.53*** (518.10)	0.05*** (0.01)	4.20*** (0.89)	0.44*** (0.14)	−11377.34*** (649.18)	−11543.70*** (617.02)	0.13*** (0.01)	8.46*** (1.16)	1.37*** (0.14)	−8174.14*** (847.02)	−7836.93*** (681.75)	0.05*** (0.01)	3.04*** (1.07)	0.58*** (0.17)

Table 5 (continued)

		2010					2014					2019				
		mean	median	gini	s80s20	palma	mean	median	gini	s80s20	palma	mean	median	gini	s80s20	palma
ISCO classification (SBTC)	Managers	15205.82*** (1563.59)	7403.85*** (806.90)	0.10*** (0.04)	2.09 (1.60)	1.10*** (0.37)	14551.98*** (1659.08)	7791.10*** (1113.35)	0.12*** (0.03)	6.03*** (2.06)	1.40*** (0.36)	21292.23*** (2720.81)	7724.32*** (954.63)	0.23*** (0.06)	10.42*** (3.03)	2.59*** (0.72)
	Professionals	15922.93*** (749.17)	10222.52*** (612.21)	0.03* (0.02)	0.58 (1.00)	0.21 (0.16)	13120.38*** (778.15)	9597.22*** (780.99)	0.02 (0.02)	0.83 (1.38)	0.24 (0.18)	15408.26*** (1123.67)	9147.28*** (702.94)	0.04 (0.03)	0.50 (1.66)	0.36 (0.29)
	Technicians and ass. professionals	6745.97*** (704.62)	7283.92*** (584.21)	−0.08*** (0.02)	−4.10*** (0.95)	−0.77*** (0.16)	5849.72*** (737.82)	6184.53*** (726.35)	−0.03** (0.02)	−2.52** (1.24)	−0.27 (0.17)	7682.00*** (964.30)	6393.87*** (622.53)	−0.04** (0.02)	−2.84* (1.57)	−0.49** (0.25)
	Clerical support workers	3114.42*** (496.69)	5916.48*** (562.33)	−0.12*** (0.01)	−6.48*** (0.88)	−1.10*** (0.11)	2192.55*** (531.65)	4225.50*** (728.06)	−0.08*** (0.01)	−5.49*** (1.06)	−0.83*** (0.12)	3257.28*** (651.56)	4519.51*** (653.69)	−0.09*** (0.01)	−6.86*** (1.25)	−0.98*** (0.16)
	Service and sales workers	1654.32*** (392.14)	1344.80*** (515.03)	−0.03*** (0.01)	−2.38*** (0.82)	−0.30*** (0.09)	1880.66*** (445.42)	967.22 (637.23)	−0.00 (0.01)	−0.53 (1.13)	−0.02 (0.11)	2991.50*** (507.56)	1749.67*** (580.60)	−0.03** (0.01)	−3.21*** (1.22)	−0.37*** (0.14)
	Skilled agriculture, forestry—fishery	1419.81 (953.08)	1193.24 (941.24)	−0.01 (0.03)	−1.27 (2.84)	−0.12 (0.26)	2817.16*** (941.34)	4580.19*** (1201.73)	−0.12*** (0.02)	−9.06*** (2.28)	−1.20*** (0.23)	1614.58 (1017.57)	607.58 (1129.23)	−0.10*** (0.03)	−9.58*** (2.75)	−1.15*** (0.30)
	Craft and related trades workers	14.96 (477.78)	1680.89*** (647.29)	−0.09*** (0.01)	−4.67*** (0.97)	−0.83*** (0.11)	−452.89 (582.66)	2386.69*** (796.14)	−0.09*** (0.01)	−6.02*** (1.22)	−0.90*** (0.14)	−446.65 (625.93)	1678.72** (732.08)	−0.10*** (0.01)	−6.75*** (1.24)	−1.08*** (0.15)
	Plant/machine operators/assemb	157.08 (665.11)	2672.54*** (703.05)	−0.10*** (0.02)	−5.11*** (1.08)	−0.95*** (0.16)	466.88 (641.46)	3547.98*** (870.20)	−0.12*** (0.01)	−6.99*** (1.21)	−1.20*** (0.15)	456.96 (615.62)	2413.19*** (740.35)	−0.11*** (0.01)	−7.54*** (1.35)	−1.18*** (0.16)
	Elementary occupations	base	base	base	base	base	base	base	base	base	base	base	base	base	base	base

Table 5 (continued)

		2010					2014					2019				
		mean	**median**	**gini**	**s80s20**	**palma**	**mean**	**median**	**gini**	**s80s20**	**palma**	**mean**	**median**	**gini**	**s80s20**	**palma**
ISCED – Education (SBTC)	Primary	base	base	base	base	base	base	base	base	base	base	base	base	base	base	base
	Secondary	2948.53*** (346.32)	1978.34*** (454.46)	0.01 (0.01)	−0.13 (0.71)	0.08 (0.08)	2886.66*** (486.74)	3008.37*** (601.53)	0.00 (0.01)	1.27 (0.98)	0.04 (0.10)	2279.53*** (510.59)	1296.77** (652.86)	−0.00 (0.01)	−0.60 (1.22)	−0.00 (0.13)
	Tertiary	7074.15*** (547.23)	4264.90*** (535.03)	0.05*** (0.01)	1.75** (0.87)	0.45*** (0.12)	6663.47*** (631.91)	5259.45*** (698.89)	0.03*** (0.01)	3.46*** (1.13)	0.35*** (0.13)	6642.28*** (672.29)	3631.68*** (715.32)	0.02 (0.01)	0.37 (1.38)	0.25 (0.16)
		2010					**2014**					**2019**				
		mean	**median**	**gini**	**s80s20**	**palma**	**mean**	**median**	**gini**	**s80s20**	**palma**	**mean**	**median**	**gini**	**s80s20**	**palma**
NACE—sector (structural change)	Agriculture, forestry and fishing	−3853.27*** (926.24)	−3650.59*** (871.16)	0.08*** (0.02)	7.13*** (1.84)	0.71*** (0.21)	−4236.04*** (887.84)	−4112.52*** (1016.54)	0.07*** (0.02)	5.27** (2.09)	0.72*** (0.22)	−5295.01*** (978.44)	−3407.50*** (881.77)	0.07*** (0.02)	8.45*** (2.23)	0.78*** (0.26)
	Mining; manufacturing; utilities	base	base	base	base	base	base	base	base	base	base	base	base	base	base	base
	Construction	−1611.15*** (561.51)	−1081.39* (641.04)	−0.01 (0.01)	0.42 (0.90)	−0.13 (0.12)	−4328.89*** (831.39)	−3570.83*** (894.31)	0.01 (0.02)	2.61* (1.50)	0.14 (0.20)	−2483.85** (978.68)	−2012.68*** (769.26)	−0.01 (0.02)	−1.10 (1.35)	−0.13 (0.24)
	Wholesale, retail trade; repair of motor vehicles	−2027.05*** (593.79)	−2691.18*** (571.44)	0.00 (0.01)	−0.32 (0.73)	0.01 (0.13)	−4640.10*** (674.21)	−4200.48*** (683.39)	−0.04*** (0.01)	−3.17*** (1.02)	−0.48*** (0.15)	−5056.05*** (773.43)	−3613.00*** (602.65)	−0.02 (0.02)	−1.59 (1.20)	−0.23 (0.18)
	Transportation and storage	−508.92 (1359.49)	−1233.92 (763.87)	0.03 (0.04)	1.90 (1.53)	0.28 (0.35)	−1704.79* (913.14)	−1889.15** (863.55)	0.01 (0.02)	−0.56 (1.29)	0.10 (0.22)	−2693.68*** (918.52)	−1024.93 (795.64)	−0.03* (0.02)	−1.89 (1.26)	−0.38* (0.22)

Table 5 (continued)

Accommodation and food services	−3307.08*** (647.14)	−3296.06*** (690.41)	−0.02 (0.01)	−1.47 (0.94)	−0.23* (0.14)	−5696.79*** (826.06)	−5287.05*** (828.24)	−0.01 (0.02)	0.40 (1.51)	−0.17 (0.19)	−6367.11*** (890.75)	−3922.27*** (835.20)	−0.03 (0.02)	−1.52 (1.57)	−0.26 (0.23)
Information and communication	−626.99 (1475.48)	−2403.14*** (840.76)	0.06* (0.03)	3.20** (1.41)	0.52 (0.32)	−3248.10** (1433.75)	−3524.90*** (1106.51)	0.03 (0.03)	3.00 (2.09)	0.33 (0.33)	−2528.07 (2330.77)	−3638.00*** (878.13)	0.03 (0.05)	0.92 (2.63)	0.30 (0.61)
Financial and insurance services	8639.47*** (1467.02)	2461.97*** (711.77)	0.15*** (0.03)	7.68*** (1.43)	1.37*** (0.34)	7888.00*** (1525.45)	3635.92*** (825.93)	0.10*** (0.03)	6.84*** (1.82)	1.07*** (0.38)	4949.33** (2218.90)	1500.91* (890.59)	0.07 (0.05)	5.27** (2.40)	0.72 (0.58)
Real estate, professional, scientific, technical, administrative act.;	−3650.95*** (751.45)	−2663.20*** (663.52)	−0.01 (0.02)	−0.55 (0.87)	−0.07 (0.16)	−5531.95*** (824.79)	−3792.57*** (762.91)	−0.04** (0.02)	−2.84** (1.17)	−0.37** (0.18)	−5699.44*** (1072.17)	−3159.23*** (676.69)	−0.02 (0.02)	−1.06 (1.37)	−0.22 (0.27)
Public administration	76.52 (662.05)	3060.18*** (516.14)	−0.05*** (0.01)	−0.63 (0.80)	−0.45*** (0.14)	−755.70 (756.39)	4063.71*** (615.56)	−0.09*** (0.02)	−2.99*** (0.96)	−0.88*** (0.17)	−1560.29 (1007.40)	2420.74*** (616.35)	−0.07*** (0.02)	−2.05* (1.21)	−0.74*** (0.24)
Education	−4908.86*** (835.65)	−795.14 (660.23)	−0.12*** (0.02)	−4.19*** (0.92)	−1.25*** (0.17)	−6976.66*** (852.80)	−1507.83** (722.10)	−0.11*** (0.02)	−4.00*** (1.33)	−1.23*** (0.21)	−7903.53*** (1115.52)	−2352.54*** (725.70)	−0.11*** (0.02)	−4.17*** (1.49)	−1.28*** (0.27)
Human health and social work	1218.10 (835.52)	695.23 (625.54)	−0.01 (0.02)	−1.10 (0.91)	−0.07 (0.18)	−4045.64*** (822.78)	−1469.55** (743.14)	−0.07*** (0.02)	−4.10*** (1.21)	−0.75*** (0.19)	−5930.68*** (1318.64)	−2339.92*** (712.72)	−0.06** (0.03)	−4.15*** (1.59)	−0.67** (0.33)

