Key sources of income (and wage) inequalities: from the State to the individuals

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TESI DOCTORAL UPF / 2022

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To everyone who helped me to find dawn in the twilight...

In appreciation

Probably any PhD candidate looks forward to writing this section to close this first (hopefully) academic journey. Thinking about what I'm typing on this 'wise' keyboard I have mixed feelings…

The first immediate question is: and now what? What's next? Notwithstanding all the difficulties, these 4 years have been an anchor, a reference point, and the 20.133A office in Barcelona my comfort-zone. Now it's the time of uncertainty, of the 'natural tension' towards the unknown future. This tension makes me a bit melancholic and scared about ending this process, to leave the certainty for the uncertainty. Probably Spinoza would be upset with me, as this movement towards the future (of 'becoming') frees our *conatus vivendi* and allow us to improve our 'being'.

On the other side, it is undoubtedly true that viewing the end of this path is a mental relief, a way to get rid of – for a while – constant academic pressions, frustrations, lack of self-esteem characterising the academic career under the neo-liberal culture. On the contrary, it is the moment to realize that you were actually able to resist all the difficulties – not least a pandemic – and to marginally contribute to the scientific research. This achievement would not have been possible without the precious, if not fundamental, help of all persons who have supported me both academically and emotionally.

First of all, I have to thanks my academic supervisors Jorge (Rodriguez) and Gosta (Esping-Andersen): all my current research lines are inspired by their presence. They gave me the opportunity to combine my economic and sociological interests, guiding me toward the right paths, suggesting me how and where to improve. (I also have to admit that I consider Gosta as a sort of wise grandfather, able to make me feel cared). All in all, my (little) success needs to be absolutely shared with them.

Personally, and professionally speaking, Marta (Fana) is not of less importance. Her passion, intellectual strength and working activities inspired my PhD. I always admired her capacity 'to fight' against the mainstream narrative and the possibility to learn from and work with her have been detrimental for my academic and personal achievements. I also appreciate her patience to digest all my errors and working chaos…sorry!

I also need to thank everyone who has supported me emotionally during the common burnouts and/or down-phases characterising a PhD. The list would be long and would not do justice to those who can stand close to me during these 4 years, but I thank you all, with love.

I guess it's now time to really think about my next stop, whatever it will be. But before doing that and close this section, I would like to thank myself, writing to the future Luca in case he will need to read these few lines. I'm writing these concluding remarks because I was able to resist all the negative feelings embedded in the academic path. I know you have encountered new difficulties, chosen your path, struggling with your 'Uncertainty' enemy, but I'd like to remind you that you can always rely on yourself, and think on what you were able to achieve. Paraphrasing Franco Battiato, 'you will always find the dawn in the twilight'.

Abstract

The following thesis aims to provide a general picture of to what extent different important sources – at the macro and the micro level – affect income inequality over time.

Indeed, given the natural interdependence between society (macro) and individuals (micro), a comprehensive perspective is required for studying the dynamics of outcomes. For example, the structural characteristics of the welfare system of a given country directly affects individual labour supply choices, but also the labour market institutional structure. Furthermore, there are also micro dynamics at play, mostly regarding individual choices – such as education – as well as social class dynamics, i.e., actions to preserve/improve one's socio-economic status. These family and class actions may directly facilitate or limit the transmission of income inequalities, but may also indirectly affect the types of workers available on the labour market. In this sense, these different dynamics must be analysed in order to identify the key mechanisms through which inequality could develop, and this analysis could also be useful in better guiding policy actions.

1. General introduction

1.1. Relevance of the topic

The concept of (in)equality has always been at the core of philosophical discussions. The core idea of inequality is about different – mainly socio-economic – conditions, between societies as well as within them, throughout history. For example, Aristotle argues that in ancient Athens, one of the main reasons for political changes – i.e., constitutions – was the perceived unfairness in the distribution of power and resources. According to Aristotle, to obtain a just distribution, it is necessary to ensure "proportional equality", where shares of goods/power are allocated proportionally to individual virtues or qualities. This means that according to the Greek philosopher, the guiding principles of equality are "to everyone in proportion to his worth or rank" and "equal shares to equals, unequal shares to unequals".

However, the first true theorist of inequality was Rousseau. In the "A discourse on inequality" (1775), he argues that natural differences between humans – what Rawls (1971) would define as exogenous characteristics beyond individual control – are not the primary source of inequality. Instead, it is the different societal organisations and socio-economic institutions that shape inequalities and force some classes to sell their labour and others to benefit. It follows that we may expect different distributional outcomes depending on the type of social contract that institutionalises a given State.

If we focus on economic inequality – that is, inequality originating from the economic structure, where an individuals' endowments are the result of different distributions of income and/or wealth – it is possible to observe significant changes between different moments in time and types of societies. For example, the socio-economic structure of the Ancien Régime and its distributional outcomes are radically different from the structure that existed after the French Revolution and to the society that was established after the industrial revolution.

Piketty (2014), in his book "Capital in the Twenty-First Century", presented the longest time-series analysis of income and wealth inequality in industrial and post-industrial societies. He observes different patterns both within and between countries between 1910 and 2010: the US and the UK are characterised by a U-shape pattern of income inequality, while Continental Europe and Japan are characterised by a pattern that looks L-shaped, but with heterogeneous rising trends beginning in the 1990s. Such results confirm that depending on the moment in time and on socio-economic institutions, as well as exogenous shocks like world wars, different patterns of income distributions can be observed. One of the most diffused examples is the "Glorious Thirty" (the years between 1945 and 1975), characterised by sustained economic growth and extraordinarily low levels of income inequality. In a more recent book, Piketty (2021) considers the development of the welfare state together with progressive fiscal systems as the primary determinants of this pattern of decreasing inequality. In fact, beginning in 1914 – and more heavily after the Second World War – the largest share of national income has been invested to finance social expenditures – such as public education, health, and public pension schemes – compared to 6-8% of national income during the "Belle Époque" which was dedicated to military spending. Similarly, during the 1914-1980 period, an effective marginal tax rate of around 60-70% contributed positively to reducing inequality, without harming economic growth. Symmetrically, Alvaredo et al. (2013) compute the elasticity between the change in the top 1% share and the change in the top marginal income tax rate from the 1960-64 period to the 2005-09 one, and finds a strong negative elasticity. In other words, they observe that the top 1% income share increases because of cuts in the top marginal income tax rate.

The labour market is the institution with the most clear-cut income inequality. Indeed, wages and salaries account for about 75% of the income of the working-age population in OECD countries (OECD, 2011). The economic and sociological literature explains the steady increase in income and wage inequality – starting from the 1980s – by changes in the demand and supply of labour, but also by the structural characteristics of labour markets. For example, Katz & Murphy (1992) were the first to introduce the idea of Skill-Bias Technological Change (SBTC), arguing that increasing inequality within a country is a direct consequence of technological development and of the expansion of higher education, when the supply of highly-skilled workers lags behind the increase in demand. In this framework, the resulting higher wage inequality is simply the consequence of supply-demand dynamics in the labour market. According to this theory, advanced economies should have experienced a progressive upgrading in their occupational structure. However, such predictions do not match the empirical evidence for either the US – characterised by polarisation patterns (Wright and Dwyer, 2003) – or for European countries, which are characterised by heterogeneous patterns of upgrading,

polarisation or even downgrading occupational structures (e.g., Fernández-Macías, 2012; European Jobs Monitor, 2017).
As a consequence, the SBTC has been revised, forming the Routine-Biased Technological Change theory (e.g. Acemoglu and Autor, 2011; Autor et al., 2003), according to which employment changes (and wage inequality) can be better understood by shifting the focus of analysis from individual skills endowment to tasks. It follows that tasks that are more routine in nature are more easily substituted by machines rather than people doing them. Because of this, we should expect a fall in the share of mid-range occupations (routine clerical jobs) and an increase at the extremes of the distribution, causing a polarizing occupational and income structure.
Conversely, other theoretical arguments have been introduced to explain how wage inequality arises and evolves in the labour markets. Authors like Card and Di Nardo (2002), Lemieux (2006), and Di Nardo and Pischke (1997) argue that the real causal factors are not market-driven, but instead institutional (minimum wages, union density, atypical and precarious employment, labour market liberalisation/flexibilisation, etc.).

Although outcome inequality is the most visible and studied concept over time, it is not sufficiently explanatory on its own. For example, according to Rawls' (1971) idea of justice, formal equality – i.e. the combination of equality before the law and the absence of direct/unfair discrimination – is not sufficient because natural differences that are exogenous to individual controls are likely to alter fair "competition" among individuals. Therefore, while inequalities stemming from individual actions and economic choices are accepted, those resulting from characteristics such as gender, ethnicity and social class are not. This means that according to Rawls, inequality is just when the formal equality of opportunity and the "difference principle" – i.e. the greatest advantage to the least disadvantaged individuals – coexist. If only formal equality is respected, then outcome inequalities are more likely to deteriorate because of the opportunities gap due to the lack of substantive equality. The latter consists of the absence of an indirect opportunities gap due to the exogenous characteristics of the individual, such as the class they were born into, gender, place of birth, etc.
Indeed, as Bukodi and Goldthorpe (2021) argue, the most advantaged classes have more political and economic power to secure their positions, and establish both glass floors (limits to downward mobility) and glass ceilings (limits to upward mobility). For example, individuals with more resources available to them are more likely to access

higher quality education and networks that may help them gain experiences and facilitate their career development. Conversely, individuals with fewer resources may downgrade their aspirations and ambitious for the future, as they perceive a lack of opportunities open to them. This may lead to a reduction in personal investments in education, self-reinforcing an unequal outcome. Corak (2013) provides some empirical evidence by introducing the "Great Gatsby curve", i.e. a positive association between income inequality and inequality of opportunities usually proxied by intergenerational income elasticity.

The relevance of inequality is also discussed by institutions such as the International Monetary Fund (2017) and the OECD (2015) which claim that excessive inequality is detrimental for economic growth and can cause political instability, confirming that constant research into the field of inequalities – both in terms of outcomes and of opportunities – is always required.
For these reasons, throughout this dissertation, I will primarily focus on income inequality i.e. the extent to which income sources are (un)evenly distributed among individuals, and how this has evolved over the last decade. In this sense, income will be the outcome analysed in all the chapters of the thesis. Because of the dominance of economics within the social sciences in academia and politics, there has been also a shift in the political language used. This used to exclude the concept of social class from the political arena and public debates. The choice of income as the key outcome across the thesis reflects such patterns and aims to allow the themes of this dissertation to enter into the existing academic and political debate more easily. Furthermore, the focus on income has the advantage of providing some clues about the direction of wealth inequality, without considering macroeconomic models that are focused, for example, on savings rates and/or comparison between rates of returns on capital and economic growth rates. Indeed, earnings inequality is one of the determinants of wealth accumulation, especially after the surge of labour earnings at the top of the income distribution (Piketty, 2014). In other words, if income inequality is on the rise, wealth inequality is going in the same direction. Finally, inequality trends and the impact of its determinants may change depending on whether the inequality measure refers to annual, monthly, or hourly incomes. As Franzini and Raitano (2019) argue, the annual definition best proxies the workers' living standard, including all the possible influences of labour market outcomes on workers' living standard (i.e., annual wages depend on

hourly wages determined by the number of hours worked per week and therefore on time-arrangements and number of working weeks affected by contract durations). For this reason, I will adopt this definition in the first and second paper, while relying on a monthly definition in the last paper due to lack of annual information.

Therefore, the aim of the three chapters is to contribute to the analysis of the dynamics of income inequality over the last decade, "moving from the state to individuals" or, in other words, combining both macro and micro perspectives.
Specifically, the first chapter will verify to what extent cash transfers and in-kind benefits – i.e. the structure of government budgets and the factor sources of income – contribute to income inequality dynamics across countries. Following this examination of the institutional framework, the second chapter will inspect – *in a non-causal way* – the trends and determinants of inequality at different points on the wage distribution, to capture if and to what extent individual characteristics, employment and structural compositions (proxies for labour market institutions) affect those changes.
Finally, in the third and last chapter, I will identify whether some individual characteristics – particularly social class and horizontal educational choices – can facilitate the transmission and reproduction of income inequality. I will do so by answering the following question: does the impact of social background on first-occupation wage vary for university graduates in Italy according to their fields of study?

1.2. Descriptive evolution of income inequality and focus on Italy

As the thesis has a dynamic perspective, it might be useful to briefly introduce how income inequality has evolved and followed different trajectories depending on the organisation of societies and institutions at given points in time. It follows that although a similar "exogenous" and concomitant context exists – i.e. the European Union – single countries still preserve their institutional characteristics and experience different inequality trends.

The OECD (2015, 2011, 2008) has documented this trend, showing how almost all advanced countries have experienced increased income inequality, expanding the p90/p10 ratio to 9:1, compared to 7:1 in the 1980s: an increase of around 10% in the Gini coefficient. The dynamic has also involved traditionally egalitarian countries such as Denmark, Sweden, Finland, and Norway, while countries characterised by already high level of inequality – such as the UK– have experienced even higher rates of inequality. Other sharp increases have been registered in Italy, Germany, and Portugal, while countries like France and Belgium have experienced very little increase (i.e. less than 1.5%) in their Gini coefficients.

Recent debate has shifted away from traditional indexes like Gini coefficient or share ratios to examine dynamics within the top 1% of earners. For example, Piketty et al. (2018) apply this perspective to the case of the United States and observe that between 1980 and 2014, pre-tax income collapsed for the bottom 20% of wage-earners, stagnated for the bottom 50%, but tripled for the top 1%, even going up to +636% for the top 0.001%. Blanchet et al. (2019) present the same analysis for Europe. They provide evidence for the lack of convergence between European countries in terms of national income growth, implying heterogeneity across countries. For example, southern Europe has always had an income growth rate below that of the central European and Scandinavian countries, but this distance widened further with the financial crisis of 2007-2008, since southern countries experienced negative income growth. The figure does not change when using different inequality measures, with the top 10% shares experiencing different trajectories across countries. Italy, for example, experience a widening gap in the p90/p10 ratio, while this ratio remained almost stable in Spain between 1980-2017. Overall, European citizens in the bottom 50% experienced an income increase of 30-40% between 1980 and 2017. This percentage was 40-50% for earners between the 50th and 90th percentiles, while the top 1% captured 17% of the total income growth. Indeed, all earnings within the top 1% doubled in the period studied, and within the top 0.001%, earnings tripling compared to 1980.

Within a strong heterogenous Europe, Italy stands out as one of the countries where the labour market changed the most, with consequences on the outcome distribution. Specific stylised facts are reported, for example, by the Italian National Social Security Institute (INPS, 2019). It shows that from the mid-1990s, wages in the bottom 10 percentiles started to lag, with gains being made in both the top decile and top 99th percentile. Brandolini et al. (2001) and Manacorda (2004) confirm this steady increase beginning in the 1990s, associated with the elimination of the so-called "*scala mobile*" i.e. the indexation mechanism.

Those were also the years when the Italian labour market began to be liberalised. This resulted in one of the sharpest changes in the European Employment Protection Legislation index (EPL), which fell from 5.85 in 1985 to 1.96 in 2018 (OECD, Employment Protection Legislation Database, 2020). However, the expected employability and productivity gains of such reforms clearly did not pay off. On the contrary, most new employment is characterised by atypical contracts, with the share of temporary and part-time contracts reaching around 20% and 14% respectively at the end of 2018; in addition, involuntary part-time work almost doubled the European average: 67% compared to the EU average of 35% (Eurostat, 2020). Moreover, 70% of the employment recovery that occurred between 2014 and 2019 was characterised by employees with fixed contract arrangements (Istat, 2021), in line with the prescriptions of the last major labour market reform – the Jobs Act (2014). In terms of productivity, Ricci and Cirillo (2019) show that the increase in temporary employment led to a decline in labour productivity and wages, while Cetrulo et al. (2019) observe that a higher share of temporary employment is detrimental for innovation, research & development. Such mechanisms characterised and shaped the structure of the Italian labour market, resulting in a downgrading pattern in the occupational structure, compared to the other principal European countries (Hurley et al., 2019).

Italy also stands out compared to other countries in terms of unequal opportunities. Indeed, both occupational and educational transmission and intergenerational income elasticity (IGE) confirm its lack of mobility. Bernardi and Ballarino (2016) confirm this lack of mobility in terms of occupational and educational transmission, while Esping-Andersen and Cimentada (2018) observe that in Italy, the class that one is born into matters even more than an individual's own abilities. Similarly, in terms of income, on Corak's (2013) "Great Gatsby curve", Italy stands out together with the US and UK, with an IGE value of around 0.50, i.e. around 50% of parents' income is transmitted to their children. In other words, Italy is one of the countries with the highest income-class transmission rates.

It is therefore not surprising that Italy is the *only* OECD country where the average wages in 2020 are *lower* than in 1990: while in all other advanced countries, average wages have increased over the last 30 years, in Italy they have fallen by 2.9% (OECD, 2022).

All these facts make Italy as an ideal case study for wage inequality dynamics and class-advantage transmission.

1.3. Contributions and structure of the thesis

As already shown, increasing and persistent income and wage inequality in most advanced economies has been one of the hot topics in academic and policy debate over the last few decades. With a compendium of three papers, the academic aim of this thesis is to provide further evidence regarding the dynamics of outcome and opportunity inequality, moving from a macro-descriptive perspective – the first paper – to the micro-individual determinants in the paradigmatic case of Italy – the second and the last papers.

Considering the lack of European convergence in terms of national incomes and inequalities (Blanchet et al., 2019), the dissertation firstly focuses on the evolution across countries of income inequality in the decade between 2008 and 2017 in the EU-15. The purpose of this chapter is to contribute to the scant literature (e.g., Aaberge et al., 2010; Aaberge and Langorgen, 2006; Fuest et al., 2010; Rani and Furrer, 2016) on the decomposition of inequality indexes by factor sources and – above all – by in-kind benefits, compared with the standard cash transfer programmes distinguished not only by functions but also by type of social benefits (contributory vs non-contributory, or means-tested vs non-means tested). The final aim of the analysis is therefore to identify the main macro-sources of inequalities, and to what extent differences in the welfare constituencies i.e. combinations of in-kind benefits, cash-transfer types and taxes, contribute to the redistribution. Therefore, this analysis should provide further suggestions on what the best welfare prescription to reduce income inequality could be.

This macro-descriptive decomposition of inequality changes carried out in the first paper opens the floor for further micro analysis of the possible determinants of these trends. As argued, Italy represents an ideal case study, since it is the only OECD country with average wages that are lower in 2020 than in 1990; it also stands out in the statistics for both income and opportunity inequality. Furthermore, from the first chapter, it emerges that wages and salaries are the primary source of inequalities in all countries being assessed.

Consequently, the second chapter focuses on wages, and enters into the debate about what is behind the rising trend of wage inequality, examining the standard theory of Skilled-Biased-Technological Change (Katz and Murphy, 1992 among others) and the role of institutions and the structure of the labour market (e.g. Card and DiNardo, 2002; DiNardo and Pischke, 1997).

The aim is to identify what the true determinants are behind the changes in wage distributions over the decade of 2007-2017 in Italy, and to understand whether the SBTC theory applies (or not) to the case of Italy. In order to do this, the chapter will analyse to what extent inequality trajectories are explained by changes in occupations and sector compositional structure, together with labour market institutions proxied by workers' contractual arrangements and working times. In other words, it will try to understand whether the wage inequality trends in Italy can be better explained by labour market characteristics or by the predictions of the SBTC theory.

Knowing what the underlying determinants of wage inequality are may be useful for understanding the ongoing dynamics in the labour market and to – eventually– intervene in order to implement policy corrections.

Continuing with the micro-analysis and potential mechanisms behind wage inequality in Italy, the last chapter focuses on the possible class advantages regarding wage returns. The existence of such class advantages is detrimental for so-called opportunity equality – or "meritocracy" – since individual characteristics and productivity are not the main determinants of labour market outcomes. Most of the economic and sociological literature focuses on the role of educational attainment as a possible mediator of such intergenerational transmission, but confirms the failure of the vertical dimension of education as a "great equalizer" (e.g., Bernardi and Ballarino, 2016; Fiel, 2020; Torche, 2011). However, there is still an additional source of class transmission that is not widely considered in the standard sociological and economic literature; this is the horizontal dimension of education i.e. educational fields. Therefore, the last paper aims to fill this gap and to shed light on the role of educational fields in intergenerational social mobility in Italy, testing whether the impact of social background on first-occupation wage varies depending on graduates' fields of study. This may represent an additional mechanism through which wage inequality may be high in Italy.

Overall, moving "from the state to individuals" aims to provide a general picture of to what extent different important sources – at the macro and the micro level – affect income inequality over time.

Indeed, given the natural interdependence between society (macro) and individuals (micro), a comprehensive perspective is required for studying the dynamics of outcomes. For example, the structural characteristics of the welfare system of a given country directly affects individual labour supply choices, but also the labour market institutional structure. Furthermore, there are also micro dynamics at play, mostly regarding individual choices – such as education – as well as social class dynamics, i.e. actions to preserve/improve one's socio-economic status. These family and class actions may directly facilitate or limit the transmission of income inequalities, but may also indirectly affect the types of workers available on the labour market. In this sense, these different dynamics must be analysed in order to identify the key mechanisms through which inequality could develop, and this analysis could also be useful in better guiding policy actions.

Based on this theoretical idea, I have observed that although the primary source of inequality lies in the labour market, in order to reduce income inequality, it is beneficial to have a more balanced combination of cash transfers – especially non-contributory means-tested transfers – and in-kind benefits. The structure of the labour market derived from the institutions and characteristics of the state seems to be more important in determining wage inequality in Italy, compared to the market-based view proposed by the Skill-Biased-Technological change theory. In addition, class background plays an additional (direct) role in shaping wage distribution in the Italian labour market, particularly for individuals who have graduated in non-technical areas, where social background may provide a stronger signal for sorting workers along occupational lines. In the Italian case, this mechanism further contributes to reproducing inequality.

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Table of contents

List of Figures

List of tables

2. Welfare type and income inequality: an income source decomposition including in-kind benefits and cash-transfers entitlement

Abstract

This paper aims to understand whether a shift toward a more balanced cash transfer and service-based welfare system is valuable in terms of reducing income inequality and what factors mostly contributes to the income inequality evolution.

To examine this, I first impute the monetary values of in-kind benefits, and then reassess Gini coefficients and welfare regimes across countries. I also compare the role of cash transfers by functions and, more importantly, by how they are allocated. By means of factor source decomposition, the elasticities confirm wages as being the income source that creates most inequalities, while taxes play the most equalising role together with cash transfers. However, universal services such as healthcare and compulsory education outperform most of the cash transfers included in the analysis, with a stronger effect in the Mediterranean countries. Although in-kind services play a marginal role in explaining the changes in the Gini coefficient between 2008 and 2017, results suggest that shaping a state intervention strategy with a more balanced combination of cash benefits and in-kind transfers, as well as increasing the share of non-contributory means tested transfers, can improve equality outcomes.

Keywords: Cash transfers; Income inequality; Inequality measurement; In-kind benefits; Welfare provision

2.1 Introduction

Inequality is currently one of the most discussed topics in socio-economic and political debates. In 2017, the International Monetary Fund (IMF, 2017) also warned that excessive inequality could generate social and political instability and, in turn, damage economic growth. In Europe, income inequality is on the rise and it is significantly heterogenous across countries.

Atkinson (2003) has argued that the theoretical explanations of changes in inequality should be sufficiently wide to allow for such diversity in inequality outcomes. According to the current literature (Bourguignon (2017); Gustafsson and Johansson (1999); Milanovic (2015); OECD (2008); Rodrik (1998), etc.), the main drivers that could explain inequality changes are the following: globalisation and technology, labour markets, demography and the welfare regime.

Focusing on the welfare regime, it is clear that each single state can shape and adjust total income distribution through taxes and transfers at all stages of the business cycle. However, state intervention is more evident in times of recession through its actions on fiscal policy: cash transfers to poorer households, liquidity transfers to companies, tax relief and higher levies on the highest bands of income/wealth (IMF, 2021).

In this sense, there is a substantial body of literature that studies the general redistributive effects of taxes and social transfers (for example OECD, 2008; Caminada et al. 2017; Raitano 2016; etc.).

Depending on the methodological approach used, either cash transfers or taxes can be seen to have stronger effects, but in all cases, the state performs a redistributive function. The first approach – known as the *sequential accounting approach* – relies on the contributions of Kakwani (1977) and Reynolds-Smolensky (1977-78). The overall redistributive effect is computed as the percentage reduction in the Gini coefficient, i.e., as the relative difference between the Gini coefficient for disposable income – computed after taxes and transfers – and the Gini coefficient for market income.

Following this method, the OECD (2008, 2011) has shown that the redistributive impact of taxes and transfers in OECD countries could be quantified, on average, as one third, with three-quarters of this reduction achieved through cash transfers from public administrations to people in need. Caminada et al. (2017, 2019) implement the same approach on a larger sample of countries using LIS data. They observe that the countries with the largest total redistributive effects are the Scandinavian ones and confirm the

OECD results. Esping-Andersen and Myles (2011) confirm this association, showing that the larger the social expenditure over GDP, the more equal a country is.

The alternative approach used to measure the state's redistributive effect is based on the *factor source decomposition* first introduced by Fei et al. (1978) and Pyatt et al. (1980) and extended by Shorrocks (1982). It consists of determining which income source contributes the most to income inequality.

Scholars using this technique have obtained results showing that taxes have the strongest redistributive effect.

For example, Jännti (1997) found that the primary source of inequality is wage inequality originating in the labour market, and confirmed that taxes and social transfers reduce inequality, with taxes playing the larger part. Raitano (2016) adopted Shorrocks' method and confirmed the results of Jännti (1997): proportionally, earnings from work make up the largest contribution to total inequality. Adopting a welfare-regime perspective, he found, in agreement with Caminada et al. (2017), that the largest overall redistribution occurred in the Scandinavian countries. Rani and Furrer (2016) and Fuest et al. (2010) obtain similar results.

Independently of the method,[1] one main limitation of this current evidence is the exclusion of some important income sources – particularly public services. The Canberra Group (2011) argues that the best proxy of economic wellbeing is the extended (disposable) income approach i.e., the sum of all equivalised income sources received in the market, including all welfare transfers, net of taxes and including all imputed incomes and in-kind benefits. Therefore, extending the existing results adopting a full income approach allow to understand how different combinations of market incomes, taxes, cash transfers – distinguished not only by functions but also by entitlement criteria – and even in-kind benefits can have different results in terms of inequality in final disposable incomes.

Furthermore, from a policy perspective it would be useful to know which social benefits favour a more equal income distribution. One difficulty is that the classification by function – the most common focus of the current literature – is not unique. There is also the issue of what type of assessment is most useful for policymakers i.e., one that predicts the inequality effects of higher shares of contributory cash transfers (means-tested or not

[1] A more advanced technique is to use tax-benefit microsimulations using EUROMOD. Paulus et al. (2010) is an example of applying the study of distributional effects of in-kind benefits using such microsimulations.

means-tested), or one that uses non-contributory transfers. This element is rarely addressed by the previous studies about welfare redistribution and this paper aims to fill this gap.

Moreover, the budget structure of a country evolves over time and is increasingly shifting toward a service-based welfare system with higher ratios of in-kind benefit expenditure over GDP (Eurostat Social Expenditure Dataset). Is this a valuable strategy in terms of reduction of inequality? And what type of cash transfers still outperform the in-kind benefits?

While the existing literature mostly deal with levels i.e., the impact of a given program (being a cash-transfer or an in-kind service) on inequality at given points in time, this paper extends the previous literature providing a better understanding of the dynamic redistributive effects of both cash transfers and public services. In other words, what are the income sources that mostly determine the income inequality evolution? According to the author's knowledge, this is the first paper addressing this dynamic perspective across countries including a detailed comparison between types of cash-transfers (function and entitlement) and in-kind services.

The aim of this paper is therefore to answer these questions enriching the existing literature providing new evidence about the redistributive effects of cash-transfers allocation, in-kind benefits and – more importantly – their contribution to the dynamic of income inequality.

For this purpose, I use the Lerman and Yitzhaki (1985) Gini decomposition approach focusing on the EU15 countries. Specifically, I estimate the elasticities of income inequalities to changes in labour income (employee wages and self-employment), capital income, private transfers, taxes, and cash transfers. Differently from most previous work, these cash transfers are distinguished not only by functions (allowances for unemployment, old-age, survivors, sickness, disability, education, family/child, housing and social exclusion), but also by entitlement criteria (contributory means-tested and not means-tested and non-contributory means-tested and not means-tested). I then look at the elasticity of income inequality to changes in in-kind benefits in healthcare, pre-primary, compulsory and tertiary education and in social-housing services.

The most important advantage of this decomposition technique is the possibility to estimate the effects of a small percentage change in one specific income factor on the total Gini coefficient (holding the others constant). These elasticities – rarely displayed in the existing studies – are the most relevant elements in terms of policy implications.

Furthermore, the Lerman and Yitzhaki (1985) technique permits to identify the factors that most contribute to the change in income inequality over the decade 2008-2017. Results confirm wages as being the income source with the highest disequalizing effects, while taxes play the most equalising role together with cash transfers, particularly in the Scandinavian countries. However, universal services such as healthcare and compulsory education outperform the redistributive power of most of the cash transfers included in the analysis, with a stronger effect in the Mediterranean countries. Although in-kind services play a marginal role in explaining the changes in the Gini coefficient between 2008 and 2017, results suggest that shaping a state intervention strategy with a more balanced combination of cash benefits and in-kind transfers, as well as increasing the share of non-contributory means tested transfers, can improve equality outcomes.

The paper is organised as follows. In section 2, I introduce the relevance of the in-kind benefits in public budgets. In section 3, I introduce the Lerman and Yitzhaki (1985) decomposition method along with the imputation techniques of the in-kind services. In section 4, I present the results that stem from the above-mentioned technique, and further discuss them in section 5.

2.2 The role of in-kind benefits

The existing literature on in-kind benefits and cash-transfers address mostly two lines of research: the welfare effects on the labour supply decisions and welfare redistributive effects i.e., their impact on income inequality (or other relevant economic outcomes). The standard economic theory predicts lower labour supply because of cash-transfers programs (e.g., Becker, 1965). However, some mixed evidence exists with studies observing the expected negative effects, while others non-significant labour supply changes (see Moffitt 2002 for a review of existing studies in the US). More recently, Baird et al. (2018) provide a comprehensive review of the labour market effects of different cash-transfers program. They conclude that both conditional and unconditional cash-transfers result in little or no change in labour supply decisions.

As for the in-kind transfers, the theoretical literature is scant (Murray, 1980; Leonesio, 1988; Muffitt, 2002) and mostly conclude that when in-kind transfers are structured in a way such that the individual is constrained to over-consume the provided good, if such good is substitute with labour, then the labour supply is likely to increase. On the contrary, when labour and the in-kind transfer are perfect complement the labour supply tends to decrease. Few studies empirically test this theoretical prediction. For example, Binglay and Walker (2013) consider in-work cash and in-kind transfers and find large positive effects on the labour supply among single-mothers in UK.

In terms of inequality reduction, an extensive literature has been produced on the redistributive effects of taxes, cash transfers, and in-kind benefits. Focusing on the latter, Callan et al. (2008) have argued that distributional analysis based on disposable income considering only cash transfers may severely bias estimates and results. In the first seminal study evaluating the impact of in-kind benefits (education, health and social housing), Smeeding et al. (1993) concluded that adding the monetary value of these services to final income has a positive and significant effect in terms of reducing poverty and inequality. Subsequently, this line of research has been developed further with the contributions of Garfinkel et al. (2005, 2006), Marical et al. (2006), Callan et al. (2008), Verbist et al. (2019), Vaalavuo (2011, 2020), Aaberge et al. (2013, 2017), and Törmälehto and Sauli (2013), which have all used varieties of a sequential accounting approach. Conversely, Aaberge and Langørgen (2006) and Aaberge et al. (2010) use the Gini decomposition technique to analyse the distributional role of local government services.

However, these studies do not include an integrated analysis comparing cash-transfers (by functions and entitlements) and in-kind benefits and – more importantly – lack a dynamic perspective focused on marginal contributions of each income source. Therefore, in this paper, I will try to combine these contributions, by comparing cash transfers and in-kind benefits – across countries and welfare types – with the aim of understanding whether in-kind benefits have a more, less or equivalent redistributive efficacy, and if this has changed over time.

The above-mentioned literature has developed two main approaches for the estimation and imputation of non-cash transfers.

Firstly, their production cost is used to value them, since these products and services are produced and supplied outside a typical market framework and do not typically display a price. Alternatively, they can be valued by calculating their cash-equivalence i.e., the amount that the household would have paid for similar services in the private market. However, this latter approach is much more data-demanding and does not consider that public services may have characteristics that are extremely different from services produced and supplied by the market.

As for allocation of monetary value to the household income, this depends on the type of service being assessed. The actual use allocation i.e., monetary values allocated to the households according to the effective consumption of the service, are mostly used for public services like education (including pre-primary), social housing, and public transport (Verbist et al., 2019). However, this method is highly data-demanding and difficult to implement, as microdata reporting information about social services consumption may be rare.

The alternative method adopted in the literature, mostly for health-care services and long-term elderly care, is the insurance value approach as the availability of the services and the possibility to use them may be more important than their actual use. For example, for a chronically ill person it is more valuable the possibility to intensively access the public healthcare rather its actual consumption. Indeed, the actual use approach may falsely represent he/she as better off compared to a healthy individual.

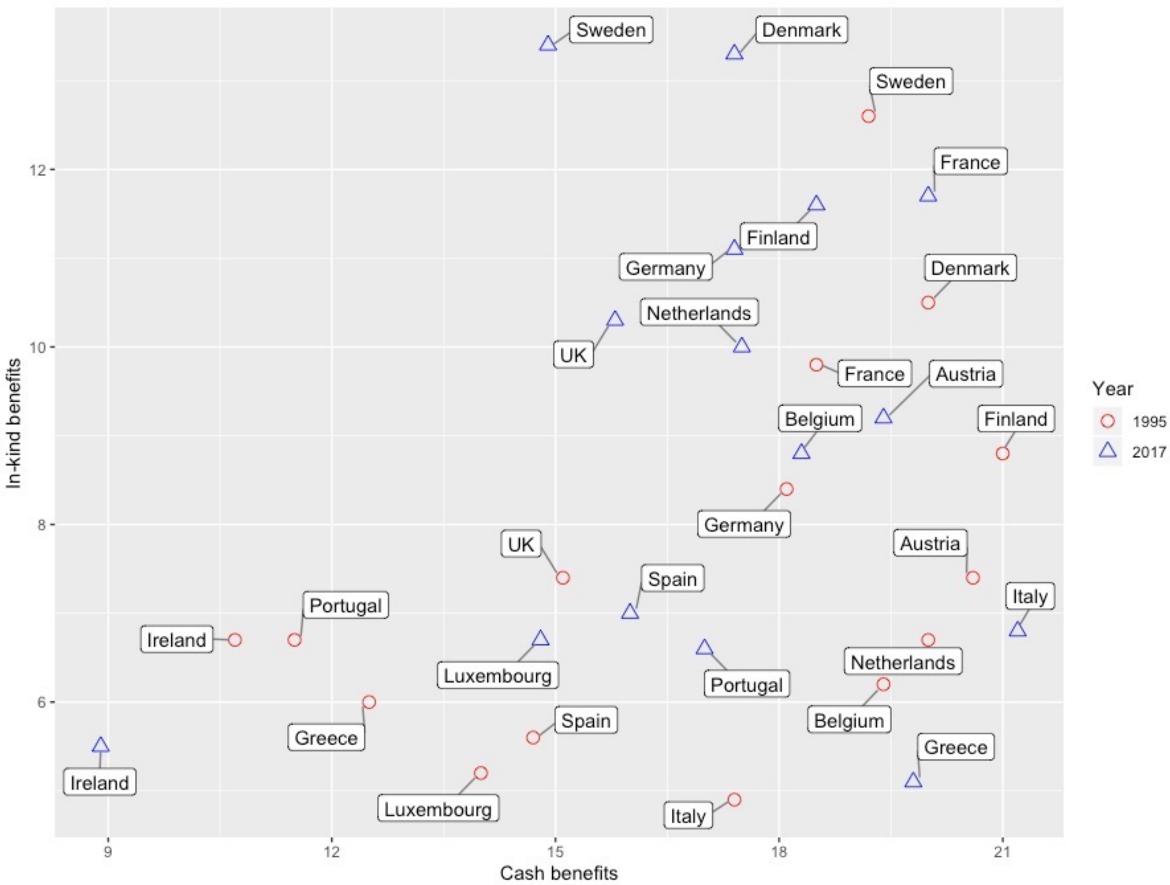
With the insurance approach, the aggregate value of the service will be imputed equally between individuals who share the same characteristics (age, gender) and/or household structure (with children, employed, etc.). This can be thought of like the State paying an insurance premium that is equal for all individuals who having the same probability of accessing the service.

Independently of the method adopted, the literature observes in-kind services as positively reducing poverty and inequality. If such positive effects of in-kind benefits on reducing income inequality exist, the underlying hypothesis is that an expansion of this kind of expenditure may imply a stronger redistributive impact over time. Symmetrically, a contraction of such services due to financial crises may undermine the equalising effects of in-kind services.

Indeed, as Esping-Andersen and Myles (2011) argue, the structure of welfare regimes is changing and shifting from cash transfers to in-kind benefits. This is confirmed by looking at the evolution of cash and in-kind expenditures over GDP across the EU15. Comparing the overall average cash benefits in terms of GDP in 1995 and in 2017, there is a 0.3 percentage point increase, while in-kind expenditures increased by 1.3 percentage points.[2]

Focusing on cross-country heterogeneity in the expenditure composition, Kautto (2002) has complemented Esping-Andersen's (1990) categorisation of welfare regimes by including in-kind services. According to his analysis, the Scandinavian countries are characterised by high share of both cash transfers and in-kind services; the liberal regime is characterised by a high share of services, but a low share of cash transfers; the conservative regime has high levels of cash transfers and low levels of services; and lastly, the Southern European countries have low levels of both cash transfers and services. The relationship between the two variables can be clearly observed in Figure 2.1.

Figure 2.1: Cash and in-kind benefits plot – percentage of GDP



Source: author's own elaboration based on representation using Eurostat Social Expenditures Dataset.

[2] I used the Eurostat Social Expenditures Dataset (https://ec.europa.eu/eurostat/web/social-protection/data/database). I acknowledge that net social expenditures over GDP is a better measure, but neither Eurostat nor SOCX OECD disentangle the net measure by functions and by type of transfer.

Note: The comparison between 1995 and 2017 is intended to provide a longer-term perspective on changes in budget composition, which may not be detectable over a shorter time period.

2.3 Welfare regimes

In this section, I briefly discuss the welfare regime typology applied in the analyses, following the contribution made by Esping-Andersen (1990). Esping-Andersen's analysis of the main cross-national and historical variations in social rights and welfare state stratification led him to group European countries into three basic welfare regime clusters.

The *liberal welfare state* is characterised by means-tested programmes, modest universal transfers and/or modest social-insurance plans. The beneficiaries of these programmes tend to be the poorest in society, but the low number of people entitled to them, the limited benefits of the programmes and the stigma associated with them often lead the beneficiaries to rely on the labour market to supplement or extend their incomes. The UK and Ireland are the main proponents of this welfare regime.

In the *social-democratic welfare state,* universalistic and de-commodification principles dominate, with the aim of overcoming the dualism between the State and the market, and of promoting equality of the highest standards and not just of minimum needs. In this way everyone is included in the universal insurance system.

Countries in central Europe (most notably France and Germany) constitute the third regime, the *corporatist welfare state*. Here, the most important characteristic is the preservation of the differential status generated in the active labour force: consequently, rights are tied to contributions, and hence, also to class and status. The state is the key actor in providing welfare policies, but the focus on the horizontal dimension of the welfare distribution limits its redistributive impact.

Ferrera (1996) extends Esping-Andersen's contribution, adding a new welfare specification. Differently from the other models, in the *Mediterranean welfare state,* family and Church are the main actors that provide social support, whereas the state is just a residual actor. An individual's current and previous employment status determines whether he or she is entitled to social security benefits. Mediterranean countries show a dualised labour market, where on the one hand the male breadwinner is more likely to enjoy employment stability, and on the other, women, young people and immigrants suffer more precarious employment. Spain, Italy, Portugal and Greece are example of these Southern European welfare states.