Table 5 (continued)

	Arts, Entertainment and recreation; other services activities	−4442.00***	−3498.11***	0.03**	2.04*	0.32**	−6397.74***	−5113.70***	0.02	1.84	0.16	−7212.76***	−4287.37***	0.01	2.70*	0.11
		(619.12)	(631.32)	(0.01)	(1.11)	(0.14)	(755.05)	(793.63)	(0.02)	(1.33)	(0.17)	(988.59)	(833.87)	(0.02)	(1.39)	(0.20)
	Regional Unemployment Rate	−281.19***	−189.55***	0.00	0.15***	0.01	−203.94***	−110.06***	−0.00	0.08	−0.00	−407.74***	−226.91***	−0.00	−0.08	−0.02
		(42.65)	(35.10)	(0.00)	(0.05)	(0.01)	(33.82)	(35.45)	(0.00)	(0.06)	(0.01)	(65.00)	(45.80)	(0.00)	(0.09)	(0.02)
Robots (SBTC)	Regional Exposure to Robotization	−23.84	783.74***	−0.00	0.48	−0.03	680.75**	895.47***	−0.01	−0.17	−0.09	−544.85*	272.20	−0.01**	−0.49	−0.13*
		(363.03)	(275.15)	(0.01)	(0.42)	(0.08)	(289.61)	(258.81)	(0.01)	(0.44)	(0.07)	(279.43)	(172.60)	(0.01)	(0.38)	(0.07)
International competition (globalisation—trade)	Regional Export of goods (% on gdp)	−57.97***	−48.56***	−0.00*	−0.05**	−0.01*	−81.81***	−69.21***	0.00	0.01	−0.00	−71.83***	−29.41*	−0.00*	−0.03	−0.01*
		(16.14)	(14.20)	(0.00)	(0.02)	(0.00)	(17.15)	(17.39)	(0.00)	(0.03)	(0.00)	(21.09)	(15.72)	(0.00)	(0.03)	(0.01)
	Constant	11093.03***	11675.06***	0.24***	−0.80	0.42	12701.68***	11967.70***	0.29***	1.10	0.62*	12526.74***	11458.18***	0.41***	13.49***	2.01***
		(1424.27)	(1287.31)	(0.03)	(2.08)	(0.31)	(1506.07)	(1640.82)	(0.03)	(2.69)	(0.33)	(1790.38)	(1529.86)	(0.04)	(2.79)	(0.43)
	N	12348	12348	12348	12348	12348	9777.00	9777	9777	9777	9777	13854	13854	13854	13854	13854
	r2	0.39	0.39	0.11	0.14	0.10	0.45	0.43	0.19	0.17	0.18	0.34	0.36	0.09	0.12	0.09

Robust standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; s80s20 = top 20%/bottom 20%; palma = palma ratio (top 10%/bottom 40%)

robotization and inequality emerges. To the extent that SBTC-related mechanisms are reflected in the Spanish results, they appear to be captured primarily by differences across ISCO occupational categories rather than by regional robot exposure.

The most consistent and interpretable result across all four countries concerns the fragmentation of employment and contractual arrangements, and by extension, the regulation of the labour market. In each country, the prevalence of non-standard forms of employment – namely, arrangements other than full-time, permanent employee contracts – is associated with a significant and quantitatively meaningful increase in inequality.

In interpreting the result related to regional unemployment, it is important to reiterate that unemployed individuals are not included in our sample. Therefore, the observed association cannot capture the direct increase in inequality that typically follows income losses due to job loss. Within the present framework, regional unemployment can only be interpreted as a contextual labour-market condition that may affect different parts of the earnings distribution among employed workers. In this specific case, results for mean and median earnings provide useful auxiliary information, since they help clarify whether higher unemployment is associated with a general downward pressure on earnings or with changes concentrated in specific parts of the distribution. From a microeconomic perspective, this may occur through the mechanisms emphasised by efficiency-wage theories or, more generally, through changes in workers' bargaining power. The implications for inequality, however, depend on how such pressures are transmitted across the earnings distribution and on the institutional constraints that limit wage adjustment at the bottom.

In France, the unemployment rate appears to have no discernible effect on either average or median earnings. With regard to inequality, a reduction is visible only in 2019, whereas in the earlier years (2010 and 2014) the estimates point to a modest but statistically significant increase in inequality. This mixed pattern is consistent with institutional features of the French labour market, notably the fact that France has the highest minimum wage in Europe – amounting to 66% of median gross earnings, according to Eurostat. As a consequence, the decline in workers' bargaining power typically associated with rising unemployment cannot exert downward pressure on the lowest wages, which are effectively protected. Instead, it affects higher wages, resulting in a compression at the top end of the earnings distribution and, consequently, a reduction in inequality.

In the case of Italy, the expected negative correlation between unemployment and both average and median earnings is observed, without any significant implications for inequality. This can be related to the absence of a statutory minimum wage. As a result, the decline in earnings linked to higher unemployment affects all income groups uniformly across the distribution. It is important to recall that the analysis controls for all other variables, and the reasoning here is strictly *ceteris paribus*.

Portugal presents an intermediate case in which no statistically significant association emerges between the unemployment rate and either average or median earnings, nor with standard measures of inequality or polarisation. Portugal has a relatively generous minimum wage, which in 2024 reaches 66% of median earnings – on par with France (Eurostat). It is worth noting, however, that the minimum wage has experienced a marked increase since 2015, already reaching close to 60% of the median by 2019. As previously discussed in Sect. 3.3, Olivera et al. (2023) argue that in Portugal, the minimum wage exerts a compressive effect on the lower end of the earnings distribution. The pattern observed in our findings regarding the relationship between unemployment and inequality appears consistent with this interpretation.

Spain's results are closer to those of Italy: earnings decline as unemployment rises, while associations with inequality are statistically significant only in a limited number of cases and remain modest in magnitude. Although Spain currently has a relatively generous minimum wage, this was not the case in earlier years such as 2018 and 2019. As highlighted in Sect. 3.4, the literature on Spain emphasises that the temporal dynamics of inequality are closely tied to the economic cycle and to fluctuations in unemployment. However, these dynamics are largely driven by job losses, often connected to the widespread use of temporary contracts, and by the resulting loss of income. Since the present analysis is restricted to employed workers, this channel is necessarily excluded. This helps explain why regional unemployment plays only a limited role in the RIF estimates, despite its broader relevance for overall income inequality in Spain.

5.2 Results from the RIF-based decomposition

This section presents the results obtained from the RIF-based Oaxaca-Blinder decomposition applied to two summary indicators of income inequality, namely the Gini coefficient and the S80/S20 ratio, for the countries under analysis and over the time spans specified in Sect. 4.1.2. As noted earlier, the decomposition is performed using the normalization procedure proposed by Yun (2005a,b), which ensures that the detailed decomposition results are invariant to the choice of the omitted reference category.

The detailed results presented in this section pertain exclusively to the endowment effect (commonly referred to in the literature as the "explained" component of the decomposition). While the coefficient and interaction components are estimated within the same empirical framework, their detailed disaggregation is not reported here; these results can be made available upon request. The discussion therefore concentrates on the extent to which changes over time in the selected inequality indicators are accounted for by shifts in the distribution of observable characteristics across countries and over the periods considered.

Whenever the discussion highlights that the change in a given characteristic is correlated with changes in an inequality indicator, it is always necessary to consider how that characteristic evolved over the period under analysis (that is, whether it increased or decreased). This can be inferred from the arrows used in the figures and makes it possible both to relate the decomposition results to those of the original RIF regressions and to provide an economic interpretation of the findings. For the sake of brevity, this point is taken as implicit in the remainder of the discussion. However, it is crucial for a correct reading of the results.

For sectoral dummies, in particular, an upward arrow indicates an increase in the share of workers employed in that sector over the period considered, while a downward arrow indicates a decline. Reading these arrows together with the sign and magnitude of the corresponding decomposition bars makes it possible to assess whether sectoral reallocation contributed to higher or lower values of the inequality indicator under analysis. In this sense, the NACE sectoral dummies provide a descriptive way of connecting the RIF-based decomposition results to the broader process of structural change discussed in Sects. 2 and 3.

5.2.1 France

Figure 5 presents the RIF decomposition results for France over the period 2010–2019, with the upper panel referring to the Gini coefficient and the lower panel to the S80/S20 ratio. For both indicators, the estimated overall change between 2010 and 2019 is not statistically significant. At the aggregate level, the explained (endowment) component is statistically significant for the Gini, whereas no robust pattern emerges for the S80/S20 ratio.

For the Gini, several dimensions are noteworthy. Within the demographic and education block, shifts in age composition are associated with a positive and well identified share of the explained component. Educational attainment also appears relevant when assessed jointly. Primary, secondary, and tertiary education display positive estimates within the explained component, suggesting that changes in educational composition align with higher measured inequality. Over the period, the shares of both primary and secondary education decline; however, the estimate for primary education is not statistically significant, whereas the secondary education estimate is statistically robust. Tertiary education is associated with a positive and statistically significant portion of the endowment effect. Taken together, reallocation across education groups – particularly the expansion of tertiary attainment alongside the contraction of secondary education – emerges as a salient element within the RIF-based Gini decomposition.

Employment type shows limited evidence of systematic effects. Temporary part-time employment is negative and statistically robust within the endowment component, while the remaining categories are not distinguishable from zero.

Within the occupational block, professionals are associated with a positive and well identified share of the explained component of the overall Gini's difference, whereas managers display a negative and statistically significant share. Clerical support, services and sales, and craft occupations also show positive and statistically robust estimates, while the remaining occupational categories are not distinguishable from zero.

Sectoral variables exhibit limited evidence of statistically robust differences. The public administration sector is associated with a positive and well identified portion of the explained component, whereas the education sector displays a negative and statistically significant estimate. For the remaining sectors, no robust pattern emerges. Regional indicators – unemployment, robotization, and goods exports over GDP – are not statistically significant in the Gini decomposition.

For the S80/S20 ratio, both the aggregate change and the overall explained component are not statistically significant. Within the demographic and education block, age and tertiary education are positive but not distinguishable from zero; the remaining variables in this block similarly show that no robust pattern emerges, with the partial exception of secondary education.

Employment type follows a pattern similar to that observed for the Gini. Temporary part-time employment is negative and statistically robust, whereas the other categories are not statistically significant. In the occupational block, professionals display a positive and well identified share of the explained component, while managers show a negative and statistically significant share. Clerical support, services and sales, and craft occupations again exhibit positive and statistically robust estimates; the remaining categories are not distinguishable from zero.

Sectoral results for the S80/S20 ratio broadly mirror those obtained for the Gini, allowing for a similar interpretation from a structural-change perspective. The positive and well identified contribution associated with public administration should be read together with the slight decline in the share of workers employed in this sector, which nonetheless remains high in absolute terms. This pattern is consistent with an inequality-increasing contribution from the relative contraction of a traditionally more protected and institutionally regulated segment of employment. By contrast, the education sector displays a negative and statistically significant contribution, which is associated with an increase in its employment share over the same period. In this case, sectoral reallocation appears to be aligned with lower earnings inequality. Overall, as in the case of the Gini, the French evidence points to a selective rather than broad-based role of structural change: only a small number of sectoral shifts are statistically robust, and they operate in opposite directions.

Among regional variables, unemployment is negative and statistically robust within the S80/S20 explained component, while goods exports over GDP and robotization are not statistically significant.

Overall, neither the Gini nor the S80/S20 ratio exhibits a statistically significant change over 2010–2019. The detailed decomposition indicates that occupational composition represents the most consistently statistically robust dimension across both indicators, whereas age and tertiary education are well identified only in the Gini decomposition.

5.2.2 Italy

Figure 6 extends the RIF-based Oaxaca-Blinder decomposition to Italy. For both the Gini coefficient and the S80/S20 ratio, the increase observed over 2010–2019 is positive and statistically significant. In addition, the aggregate endowment component accounts for a statistically robust share of the total change in both inequality measures, indicating that shifts in observable characteristics are associated with a meaningful portion of the overall variation.

For the Gini coefficient, several covariate groups display statistically robust estimates within the explained part. Within the demographic and education block, age is associated with a positive and well identified share of the endowment component.

Educational attainment also represents a prominent dimension of the explained increase: tertiary education corresponds to a positive and statistically significant share, while primary- and secondary-education variations also display positive and statistically robust estimates. In addition, female is linked to a negative and statistically significant portion of the explained component, and a similar pattern emerges for native individuals among the citizenship variables.

Employment type is likewise associated with a non-negligible share of the explained increase in the Gini. Permanent full-time employment, temporary part-time employment, and self-employed workers without employees each correspond to positive and statistically robust portions of the explained component. For the remaining employment categories, estimated variations are not distinguishable from zero.

With regard to occupational composition, adjustments within higher-skill groups are closely aligned with the explained variation. Professionals display a positive and statistically significant share of the increase in the Gini, whereas managers exhibit a negative and well identified share, indicating offsetting compositional movements within upper-tier occupations. Technicians, services and sales, and craft occupations also show positive and statistically robust estimates, as do – albeit to a more limited extent – operators and elementary occupations.

Sectoral reallocation appears more selective. Real estate, public administration, and entertainment correspond to positive and statistically significant portions of the explained change, whereas transport and storage are associated with a negative and statistically robust estimate. Among regional variables, robotization represents a positive and well identified share of the Gini's explained increase, while goods exports over GDP correspond to a negative and statistically significant portion of the change.

Turning to the S80/S20 ratio, the configuration broadly mirrors that observed for the Gini, in several cases with larger magnitudes. Age corresponds to a positive and statistically significant share of the explained increase, and within education both secondary and tertiary attainment display positive and statistically robust estimates, whereas primary education is not distinguishable from zero. Female shows a negative and statistically significant share, while citizenship variables overall indicate that no robust pattern emerges.

Employment structure remains relevant: permanent full-time employment, temporary part-time employment, and self-employment without employees each display positive and statistically robust shares of the explained increase, with the other categories not distinguishable from zero.

Shifts in occupational composition emerge as the most prominent dimension associated with the observed change. Professionals correspond to a positive and statistically significant share, and several additional occupational groups – technicians, services and sales, craft, operators, and elementary occupations – also exhibit positive and statistically robust estimates within the explained component.

Sectoral effects for the S80/S20 ratio broadly mirror those obtained for the Gini, allowing for a similar interpretation from a structural-change perspective. The positive and statistically significant contributions associated with real estate, professional, scientific, technical and administrative activities, and with arts, entertainment and other services, should be read together with the increase in the share of workers employed in these sectors over 2010–2019. These patterns suggest that the expansion of selected service activities was aligned with higher earnings inequality. Public administration also displays a positive and well identified contribution, but in this case the underlying compositional change goes in the opposite direction, as the share of workers employed in this sector declined over the period. This result can therefore be interpreted as an inequality-increasing contribution associated with the relative contraction of a more institutionally regulated segment of employment. By contrast, transportation and storage display a negative and statistically robust contribution, despite an increase in their employment share, indicating that not all service-sector expansion was associated with higher inequality. Overall, as in the case of the Gini, the Italian evidence points to a selective and heterogeneous role of structural change: the reallocation of employment across sectors contributed to the increase in inequality, but with different service activities operating in opposite directions. Among regional variables, robotization represents a large and well identified share of the explained increase, and export intensity a negative and statistically significant one, whereas unemployment is not distinguishable from zero.

Overall, the Italian evidence indicates that compositional shifts are aligned with a statistically significant share of the increase in both inequality measures over 2010–2019. The most consistently statistically robust dimensions of the explained variation relate to occupational restructuring together with selected employment-type adjustments and regional technology- and trade-related factors, particularly robotization.

5.2.3 Portugal

Figures 7 and 8 present the RIF decomposition results for Portugal over the two sub-periods 2010–2014 and 2014–2019, respectively. The temporal partition reflects the non-monotonic trajectory of inequality documented in Section 3.3, characterized by a statistically significant increase up to 2014 followed by a statistically significant decline thereafter.

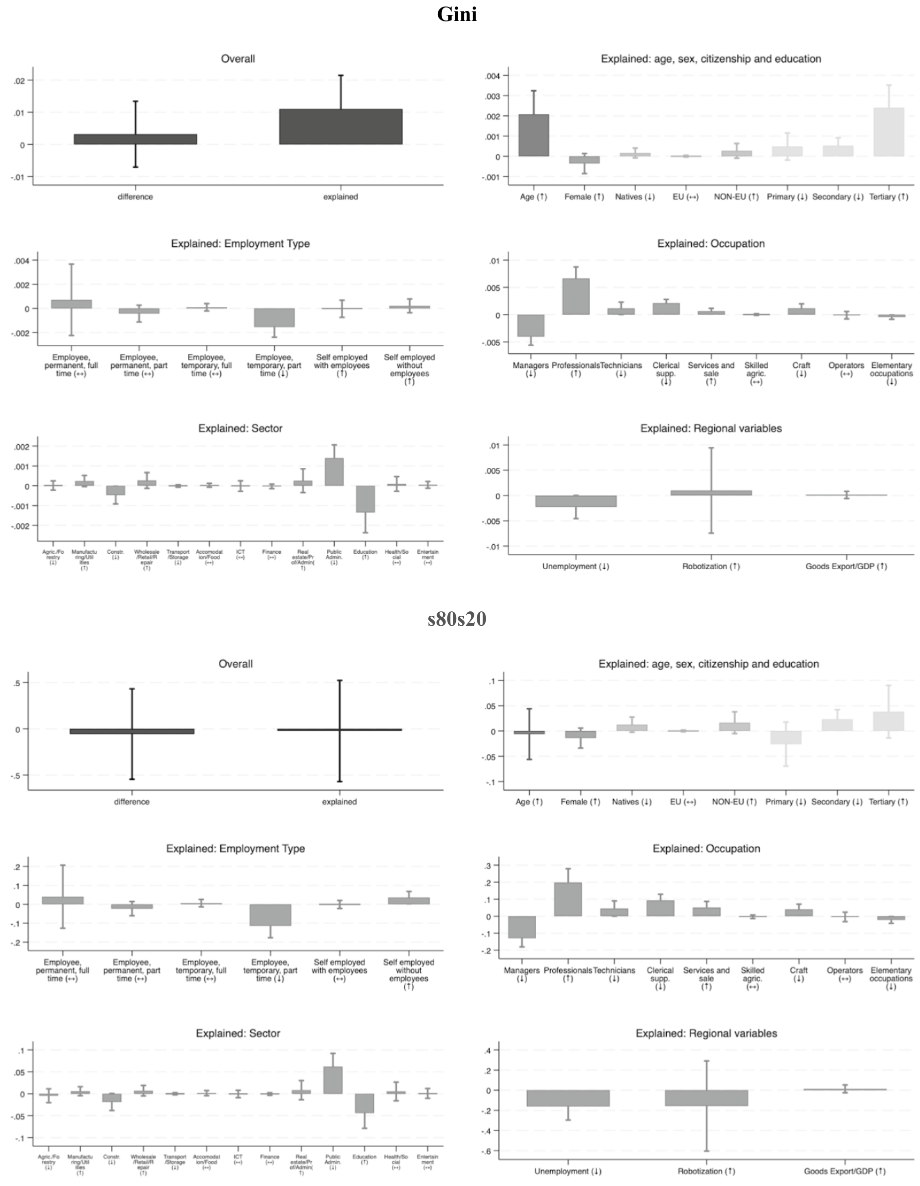

Fig. 5 Rif-based Oaxaca-Blinder decomposition**,** France (2010–2019)

Consistent with this pattern, both the Gini coefficient and the S80/S20 ratio increase significantly in the first sub-period and decrease significantly in the second.[9]

[9] A caution is warranted when comparing inequality trends across sections of the paper. The figures presented in the descriptive analysis – showing an increase up to around 2014 followed by a subsequent decline – are based on household gross and disposable income, whereas our empirical analysis, as explicitly noted in Section 4.2, relies on individual labour income. The same applies to Spain, whose results are discussed in the following section.

In both sub-periods, the endowment effect accounts for a statistically significant share of the total change. Importantly, it represents a positive share of overall variation even when the latter is negative, as in 2014–2019, indicating that compositional shifts remain systematically aligned with pro-inequality variation across both expansionary and contractionary phases.[10]

Several covariate patterns display marked stability across the two sub-periods. Age consistently accounts for a positive and statistically robust share of the explained component in both sub-periods and for both inequality measures, thus representing a persistent source of explained variation irrespective of the direction of overall inequality dynamics. A similar degree of continuity characterizes the education block: primary and tertiary attainment each display positive and well identified shares of the explained change, whereas secondary education remains not distinguishable from zero in either sub-period and for either measure. By contrast, the gender term varies across sub-periods and indicators. The female coefficient accounts for a negative and statistically significant share in 2010–2014 for the S80/S20 ratio but becomes not distinguishable from zero in 2014–2019 for both inequality measures. Citizenship terms variations are generally limited in magnitude, and no robust pattern emerges across periods.