2.3.1 Welfare types and inequality

The structural characteristics of the welfare system of a given country directly affects individual labour supply choices, but also the labour market institutional structure. Therefore, the structural differences across the welfare types are likely to influence both the market and disposable income distributions, generating different levels of redistribution.

Korpi and Palme (1998) adjusted the classification model introduced in the previous section to account for the types of social insurance programs. They found that countries with targeted benefits (flat-rate means-tested amounts) have higher income inequality, introducing the 'paradox of redistribution'. Korpi (2000), extended the previous work and observe that mostly all liberal countries (US, UK, Australia and Ireland) display high level of income inequality, while the Scandinavian countries (Sweden, Norway and Finland) present the lowest level of inequality. These findings have been confirmed more recently, with Esping-Andersen and Myles (2011) showing a negative correlation between social public expenditures over GDP and income inequality. Similarly, Raitano (2016) and Caminada et al., (2017) find that the Scandinavian countries are the most equal ones, while countries in the liberal regimes the most unequal. The validity of this classification is confirmed also when adding in-kind benefits (Vaalavuo, 2011).

I will use the presented (exogenous) classification to interpret the redistributive analysis and factor source decomposition. However, I will test how valid this classification is in explaining the relative contributions of different factors to inequality with a hierarchical cluster analysis (see Appendix – cluster analysis).

2.4 Data & Methods

I use the European Union Statistics on Income and Living Conditions (hereafter EU-SILC) microdata on the EU15 countries[3] (Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Sweden and

[3] I focus on the EU15 in order to consider the standard classification of welfare regimes, excluding post-socialist countries that may present different structural characteristics.

United Kingdom) to estimate the redistributive effects of various income sources across countries and over time (comparing 2008 with 2017). In this way, I can explore the main income sources that contribute to changes in equality levels.

Since 2008, data for the EU15 countries include all the necessary gross-income components, allowing me to estimate the inequality effect of each income factor[4]. Moreover, in 2017 the EU-SILC data breaks down social transfers not only by function (unemployment, old-age, survivors, sickness, disability, education, family allowances, housing allowances and social exclusion allowances), but also distinguishes the contributory or non-contributory nature of the transfers (and whether they are means-tested or not). This allows to work with the same definition of income over time – thus avoiding comparability issues[5] – and to take into account the nature of the cash transfer (only in 2017).

Furthermore, the EU-SILC data also includes a variable which imputes respondents' housing rental payments. The monetary value of the social housing service can therefore be directly estimated (further details in the subsequent section).

I will rely on the Gini coefficient as my inequality measure due to its simplicity and common use as a summary index. Because it is very sensitive to the values at the extremes of the distribution and these will be trimmed, it is possible that there is some bias in the estimates provided below. There are no significant differences between the Gini coefficients obtained with the method implemented here and the official EUROSTAT statistics.

Furthermore, as the basis for computing any income inequality measures is total disposable household income, I use the assumption of income pooling – i.e., that household resources are equally shared by its members. Therefore, the total disposable household income is adjusted to the household size using the modified OECD scale[6] to obtain the equalised disposable income. As for the in-kind benefits, the current literature proposes different approaches. Smeeding et al. (1993) assume no income-sharing for the

[4] The only limitation refers to the lack of important capital income components, like capital gains. The absence of such income components may underestimate the overall income inequality.

[5] Formally, the EU-SILC income definition is evolving over time. The main change is between 2008 and 2011, where pensions received through individual private plans (PY080G) are added to the definition of total disposable household income. However, the microdata include this information for all years, allowing me to simply add this component to the income in 2008 and obtain exactly the same definition of income for the two selected years.

[6] This scale assigns a weight of 1 to the head of household, a weight of 0.5 to each additional adult in the household, and a value of 0.3 to each child.

services in kind and aggregate the non-cash services at the household level and express it in per-capita terms. Differently, Garfinkel et al. (2006), argue that the standard approach is to apply the same equivalence scale to both cash and in-kind transfers. The underlying reason is that such simple approach is half-way solution between the absence of economies of scale argument – implying in-kind benefits expressed in per-capita terms – and the absence of (equal) income sharing within the household, which involve that in-kind benefits should be added to the equivalent income on individual basis. Aaberge et al. (2010) develop a new equivalent scale as a weighted average of scales for cash-income and in-kind transfers, differentiating the needs for cash and non-cash incomes. However, this approach requires detailed data to distinguish the heterogeneity of public expenditures by individual needs. For this reason, I apply the solution proposed by Garfinkel et al. (2006), using the same equivalence scale for both cash and in-kind monetary values. As a robustness, I will replicate the analysis adding the (non-equivalised) in-kind benefits to the equivalent income on individual basis.

2.4.1 Data limitations

One of the main problems with the data has to do with its harmonisation or, specifically, with how to treat the negative and null income values. The EUROSTAT recommendation for bottom coding is to set all negative values to zero and then bottom code at 15% of the median equivalised disposable income. However, for the income source decomposition it is necessary for each income component to add up exactly to the total disposable household income. This means that it necessary to bottom-code each single income component. However, because the proportions of negative and null incomes are very close to 0 in all countries, here all negative total disposable household incomes and their relative factor components will be set to zero. As for top-coding, here the incomes are trimmed at the top 0.5 percent.

Another additional caveat is the potential lack of perfect comparability in detailed income components across countries (Zardo Trinidade & Goedemé, 2020). Specifically, since 2014 countries started to report cash benefits disaggregated by eligibility (contributory vs non-contributory means and non-means tested). However, some misallocations may exist between the component and the target variable in the dataset due to the heterogeneity in the recording process across countries.

An important limitation about data and consequent estimates refers to the impossibility to take into account neither the financing side of public services nor the possible costs of access to such services that need to be deducted. In the same logic, these data do not permit to take to discount the private provisions of healthcare and education services. These limits may bias the estimates associated to the public services.

An additional aspect that should be consider refers to the differences in quality both within and between countries in the services provided were not considered. It should also be necessary to develop service efficiency indexes in relation to expenditures to weight the monetary value of the quality of the service, but unfortunately this is not feasible with the adopted data.

Lastly, some important (capital) income components like capital gains are not included in the income definition, resulting in an underestimation of income inequality.

2.5 Lerman and Yitzhaki Gini decomposition

Before introducing the decomposition technique, it is useful to illustrate the total income definitions that will be used in the Lerman and Yitzhaki approach. The following equations synthetise the total income definitions and the income components that will be used:

$$Y_1 = W + SE + K + PT + CT \qquad (1)$$

where is the total income, W are wages and employee incomes, SE are incomes from self-employment, K incomes from capital, PT are private transfers within and between households and CT are the cash-transfers from the state (allowances for unemployment, old-age, survivors, sickness, disability, education, family/child, housing and social exclusion). Subsequently to this first definition, I will add the monetary values of in-kind benefits (IK) i.e., healthcare, compulsory and tertiary education and social housing:

$$Y_2 = Y_1 + IK \qquad (2)$$

As mentioned in previous sections, *factor source decomposition* has been extensively discussed in Shorrocks (1982), and its extension to the Gini coefficient is seen in Lerman and Yitzhaki (1985). This is the Gini decomposition that is used here to identify the redistributive effect of each income component, including in-kind benefits.

Lerman and Yitzhaki (1985) demonstrate that the total income inequality measured by the Gini coefficient can be decomposed in the following way:

$$G = \sum_{k=1}^{K} S_k G_k R_k \qquad (3)$$

That is, the total Gini coefficient is equal to the sum of the product of three elements for each income component *k:*

1. S_k, which is the share of the income source *k* on the total income.
2. G_k, which is the inequality index for the specific k-th source of income, in this case, the Gini coefficient.
3. R_k, which is the (rank) correlation between the *k*-th income source and the total income. A positive (negative) value means that factor *k* is positively (negatively) correlated with the total income.

Therefore, if an income source is unequally distributed (high G_k) and negatively correlated ($R_k < 0$) with the total income, its increase might reduce income inequality. Conversely, if the *k*-th source is unequally distributed and also significantly and positively related with total income, then its increase might contribute positively to deepening income inequality.

The valuable aspect of the Lerman and Yitzhaki (1985) approach is that it makes it possible to estimate the effect on inequality caused by a marginal change in each income source.

For example, consider a proportional change in the *household* income source *k* equal to ε. The partial derivative of the Gini coefficient with respect to the proportional change (ε) is:

$$\frac{\partial G}{\partial \varepsilon} = S_k (G_k R_k - G) \qquad (4)$$

where G is the Gini coefficient before the marginal change in the *k*-th source.

Therefore, the percentage change in income inequality as a consequence of a 1 percentage point change in income source *k* is:

$$\frac{\partial G / \partial \varepsilon}{G} = \frac{S_k G_k R_k}{G} - S_k \qquad (5)$$

In other words, the Gini elasticity is equal to the relative contribution ($\frac{S_k G_k R_k}{G}$) to inequality of income source *k* minus the share of source *k* in the total income. It should be noticed that the sum of the elasticities across all sources *k* is zero: multiplying all *k* household income sources by ε leaves the total Gini coefficient unchanged. It follows that the elasticity of a given source k is interpreted ceteris paribus i.e., the percentage change in the Gini coefficient because of 1% increase in source k when all the other sources are constant. Furthermore, from equation 4 it emerges that the percentage change in the Gini coefficient will be negative if the share of the source k is larger than the relative contribution to income inequality. This means that if the source k has a relative high share but its relative contribution to the overall income inequality is low (because of low correlation with the total income, R_k, or because of low within inequality G_k), its marginal increase will reduce the overall Gini coefficient.

An additional property of the Lerman and Yitzhaki (1985) method is that the following relationship is true:

$$\Delta Gini = \sum_{k=1}^{K} \Delta(S_k G_k R_k) \qquad (6)$$

In words: the change in income inequality equals the sum of the changes in the contributions to income inequality of each single component k. The contribution can be further decomposed following Podder and Chatterjee (2002) who define the evolution of the Gini coefficient over time as the sum of the share effect and the concentration coefficient effect. The former represents the change in the Gini coefficient due to changes in the shares of the different sources of income (S_k); the latter is the change in the inequality over time because of changes in the concentration coefficient ($G_k R_k$). Jurkatis and Strehl (2014) propose a similar decomposition and argue that an increase in the concentration coefficient – due to higher rank correlation and/or higher inequality of income source k – always rises the Gini coefficient. Differently, an increase in the share of an income source k leads to higher income inequality only if this source k has a disequalizing effect (concentration coefficient lower than the overall Gini index)[7].

This property will be applied in order to assess the main determinants of inequality changes between 2008 and 2017. In practical terms, to ease the discrete computation, I will take the difference in the contribution ($S_k G_k R_k$) to income inequality for all the k

[7] In continuous time the following relation holds: $\dot{G} = \sum_k (R_k G_K - G)\dot{S}_k + \sum_k S_k (\dot{R}_k G_k + R_k \dot{G}_k)$ where $\dot{G}$, $\dot{S}$, $\dot{R}$ and $\dot{G}_k$ are the time-derivative of the overall Gini coefficient, shares, rank correlation and Gini coefficient of income source k, respectively.

components between 2008 and 2017 and observe to what extent each source contributes to the evolution of the Gini coefficient over the decade.

The choice of decomposition method seems to be somewhat arbitrary (as Caminada et al. 2017 claim). Here I present some theoretical justifications for my choice.

The *sequential accounting approach* computes the redistributive effect of each component step by step, while the *factor decomposition* is simultaneous. Therefore, in the former approach, the order of the income factors matters. For example, the unemployment benefit effect is computed by adding it to the market income or subtracting it from the gross income (Caminada et al., 2017 compute it in both ways and define the inequality contribution as the average of the two computations). This means that the choice of the factor source decomposition helps avoid the ordering issue.

The second – and perhaps most important – difference between the approaches relates to their "normative" foundations. As argued by Fuest et al. (2010), the very different results obtained by the sequential accounting approach and the factor source decomposition depend on the effects of an equally distributed lump sum. It reduces inequality in the sequential accounting approach, but not in the factor source decomposition. Indeed, Shorrocks (1982) imposed the normalisation assumption to find a standard decomposition technique for any inequality measure[8]. Recalling the main elements of the income source decomposition, an equally distributed lump sum will have a correlation with the total income distribution (G_k) equal to zero and therefore a null contribution to the inequality index.

Lastly, the factor source decomposition allows us to observe the elasticity of each income factor: it is possible to calculate the effects of a small percentage change in one specific income factor on the total Gini coefficient (holding the others constant). On one hand, the calculation of such elasticities allows us to overcome Shorrocks' (1982) failure to detect the inequality reduction as a consequence of a lump-sum transfer to all individuals in a population. On the other, elasticities are very relevant from a policy perspective; Paul (2004) argues that the change made to a given income source by a government

[8] To better understand the "normative" foundation differences, consider the following example. If we add a lump sum to all households' incomes, the sequential accounting system would detect a large overall inequality reduction, as expected. However, Shorrocks' decomposition fails to detect this reduction because of the normalisation assumption. This assumption states that adding a constant to all households has zero inequality contribution because it has zero correlation to the total disposable income distribution. It is also due to this violation of the uniform addition assumption (Morduch and Sicular, 2002) that the Lerman- Yitzhaki elasticities are more valuable regarding the relevance of income components.

intervention can occur only at the margins, and therefore the elasticities are the most relevant elements to observe.
Therefore, differently from Rani and Furrer (2016) and Fuest et al. (2010), I will focus primarily on estimating the elasticity of each income component.

2.6 In-kind monetary values

To add the in-kind benefits to the total disposable household income and estimate their elasticities, it is necessary to determine the monetary value of the different services under assessment.
As anticipated in section 2.2, one way to determine the value of each service is to estimate its production costs i.e., the public expenditure on the service. This is the main method adopted here. As for the imputation of monetary values to individuals/households, a mixed approach is used, imputing their actual use or the insurance value depending on the available information.

2.6.1 Healthcare

Starting with healthcare, I use OECD data on per-capita health expenditures to determine the monetary value of the service. However, not all individuals receive the same flat monetary amount for healthcare services, since this depends on the use they make of those services. For this reason, I apply a combination of the insurance-value approach and the actual-use imputation technique. Vaalavuo (2011) applies a similar approach and calculates age-specific health expenditures based on European Commission data. In her method, each age-group has its own specific per-capita expenditure reflecting their probability of accessing the service.
Following the same underlying logic, I use information on the "actual use" of health services to predict probabilities of access to healthcare. These probabilities are then used to weight the per-capita expenditures. As a result, all individuals sharing the same observable characteristics will have the same probability of access and, in turn, the same imputed monetary value for health services.
In practical terms, I start by defining a dummy measuring whether the individual accessed the health service during the year. Next, I use a logistic regression to estimate the probabilities of accessing the service, using age-groups, gender, education, employment

status and income-quintiles as independent variables. It should be noted that in this computational exercise, it is not possible to distinguish between public or private health services. The impossibility to consider the frequency/intensity of the participation and by which type of needs is an additional drawback of this approach. For example, a chronically ill person may require higher access and/or more expensive treatment compared to a person with the same observable characteristics (in terms of logistic regression covariates). However, in this approach these two individuals will have the same imputed monetary value without differences based on intensity/type of health assistance.

2.6.2 Education: pre-primary, compulsory and tertiary

For pre-primary education I adopt the actual-use approach. The EU-SILC microdata reports information on whether a child is using a pre-primary educational service and if so, for how many hours per week. Therefore, for each country, I first compute the average number of hours that each child uses the service. Next, I divide the total expenditure incurred by the state in pre-primary education per child receiving the service by the average number of hours of use, so as to obtain a per-hour cost. Finally, this per-hour cost is multiplied by the hours effectively used by each child within a household. The underlying assumption for this computational exercise is that the per-hour cost is the same across the whole of the single country under assessment.

Regarding compulsory education, i.e., primary and secondary education, the standard and easiest approach is to assume 100% attendance for those in the age bracket to attend compulsory school and impute the per-capita expenditure to each student. However, to have a more realistic estimation that adjusts for dropping out of school, I multiply the per-student expenditure by the official (net) enrolment rate obtained by the UNESCO statistics.[9] I do not impute any monetary value to those in the compulsory secondary education (over 16s) who report that they are not enrolled in any school programme and are working.

The imputation of the monetary value of tertiary education relies on the same technique used for primary and secondary education. However, to avoid biased estimates in the redistributive (or regressive) effect of higher education per household, I follow Vaalavuo (2011) and exclude households that consist of only university students. In fact, these

[9] http://data.uis.unesco.org/Index.aspx#

households are temporarily classified as “poor” households, made up of young people that live only with money their parents give them. Including these student households may distort the distribution estimate, especially if the household is really part of another one, as it may lead to an overestimation of the redistributive effect (or a less regressive one). Ideally, it would have been better to add the value of attending tertiary education to parents’ household income, but there is no information to link the two households.

In this case, the heterogeneity in the distributions of single-students households affects the cross-country comparison. However, such distortion is likely to be significant only for countries with the highest share of excluded single-students households. The Table A.2.1 in the Appendix reports the share of excluded households by country. The Nordic countries (Denmark, Finland, Sweden) and Netherlands are those with the highest share ranging from 30 to 50 percent (in line with Valaavuo, 2011). As a robustness, I will compare the elasticities of tertiary education with and without the exclusion of single-tertiary students households, expecting differences only in the cases of Denmark, Finland, Sweden and Netherlands.

2.6.3 Social housing

Since 2007, the EU-SILC data provides a variable (HY030) with the household’s imputed rental income for leased properties in each country. Theoretically, this monetary amount could be added (excluding interest on mortgages) to owners' household incomes as a return on investment. The per-household monetary value of these imputed rents can be added to the disposable income of households living in social housing as the value of the social service.

In the EU-SILC dataset it is possible to observe tenant status and to distinguish between owners, individuals who are renting on the private market (who do not receive any returns in terms of imputed rent) and individuals renting from the social market (i.e., at a reduced rent and/or for free). Since I am interested in the monetary value of social housing services, I only add the imputed rent to the disposable income of households renting outside the private market i.e., from public or non-profit institutions. However, I also run a robustness check imputing the rents to the owners to better proxy a full-income approach (Canberra, 2011).

The main problem with this approach is comparability across countries and the stability of the estimation. As Törmalehto and Sauli (2013) note, the EU-SILC data does not adopt a unique technique for imputing rents, but each country implements its own approach.

Some countries may adopt hedonic regressions with Heckman selection-bias correction, while others adopt a simple regression approach. Another problem is that countries differ in how they report the imputed rent, i.e. gross or net, without specifying which costs are deducted in the latter case.

In the EU-SILC user dataset, there are nine countries (AT, BE, ES, EL, FR, LU, PT, SE, IE) that have both gross and net imputed rents, while five countries (DK, FI, IT, NL, UK) only provide gross rents. One country – Germany – provides only net rents. Therefore, I use the gross imputed rent in order to maximise the number of available countries. As a consequence, Germany is excluded from the imputation. Denmark does not have sufficient information to identify households renting at a reduced price or rent-free, and hence, I also exclude it from the imputation. Finally, because the Netherlands has a very high share of negative imputed rents, it is also excluded from the imputation

2.7 Results

Before introducing the decomposition results and the respective income-elasticities, I briefly provide a general overview of the changes in inequality between 2008 and 2017, and of how much each country redistributes overall, by comparing the Gini coefficient on market income and the Gini index on disposable income.

As expected, countries belonging to the liberal and the Mediterranean welfare regimes are those with the highest level of the inequality, while countries in the social democratic regime have the lowest level of income inequality. In contrast, focusing on market income inequality, all coefficients fluctuate around 0.50. This means that the redistributive capacity of each country plays a sizeable role in determining the resulting heterogeneity in disposable income inequality. Specifically, the largest effect of State intervention is in Scandinavian countries, while the reverse is true for the liberal and Mediterranean countries. Countries in the central European contributory regime are in the middle.

Comparing 2008 with 2017, inequality has increased in most countries. The exceptions are Portugal, UK, Germany, France, Belgium, and Finland. Denmark and Sweden, particularly, have experienced the highest increase in inequality in disposable incomes, which are now at comparable levels to those of some continental countries (Belgium and the Netherlands).