Employment structure displays a clear reversal across the two sub-periods. During 2010–2014, permanent full-time employment accounts for a negative share of the explained change for both the Gini and the S80/S20 ratio, whereas self-employment with employees shows positive shares; the remaining employment categories are largely not statistically significant. In 2014–2019, the estimate for the main stable employment type reverses sign: permanent full-time employment accounts for a positive and statistically robust share of the explained variation in both measures, while the other employment categories remain not distinguishable from zero during the decline phase.

Occupational composition also exhibits a distinct pattern across the two sub-periods. In 2010–2014, it emerges as a well identified source of the explained increase in inequality: professionals account for a large, positive, and statistically significant share of the change in both the Gini and the S80/S20 ratio, and craft occupations also display positive and statistically robust shares. The remaining occupational groups, however, are not distinguishable from zero. In 2014–2019, the role of occupational shifts becomes substantially more muted, as most categories show variations that are small in magnitude and for which no robust pattern emerges.

The sector of main employment also differs across the two sub-periods, and this provides a useful indication of how structural-change dynamics vary over time. In 2010–2014, construction displays a positive and statistically significant share of the explained variation for both inequality measures. This contribution should be read together with the decline in the share of workers employed in this sector over the same period, suggesting that the relative contraction of construction was aligned with higher earnings inequality. By contrast, real estate, professional, scientific, technical and administrative activities show a negative and well identified contribution, associated with an increase in their employment share. In this case, sectoral reallocation appears to have operated in the opposite direction, partially offsetting the inequality-increasing pattern observed for construction. The remaining sectors do not exhibit statistically robust

[10] As noted earlier in the paper, for Portugal the EU-SILC variable identifying individuals' region of residence is available only for 2019. Consequently, although regional variables can be incorporated into the 2019 RIF regression analysis, they cannot be included in the decomposition exercises, which require consistent information across both years of each sub-period.

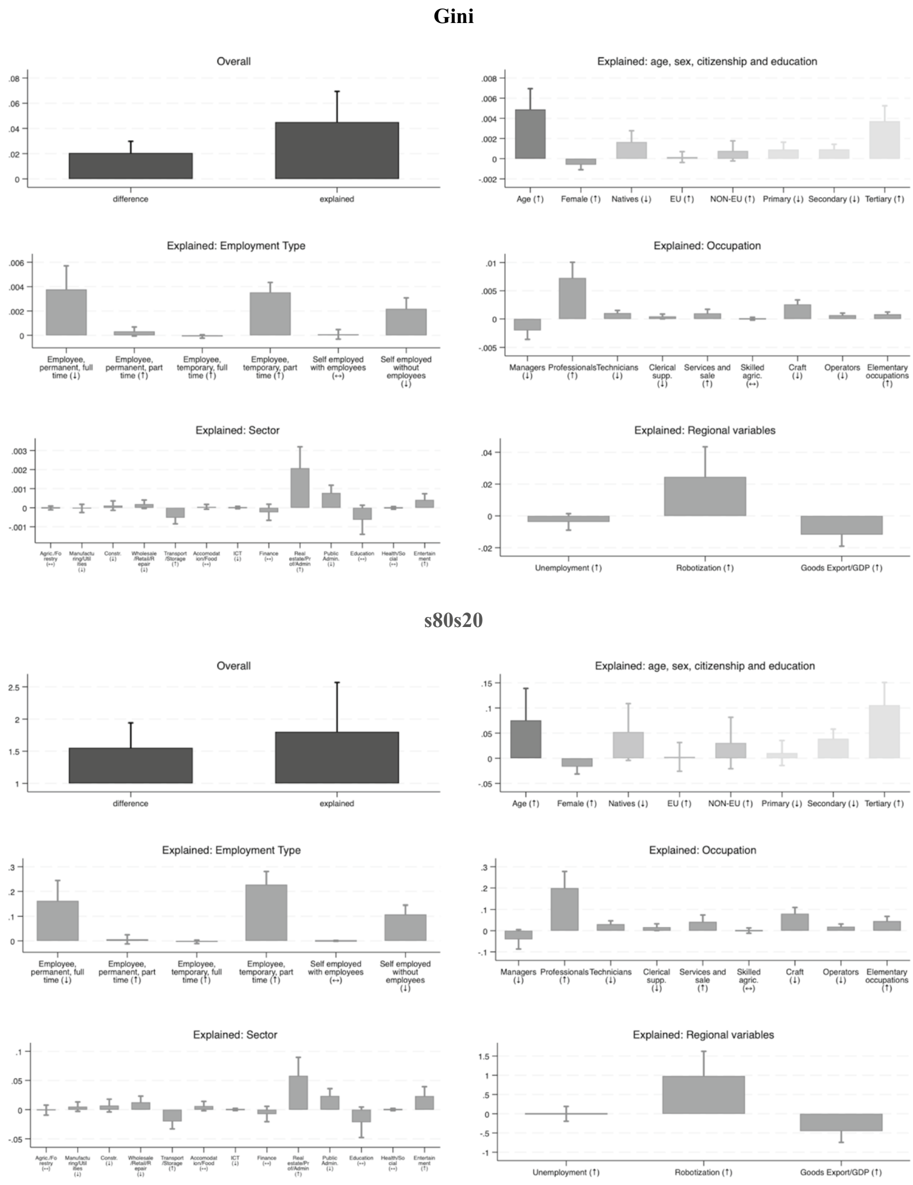

Fig. 6 Rif-based Oaxaca-Blinder decomposition**,** Italy (2010–2019)

estimates. In 2014–2019, the sectoral dimension becomes markedly attenuated: although the arrows indicate continued changes in employment shares across sectors, most sectoral contributions are not distinguishable from zero. From a structural-change perspective, the Portuguese evidence therefore suggests that sectoral reallocation was more clearly associated with the inequality-increasing phase of 2010–2014 than with the subsequent decline in inequality.

Taken together, the Portuguese results indicate that the explained component remains statistically meaningful in both sub-periods, although its internal configuration evolves over time. While shifts in age and educational attainment – specifically the positive and statistically robust shares associated with primary and tertiary education, with secondary education remaining not distinguishable from zero – are stable across periods, the clearest adjustments occur in employment type, occupational structure, and, particularly during the 2010–2014 inequality-increasing phase, sector of main activity. In these domains, categories that display statistically significant shares of explained variation during the inequality upswing (2010–2014) tend to exhibit smaller variations – often not distinguishable from zero – during the subsequent decline in 2014–2019.

5.2.4 Spain

Figures 9 and 10 present the final set of RIF-based Oaxaca-Blinder decomposition results for Spain. Unlike Portugal, where inequality measured on household income first rises and then declines across the two sub-periods, the pattern differs when inequality is evaluated using individual labour income. In Spain, both inequality indicators increase between 2010 and 2014 when measured on individual earnings, whereas no statistically significant change is observed over 2014–2019.

Despite the absence of a statistically significant shift in the second sub-period, the decomposition reveals structured compositional patterns. Over 2010–2014, the endowment component is positive and statistically robust, indicating that changes in covariates' composition are closely aligned with the observed increase in inequality. In contrast, during 2014–2019 – when both indicators remain broadly stable – the explained component points toward pro-equality variation: it is negative and statistically significant for the S80/S20 ratio, while for the Gini it remains limited in magnitude and not distinguishable from zero.

Age exhibits the most stable and statistically robust pattern across sub-periods. It displays a positive and well identified share of explained variation for both inequality measures in 2010–2014 and retains a positive and statistically robust estimate in 2014–2019, even in the absence of aggregate inequality change. Educational attainment plays a clearer role in the earlier sub-period: tertiary education exhibits a positive and statistically significant share of the increase, whereas primary and secondary attainment are largely not distinguishable from zero. In 2014–2019, education-related estimates become smaller overall and no robust pattern emerges. Gender and citizenship variations remain limited in magnitude across sub-periods, with only isolated significant estimates and no systematic pattern.

Employment composition displays one of the most pronounced reversals across the two sub-periods. In 2010–2014, permanent full-time and temporary part-time employment are associated with positive and well identified shares of explained variation for both inequality indicators. In 2014–2019, this pattern is inverted, with the same employment types exhibiting negative and statistically robust estimates. The remaining employment categories are not distinguishable from zero, except to a limited extent.

Occupational patterns become progressively attenuated over time. In the first sub-period, managers display negative and statistically robust estimates, while operators exhibit positive and statistically significant shifts, with additional occupational groups contributing more selectively. In the second sub-period, most occupational shifts are not distinguishable from zero, with only limited evidence of statistical relevance – most notably positive and statistically significant shares for clerical support occupations.

Likewise, sectoral effects are more clearly visible in the first sub-period and attenuate sharply thereafter. In 2010–2014, agriculture, forestry and fishing displays a positive and statistically robust contribution for both inequality indicators, which should be read together with the increase in the share of workers employed in this sector. Construction also contributes positively, although more selectively across measures, despite a decline in its employment share. These patterns suggest that, during the inequality-increasing phase, sectoral reallocation was partly aligned with higher earnings inequality. At the same time, selected service activities, such as wholesale, retail and repair and finance, display negative contributions, indicating that not all sectoral shifts operated in the same direction. In 2014–2019, by contrast, the sectoral profile becomes markedly flatter: although employment shares continue to move across sectors, most sectoral contributions are not statistically distinguishable from zero. From a structural-change perspective, the Spanish evidence therefore suggests that sectoral reallocation was more closely associated with the increase in inequality observed in 2010–2014 than with the subsequent period of stability.

Finally, regional indicators play a limited role across sub-periods. In 2010–2014, unemployment exhibits a positive and statistically robust variation in the S80/S20 decomposition, while exports over GDP account for a negative and statistically significant share of the explained variation in both indicators. In the second sub-period, most regional variations are not distinguishable from zero, indicating a marked weakening of regional influences.

Taken together, the Spanish evidence indicates that compositional reallocation is closely associated with the change in inequality observed in 2010–2014, when several covariate blocks display well identified shares of explained variation. By contrast, the 2014–2019 sub-period is characterised by a broad attenuation across dimensions, with most covariates not distinguishable from zero. This generalised weakening is consistent with the absence of statistically significant variation in the inequality measures themselves, suggesting that compositional shifts in the later sub-period are comparatively limited in magnitude and more heterogeneous in nature.

6 Concluding remarks

This paper has examined inequality in gross individual earnings among employed workers – employees and the self-employed – in France, Italy, Portugal, and Spain by combining RIF regressions and a RIF-based Oaxaca-Blinder decomposition across the years 2010, 2014, and 2019. The focus is therefore on pre-tax labour earnings inequality among those in employment, rather than on overall income inequality. Nevertheless, labour earnings represent a fundamental – and arguably the central – component of overall income inequality.

A first central result is that the correlates of earnings inequality are not uniform across countries, even when the same data source, empirical strategy, and set of covariates are employed. This heterogeneity is not incidental, but one of the main substantive findings of the paper: inequality patterns are shaped by country-specific institutional settings, labour-market structures, and trajectories of structural transformation, rather than by common and homogeneous mechanisms. At the same time, the use of multiple inequality indicators confirms that different measures capture different distributional features, making it inappropriate to rely on any single summary index when analysing inequality dynamics.

Across the three benchmark years, the RIF regressions point to several recurrent patterns. First, variables linked to Skill-Biased Technological Change (SBTC) and broader

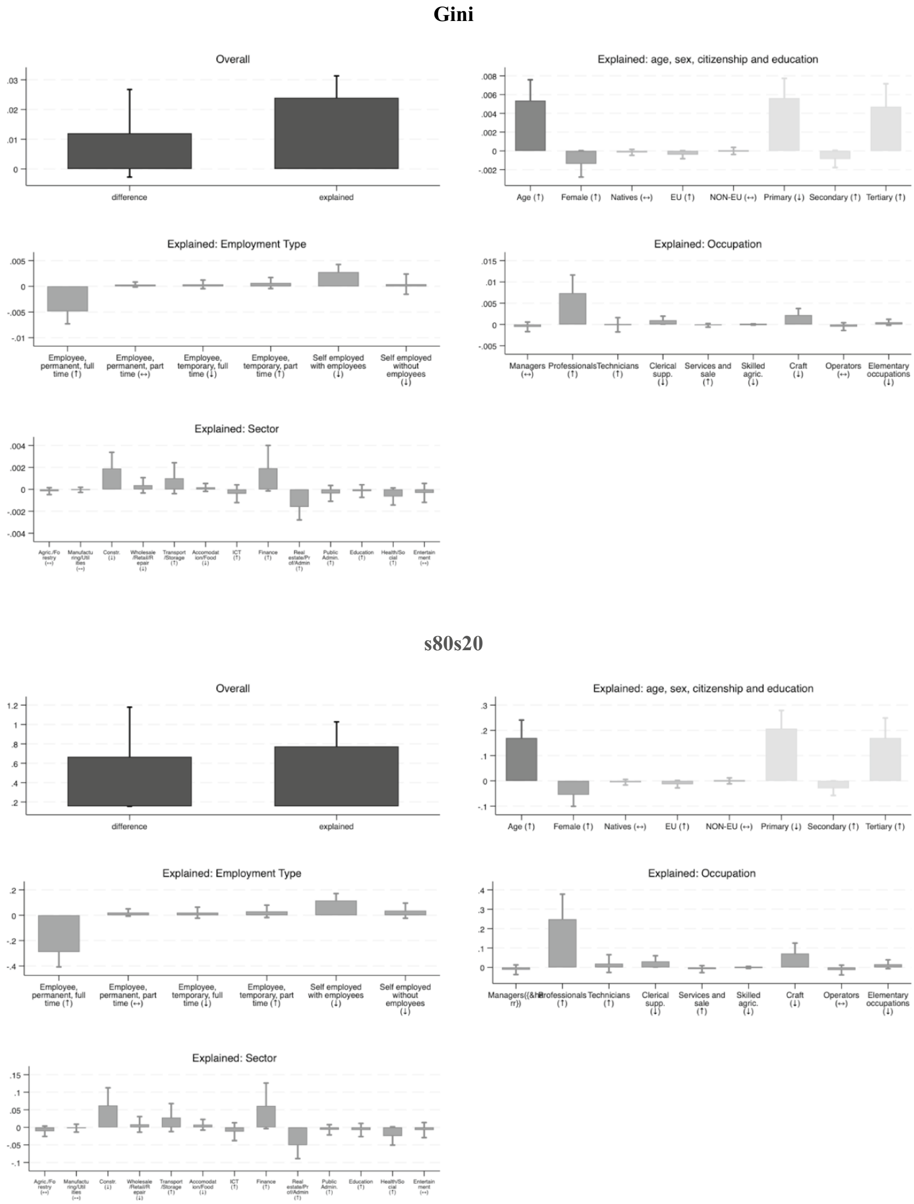

Fig. 7 Rif-based Oaxaca-Blinder decomposition**,** Portugal (2010–2014)

structural transformation are repeatedly associated with inequality, although their configuration differs markedly across countries. In France and Italy, the education gradient and parts of the occupational structure suggest a non-negligible role for the skill premium, while in Portugal the education dimension is especially prominent and in Spain SBTC appears comparatively weaker, emerging mainly through occupational differences rather than through education alone. Second, the sectoral composition of employment

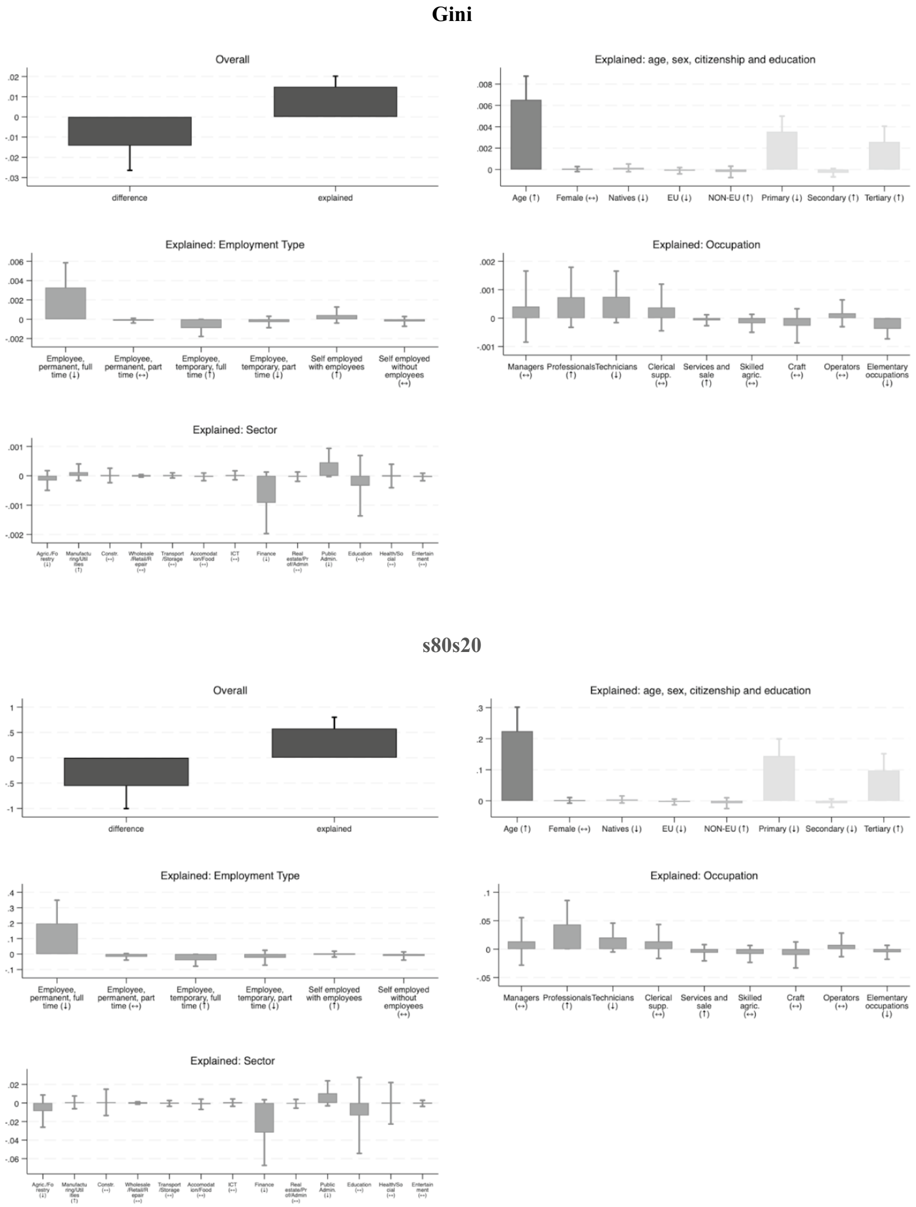

Fig. 8 RIF-based Oaxaca-Blinder decomposition**,** Portugal (2014–2019)

matters systematically, but not monotonically: de-industrialisation is not associated with higher inequality per se, since its distributive implications depend on which service sectors expand and on the weight of public employment. Third, the most robust common finding concerns labour-market fragmentation: in all four countries, shifts in the composition of employment towards non-standard arrangements are associated with higher earnings inequality, whereas shifts away from them are associated with lower inequality.

The decomposition analysis adds an explicitly dynamic dimension to these results. For France, neither the Gini coefficient nor the S80/S20 ratio changes significantly over 2010–2019, and the decomposition therefore suggests relative distributive stability, with occupational composition representing the most consistent component of the explained part of inequality variation. Italy presents a different pattern: over 2010–2019, compositional shifts account for a statistically significant share of the increase in inequality, especially through occupational restructuring, selected changes in employment composition, and regional technology- and trade-related factors, notably robotization. Portugal and Spain display more discontinuous trajectories. In Portugal, both inequality indicators rise significantly over 2010–2014 and fall significantly over 2014–2019; yet the decomposition shows that compositional shifts remain aligned with pro-inequality variation in both phases, even though their internal configuration becomes weaker in the later sub-period. In Spain, inequality in individual labour earnings increases over 2010–2014, while no statistically significant change is observed over 2014–2019; correspondingly, the explained component is much more structured in the first sub-period and becomes broadly attenuated thereafter. Taken together, these findings indicate that changes in observable characteristics help explain inequality dynamics, but that their effects are contingent on timing and national context.

From a comparative perspective, the country profiles can be summarised succinctly. France combines relatively low and stable inequality with a sectoral profile in which public-related activities play an important, though differentiated, role: the relative contraction of public administration is associated with higher inequality, whereas the expansion of education is associated with lower inequality. Italy stands out for more persistent polarisation, associated with atypical contracts, occupational restructuring, and selective sectoral changes within the service economy, with different activities operating in opposite directions. Portugal appears as the clearest case in which educational upgrading, the stabilisation or reduction of some more unequal employment forms, and institutional compression at the lower end of the wage distribution help interpret the decline in inequality after 2014, while sectoral reallocation is more clearly associated with the earlier inequality-increasing phase. Spain, by contrast, remains strongly shaped by labour-market dualism, with sectoral reallocation more clearly related to the 2010–2014 increase in inequality than to the subsequent period. These differences reinforce the view that similar broad drivers – technology, structural change, trade, migration, and labour-market regulation – operate through distinct national configurations rather than through invariant mechanisms.