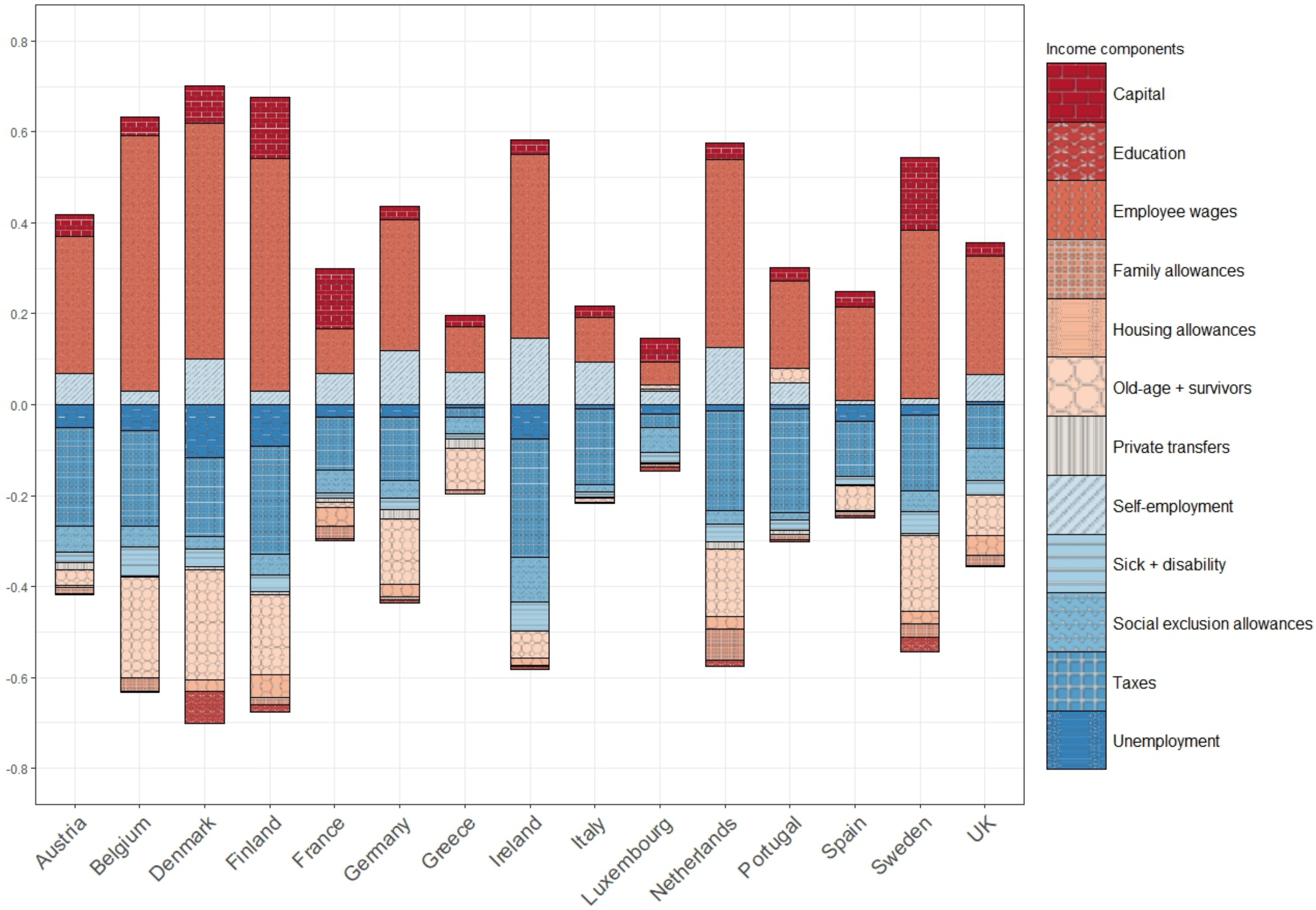
Furthermore, I also quickly report the main decomposition results at a more aggregate level (see Fig A2 in the Appendix). As I will better explained in the following sections, employee wage is the most disequalizing source across all countries, while taxes have a sizable equalizing effect. As expected, cash-transfers significantly reduce income inequality, with pensions playing the main role in this equalizing power in most countries. Indeed, excluding pensions, in-kind benefits have an equalizing effect that is comparable to cash-transfers, if not stronger as the Mediterranean countries. This distinction between cash-transfers and pensions is detrimental as pensions can be viewed as deferred market income i.e., horizontal redistribution over life cycle or as a state-transfer aimed to reduce inter-individuals' inequality (vertical redistribution). Therefore, an aggregate measure for cash-transfers may only capture the cross-country differences in the retirement schemes rather than a pure vertical redistribution through cash-transfers.

2.7.1 Income-source elasticities on the original income components

To obtain an idea of the distributional effects of each income component, in this section I firstly present the detailed decomposition results – specifically the income-source elasticities – for the last available year (2017), and then present the dynamic changes over time. It should be reminded that the absence of some important capital income components concentrated at the top of the income distribution, e.g., capital gains, is likely to underestimate the total income inequality and, in turn, the estimated elasticities (e.g., Advani and Summers, 2020).

Figure 2.2 reports the estimated income-component elasticities.

Figure 2.2: Income-component elasticity



Source: author's own calculation using EU-SILC data.

Notes: the results ought to be interpreted as follows. For a 1% increase in a given income component k, the Gini coefficient will be increased (or decreased) by the % reported in the graph. Elasticities add up to 0, meaning that if all components simultaneously change by 1%, the effect on the Gini coefficient will be 0.

As expected, the highest elasticities are observed for wages. The Gini coefficient increases by a range of 0.1 to 0.57 percent as a consequence of a 1% increase in the wage component (ceteris paribus). The highest percentage increase in the Gini coefficient is observed in the Scandinavian countries. This is explained by the fact that although they have a comparably unequal distribution of wages with respect to the other countries, the Scandinavian ones have a stronger positive correlation of wages with the total income distribution.

Conversely, the Scandinavian countries also have the highest equality-enhancing effect exerted by taxes: for a 1% increase in taxes, the average reduction in the Gini coefficient in Sweden, Finland and Denmark is about 0.20%. This is explained by the highest share of taxes (S_k) and the strongest negative correlation (R_k) with total income, compared to other countries.

However, taxes have an equalising effect in all countries: this ranges from 0.09% in the Gini reduction in the UK to 0.24% in Finland.

Among the social transfers, the most interesting component is the old-age and survivors' benefits. This has an equalising effect, with a negative elasticity in almost all countries. However, studies by Rani and Furrer (2016) and by Fuest et al. (2010) report that its relative contribution to inequality (i.e., $\frac{S_k G_k R_k}{G}$) is positive in most countries. What is causing these apparently contradictory results?

Recalling the definition of elasticity as $\frac{S_k G_k R_k}{G} - S_k$, once the share of component k is subtracted, it is possible to obtain a negative elasticity from a previous positive relative contribution.

For example, take the case of Germany. Computing the relative contribution of the old-age transfer turns out to be positive, which means that it positively contributes to inequality; however, for a 1% increase in this cash transfer, Germany's Gini coefficient drops by about 0.15%. This is because the old-age transfer has a moderate share in the total income (see Table A.2.3 in the Appendix), and in subtracting it from the positive relative contribution, the elasticity ends up being significantly negative.

All other social transfers have an inequality reduction effect which is more in line with the *sequential accounting approach* (although with a lower magnitude compared to the effect of taxes), with stronger effects observed in the Scandinavian countries.

2.7.2 Effects of In-kind benefits

In this section, I present the elasticities of in-kind benefits i.e., the effects on the Gini coefficient of a marginal increase of 1% in each service.

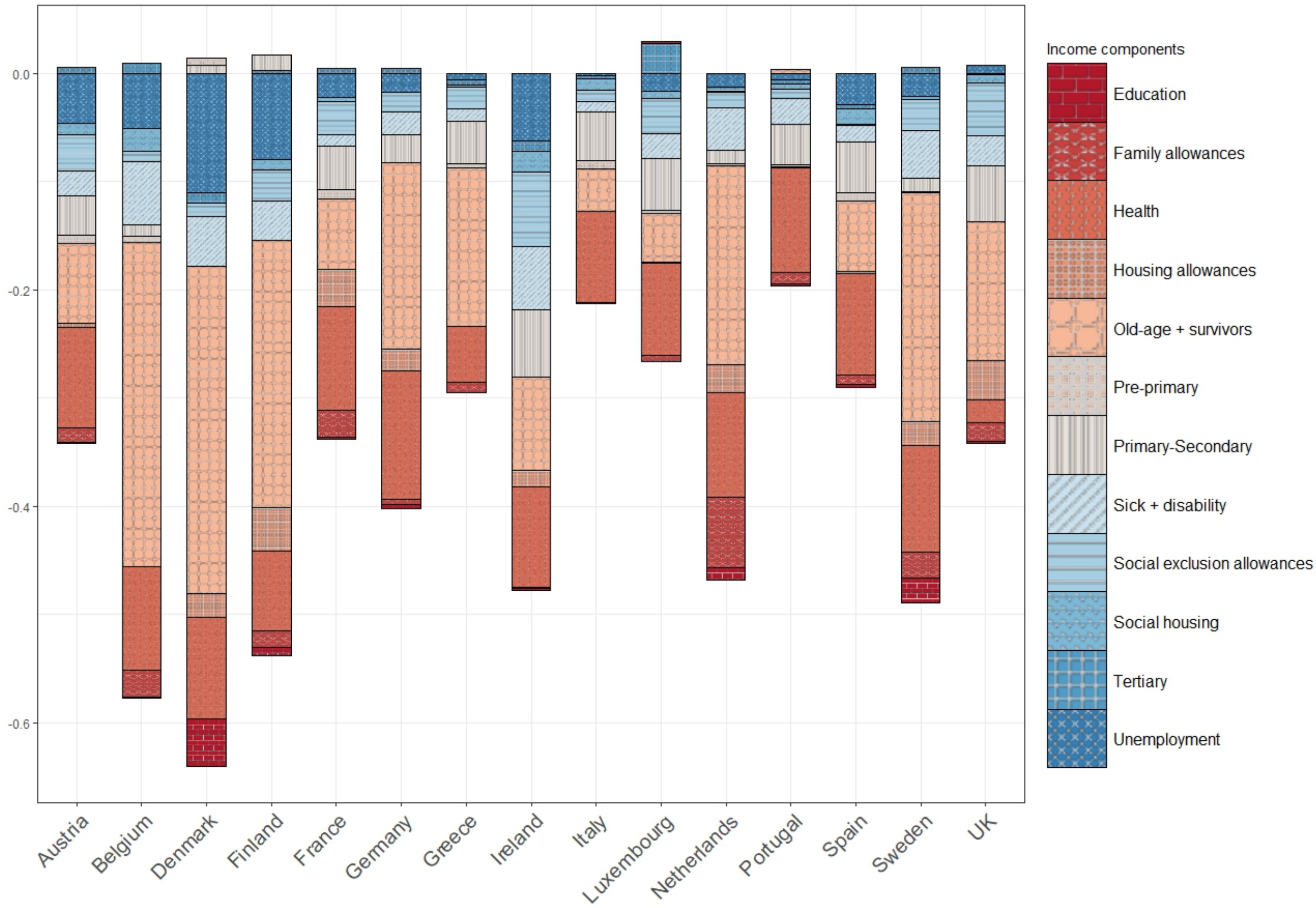
The expectation is that as the share of the population that has access to the in-kind service grows, the equalising effect of its monetary value will also increase. Indeed, the percentage difference in the average total disposable household income with and without in-kind benefits is largest in the first quintile.

However, there may be some services, specifically tertiary education, that have a regressive effect on inequality. The impact of educational transfers on inequality is likely to be regressive: if the offspring of the wealthier classes are more likely to attend the university than the offspring of the working class, then the monetary value of this service would mostly benefit the rich, worsening overall inequality. In other words, the rich would be the ones benefitting the most from this in-kind service. This effect can be magnified if the single-tertiary students' who are currently classified as 'poor households' are mostly linked to richest original households. The robustness test for the tertiary education reveals that the elasticities are almost identical with and without excluding the single-tertiary students' households for almost all countries but Denmark, Finland, Sweden and Netherlands. As expected, excluding the single-students household in these countries imply a less equalizing/stronger disequalizing effect of tertiary education (see Table A.2.2 in the Appendix).

Figure 2.3 reports the elasticities for both cash transfers and in-kind benefits.

Figure 2.3: Elasticities of in-kind benefits and cash transfers

Source: author's own calculation using EU-SILC data.



Note: The results are for 2017, but similar results were obtained for 2008.

Excluding old-age cash transfers, healthcare and primary-secondary in-kind benefits have the strongest inequality reduction effect in most countries. This is particularly true for the Mediterranean countries, where the in-kind services perform systematically better than cash transfers in reducing inequality. Indeed, these are the countries where the percentage change in average incomes, with and without monetary values for health services, displays the highest change in the bottom quintiles.

Specifically, for a 1% increase in the monetary healthcare component, the Gini coefficient declines by between 0.02 and 0.11%, while the primary and secondary monetary transfers account for a variation in the Gini coefficient of between +0.01% and -0.06%.

Regarding the effect of compulsory primary and secondary education, in all countries except Denmark and Finland, it is redistributive. The null impact of compulsory education on reducing inequality in these countries is due to the highest positive correlation between education benefits and total income distributions; this offset all the equalising effects that might have been expected, compared to all other countries. This may suggest that in countries with a more compressed income distribution, in-kind benefits have a lower equalising effect. Indeed, compared to all other countries, Denmark and Finland display the lowest percentage change in the average income at the lowest quintile when adding the monetary values of primary and secondary education. This result seems to be coherent with the low elasticity of inequality to the benefits obtained from compulsory education.

In all countries, pre-primary education, tertiary education and social housing have a negligible share of total disposable household income – not exceeding 1% in any country – and therefore a minor effect on the Gini coefficient. However, this is not sufficient to argue that these services are not valuable in terms of policy strategies, as the redistributive effects of in-kind benefits strongly depend on the share of spending i.e., on the program/service extension. For example, investing in pre-primary education more than for other large programs like healthcare, may be beneficial for inequality reduction.[10]

Lastly, when adding the imputed rents to the owners as robustness check, the redistributive effects of social housing do not change, and the imputed rents as a return to

[10] The current method is not suitable for evaluating the redistributive effects of changes in euro terms in one program compared to the same euro change in another program. For this purpose, a more detailed micro-simulation (e.g., EUROMOD) is recommended. However, as a raw exercise, I estimate the elasticities adding 100 euros firstly to healthcare transfers (all other elements at their original values) and subsequently the same 100 euros to the pre-primary service (all other elements at their original values). Comparing these scenarios to the baseline model, the augmented pre-primary service displays a stronger increase in its equalizing power compared to the augmented healthcare values. Tables and results available upon request.

investment marginally reduce income inequality in line with Törmalehto and Sauli (2013).

All in all, these results confirm the equalising effects of in-kind benefits, and are coherent with the expectation that lower amounts distributed to a small share of households do not significantly affect the inequality measure. Results hold when in-kind benefits are added to the individuals in non-equivalised form. [11]

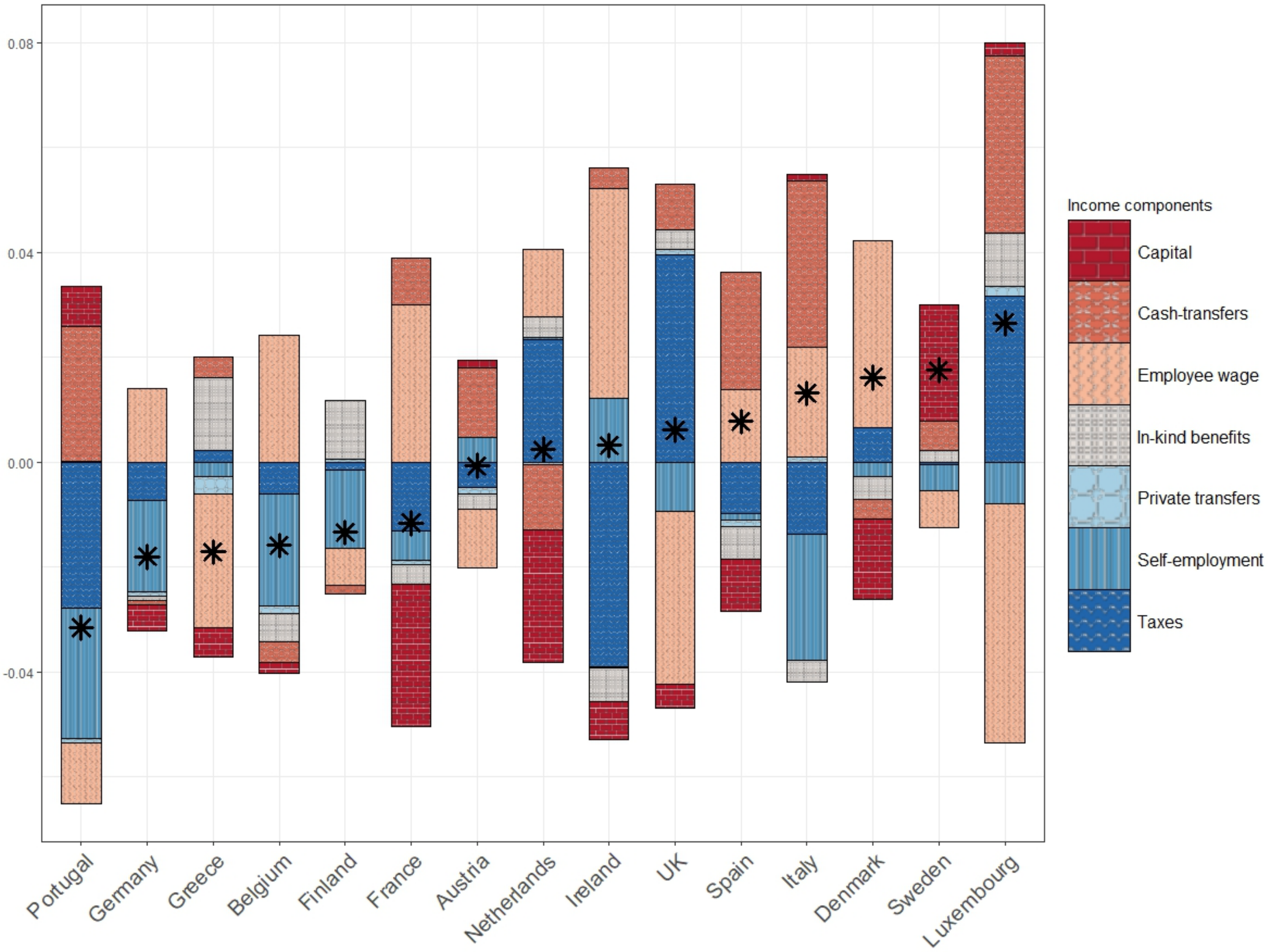
2.7.3 Decomposing the Gini coefficient changes between 2008 and 2017

Finally, I present the main determinants behind the changes in the Gini coefficient between 2008 and 2017 across countries, using all income components, i.e., including in-kind benefits.[12]

Figure 2.4 displays the absolute differences between 2008 and 2017 in each component's contributions ($S_k G_k R_k$) to the change in the Gini coefficient over time, while Table A.2.5 in Appendix shows the same information in table format. In other words, this figure helps to understand how much of the evolution of the income inequality is explained by the changes in the contributions of the different income sources.

[11] Tables are available upon request.
[12] The inclusion of in-kind benefits lowers income inequality compared to the measure based on disposable income.

Figure 2.4: Determinants of changes in the Gini coefficient over time



Source: author's own calculation, based on EU-SILC data

Note: countries are ordered according to the absolute change in the Gini coefficient (star-pointer). Positive values mean that the change is towards an increase in inequality; negative, that the change is towards a decrease in inequality.

Independently of whether inequality increased or decreased over time, changes in the contribution of employee wages, taxes and cash transfers are the most important elements in determining the evolution of income inequality between 2008 and 2017. Given the years of financial crisis, it seems reasonable that the most important determinants of changes in inequality are those stemming from the labour market – labour income – and fiscal policies (taxes and cash transfers).

To go into more detail, when the source of the increased inequality was a change in taxes, as in the case of the UK (or Luxembourg), the negative contribution of taxes to inequality in 2017 was lower than in 2008 i.e., it became less equalising. Conversely, in Portugal the equalising effects of taxes increased over time.

When it came from wages, the inequality stemming from the labour market gained even more importance. This was the case in Spain, Italy, and Denmark.

Cash transfers positively contributed to the rise of inequality in all countries, meaning that their equalising power decreased over time. This is probably due to the policies of shrinking public budgets and spending cuts implemented to tackle the crisis. Specifically, old-age benefits were hit the most: in Spain and Italy their negative elasticities between 2008 and 2017 dropped almost by half, making them far less equalising (compare the elasticities in Table A.2.3 and A.2.4 in the Appendix).

As for in-kind benefits, their equalising contribution to the Gini change tend to be relatively small, due to the minor changes in the share of in-kind benefits over GDP. The most relevant exception is Greece, where in-kind benefits contribute positively to the Gini change i.e., they are far less equalising in 2017 compared to in 2008. This is reasonable since Greece experienced the harshest austerity measures with severe cuts to the balance and to services. As observable in Figure 1, it is the only country with a lower share of both cash and in-kind expenditures over GDP in 2017 compared to 1995.

The equalising effects of in-kind benefits decreased over time – therefore pointing towards higher income inequality – in Luxembourg, Finland, Netherlands, and the UK. In Luxembourg this is explained by the contraction in per-capita health expenditure, which passed from 4,700 euros in 2008 to 4,271 in 2017, and by the regressive effect played by tertiary education. Similarly, in Netherlands and the UK, the share (S_k) of health expenditures decreased over time, contributing to decreased equalising power (*share-effect*). In Finland, the main source of these lower effects on equality is due to primary and secondary education. As mentioned in the previous section, Finland has a neutral/null effect due to the highest rank correlation with total income distribution (R_k), which increased during the decade. This implies that the effect of primary and secondary education limits the reduction in the Gini coefficient (*concentration coefficient effect*).

Therefore, it can be concluded that where per-capita monetary values of in-kind benefits increased over time and their contributions to the change in the Gini coefficient are fairly constant, the hypothesis that in-kind benefits contribute to the decreasing income inequality trend is verified.

2.7.4 Contributory vs non-contributory cash transfers

Based on the results in the previous section, it is possible to conclude that cash transfers still outperform in-kind benefits in determining (dis)equalising effects. In this section, I further disentangle what type of cash transfers have the strongest equalising power.

For this purpose, I compare the effects of contributory means-tested, contributory non-means-tested, non-contributory means tested and non-contributory non-means-tested factors on income inequality. I do not divide the cash transfers by functions, but rather aggregate them by entitlement criteria, exploiting the additional information included in the EU-SILC data starting from the year 2014. I start by distinguishing each social transfer by function (unemployment, old-age, survivors, sickness, disability, education, family, social exclusion and housing); next, I divide the total amount of the transfer for each function by entitlement criteria; finally, I add these amounts across functions. For example, the total of the contributory means-tested transfers equals the sum of the monetary amounts of all functions registered as being contributory and means-tested. Note that in some countries (Greece, Finland, France, Luxembourg, Netherlands, Sweden and the UK), the contributory means-tested amounts are not reported, because this type of scheme is not available at the national level.[13] Table 2.1 shows the elasticities for each country and entitlement criteria of the benefits.

[13] EU-SILC data flags all contributory means-tested entitlement criteria that do not exist at the national level.

Table 2.1: Differences in entitlement criteria elasticities by country

Country	Contributory mt	Contributory non-mt	Non-contributory mt	Non-contributory non-mt
Austria	0,002	-0,093	-0,043	-0,062
Belgium	0,000	-0,425	-0,034	0,014
Germany	-0,037	-0,189	-0,049	0,008
Denmark	-0,045	-0,075	-0,374	-0,044
Greece		-0,155		0,000
Spain	-0,019	-0,051	-0,053	0,000
Finland		-0,274	-0,155	-0,025
France		-0,083	-0,091	-0,015
Ireland	-0,009	-0,070	-0,181	-0,035
Italy	-0,008	-0,027	-0,013	-0,013
Luxembourg		-0,063	-0,006	-0,052
Netherlands		-0,068	-0,108	-0,177
Portugal	-0,004	-0,015	-0,024	-0,004
Sweden		-0,253	-0,038	-0,083
UK		-0,119	-0,100	-0,034

Source: author's calculation based on EU-SILC data.

Note: we report results for 2017, but the same holds for 2008; "mt" stands for means-tested.

As can be seen, contributory non-means-tested and non-contributory means-tested cash transfers are the most effective in reducing inequality. I also observe significant heterogeneity across countries, mostly depending on the share of each component compared to the total income. The interaction between the non-means tested and contributory nature of a transfer has an especially important equalising effect in Belgium, Sweden and Finland, followed by Austria, Germany and France, i.e., in the continental regimes. On average, in these countries, a 1% increase in all contributory non-means tested transfers reduces the Gini coefficient by 0.192 per cent.

The Scandinavian countries are where cash transfers have the strongest equalising effects – consistently with the results of previous sections – but while in Finland and Sweden the largest part of the equalising effect comes from contributory non-means-tested transfers, in Denmark it is the opposite. In fact, in Denmark a marginal increase in non-contributory means-tested transfers makes the Gini coefficient decrease by 0.37% (all else being equal).

These differences observed between contributory and non-contributory transfers are due to elements of source decomposition (see Table A.2.6 in the Appendix). The correlation (R_k) between non-contributory means-tested transfers and total income is highly negative, i.e., favouring the poorest, but the shares of these transfers on this total income are much lower than the contributory non-means tested transfers in all countries. The only exception is Denmark, where the share of contributory non-means-tested transfers represents 9% of total income while that of non-contributory means-tested transfers represents 13%. Given the strong negative correlation between the latter component and income, the resulting elasticities for Denmark are reasonable.

In sum, on the one hand, the low share of the non-contributory cash transfers, a typical consequence of their means-tested nature, prevents them from having a much larger equalising impact, one expected from their strong negative correlation with total income distribution. On the other hand, the equalising impact that contributory transfers could exert because of their higher share only materialises in countries where these transfers have a strong negative correlation with total income, which explains the apparent contrasting results between relative contribution and elasticities presented in the previous sections.

2.8 Conclusions and Discussion

This paper aims at enriching the existing literature providing new evidence about the redistributive impact of in-kind benefits compared to the cash-transfer structure (by function and entitlement criteria), and – more importantly – their contribution to the evolution of income inequality over time.

If efficiency and optimization concepts constantly guide governments and policymakers' actions, this paper tries to provide additional guidelines in terms of how shaping fiscal policy interventions aimed at reducing income inequality. This is very relevant in a context of rapidly evolving welfare systems and high budgetary pressures. Indeed, from a policy perspective it would be useful to know which social benefits – both in terms of functions and entitlements – favour a more equal income distribution so to adjust resources from an unequal to a more equal welfare program. Furthermore, to explore whether the increase in in-kind service expenditures over GDP is a valuable strategy in terms of income inequality, the analysis included the per-capita monetary values of healthcare, pre-primary, compulsory and tertiary education, as well as social housing services.

For this purpose, I have adopted the Lerman and Yitzhaki (1985) Gini decomposition approach focusing on the EU15 countries. More specifically, this method permits to identify the factors that most contribute to increase and decrease in income inequality estimating the direct effects of a marginal change in specific income components on the inequality index. Analysing the elasticities is more relevant from a policy perspective and has an immediate interpretation. In the same metric, the elasticities display the contribution of the various income-components to the reduction or increase in inequalities, and hence facilitate governments' decisions in favouring one policy or another from an equality perspective.

The results showed – in line with past research and economic theory – that wages are the most relevant component in shaping overall income inequality. Indeed, wages have the highest disequalising elasticities, ranging from a 0.1 to a 0.57 percent increase in inequality for a 1% increase in the wage component (ceteris paribus). Conversely, taxes play the most equalising effect, with stronger results in the Scandinavian countries where, for a marginal increase in taxes, the average reduction in the Gini coefficient is of about 0.20%. Cash transfers also have equalising effects in almost all countries, with once again stronger effects in the Scandinavian ones. Among these cash transfers, the old-age and survivors benefits contribute the most to reducing inequalities. This was to be expected, as these benefits represent, on average, 18% of the total income in the EU15, while all other benefits do not exceed 1.4%. In other words, the reason for the high equalising effect of old-age and survivors transfers is that they make up a relatively high share of total income.

In-kind benefits, particularly universal services such as healthcare and compulsory education, further contribute to a reduction in inequality, especially in countries with high levels of inequality. The strongest equalising effects of healthcare and compulsory education are observed in the Mediterranean countries, characterised by high Gini indexes and low shares of in-kind benefits over GDP. In general, these services outperform all other cash transfers in terms of marginal contributions, while pre-primary and tertiary education and social housing do not display such relevant effects, probably due to their lower numbers and/or low share of beneficiaries relative to the whole income distribution.

To understand what the contribution of in-kind benefits is to the evolution of the Gini coefficient between 2008 and 2017, I decomposed the change in the Gini coefficient. This exercise reveals that changes in employee wages, taxes and cash transfers are the most important elements in determining the evolution of income inequality. Indeed, countries with increasing income inequality are characterised by higher contributions made by labour income and lower relevance of taxes and cash transfers.

In-kind benefits play a minor role in explaining the changes that took place in the decade under assessment, but evidence from almost all countries shows that they contribute to reducing the Gini coefficients, confirming the hypothesis that expansionary in-kind benefits are beneficial for reducing inequalities over time. The most relevant exception is Greece, whose severe cuts in benefits contributed to the disequalising effects of in-kind services.

Finally, I widen the comparison to consider the social transfer entitlement criteria. Results show that contributory and non-contributory means-tested transfers are the most effective schemes for reducing inequalities. Continental countries – Austria, Belgium, Germany and France – and Finland and Sweden appear to rely more on contributory non-means-tested schemes. The effects of these schemes are stronger in Scandinavian countries, with Denmark being the only country with a strong Gini reduction due to a non-contributory means-tested scheme (0.37% for a 1% increase in these transfers).

The main reason why contributory non-means tested transfers are more relevant than non-contributory ones is that they occupy a larger share of total income. If non-contributory means-tested schemes had the same share as contributory ones – as in case of Denmark – they would have a stronger redistributive impact, since they are strongly and negatively correlated with the total income distribution, thus favouring the most economically disadvantaged.

All in all, it has been observed that the primary source of inequality lies in the labour market – and that policy interventions should be directed in that direction – but differently from the existing literature, it is also observed that a more balanced combination of cash benefits and in-kind transfers, together with an increasing share of non-contributory means-tested transfers can improve equality outcomes. Furthermore, the analysis on the main determinants of income inequality dynamics confirms the necessity for governments to adopt a *coordinated view* of taxes, cash-benefits – both in terms of functions and entitlements – and in-kind benefits when shaping their fiscal actions (Lustig, 2018).

There are some important limitations to the present work that could be addressed in future research. In particular, the analysis of in-kind benefits does not take into account the costs of accessing the services, which should be discounted. Moreover, differences in quality both within and between countries in the services provided were not considered. It is also necessary to develop service efficiency indexes in relation to expenditures to weight the monetary value of the quality of the service. More importantly, it may be necessary to discount the part of the services provided by the private sector, both in healthcare and in education.

Finally, some important (capital) income components like capital gains are not included in the income definition, resulting in an underestimation of income inequality. These (important) technical aspects should be the subject of future research.

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2. Appendix

Cluster analysis

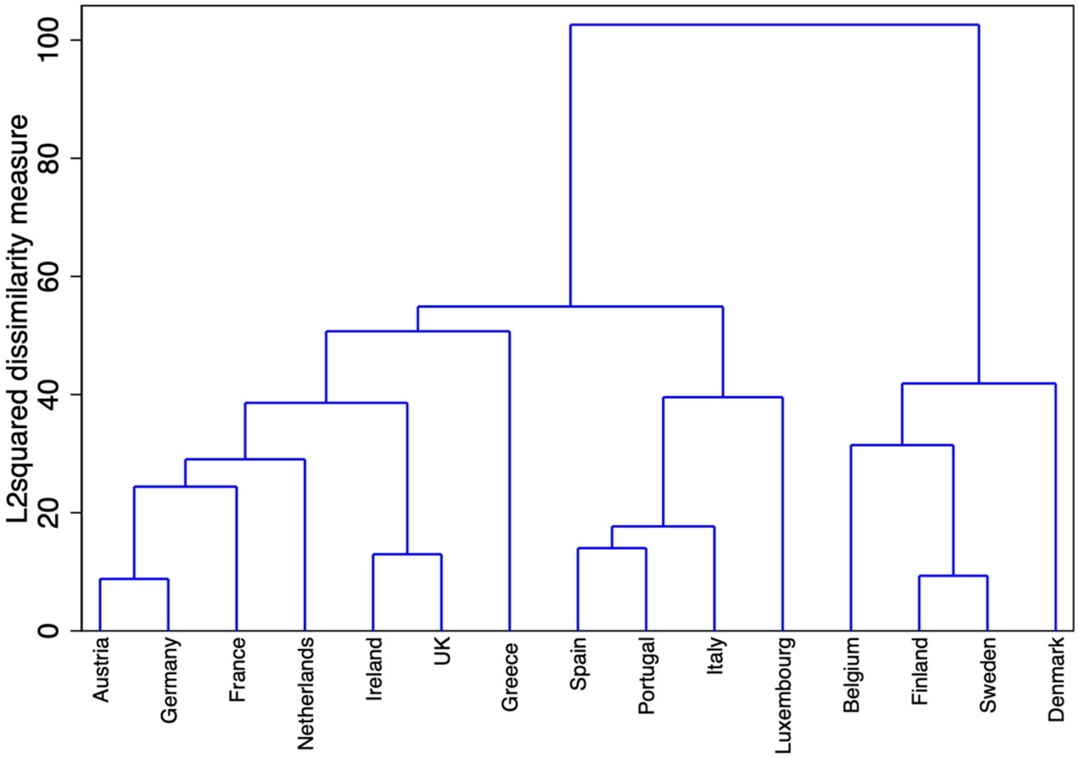
Within the paper I have taken as exogenous the welfare-regime definitions following the Esping-Andersen's (1990) contributions. Although results seem to suggest that this classification is fairly appropriate, I perform a hierarchical cluster analysis to check whether countries fit this external definition, based on the elasticities of the income components and on the level of income inequality.

In the hierarchical cluster the default distance of measure is the Euclidean distance, however there are different ways to clustering the units of analysis. In this case, I use the most common criteria: the Ward's approach. It minimizes the within-cluster variance and therefore defines the groups of clusters leading to the minimum increase in the total within-cluster variance once merging observations.

The result is a dendogram, which continues to link countries until all are grouped together. This means that the closest countries are linked firstly and more distant lastly – the height of the link determines the distance between countries.

I report here the resulting cluster analysis based on the elasticities and income inequality. All measures have been standardized.

Figure A.2.1: Hirerarchical cluster resulting dendogram



Source: Own elaboration on EU-SILC data

As plotted, the social-democratic countries are the most distant ones, linked as last ones to the other groups of countries. The first linking are the continental countries on the left-corner, although Greece seems to be closest to the continental group, while Spain, Italy and Portugal cluster all together as the Mediterranean regime.

Belgium and Netherlands are the strongest exception of the traditional welfare regime definition: they are theoretically closer to the continental one, but here they are clustered with the social-democratic countries. Indeed, over-time the level of inequality of Belgium and Netherlands behaves more similarly to the Nordic countries. However, it is more likely that it is the increasing level of inequality in the Scandinavian countries that closes the distance with Belgium and Netherlands, rather than the other way round.

Table A.2.1: Share of excluded single-student households attending tertiary education

Country	2008	2017
Austria	0,121	0,150
Belgium	0,043	0,017
Germany	0,232	0,187
Denmark	0,568	0,389
Greece	0,231	0,149
Spain	0,012	0,011
Finland	0,348	0,344
France	0,145	0,112
Ireland	0,021	0,012
Italy	0,032	0,023
Luxembourg	0,006	0,026
Netherlands	0,319	0,341
Portugal	0,004	0,020
Sweden	0,466	0,464
UK	0,067	0,030

Source: Own computation on EU-SILC data.

Figure A.2.2: aggregate decomposition analysis – 2017 only

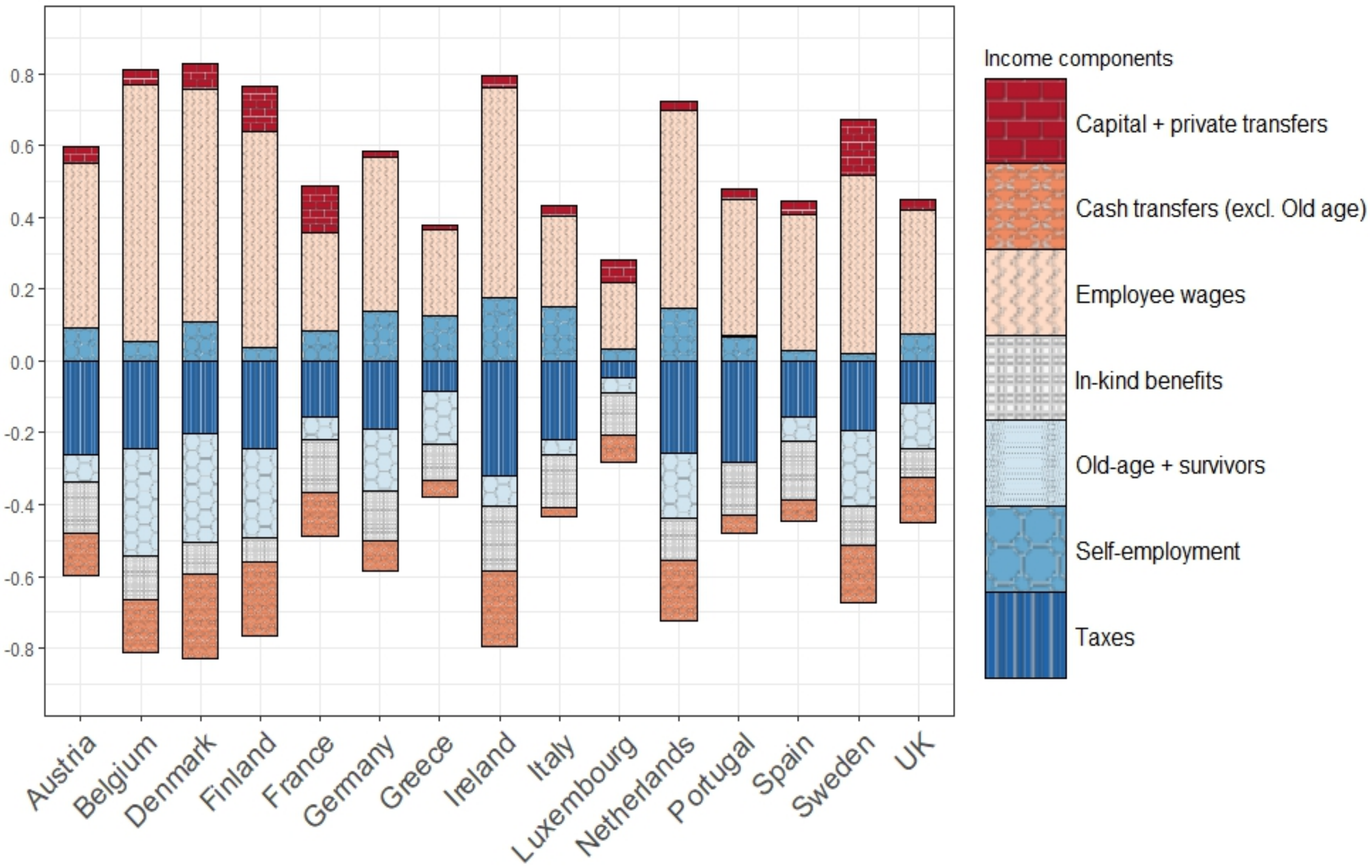


Table A.2.2: Elasticities of tertiary education with and without excluding single-student households

	2008		2017	
	Without exclusion	With exclusion	Without exclusion	With exclusion
Austria	0,013	0,015	0,002	0,006
Belgium	0,013	0,014	0,008	0,009
Germany	0,005	0,008	0,001	0,005
Denmark	-0,012	0,002	-0,029	-0,010
Greece			-0,006	-0,005
Spain	0,002	0,002	-0,004	-0,003
Finland	0,004	0,010	-0,007	0,003
France	0,006	0,008	0,002	0,005
Ireland	0,015	0,015	-0,010	-0,009
Italy	-0,004	-0,004	-0,003	-0,003
Luxembourg			0,028	0,028
Netherlands	0,001	0,006	-0,018	-0,004
Portugal	0,001	0,001	-0,004	-0,003
Sweden	-0,003	0,005	0,000	0,006
UK	-0,004	-0,003	-0,001	-0,001

Source: Own computation on EU-SILC data.