Two limitations should be kept in mind. First, the empirical strategy identifies statistical associations rather than causal effects, and the results should therefore be interpreted as correlational evidence. Second, many of the dimensions considered – technology, education, occupations, sectors, labour-market institutions, and trade exposure – are likely to interact with one another in ways that are only partially captured by the additive specification adopted here. Future research could therefore extend the analysis in two directions: by exploring designs better suited to causal identification, and by modelling relevant interaction structures more explicitly, especially those linking technological change, labour-market dualisation, and institutional wage-setting arrangements. Nonetheless, the comparative evidence presented here already supports a clear conclusion: earnings inequality in advanced European economies is best understood as the outcome of multiple, overlapping, and country-specific processes, rather than as the expression of uniform mechanisms operating similarly across countries.

7 Competing interests

The authors declare no competing interests.

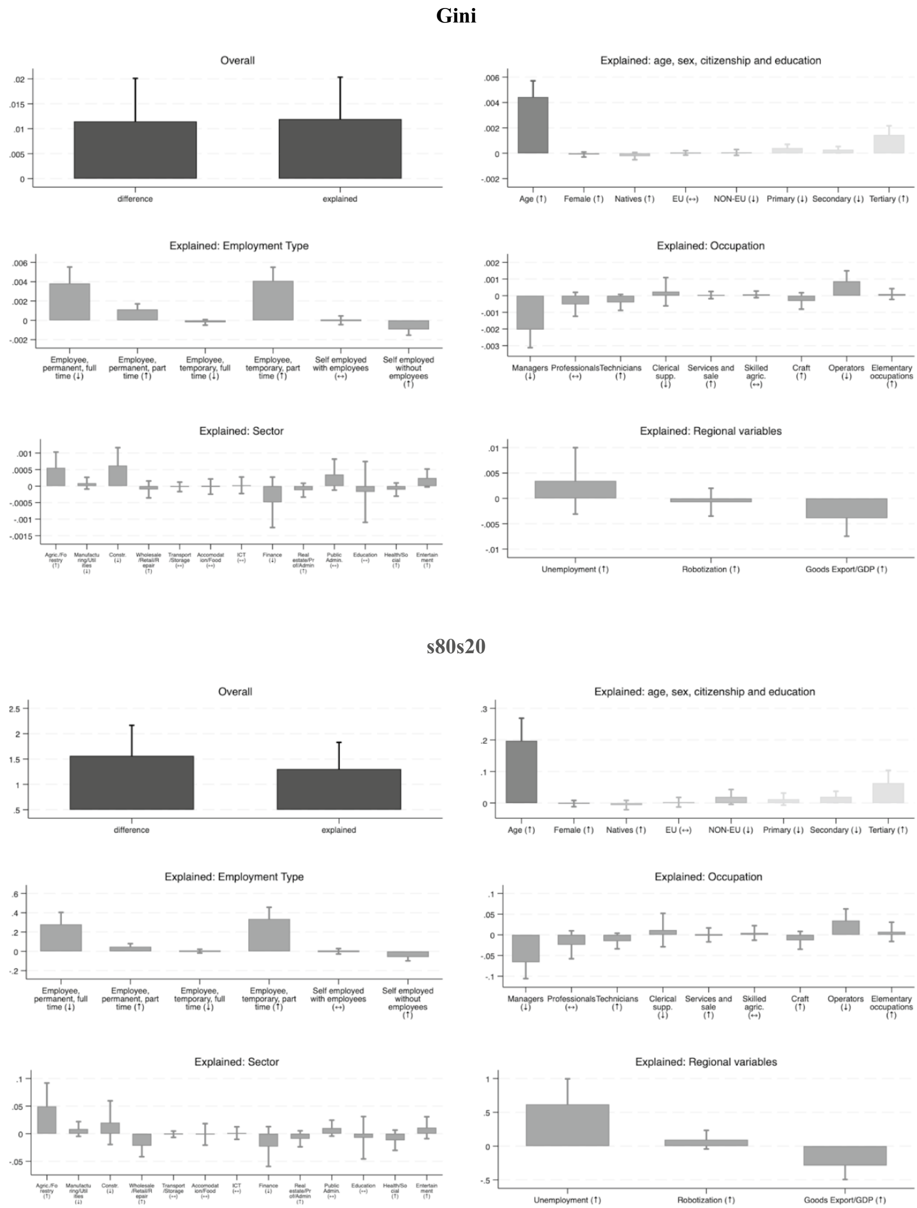

Fig. 9 RIF-based Oaxaca-Blinder decomposition, Spain (2010–2014)

Appendix 1 Summary Statistics

Tables 6, 7, 8, 9

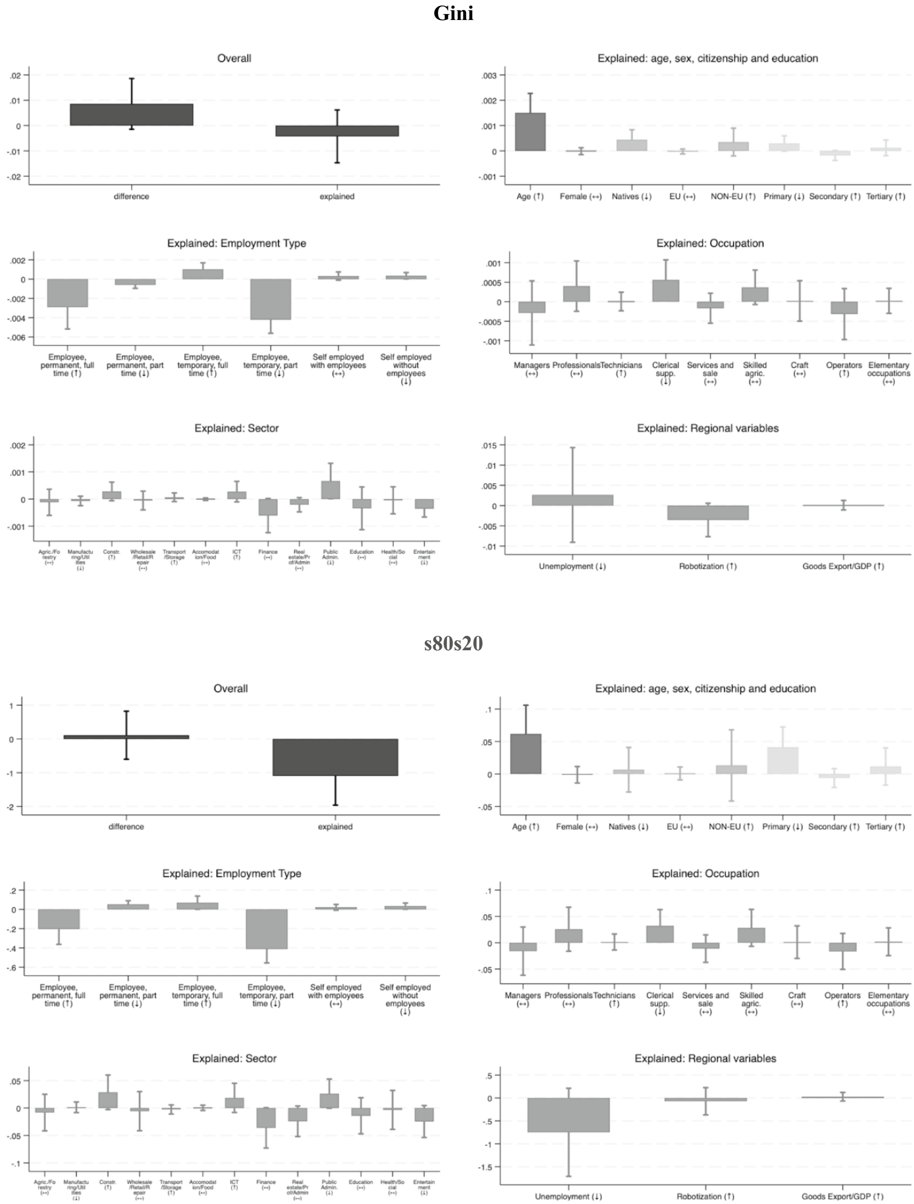

Fig. 10 RIF-based Oaxaca-Blinder decomposition**,** Spain (2014–2019)

Table 6 Summary Statistics (weighted), France (authors' calculation on EU-SILC data)

	2010 N (observations): 9646 N (weights sum): 22,491,040				**2014** N (observations): 8916 N (weights sum): 21,657,910				**2019** N (observations): 9581 N (weights sum): 24,395,304			
	mean	SD	min	max	mean	SD	min	max	mean	SD	min	max
Income	25,678	19,161	110	637,910	26,982	19,298	110	334,930	31,093	22,127	120	517,350
Age	41.0	11.2	17.0	81.0	41.5	11.4	17.0	81.0	42.6	11.6	17.0	81.0
Sex: Male	0.52	0.50	0	1	0.49	0.50	0	1	0.51	0.50	0	1
Sex: Female	0.48	0.50	0	1	0.51	0.50	0	1	0.49	0.50	0	1
Citizenship: Native	0.91	0.29	0	1	0.90	0.29	0	1	0.89	0.31	0	1
Citizenship: EU	0.03	0.17	0	1	0.03	0.17	0	1	0.03	0.17	0	1
Citizenship: Non-EU	0.06	0.24	0	1	0.06	0.25	0	1	0.08	0.27	0	1
Employment: Employee, permanent, full time	0.66	0.47	0	1	0.63	0.48	0	1	0.66	0.47	0	1
Employment: Employee, permanent, part time	0.12	0.32	0	1	0.13	0.33	0	1	0.12	0.33	0	1
Employment: Employee, temporary, full time	0.10	0.30	0	1	0.11	0.31	0	1	0.10	0.30	0	1
Employment: Employee, temporary, part time	0.05	0.21	0	1	0.05	0.21	0	1	0.04	0.19	0	1
Employment: Self-employed with employees	0.02	0.15	0	1	0.01	0.08	0	1	0.02	0.15	0	1
Employment: Self-employed without employees	0.05	0.22	0	1	0.08	0.28	0	1	0.06	0.24	0	1
ISCO: Managers	0.08	0.27	0	1	0.08	0.27	0	1	0.05	0.22	0	1
ISCO: Professionals	0.14	0.34	0	1	0.16	0.36	0	1	0.21	0.41	0	1
ISCO: Technicians and associate professionals	0.22	0.41	0	1	0.22	0.41	0	1	0.20	0.40	0	1
ISCO: Clerical support workers	0.12	0.33	0	1	0.10	0.30	0	1	0.08	0.27	0	1
ISCO: Service and sales workers	0.13	0.33	0	1	0.17	0.37	0	1	0.16	0.36	0	1
ISCO: Skilled agriculture, forestry and fishery	0.03	0.17	0	1	0.03	0.16	0	1	0.03	0.16	0	1
ISCO: Craft and related trades workers	0.10	0.31	0	1	0.07	0.26	0	1	0.09	0.29	0	1
ISCO: Plant and machine operators and assemblers	0.09	0.28	0	1	0.05	0.23	0	1	0.09	0.28	0	1
ISCO: Elementary occupations	0.10	0.30	0	1	0.12	0.33	0	1	0.09	0.29	0	1
Education: Primary (or under)	0.10	0.30	0	1	0.04	0.19	0	1	0.05	0.21	0	1