Income-source decomposition tables

Table A.2.3: Income-source elasticities in 2008

	Austria	Belgium	Germany	Denmark	Greece	Spain	Finland	France	Ireland	Italy	Luxembourg	Netherlands	Portugal	Sweden	UK
Income source															
Employee wages	0,486	0,511	0,343	0,556	0,223	0,316	0,505	0,138	0,509	0,221	0,406	0,431	0,304	0,594	0,431
Self-employment	0,068	0,116	0,166	0,126	0,085	0,027	0,073	0,102	0,127	0,238	0,071	0,164	0,087	0,033	0,117
Capital	0,048	0,036	0,034	0,142	0,038	0,064	0,121	0,201	0,050	0,031	0,052	0,116	0,014	0,095	0,037
Private transfers	-0,004	0,009	-0,010	-0,002	0,001	0,005	-0,006	-0,002	0,001	-0,004	-0,003	-0,011	0,000	-0,002	-0,002
Cash-transfers:															
Unemployment b.	-0,034	-0,083	-0,041	-0,098	-0,008	-0,013	-0,063	-0,018	-0,050	0,008	-0,004	-0,012	-0,012	-0,028	-0,006
Old-age + survivors b.	-0,122	-0,243	-0,165	-0,271	-0,057	-0,113	-0,198	-0,107	-0,084	-0,127	-0,129	-0,117	-0,056	-0,261	-0,135
Sick + disability b.	-0,025	-0,041	-0,016	-0,084	-0,014	-0,013	-0,045	-0,005	-0,063	-0,011	-0,026	-0,040	-0,017	-0,063	-0,023
Education.	-0,001	0,000	-0,004	-0,031	0,001	0,000	-0,006	-0,002	0,000	0,001	-0,002	-0,012	0,002	-0,024	-0,002
Social exclusion b.	-0,044	-0,008	-0,026	-0,009	-0,006	-0,002	-0,042	-0,030	-0,086	-0,009	-0,033	-0,016	-0,009	-0,025	-0,033
Family allowances	-0,004	-0,010	-0,017		-0,007	-0,001	-0,016	-0,010	-0,002	0,000	-0,017	-0,059	-0,008	-0,019	-0,023
Housing b.	-0,006	0,000	-0,002	-0,031	-0,001	0,000	-0,029	-0,032	-0,021	0,000	-0,005	-0,021	0,000	-0,027	-0,031
Taxes	-0,233	-0,183	-0,153	-0,242	-0,177	-0,132	-0,207	-0,110	-0,220	-0,204	-0,164	-0,297	-0,174	-0,194	-0,194
In-kind transfers:															
Health	-0,096	-0,086	-0,086	-0,085	-0,078	-0,071	-0,080	-0,085	-0,085	-0,083	-0,103	-0,106	-0,070	-0,073	-0,072
Pre-primary	-0,008	-0,006	0,000	-0,001		-0,010	-0,001	-0,011		-0,006	-0,007	-0,005	-0,002	-0,003	-0,004
Primary-Secondary	-0,031	-0,006	-0,030	0,027		-0,048	-0,009	-0,032	-0,070	-0,038	-0,032	-0,019	-0,055	-0,006	-0,050
Tertiary	0,015	0,014	0,008	0,002		0,002	0,010	0,008	0,015	-0,004		0,006	0,001	0,005	-0,003
Social housing	-0,010	-0,019			-0,001	-0,011	-0,006	-0,005	-0,023	-0,011	-0,004		-0,004	-0,002	-0,008

Table A.2.4: Income-source elasticities in 2017

	Austria	Belgium	Germany	Denmark	Greece	Spain	Finland	France	Ireland	Italy	Luxembourg	Netherlands	Portugal	Sweden	UK
Income source															
Employee wages	0,458	0,715	0,429	0,648	0,239	0,376	0,601	0,272	0,587	0,250	0,187	0,550	0,376	0,498	0,347
Self-employment	0,093	0,054	0,138	0,109	0,127	0,031	0,039	0,085	0,175	0,152	0,034	0,149	0,069	0,019	0,076
Capital	0,054	0,042	0,032	0,074	0,029	0,041	0,131	0,138	0,034	0,031	0,056	0,038	0,033	0,160	0,028
Private transfers	-0,007	0,000	-0,014	-0,003	-0,017	-0,001	-0,004	-0,007	0,000	0,000	0,005	-0,012	-0,003	-0,002	0,000
Cash-transfers:															
Unemployment	-0,046	-0,051	-0,018	-0,110	-0,006	-0,029	-0,079	-0,022	-0,063	-0,002	-0,016	-0,012	-0,006	-0,021	0,007
Old-age + survivors	-0,074	-0,299	-0,172	-0,302	-0,146	-0,064	-0,247	-0,065	-0,086	-0,039	-0,045	-0,183	0,004	-0,211	-0,128
Sick + disability	-0,023	-0,058	-0,021	-0,046	-0,012	-0,015	-0,036	-0,010	-0,058	-0,010	-0,023	-0,040	-0,024	-0,044	-0,028
Education.	-0,001	-0,001	-0,004	-0,044	0,000	-0,003	-0,008	-0,001	-0,002	0,000	0,002	-0,012	-0,002	-0,023	-0,002
Social exclusion	-0,033	-0,009	-0,018	-0,012	-0,020	-0,001	-0,028	-0,031	-0,069	-0,010	-0,033	-0,014	-0,009	-0,029	-0,048
Family allowances	-0,013	-0,024	-0,005		-0,010	-0,009	-0,015	-0,025	-0,001	-0,001	-0,005	-0,065	-0,010	-0,024	-0,017
Housing allowances	-0,004	0,000	-0,020	-0,022	0,000	-0,003	-0,040	-0,034	-0,016	0,000	-0,001	-0,026	0,000	-0,022	-0,036
Taxes	-0,263	-0,243	-0,188	-0,202	-0,084	-0,157	-0,246	-0,156	-0,318	-0,221	-0,045	-0,257	-0,283	-0,193	-0,116
In-kind transfers:															
Health	-0,092	-0,096	-0,119	-0,093	-0,052	-0,094	-0,074	-0,095	-0,092	-0,084	-0,085	-0,097	-0,097	-0,098	-0,021
Pre-primary	-0,008	-0,006	0,000	0,007	-0,004	-0,008	0,000	-0,008	0,000	-0,007	-0,003	-0,002	-0,002	-0,001	0,000
Primary-Secondary	-0,037	-0,010	-0,026	0,008	-0,039	-0,047	0,014	-0,040	-0,062	-0,045	-0,049	-0,012	-0,038	-0,013	-0,051
Tertiary	0,006	0,009	0,005	-0,010	-0,005	-0,003	0,003	0,005	-0,009	-0,003	0,028	-0,004	-0,003	0,006	-0,001
Social housing	-0,011	-0,021			-0,002	-0,015	-0,010	-0,004	-0,019	-0,011	-0,006		-0,005	-0,003	-0,007

Source: Own computation on EU-SILC data.
Note: blank cells refer to income sources not available. Social housing is not available in Germany, Netherlands and Denmark.

Table A.2.5*:* Gini coefficient and income-source contribution changes between 2008 and 2017

	Austria	Belgium	Germany	Denmark	Greece	Spain	Finland	France	Ireland	Italy	Luxembourg	Netherlands	Portugal	Sweden	UK
Income source															
Employee wages	-0,011	0,024	0,014	0,036	-0,025	0,014	-0,007	0,030	0,040	0,021	-0,045	0,013	-0,012	-0,007	-0,033
Self-employment	0,005	-0,021	-0,017	-0,003	-0,003	-0,001	-0,015	-0,005	0,012	-0,024	-0,008	0,000	-0,025	-0,005	-0,009
Capital	0,001	-0,002	-0,005	-0,015	-0,006	-0,010	0,000	-0,027	-0,007	0,001	0,003	-0,025	0,008	0,022	-0,005
Private transfers	-0,001	-0,001	-0,001	0,000	-0,003	-0,001	0,001	-0,001	0,000	0,001	0,002	0,000	-0,001	0,000	0,001
Unemployment	-0,002	0,005	0,004	-0,003	0,000	-0,004	-0,002	-0,001	-0,002	0,000	-0,002	0,001	0,002	0,000	0,005
Old-age + survivors	0,015	-0,002	-0,005	-0,001	0,005	0,029	-0,001	0,015	0,004	0,033	0,032	-0,010	0,028	0,009	0,007
Sick + disability	0,000	-0,002	-0,001	0,001	0,001	0,000	0,001	-0,003	0,000	0,001	0,001	-0,001	-0,002	-0,001	-0,001
Education	0,000	0,000	0,000	-0,002	0,000	-0,001	0,000	0,000	-0,001	0,000	0,002	0,000	-0,002	0,000	-0,001
Social exclusion	0,001	-0,002	0,003	0,000	-0,001	0,000	0,002	-0,001	0,001	-0,001	-0,002	0,001	0,000	-0,002	-0,003
Family allowances	-0,001	-0,002	0,002		-0,001	-0,001	0,000	-0,002	0,000	0,000	0,002	-0,002	0,000	-0,001	0,002
Housing allowances	0,000	0,000	-0,003	0,001	0,000	0,000	-0,001	0,000	0,001	0,000	0,001	-0,001	0,000	0,001	-0,001
Taxes	-0,005	-0,006	-0,007	0,007	0,002	-0,010	-0,001	-0,013	-0,039	-0,014	0,032	0,023	-0,028	-0,001	0,040
Health	-0,001	-0,001	0,000	-0,002	0,001	-0,003	0,000	0,000	0,000	0,000	-0,001	-0,001	-0,007	0,001	0,002
Pre-primary	0,001	0,000	0,000	0,005	0,003	0,000	0,000	0,001	0,001	0,000	-0,001	0,000	0,000	0,002	-0,001
Primary-Secondary	-0,002	-0,003	0,001	-0,005	0,009	0,000	0,013	-0,003	-0,002	-0,002	-0,005	0,008	0,009	-0,001	0,002
Tertiary	-0,001	-0,002	-0,002	-0,002	0,000	-0,002	-0,002	-0,001	-0,007	0,000	0,017	-0,003	-0,001	0,000	0,000
Social housing	0,000	0,000			0,000	-0,001	-0,001	-0,001	0,002	-0,002	0,000	0,000	0,000	0,000	0,000
Gini	-0,001	-0,016	-0,018	0,016	-0,017	0,008	-0,013	-0,012	0,003	0,013	0,027	0,002	-0,032	0,018	0,006

Table A.2.6: Income-source elasticities by cash-transfers entitlements – 2017

	Austria			Belgium			Germany			Denmark			Greece			Spain			Finland		
Income source	**S**	R	G	**S**	R	G	**S**	R	G	**S**	R	G	**S**	R	G	**S**	R	G	**S**	R	G
contributory means	0,022	0,259	0,968	0,000	-0,152	0,999	0,020	-0,219	0,942	0,024	-0,217	0,927	-	-	-	0,009	-0,323	0,939	-	-	-
contributory non-mt	0,186	0,143	0,792	0,234	-0,278	0,621	0,123	-0,157	0,821	0,086	0,036	0,858	0,349	0,238	0,692	0,200	0,276	0,750	0,219	-0,078	0,719
non-contributory means	0,014	-0,479	0,933	0,009	-0,581	0,963	0,022	-0,328	0,908	0,131	-0,611	0,708	-	-	-	0,023	-0,407	0,874	0,048	-0,625	0,809
non-contributory non-mt	0,058	-0,019	0,680	0,005	0,797	0,998	0,067	0,342	0,797	0,033	-0,099	0,788	0,000	0,435	0,999	0,000	0,373	0,992	0,030	0,053	0,718
taxes	-0,271	-0,853	-0,523	-0,251	-0,804	-0,520	-0,313	-0,778	-0,493	-0,388	-0,913	-0,389	-0,411	-0,860	-0,406	-0,153	-0,898	-0,627	-0,275	-0,907	-0,467
health	0,105	0,206	0,128	0,108	0,153	0,149	0,138	0,269	0,118	0,106	0,218	0,128	0,075	0,555	0,160	0,096	0,053	0,117	0,090	0,287	0,139
pre-primary	0,009	0,025	0,933	0,013	0,128	0,900	0,000	0,324	0,998	0,017	0,355	0,914	0,015	0,190	0,920	0,013	0,122	0,901	0,004	0,223	0,964
primary-secondary	0,059	0,115	0,753	0,071	0,253	0,720	0,046	0,140	0,764	0,068	0,357	0,727	0,072	0,114	0,736	0,050	0,024	0,740	0,068	0,357	0,758
tertiary	0,019	0,319	0,925	0,021	0,336	0,902	0,015	0,340	0,936	0,015	0,075	0,962	0,007	0,075	0,927	0,014	0,232	0,903	0,011	0,289	0,968
housing	0,009	-0,062	0,917	0,011	-0,218	0,931	-	-	-	-	-	-	0,012	0,235	0,961	0,011	-0,105	0,943	0,005	-0,215	0,971

	France			Ireland			Italy			Luxembourg			Netherlands			Portugal			Sweden			UK		
Income source	**S**	R	G	**S**	R	G	**S**	R	G	**S**	R	G	**S**	R	G	**S**	R	G	**S**	R	G	**S**	R	G
contributory means	-	-	-	0,005	-0,200	0,958	0,007	-0,062	0,836	-	-	-	-	-	-	0,002	-0,405	0,991	-	-	-	-	-	-
contributory non-mt	0,223	0,197	0,746	0,111	0,108	0,831	0,274	0,331	0,732	0,202	0,216	0,798	0,146	0,152	0,816	0,262	0,337	0,767	0,184	-0,117	0,759	0,140	0,051	0,833
non-contributory means	0,034	-0,519	0,754	0,068	-0,516	0,764	0,005	-0,426	0,968	0,008	0,065	0,872	0,030	-0,664	0,894	0,011	-0,369	0,868	0,011	-0,660	0,924	0,049	-0,359	0,831
non-contributory non-mt	0,018	0,043	0,765	0,029	-0,097	0,489	0,016	0,060	0,938	0,054	0,011	0,680	0,085	-0,338	0,740	0,003	-0,060	0,968	0,053	-0,186	0,709	0,039	0,053	0,735
taxes	-0,203	-0,856	-0,481	-0,198	-0,882	-0,708	-0,270	-0,900	-0,544	-0,161	-0,545	-0,591	-0,325	-0,877	-0,472	-0,251	-0,930	-0,627	-0,281	-0,913	-0,435	-0,205	-0,816	-0,562
health	0,109	0,215	0,136	0,106	0,212	0,145	0,095	0,248	0,124	0,093	0,149	0,129	0,111	0,183	0,153	0,099	0,047	0,110	0,122	0,321	0,143	0,034	0,161	0,706
pre-primary	0,011	0,064	0,906	0,005	0,238	0,953	0,012	0,114	0,921	0,005	0,105	0,971	0,006	0,154	0,925	0,008	0,224	0,938	0,012	0,227	0,939	0,002	0,254	0,981
primary-secondary	0,060	0,109	0,712	0,069	0,038	0,619	0,056	0,070	0,751	0,071	0,112	0,714	0,059	0,247	0,745	0,078	0,201	0,710	0,077	0,268	0,732	0,072	0,121	0,704
tertiary	0,015	0,331	0,927	0,017	0,120	0,891	0,010	0,206	0,929	0,041	0,470	0,900	0,012	0,161	0,934	0,014	0,228	0,915	0,008	0,416	0,972	0,002	0,125	0,977
housing	0,006	0,071	0,957	0,018	-0,026	0,903	0,011	0,016	0,936	0,006	0,001	0,970	-	-	-	0,004	-0,060	0,957	0,001	-0,249	0,994	0,004	-0,242	0,933

3. What's behind increasing wage inequality? Explaining the Italian case using RIF-OLS

Abstract

This paper aims to identify how and to what extent the Italian labour market structure, in terms of job composition and institutional changes, shaped the dynamics of wages and wage inequality in the decade between 2007 and 2017. We investigate the main determinants behind the rise in wage inequality in Italy by using Recentered Influence Function (RIF) regressions. This econometric approach allows – on the one hand – to directly assess the effects on unconditional distribution and on "beyond the mean" statistics, like the Gini coefficient. On the other, it decomposes inequality into endowment and wage effects, following the standard Oaxaca-Blinder technique.

We observe that working structures and institutional changes – contractual arrangements (permanent vs temporary contracts) and working hours (full time vs part time) – are the main factors in explaining the deterioration in wages at the bottom of the income distribution scale, and the consequent increase in wage inequality.

Keywords: inequality decomposition; labour market structure; unconditional regressions; wage inequality

3.1 Introduction

Until recently, mass unemployment, increased inequality among workers and surges in in-work poverty have been considered side effects of ongoing historical changes, mostly related to the Fourth Industrial Revolution and globalisation. These approaches have gained unprecedented consensus in the political debate, especially in Europe and the US (Atkinson, 2001; Bogliacino, 2014). More interestingly, the resulting hegemonic narrative, according to which the asymmetric gains from technological change are a deterministic outcome, disempowers policy makers since they exist outside their goodwill and beyond their powers. An explicit corollary of this stream of thought puts individuals and their choices at the forefront of historical challenges and assumes that institutions are neutral and inclusive by default. To respond to historical challenges, be they mass unemployment or increasing inequality, the political agenda has highlighted the adaptability and resilience of productive systems; this is in line with supranational institutions' recommendations: "Adaptation is fundamental to progress in a world of new technologies, globalisation and intense national and international competition" (OECD, 1994). Resilience can therefore be achieved by implementing a series of policies, nowadays known as "structural reforms", such as more flexible working schedules and wages, and reskilling of the workforce. These types of recommendations have been suggested and/or imposed both to address the downturn caused by the Great Recession and to recover from it, as well as to gain competitiveness during expansions of the business cycle. All in all, the political agenda and hegemonic ideas to tackle contemporary challenges have remained unchanged over the last few decades, although eventually the same international institutions that have supported them have had to acknowledge that labour market liberalisation creates inequality among workers and between workers and profit earners (Dabla-Norris et al., 2015; OECD, 2015). After decades, inequality is still rising and not even the labour market is healthy, at least from the workers' standpoint.

During the 1980s, the steady increase in wage inequality in the US held the attention of scholars from different fields who were interested in explaining the causes of this trend. Katz & Murphy (1992) were the first to introduce the idea of Skill-Bias Technological Change (SBTC), arguing that increasing inequality within a country is a direct consequence of technological development and of the expansion of higher education, when the supply of highly-skilled workers lags behind the increase in demand. Their progressively higher wages, compared to less skilled workers, simply stem from their complementarity (and therefore higher productivity) with respect to machines. In this framework, the resulting higher wage inequality is simply the consequence of supply-demand dynamics in the labour market.

According to SBTC, advanced economies should have experienced a progressive upgrading in their occupational structure. However, the available empirical evidence shows differing and puzzling patterns for both the USA and some European countries. Indeed, the SBTC hypothesis cannot even match the empirical evidence for the US economy, where employment expansion occurred not only at the top but also at the bottom of the wage distribution scale, leading to so-called employment polarisation (Wright and Dwyer, 2003). To adapt to this evidence, the SBTC was revised into Routine-Biased Technological Change (RBTC), according to which employment changes (and wage inequality) can be better understood by shifting the focus of analysis from individual skills endowment to tasks, i.e., the unit of input labour required to produce a unit of output (Acemoglu and Autor, 2011; Autor et al., 2003). More specifically, the substitution/complementarity between human labour and machines (capital) depends on the degree of routine tasks required in a certain job. Tasks that are more routine are easier to codify, and therefore easier to substitute with machines. It is for this reason that we should expect a drop in the mid-range occupations (routine clerical jobs) and an increase at the extremes of the distribution.

On the other side, there are other theoretical arguments that aim to explain the relationship between wage inequality and labour structure. Called the “revisionists” by Autor et al. (2008), authors like Card and Di Nardo (2002), Lemieux (2006), Di Nardo and Pischke (1997) criticise the SBTC argument, and claim that the real causal factors are not market-driven, but instead institutional. Specifically, the “revisionists” claim that the main factors driving the rise in inequality relate to the declining real value of the minimum wage and to the de-unionisation process (Card, 1996; Visser and Checchi, 2011). Others, like Piketty and Saez (2003) and Piketty et al. (2018), argue that rising wage inequality is the consequence of the enormous gains in terms of labour income for those at the very top of the income distribution; consequently, technological change cannot be the real cause of wage inequality. This literature is more coherent with the sociological theory that highlights the importance of institutional design in terms of the welfare system and of the power relations and regulation of labour structure (Fernández-Macías, 2012; G. Esping-Andersen, 1990, 2000).