Table 6 (continued)

	2010 N (observations): 9646 N (weights sum): 22,491,040				**2014** N (observations): 8916 N (weights sum): 21,657,910				**2019** N (observations): 9581 N (weights sum): 24,395,304			
	mean	SD	min	max	mean	SD	min	max	mean	SD	min	max
Education: Secondary	0.54	0.50	0	1	0.56	0.50	0	1	0.52	0.50	0	1
Education: Tertiary	0.36	0.48	0	1	0.40	0.49	0	1	0.43	0.50	0	1
NACE: Agriculture, forestry and fishing	0.03	0.17	0	1	0.04	0.19	0	1	0.02	0.15	0	1
NACE: Mining; manufacturing; utilities	0.15	0.36	0	1	0.09	0.29	0	1	0.16	0.37	0	1
NACE: Construction	0.08	0.28	0	1	0.09	0.28	0	1	0.07	0.26	0	1
NACE: Wholesale, retail trade; repair of motor vehicles	0.11	0.31	0	1	0.11	0.32	0	1	0.12	0.32	0	1
NACE: Transportation and storage	0.06	0.23	0	1	0.05	0.23	0	1	0.05	0.23	0	1
NACE: Accommodation and food services	0.03	0.18	0	1	0.04	0.19	0	1	0.03	0.18	0	1
NACE: Information and communication	0.04	0.19	0	1	0.04	0.20	0	1	0.04	0.19	0	1
NACE: Financial and insurance services	0.03	0.18	0	1	0.03	0.17	0	1	0.03	0.18	0	1
NACE: Real estate, prof., scientific, tech and admin. activities	0.08	0.26	0	1	0.10	0.30	0	1	0.09	0.29	0	1
NACE: Public administration	0.11	0.31	0	1	0.09	0.29	0	1	0.09	0.28	0	1
NACE: Education	0.08	0.26	0	1	0.11	0.31	0	1	0.09	0.28	0	1
NACE: Human health and social work	0.16	0.36	0	1	0.16	0.37	0	1	0.16	0.37	0	1
NACE: Arts, Entert. recreation; other services activities	0.04	0.21	0	1	0.05	0.21	0	1	0.04	0.19	0	1
Regional Exposure to Robotization	1.18	0.36	0.36	1.90	1.34	0.46	0.36	2.77	1.67	0.62	0.59	3.72
Regional Export of goods (% on GDP)	20.7	11.9	0.5	52.4	21.5	12.3	0.5	53.3	22.2	12.5	0.9	58.0
Regional Unemployment Rate (15–74)	8.93	1.67	6.0	13.7	10.0	1.65	7.3	13.8	8.16	1.30	5.6	11.2

Table 7 Summary Statistics (weighted), Italy (authors' calculation on EU-SILC data)

	2010 N (observations): 16,412 N (weights sum): 20,659,228				**2014** N (observations): 16,589 N (weights sum): 21,339,828				**2019** N (observations): 16,222 N (weights sum):22,291,518			
	mean	SD	min	max	mean	SD	min	max	mean	SD	Min	max
Income	26,852	24,634	175	738,049	26,433	21,445	145	588,898	26,986	22,484	184	582,477
Age	42.9	10.7	17.0	81.0	44.4	10.8	17.0	81.0	45.1	11.3	17.0	81.0
Sex: Male	0.60	0.49	0	1	0.59	0.49	0	1	0.58	0.49	0	1
Sex: Female	0.40	0.49	0	1	0.41	0.49	0	1	0.42	0.49	0	1
Citizenship: Native	0.92	0.27	0	1	0.87	0.33	0	1	0.84	0.37	0	1
Citizenship: EU	0.02	0.15	0	1	0.04	0.21	0	1	0.05	0.21	0	1
Citizenship: Non-EU	0.05	0.23	0	1	0.08	0.28	0	1	0.11	0.32	0	1
Employment: Employee, permanent, full time	0.61	0.49	0	1	0.58	0.49	0	1	0.59	0.49	0	1
Employment: Employee, permanent, part time	0.07	0.25	0	1	0.09	0.29	0	1	0.09	0.28	0	1
Employment: Employee, temporary, full time	0.08	0.27	0	1	0.08	0.27	0	1	0.09	0.28	0	1
Employment: Employee, temporary, part time	0.02	0.14	0	1	0.03	0.17	0	1	0.04	0.20	0	1
Employment: Self-employed with employees	0.07	0.25	0	1	0.06	0.23	0	1	0.07	0.26	0	1
Employment: Self-employed without employees	0.16	0.36	0	1	0.17	0.37	0	1	0.13	0.34	0	1
ISCO: Managers	0.09	0.28	0	1	0.04	0.21	0	1	0.04	0.20	0	1
ISCO: Professionals	0.11	0.31	0	1	0.16	0.37	0	1	0.18	0.38	0	1
ISCO: Technicians and associate professionals	0.20	0.40	0	1	0.17	0.37	0	1	0.18	0.38	0	1
ISCO: Clerical support workers	0.12	0.33	0	1	0.13	0.33	0	1	0.11	0.32	0	1
ISCO: Service and sales workers	0.11	0.31	0	1	0.16	0.37	0	1	0.16	0.36	0	1
ISCO: Skilled agriculture, forestry and fishery	0.02	0.15	0	1	0.02	0.15	0	1	0.02	0.12	0	1
ISCO: Craft and related trades workers	0.17	0.38	0	1	0.16	0.37	0	1	0.12	0.33	0	1
ISCO: Plant and machine operators and assemblers	0.09	0.28	0	1	0.06	0.24	0	1	0.07	0.26	0	1
ISCO: Elementary occupations	0.09	0.28	0	1	0.10	0.30	0	1	0.11	0.32	0	1
Education: Primary (or under)	0.06	0.24	0	1	0.03	0.18	0	1	0.03	0.17	0	1

Table 7 (continued)

	2010 N (observations): 16,412 N (weights sum): 20,659,228				2014 N (observations): 16,589 N (weights sum): 21,339,828				2019 N (observations): 16,222 N (weights sum):22,291,518			
	mean	SD	min	max	mean	SD	min	max	mean	SD	Min	max
Education: Secondary	0.76	0.43	0	1	0.73	0.44	0	1	0.74	0.44	0	1
Education: Tertiary	0.18	0.38	0	1	0.24	0.43	0	1	0.24	0.42	0	1
NACE: Agriculture, forestry and fishing	0.03	0.18	0	1	0.03	0.18	0	1	0.03	0.18	0	1
NACE: Mining; manufacturing; utilities	0.24	0.43	0	1	0.21	0.41	0	1	0.23	0.42	0	1
NACE: Construction	0.08	0.28	0	1	0.07	0.26	0	1	0.07	0.26	0	1
NACE: Wholesale, retail trade; repair of motor vehicles	0.14	0.35	0	1	0.14	0.35	0	1	0.13	0.33	0	1
NACE: Transportation and storage	0.04	0.21	0	1	0.05	0.21	0	1	0.05	0.23	0	1
NACE: Accommodation and food services	0.05	0.21	0	1	0.05	0.21	0	1	0.05	0.22	0	1
NACE: Information and communication	0.03	0.16	0	1	0.03	0.16	0	1	0.02	0.15	0	1
NACE: Financial and insurance services	0.03	0.17	0	1	0.03	0.18	0	1	0.03	0.17	0	1
NACE: Real estate, prof., scientific, tech and admin. activities;	0.09	0.28	0	1	0.10	0.31	0	1	0.11	0.31	0	1
NACE: Public administration	0.06	0.25	0	1	0.06	0.24	0	1	0.05	0.23	0	1
NACE: Education	0.07	0.25	0	1	0.07	0.26	0	1	0.07	0.26	0	1
NACE: Human health and social work	0.07	0.26	0	1	0.08	0.27	0	1	0.07	0.26	0	1
NACE: Arts, Entert. recreation; other services activities	0.06	0.23	0	1	0.08	0.26	0	1	0.07	0.25	0	1
Regional Exposure to Robotization	1.43	0.48	0.51	1.98	1.70	0.61	0.54	2.41	2.23	0.81	0.67	3.12
Regional Export of goods (% on GDP)	20.1	7.87	9.58	29.8	23.4	9.27	10.4	34.3	25.4	9.52	12.1	37.6
Regional Unemployment Rate (15–74)	8.32	3.23	5.50	14.5	12.5	5.16	7.70	21.2	9.84	4.95	5.50	18.4

Table 8 Summary Statistics (weighted), Portugal (authors' calculation on EU-SILC data)

	2010 N (observations): 4453 N (weights sum): 4,015,473				**2014** N (observations): 5464 N (weights sum): 3,575,586				**2019** N (observations): 12,518 N (weights sum): 4,223,276			
	mean	SD	min	max	mean	SD	min	max	mean	SD	min	max
Income	14,699	13,108	132	154,955	15,105	14,003	134	204,890	16,159	15,082	140	336,302
Age	41.1	11.0	17.0	80.0	42.4	10.6	19.0	80.0	43.8	11.5	18.0	80.0
Sex: Male	0.54	0.50	0	1	0.50	0.50	0	1	0.51	0.50	0	1
Sex: Female	0.46	0.50	0	1	0.50	0.50	0	1	0.49	0.50	0	1
Citizenship: Native	0.91	0.28	0	1	0.91	0.29	0	1	0.90	0.30	0	1
Citizenship: EU	0.02	0.14	0	1	0.03	0.16	0	1	0.02	0.15	0	1
Citizenship: Non-EU	0.07	0.25	0	1	0.07	0.25	0	1	0.08	0.27	0	1
Employment: Employee, permanent, full time	0.70	0.46	0	1	0.75	0.43	0	1	0.73	0.44	0	1
Employment: Employee, permanent, part time	0.02	0.13	0	1	0.02	0.14	0	1	0.02	0.13	0	1
Employment: Employee, temporary, full time	0.14	0.34	0	1	0.13	0.34	0	1	0.15	0.36	0	1
Employment: Employee, temporary, part time	0.01	0.11	0	1	0.02	0.12	0	1	0.01	0.11	0	1
Employment: Self-employed with employees	0.04	0.20	0	1	0.02	0.15	0	1	0.03	0.16	0	1
Employment: Self-employed without employees	0.09	0.29	0	1	0.06	0.24	0	1	0.06	0.25	0	1
ISCO: Managers	0.06	0.24	0	1	0.06	0.23	0	1	0.06	0.23	0	1
ISCO: Professionals	0.11	0.31	0	1	0.18	0.38	0	1	0.20	0.40	0	1
ISCO: Technicians and associate professionals	0.10	0.30	0	1	0.13	0.33	0	1	0.12	0.32	0	1
ISCO: Clerical support workers	0.11	0.31	0	1	0.09	0.29	0	1	0.09	0.28	0	1
ISCO: Service and sales workers	0.17	0.38	0	1	0.18	0.39	0	1	0.19	0.39	0	1
ISCO: Skilled agriculture, forestry and fishery	0.03	0.16	0	1	0.02	0.15	0	1	0.02	0.14	0	1
ISCO: Craft and related trades workers	0.20	0.40	0	1	0.14	0.34	0	1	0.14	0.35	0	1
ISCO: Plant and machine operators and assemblers	0.10	0.30	0	1	0.10	0.30	0	1	0.10	0.30	0	1
ISCO: Elementary occupations	0.12	0.33	0	1	0.10	0.31	0	1	0.09	0.29	0	1
Education: Primary (or under)	0.37	0.48	0	1	0.28	0.45	0	1	0.22	0.42	0	1

Table 8 (continued)

	2010 N (observations): 4453 N (weights sum): 4,015,473				**2014** N (observations): 5464 N (weights sum): 3,575,586				**2019** N (observations): 12,518 N (weights sum): 4,223,276			
	mean	SD	min	max	mean	SD	min	max	mean	SD	min	max
Education: Secondary	0.44	0.50	0	1	0.48	0.50	0	1	0.50	0.50	0	1
Education: Tertiary	0.19	0.39	0	1	0.24	0.43	0	1	0.28	0.45	0	1
NACE: Agriculture, forestry and fishing	0.03	0.18	0	1	0.03	0.16	0	1	0.02	0.15	0	1
NACE: Mining; manufacturing; utilities	0.20	0.40	0	1	0.20	0.40	0	1	0.21	0.41	0	1
NACE: Construction	0.10	0.31	0	1	0.06	0.24	0	1	0.06	0.24	0	1
NACE: Wholesale, retail trade; repair of motor vehicles	0.17	0.38	0	1	0.15	0.35	0	1	0.15	0.35	0	1
NACE: Transportation and storage	0.03	0.18	0	1	0.05	0.21	0	1	0.05	0.21	0	1
NACE: Accommodation and food services	0.07	0.25	0	1	0.06	0.24	0	1	0.06	0.25	0	1
NACE: Information and communication	0.02	0.15	0	1	0.03	0.16	0	1	0.03	0.16	0	1
NACE: Financial and insurance services	0.02	0.14	0	1	0.03	0.16	0	1	0.02	0.15	0	1
NACE: Real estate, prof., scientific, tech and admin. activities;	0.07	0.25	0	1	0.08	0.27	0	1	0.08	0.28	0	1
NACE: Public administration	0.08	0.27	0	1	0.09	0.28	0	1	0.08	0.26	0	1
NACE: Education	0.08	0.27	0	1	0.09	0.29	0	1	0.09	0.29	0	1
NACE: Human health and social work	0.08	0.27	0	1	0.10	0.30	0	1	0.10	0.30	0	1
NACE: Arts, Entert. recreation; other services activities	0.05	0.22	0	1	0.05	0.21	0	1	0.05	0.21	0	1
Regional Exposure to Robotization									2.04	0.69	0.35	2.78
Regional Export of goods (% on GDP)									27.8	9.01	1.93	36.1
Regional Unemployment Rate (15–74)									6.41	0.79	4.90	7.70

Table 9 Summary Statistics (weighted), Spain (authors' calculation on EU-SILC data)

	2010 N (observations): 12,348 N (weights sum): 16,545,400				**2014** N (observations): 9777 N (weights sum): 15,292,392				**2019** N (observations): 13,854 N (weights sum): 17,434,340			
	mean	SD	min	max	mean	SD	min	max	mean	SD	min	max
Income	22,137	18,270	120	422,368	20,948	16,351	105	190,032	22,120	20,083	104	483,060
Age	41.3	10.6	17.0	81.0	43.0	10.4	18.0	81.0	43.7	10.8	17.0	81.0
Sex: Male	0.56	0.50	0	1	0.55	0.50	0	1	0.55	0.50	0	1
Sex: Female	0.44	0.50	0	1	0.45	0.50	0	1	0.45	0.50	0	1
Citizenship: Native	0.86	0.35	0	1	0.87	0.33	0	1	0.85	0.36	0	1
Citizenship: EU	0.04	0.20	0	1	0.04	0.20	0	1	0.04	0.19	0	1
Citizenship: Non-EU	0.10	0.30	0	1	0.08	0.28	0	1	0.12	0.32	0	1
Employment: Employee, permanent, full time	0.63	0.48	0	1	0.59	0.49	0	1	0.61	0.49	0	1
Employment: Employee, permanent, part time	0.06	0.23	0	1	0.07	0.26	0	1	0.05	0.22	0	1
Employment: Employee, temporary, full time	0.16	0.36	0	1	0.14	0.34	0	1	0.18	0.38	0	1
Employment: Employee, temporary, part time	0.04	0.20	0	1	0.06	0.24	0	1	0.04	0.20	0	1
Employment: Self-employed with employees	0.03	0.18	0	1	0.03	0.18	0	1	0.03	0.17	0	1
Employment: Self-employed without employees	0.08	0.28	0	1	0.10	0.30	0	1	0.08	0.28	0	1
ISCO: Managers	0.05	0.21	0	1	0.03	0.18	0	1	0.03	0.17	0	1
ISCO: Professionals	0.18	0.39	0	1	0.18	0.38	0	1	0.18	0.39	0	1
ISCO: Technicians and associate professionals	0.11	0.32	0	1	0.12	0.33	0	1	0.13	0.34	0	1
ISCO: Clerical support workers	0.14	0.34	0	1	0.13	0.34	0	1	0.12	0.33	0	1
ISCO: Service and sales workers	0.18	0.38	0	1	0.19	0.40	0	1	0.19	0.39	0	1
ISCO: Skilled agriculture, forestry and fishery	0.03	0.16	0	1	0.03	0.17	0	1	0.03	0.16	0	1
ISCO: Craft and related trades workers	0.10	0.30	0	1	0.11	0.31	0	1	0.11	0.31	0	1
ISCO: Plant and machine operators and assemblers	0.09	0.28	0	1	0.07	0.26	0	1	0.08	0.27	0	1
ISCO: Elementary occupations	0.12	0.33	0	1	0.13	0.33	0	1	0.13	0.33	0	1
Education: Primary (or under)	0.11	0.32	0	1	0.09	0.29	0	1	0.06	0.24	0	1

Table 9 (continued)

	2010 N (observations): 12,348 N (weights sum): 16,545,400				2014 N (observations): 9777 N (weights sum): 15,292,392				2019 N (observations): 13,854 N (weights sum): 17,434,340			
	mean	SD	min	max	mean	SD	min	max	mean	SD	min	max
Education: Secondary	0.49	0.50	0	1	0.46	0.50	0	1	0.48	0.50	0	1
Education: Tertiary	0.40	0.49	0	1	0.45	0.50	0	1	0.46	0.50	0	1
NACE: Agriculture, forestry and fishing	0.04	0.20	0	1	0.05	0.22	0	1	0.05	0.21	0	1
NACE: Mining; manufacturing; utilities	0.16	0.37	0	1	0.15	0.36	0	1	0.14	0.35	0	1
NACE: Construction	0.08	0.27	0	1	0.05	0.22	0	1	0.06	0.24	0	1
NACE: Wholesale, retail trade; repair of motor vehicles	0.13	0.34	0	1	0.15	0.35	0	1	0.15	0.35	0	1
NACE: Transportation and storage	0.05	0.22	0	1	0.05	0.22	0	1	0.06	0.23	0	1
NACE: Accommodation and food services	0.07	0.25	0	1	0.07	0.25	0	1	0.07	0.26	0	1
NACE: Information and communication	0.03	0.17	0	1	0.03	0.18	0	1	0.04	0.19	0	1
NACE: Financial and insurance services	0.04	0.18	0	1	0.03	0.18	0	1	0.03	0.16	0	1
NACE: Real estate, prof., scientific, tech and admin. activities;	0.08	0.27	0	1	0.09	0.28	0	1	0.09	0.29	0	1
NACE: Public administration	0.09	0.29	0	1	0.09	0.28	0	1	0.08	0.27	0	1
NACE: Education	0.08	0.27	0	1	0.08	0.27	0	1	0.08	0.27	0	1
NACE: Human health and social work	0.08	0.27	0	1	0.09	0.28	0	1	0.09	0.28	0	1
NACE: Arts, Entert. recreation; other services activities	0.07	0.25	0	1	0.08	0.27	0	1	0.06	0.25	0	1
Regional Exposure to Robotization	1.18	0.70	0.03	3.69	1.38	0.82	0.03	4.17	1.79	1.09	0.04	5.36
Regional Export of goods (% on GDP)	8.61	10.2	0.00	58.0	14.7	9.70	0.00	51.8	16.7	9.77	0.05	48.4
Regional Unemployment Rate (15–74)	19.5	5.16	10.7	28.6	23.8	5.93	15.7	34.8	13.8	4.23	8.20	27.0

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Data Availability The data used in Sect. 3 were downloaded from public databases, free accessible online. The specific public source for individual variables is indicated in the figure captions. Other sources publicly available: Eurostat (https://ec.europa.eu/eurostat/data/database) for Regional unemployment rate, Labour Force Survey and Structural Business Statistics (both used to calculate the robotization variable); OECD Regional Database (https://www.oecd.org/en/topics/regions-cities-and-local-statistics.html): regional exports/GDP. Data available only upon payment: International Federation of Robotics (IFR), used to calculate the robotization variable. The EU-SILC microdata used in Sect. 4 and Sect. 5 are accessible via the appropriate procedures: https://ec.europa.eu/eurostat/web/microdata/european-union-statistics-on-income-and-living-conditions. Upon request, authors can provide the.do files (Stata software) used for data processing.

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Other sources publicly available: Eurostat (https://ec.europa.eu/eurostat/data/database) for Regional unemployment rate, Labour Force Survey and Structural Business Statistics (both used to calculate the robotization variable); OECD Regional Database (https://www.oecd.org/en/topics/regions-cities-and-local-statistics.html): regional exports/GDP.
Data available only upon payment: International Federation of Robotics (IFR), used to calculate the robotization variable.
The EU-SILC microdata used in Sect. 4 and Sect. 5 are accessible via the appropriate procedures: https://ec.europa.eu/eurostat/web/microdata/european-union-statistics-on-income-and-living-conditions.
Upon request, authors can provide the.do files (Stata software) used for data processing.

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