This article contributes to this last strand of literature on Italian wage inequality and its trends during the 2007-2017 period, by studying these phenomena along the entire income distribution and accounting for changes in labour market structure. More precisely, our study inspects – *in a non-causal way* – the determinants and trends of inequality at different points on the annual wage distribution, so as to capture if and to what extent individual characteristics and employment and structural compositions affect those changes. Following Franzini and Raitano (2019), we use the annual incomes as this variable includes all the possible influences of labour market outcomes on workers' living standard (i.e., annual wages depend on hourly wages determined by the number of hours worked per week and therefore on time-arrangements and number of working weeks affected by contract durations).

For our purpose, we use the RIF approach developed by Firpo et al. (2009, 2018) to firstly estimate the cross-sectional associations and secondly the revised RIF-Oaxaca decomposition method to establish the main determinants behind wage inequality dynamics. In other words, we firstly check to what extent the associations between main covariates and wages change along the distribution and years to identify the most relevant association channels, and then we identify the main determinants behind rising wage inequality in Italy. We decided to focus on Italy, which represents a textbook case characterised by a continuous series of labour reforms, spanning the whole period from the Lira crisis in 1992 and a hard privatisation process that took place in the years following it, to the strong fiscal consolidation policies adopted to face the debt crisis in 2011.

The rest of the paper is organised as follows. Section 2 reviews some important facts about the Italian context. Section 3 introduces the methodology and data used for the analysis. Section 4 presents a summary of statistics on employment structure in Italy, as well as distributive statistics and inequality trends. In Section 5 we discuss RIF-OLS and decomposition results, and finally section 6 concludes the paper by synthesising our main findings.

3.2 The Italian case

From the annual report by the Italian National Social Security Institute (INPS, 2019) it emerges that, between 1993 and 2017, annual labour income remained on average almost flat, while the share of workers earning below the 60% of the median increased from 26 to 31 percent. Overall, during the last few decades, Italy has experienced increased inequality in income and wealth,[14] wage stagnation and increased profit share.

Just like many other Western countries (ILO, 2020), Italy experienced a significant fall in labour share (from just below 70% in the 1960s to just above 50% in 2017) and an increase in wage inequality.

In Italy, wage inequality started to widen in the 1990s reversing the trend characterising earlier decades. Brandolini et al. (2001) show that all inequality measures decreased substantially between the 1977 and the 1989 – a period when both mean and median net wages grew at 1.8 percent per year. This effect is due to a particular indexation mechanism – the *scala mobile*, literally the escalator – which, beginning in 1975, granted a wage increase in real terms to all employees as prices rose, as shown by Manacorda (2004). From its abolition in 1993 inequality started to rise and kept rising.

Lilla and Staffolani (2009) observe that the rise in inequality starting from the 1990s is basically due to the slow growth in white-collar wages and to the depression of blue-collar wages. The authors also claim that the main sources of inequality within groups are cohort differences and the higher volatility in younger workers' wages, a result explained by Italian labour market reforms that started in the 1990s. Naticchioni et al. (2010, 2008) deepen the analysis of inequality determinants within and between groups by putting SBTC arguments to the test. The authors conclude that these arguments do not apply to the Italian case, which was characterised by a decrease in the Educational Wage Premium along the entire wage distribution between 1993 and 2004. According to the authors, lagging demand for high-skilled workers may explain such pattern, at least at the top of the wage distribution. Indeed, Rosolia and Torrini (2016) find a persistent wage penalty for the youngest cohorts compared to the older generations: those entering the new flexible labour market experience a relative wage loss that is not recovered by faster career paths. Naticchioni et al. (2016) consider the heterogeneity of this penalty across

[14] For a reference: Morelli et al., 2015; Hasell et al., 2019; Acciari et al., 2021

skill levels, and observe that, compared to the older cohorts, younger higher-skilled workers are more heavily penalised than the younger unskilled workers.

This evidence suggests that other mechanisms - beyond SBTC - are at play in influencing wage inequality, ones that are more grounded in the institutions of the labour market. Furthermore, occupational shifts may also affect wage dynamics and, in turn, wage inequality.
It is therefore important to acknowledge that the country witnessed a long-lasting process of structural reforms towards a more flexible labour market starting in Early '90s. The detrimental effect of labour market flexibilization has been widely documented in recent years (Kleinknecht, 2020). Recent work by Cirillo and Ricci (2019) shows that the increase in temporary employment led to a decline in labour productivity and wages, together with an increase in profits. Temporary jobs are also associated with less innovation, especially in sectors that rely more on tacit knowledge as a driver of innovation (Cetrulo et al., 2019). These findings are in line with the weak dynamic in R&D activities, consolidating a shift toward cost-competitiveness strategies based on labour cost compression (Guarascio and Dosi, 2016; Guarascio and Simonazzi, 2016). Finally, Raitano and Fana (2019), studying the almost total liberalisation of fixed-term contracts in 2001, found a substantial and persistent wage penalty for highly educated workers entering the labour market just after the reform passed, compared to their peers who had entered it earlier.

All these mechanisms build up patterns of structural change in terms of occupational composition. However, the dynamics of occupational change is puzzling, with some results indicating upgrading, while others indicate slight upgrading or even downgrading. Piccitto (2019) shows that between 1992 and 2015 the Italian labour market experienced a clear upgrade, irrespective of gender or territorial division, with the financial crisis of 2012 not reversing the process, but slowing it down. Conversely, Fernández-Macías (2012) observes only slight upgrading for Italy between 1995-2007. Results from Hurely et al. (2019) are even more in contrast with those of Piccitto (2019), showing a clear downgrading pattern since 2007, a finding supported also by Basso (2019) and Aimone Gigio et al. (2021). Furthermore, Hurely et al. (2019) compare the Italian labour structure with that of nine other European countries. Evidence clearly shows a downgrading with respect to the EU average (of 9 countries), and this trend includes all the Italian regions, with only Lombardy having fewer lower-skilled workers compared to the other countries studied. Castellano et al. (2019) also observe a downgrading in the employment structure in Italy. In particular, they find growth in higher-skilled workers only at the median of the overall wage distribution. Finally, the European Jobs Monitor (2017) analyses the relationship between changes in the occupational structure and wage inequality. According to the report, Italy is characterised by mid-level wage inequality (compared to other European member states) and low levels of occupational wage differentials. Overall, authors find that occupational dynamics do not account for much of the variation in changes in wage inequality, which is mainly explained by within-occupation wage changes.

As for the potential relationship between occupational changes and wage inequality, we follow Firpo, Fortin and Lemieux's contribution (2009, 2018) to understand and quantify the impact of the structure of the Italian labour market on wage inequality.

3.3 Data & Methodology

3.3.1 Data

Using the EU-SILC data (User Database, UDB), we estimate the main drivers of annual wage inequality over the decade between 2007 and 2017, and provide separate estimations for 2007, 2011, 2014 and 2017.

The UDB database covers information at the individual and household levels, both cross-sectionally and longitudinally, on a wide set of information about labour market conditions, income, and socio-demographic characteristics.

In this study, we use the cross-sectional part of the database and we concentrate on employees (excluding self-employed individuals) from both the private and public sectors, aged between 16 and 65, for a total sample of 14,367 workers in 2007 and 14,430 in 2017. Employees are classified into occupations, according to the ISCO 2-digit classification provided by the EU-SILC (variable PL050 and PL051) and into economic sectors, so that it is possible to characterise them according to their positions within both the vertical and horizontal division of labour. Using all occupation-sector pairs, we are able to build a job matrix for each year of interest. To deal with the change in both occupation and sector classifications, we convert the NACE Rev. 2 into the Rev 1.1

classification by using the double information in the 2008 UDB (PL110 and PL111). As for the occupations, we create 9 classes from the 2-digit ISCO-88 and ISCO-08. We acknowledge that there might be some potential bias due to changes of the occupational codes at the margins, which may lead to classifying an employee in different classes when using the two classifications. We end up having a 9x12 occupation-sector matrix.[15]

The other two variables proxying labour market institutions are working hours (full time vs part time) and contractual arrangements, i.e., permanent vs temporary. We also include work experience as an additional covariate. Finally, we use educational attainment defined by the ISCED level, ranging from less or equal than primary to tertiary education. Together with occupational codes, education is the key variable linked to the SBTC theory,

To account for geographical heterogeneity, we control for the macro-area in which the employee is living in Italy: North-East, North-West, South & Islands, and Central Italy.

As anticipated, the outcome variable of interest is the gross annual wage,[16] converted into a logarithmic scale and adjusted to deal with very extreme observations, which may skew the computation of inequality indexes like the Gini coefficient. For this purpose, we trim off both the top and bottom 1% of the distribution. Furthermore, to eliminate inconsistent data, such as when individuals classified as employees report null values for gross income,[17] we proceed to impute their annual gross wage by multiplying monthly values by twelve: original and imputed data generate identical distributions and distributional measures (like the Gini coefficient, see Figure A.3.1 in the Appendix). Thanks to the consistency of the two distributions, we can rely on the imputed data to gain additional number of observations useful for higher statistical power.

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[15] We consider the following occupations: legislators & managers, higher professionals, technical & associate professionals, clerks, service workers, skilled agricultural workers, craftspeople & related trade workers, machine operators and elementary occupations. The economic sectors are agricultural & fishing, industrial, wholesale & retail, hotels & restaurants, transport, store & communications, financial, real estate, PA, Education, Health & social care, private services.

[16] "Employee cash or near cash income gross" (variable py010g).

[17] In the original database, there are between 1 and 5 percent of inconsistent cases depending on the year. In terms of occupational breakdown, the highest share of inconsistent cases is reported for "Technical & associate professionals" and "Service workers".

On this final gross annual wage, we apply the Eurostat HICP deflator (base year=2015) to obtain nominal values at constant prices. Finally, all the analyses exclude armed forces employees.

It must be noted that the annual income refers to the fiscal year preceding the year of the interview. This implies that the observable time-varying characteristics (e.g., contract type or occupation) and employee wages may be mismatched. Considering that such changes are more likely at the bottom end of the income distribution – where job discontinuity, precarious conditions and low-value occupations are concentrated – our estimates may underestimate the real effects of time-varying characteristics.

The empirical analysis tests specifications of different models: standard OLS, conditional quantile regressions, RIF-OLS over percentiles, the Gini coefficient, and lastly the P90/P10 ratio.[18] In all these model specifications, individual workers are the unit of analysis, and all variables are defined at the corresponding level. Furthermore, all estimations are run separately by gender. The gendered segregation in the labour market both in terms of occupation and performed tasks (Fana et al., 2021) motivates this choice. These structural differences require a separate analysis to avoid any selection bias in pooled models.

3.3.2 RIF-OLS

To understand how the structure of the Italian labour market affects wage distribution and wage inequality, we rely on the contribution of Firpo, Fortin and Lemieux (2009, 2018), which allows us to go "beyond the mean", both in our search of an explanatory association and in a decomposition using the standard Oaxaca-Blinder technique (Blinder, 1973; Oaxaca, 1973). Traditionally, the Oaxaca-Blinder method has been applied to the mean with standard linear regression model. Attempts to estimate the coefficient-endowments effects on different statistics, like quantiles, have been performed for example by Machado and Mata (2005).

The latter contribution is based on the conditional quantile regression (CQR) methods introduced by Koenker and Basset (1978) that, in contrast the standard OLS, do not permit

[18] All models will be estimated using EU-SILC individual cross-sectional weights. To take into account the survey structure, we use the rotational group as the stratum and the individual id as primary sampling unit.

unconditional interpretation i.e., the effect of a given explanatory variable X on the unconditional population outcome.

The main reason why CQR does not allow an unconditional interpretation is due to the impossibility of applying the law of iterated expectations. Applying that law to standard OLS leads to $(y|x) = x\beta = E(y) = E(x)\beta$, a property that does not hold for CQR since $Q_\tau(y|x) \neq Q_\tau(y)$. In other words, using conditional quantile regressions, we can only interpret the effect of a unit change in a covariate X on the t-th quantile of the conditional outcome distribution. Conversely, the unconditional quantile regression (UQR) introduced by Firpo, Fortin and Lemieux (2009) allows researchers to identify the high-earning or low-earning worker in an "absolute" way on the log-wage distribution, which is not redefined conditionally on covariates and, hence, on different subgroups as in the standard conditional quantile regression. In our case, it enables to understand to what extent the occupational structure, labour market characteristics and education affect the wage distribution at different points (wage percentiles), without conditioning the wage distribution.

The building block of the RIF-OLS is the influence function. Considering a given distributional statistic v(Fy) – for example the Gini coefficient – computed on the distribution F, then the influence function of v(Fy) represents the effect of an infinitesimal change in the function F at a given point y (of our individual gross annual log-wage distribution). Hampel (1974) provides a formal definition of the influence function (IF) as:

$$IF(y;\ v, Fy) = \lim_{\epsilon \to 0} \frac{v\big((1-\epsilon)Fy +\ \epsilon\Delta y\big) - v(Fy)}{\epsilon} \qquad (1)$$

FFL (2009) recentered the function, adding back the distributional statistic to the IF:

$$RIF(y; v, Fy) = v(Fy) + IF(y; v, Fy) \qquad (2)$$

and demonstrated how the distributional statistic v(Fy) can be written in terms of expectations and, applying the law of iterated expectations, also in terms of expectations of the conditional RIF:

$$v(Fy) = \int E[RIF(y; v, Fy)\mid X = x]\ *\ dFx\ (x) \qquad (3)$$

According to equation (3), when covariates are present and we are interested in understanding their association to a distributional statistic v(Fy), it is necessary to integrate over E$[RIF(y; v, Fy) \mid X]$.

To do so, FFL (2009) propose a simple OLS regression, obtaining the RIF-OLS[19]:

$$v(Fy) = E[RIF(y; v, Fy)] = E(X\beta) + E(\varepsilon) \qquad (4)$$

where the coefficient β can be interpreted unconditionally, in FFL's (2009) terms, as the unconditional partial effect (UPE). However, the interpretation of our coefficients is different from that of a standard OLS regression: β represents the expected change in our distributional statistic if the (unconditional) average of X increases by one unit.

Therefore, our final equation will be:

$$v(Fy) = E[RIF(y;\ v, Fy)] = E(X_{occ}\,\beta_{occ}) + E(X_{sector}\,\beta_{sector}) + E(X_{labour}\,\beta_{labour}) + E(X_{edu}\,\beta_{edu}) + E\big(\gamma_{regions}\big) + E(\varepsilon) \qquad (5)$$

where $v(Fy)$ will be the 10th, 50th, and 90th percentiles and the Gini coefficient; y is the (log) gross annual wage of individual workers; X_{occ} and X_{sector} are the matrix of covariates related to the occupation and sector of each individual workers. X_{labour} includes the vectors of contractual arrangements, working times and work experience; X_{edu} is the matrix of individual educational attainment; finally, $\gamma_{regions}$ represents the fixed effects for region to control for the between variations at the regional levels.
We estimate that when we use this approach, and when we consider our effects of interest along the entire (unconditional) outcome distribution – log gross wages – we will obtain more informative results compared to the standard CQR.

3.3.3 RIF-Decomposition

Although RIF-OLS provides a powerful tool for estimating unconditional effects of covariates of interest on a distributional statistic and important insights on the main contributors to wage inequality cross-sectionally, it is not sufficient for identifying gaps between groups when we want to compare two points in time. In other words, the first

[19] This is a two-step procedure consisting in estimating the recentered influence function for each observation y_i and then use these RIF as dependent variable against the covariates X.

cross-sectional analysis is a necessary but not sufficient condition for identifying the real mechanisms behind wage inequality *dynamics*.

To narrow the analysis by decomposing such differences, it is necessary to combine RIF-OLS with the standard decomposition technique introduced by Oaxaca-Blinder (1973). As anticipated, this strategy has been implemented to identify the composition and the coefficient effects at the mean through standard OLS estimation. By combining it with RIF-OLS, the Oaxaca-Blinder technique can be also applied to measures beyond the mean, preserving the unconditional interpretation.

If we consider, for example, a distribution function v(Fy), a vector of covariates X and a variable T that identifies two different groups – 0 and 1 –, to estimate the gap between the two groups based on v(Fy) it is possible to perform the following operation:

$$\Delta v = v\left(\int F^1_{Y|X}(Y|X)dF^1_X(X)\right) - v\left(\int F^0_{Y|X}(Y|X)dF^0_X(X)\right) \qquad (6)$$

Equation (6) suggests that there are two components that explain the gap between the two groups. The first is due to differences in characteristics (the distribution of covariates differ among the groups); the second refers to the different relationship between the outcome and the covariates in the two groups.

At this stage, we require a counterfactual to determine the magnitude of each effect. For this purpose, following the standard Oaxaca-Blinder technique and specifying equation (4) for our two groups, we obtain the counterfactual by applying the coefficient of group 0 to the covariate's distribution of group 1.

FFL (2009) suggest an alternative procedure for defining the counterfactual scenario. This approach relies on the identification of a reweighting factor that needs to be applied to $dF^0_X(X)$ to mimic the distribution of group 1, $dF^1_X(X)$. The most straightforward way of doing this is to perform a logistic (or probit) regression to estimate the reweighting factor, and then estimate the RIF-OLS for the counterfactual applying this factor.[20]

We now have a full decomposition - by using the "normalisation" approach to avoid the omitted-reference bias which affects the Oaxaca-Blinder decomposition when using categorical variables - like the following:

$$\Delta v = X^1(\beta_1 - \beta_C) + (X^1 - X^C)\beta_C + (X^C - X^0)\beta_0 + X^C(\beta_C - \beta_0) \qquad (7)$$

[20] The RIF-OLS for the counterfactual is the following: $E[RIF(y; v, F^C_y)] = E(X^C\beta_C) + E(\varepsilon)$

The first term represents the (pure) coefficient effect, while the third addendum is the (pure) endowment effect. The coefficient effect refers to the differences in the relation between the covariates and the outcome across the groups. The endowment effect represents the differences in the covariates' distributions across groups. The other two terms represent the reweighting and the specification errors, respectively. The reweighting error is a measure of the quality of the reweighting strategy and, as FFL report, it tends to zero when the sample size increases. The specification error, conversely, is a test on the model misspecification, since it measures the departure from linearity and, consequently, it is a way to check whether the RIF-OLS is an appropriate tool for the decomposition of endowment and coefficient effects. In brief, we ideally expect both errors to not be statistically different from zero.

FFL (2018) argue that *under the ignorability assumption*[21] the endowment (composition) effect can be interpreted as the "policy effects of changing the distribution of one covariate from its T=0 to T=1 level, holding the distributions of other covariates unchanged". The wage effect is then a "pure effect" of the covariates on wages.
In other words, even without a pure identification strategy and causal interpretation, it is possible to estimate what the "true" determinants and the effects behind changes in wage distribution and inequality measures are over time.

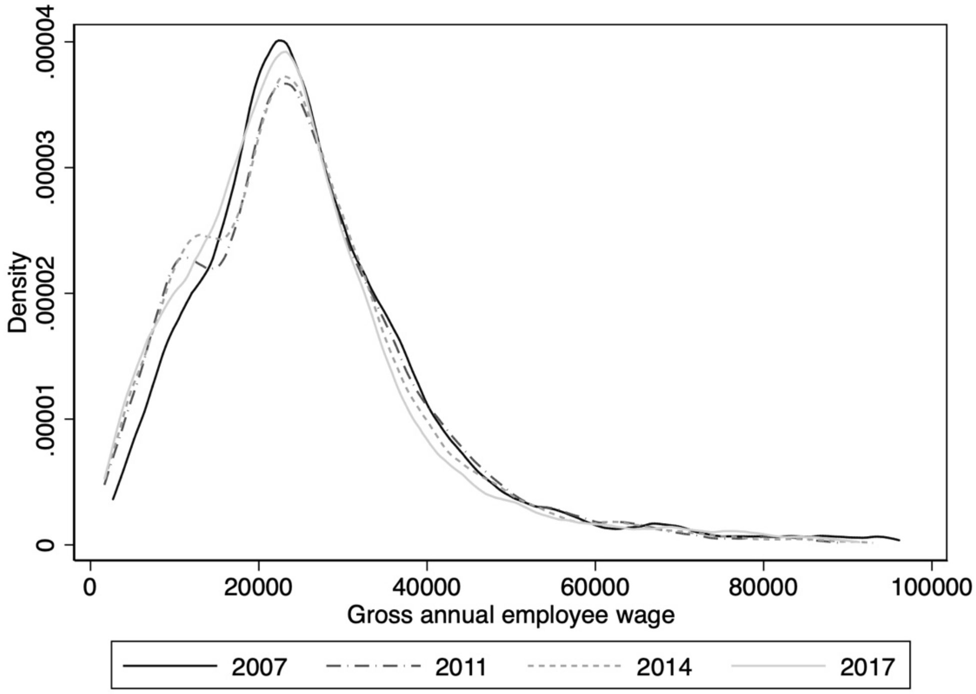
3.4 Distributive descriptives

Before presenting the outcomes of the econometric exercise, in the present section we summarise several distributive statistics. The overall wage distributions are reported in Figure 3.1, and the effect of the Great Recession emerges in 2011 and 2014: compared to the pre-2008 period and the recovery phase (2017), both years are characterised by a higher density at the bottom, with the emergence of two "bumps".[22] Although GDP

[21] The ignorability assumption – or unconfoundedness – in the identification studies replaces the standard strict exogeneity assumption and requires that the outcomes of the treated and control groups are independent from the treatment, once controlled for observable covariates. Symmetrically, it can be defined as the independence between the errors and the treatment T, once controlled for the covariates x. (FFL, 2018).
[22] Most likely, these bumps are the results of the "cassa integrazione", the dominant protection provided by the lay-off scheme. Indeed, workers should receive the 80% of the global income they would obtain if they worked all their standard contract hours. Therefore, we observe a reduction in annual gross wages of under 20,000 euros, which disappears once the "cassa integrazione" scheme ended during the recovery.

recovered in 2017 (Eurostat series), income levels remain lower compared to the pre-2008 period.[23]

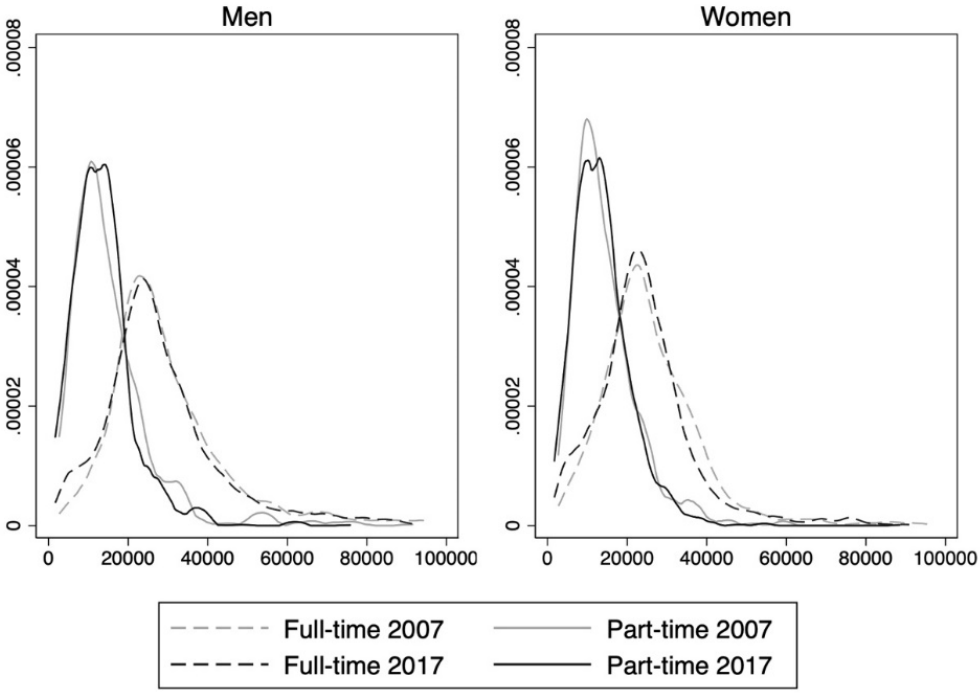
Figure 3.1: Overall gross annual employee wage



Looking at the distribution over time by gender and working hours, reported in Figure 3.2, we observe that female workers suffer a pay gap in both years when employed full time, while no major gender gaps emerge for part-time work in 2017 compared to 2007. The last piece of evidence may reflect the impoverishment of part-time male workers after the Great Recession, consistently with the increase in the share of men's involuntary part-time work (Eurostat, 2020). Finally, Figure 3.3 reports wage distributions according to other covariates. In particular, the left-hand panel contrasts the top and bottom professional groups (according to the ISCO one-digit classification), while the right-hand panel compares permanent and temporary contracts.

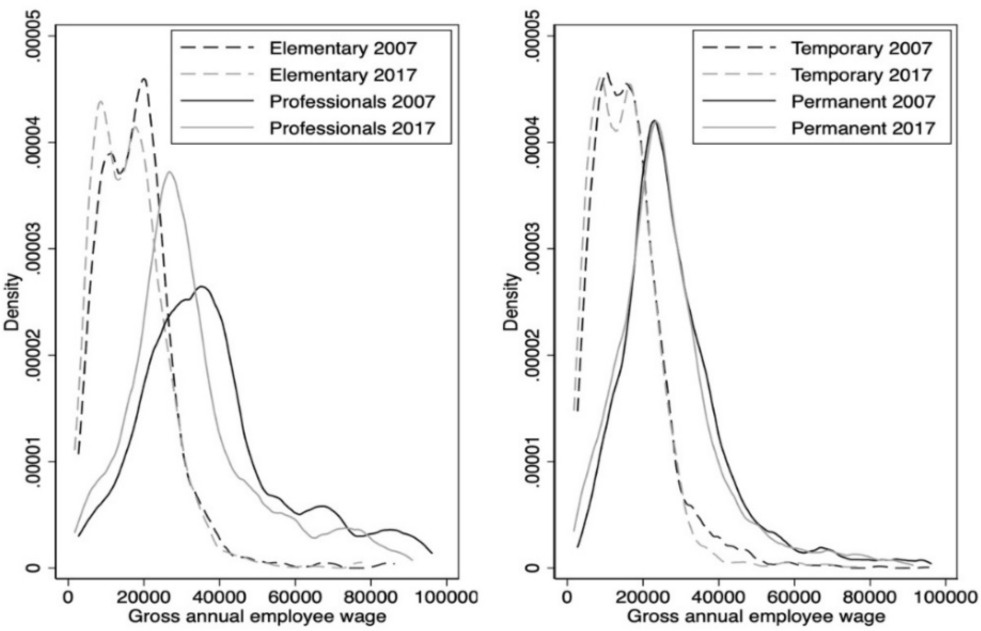
[23] The two-tailed Kolmogorov-Smirnov test of equality confirms that the distributions are statistically different by period, except for 2011 vs 2014.

Figure 3.2: Part-time vs full-time wage distribution by gender



Source: authors' elaboration on EU-SILC data

Figure 3.3: Elementary occupations vs Professionals (left) and permanent vs temporary (right)



Source: authors' elaboration on EU-SILC data

According to Figure 3.3, changes in the wage distributions for occupational groups at the top and the bottom of the scale point to the same direction with a larger share at lower percentiles and a lower density at higher percentiles. In terms of magnitude, a stronger downgrading characterises elementary occupations compared to Professionals, with a consequent increase in wage inequality, due to the bottom 10^{th} lagging behind. In line with expectations, temporary jobs are concentrated at the bottom of annual gross wages, with a distribution that is very similar to that of elementary occupations. An overall impoverishment also characterises permanent jobs: its distribution in 2017, compared to 2007, is characterised by higher density in the bottom percentiles.

The distribution of annual gross income, Table A.3.2, highlights that inequality increased at the bottom of the scale (P50/P10) and decreased at the top (P90/P50), confirming our previous intuition about the Italian employment structure's downward trend, rather than a polarising effect, as found in the US (Autor and Dorn, 2013). The increase in overall inequality, as resulting from the 90/10 wage ratio, is mainly driven by a surge in inequality at the bottom. More precisely, considering the log-distribution, it is possible to directly observe the percentage change of the wage distribution over time. In real terms, the bottom 10% lost 23%, while at the top, there was a decrease of about 6% (in nominal terms there was a decrease at the bottom of 7% and an increase at the top of around 10%). The Gini coefficient confirms the trend towards more inequality, moving from 0.28 in 2007 to 0.30 in 2017.

3.5 Results

This section discusses the results from the RIF-OLS method and the detailed Oaxaca-Blinder decomposition. In the first step – the RIF OLS - the dependent variable, the log wage at three different points of the distribution in two different years (2007 vs 2017), is regressed against a set of both structural and individual characteristics summarised in Table A.3.1[24]. Different estimations by gender are performed to account for gender bias and unobservable factors leading to gender differences in job composition and returns.

[24] For the sake of completeness, we perform standard OLS and Conditional Quantile Regression. Results are available upon request. Results using both OLS and CQR are consistent with RIF-OLS estimates presented and discussed in the text.

To check the robustness of our estimates, we also implement a RIF-OLS for two different inequality measures, i.e., the Gini coefficient and the P90/P10 income ratio. Finally, the second and last step of the econometric analysis decomposes changes that occur along the wage distribution, using Firpo et al''s detailed Oaxaca-Blinder decomposition (2018). These two steps – the static cross-sectional RIF-OLS and the Oaxaca decomposition – are complementary, as presented by Firpo et al., (2018). The first analysis helps to provide an initial intuition on how the main covariates are associated with wages and inequality measures, and how they evolved across periods. The changes in the estimates suggest what we should expect from a dynamic approach. The dynamic analysis will then clearly establish what are the 'true' determinants behind changes in wage inequality over time.

3.5.1 RIF-OLS at 10th, 50th and 90th percentiles

Figure 3.4 reports estimates from the RIF-regression at 10, 50 and 90th percentiles for women and men, respectively, at two points in time (2007 and 2017, the Figure A.3.3 in the Appendix reports the estimates for 2011 and 2014). Overall, as expected, the analysis of changes in wages across the distribution highlights the strong heterogeneity in the effect of the covariates. Looking into the association of occupation with (log) wages, the positive and significant coefficient of being employed as a Legislator or Manager increases along the distribution and also over time for the 90th percentile. Conversely, working in a mid to low-level occupation (Service workers or Elementary occupations) has a strong negative correlation at the bottom, and to a lesser extent on median wages, where the coefficient is stronger in magnitude in 2017 compared to 2007. While the effect of Legislator and Manager also holds for men, the negative effects of being employed in mid-level occupations does not affect the bottom of the distribution, but only the middle and top end.

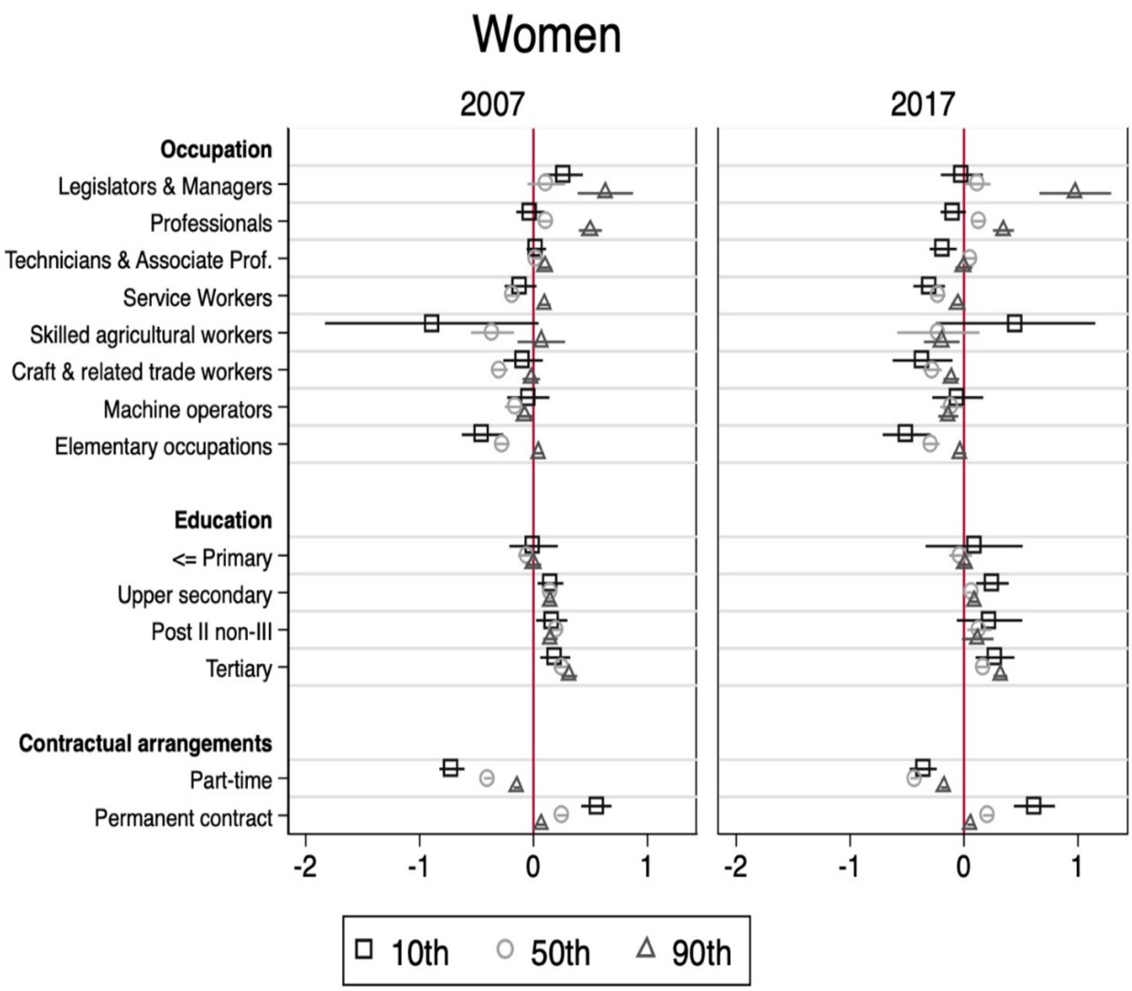
Overall, the changes in monetary rewards and penalties to occupations do not seem to be fully consistent with the SBTC and RBTC theory. We observe increasing returns associated to the high-occupations, most notably at the top 90th, while mid-bottom occupations experience a stronger wage penalty, above all at the bottom 10th of the wage distribution. Coherently with Basso (2019), these findings are more in line with a downgrading occupational and wage structure rather than upgrading or polarizing structure, as predicted by the SBTC and RBTC. Moreover, the SBTC would predict increasing returns to higher education, reinforcing the occupational upgrading and wage inequality due to skill-bias. However, we observe that returns to higher education are decreasing between 2007 and 2017 – especially for men. This is a signal that education is now racing ahead of technology (Goldin and Katz, 2008) and, as a consequence of diminishing returns, it may not be the most relevant determinant in explaining wage inequalities, as suggested by the SBTC theory.

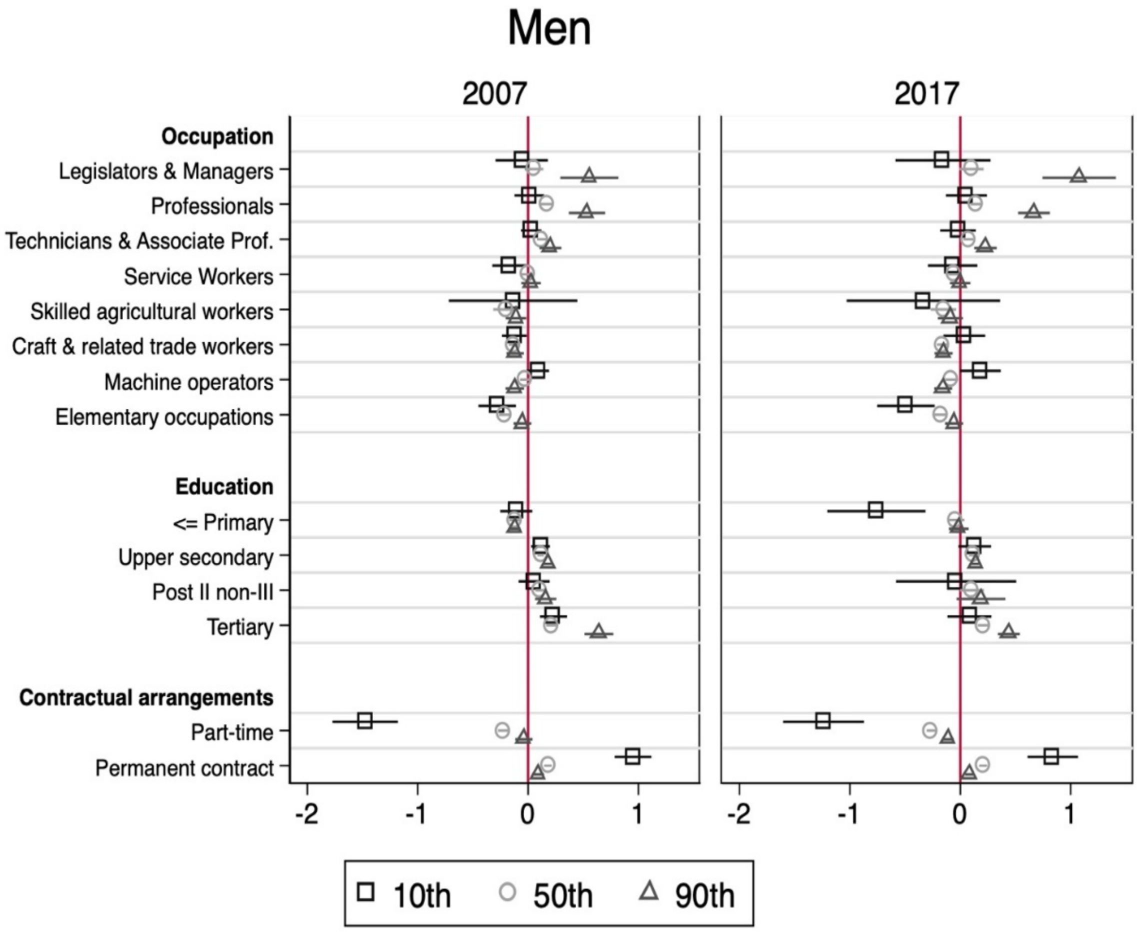
Finally, we observe that working part time has a strong negative effect, although it is declining along the entire wage distribution: it holds for both genders, with greater magnitudes for men.
The gender difference is not surprising, and it is coherent with statistics on the gender distribution of involuntary part-time work: men lose out more than women, since women already start from a lower baseline. Indeed, women's employment is more concentrated in non-standard working arrangements compared to men, who are only now experiencing these new forms of employment that penalise their wages compared to the already low wages of women.
Moreover, permanent workers enjoy higher wages compared to temporary ones, especially at the bottom of the distribution, regardless of gender. However, while for women the positive effect weakens at the 50th and 90th percentiles, men with temporary contracts suffer from lower returns even at the bottom. This finding confirms the equalising effect of standard work arrangements, especially at the bottom of the distribution; in other words, more precarious contracts enhance inequality.

As expected, labour market institutions matter in line with some strands of economic literature discussed in the previous sections (Naticchioni et al., 2016; Raitano and Fana, 2019; Rosolia and Torrini, 2016; etc.). More precisely, the expansion of more precarious work-arrangements – part-time, temporary contracts, unvoluntary part-time, on-call contracts, etc. – significantly decreases the workers' bargaining power. The observed downgrading wage and occupational structure seems to be in line with the ideas of low-added value specialization and lower productivity as a consequence of the expansion of alternative work-arrangements (Guarascio and Dosi, 2016; Guarascio and Simonazzi, 2016). In other words, the ongoing expansion of part-time and temporary contracts may constitute a more relevant theoretical explanation to the wage inequality levels and its dynamics.

Therefore, these proxies for labour market institutions appear as the main candidates in explaining the wage dynamics, alternatively to the standard SBTC prediction.

Figure 3.4: Unconditional quantile regressions at the 10th, 50th and 90th percentile by gender





Note: sectors, labour experience and macro-area included as controls; references being Clerks occupations, Wholesale & Retail sector, Lower secondary education, North-West.

3.5.2 RIF-OLS for the Gini coefficient

After presenting the effects of a rich set of covariates at different points of the (log) wage distribution, we analyse how and to what extent those covariates directly affect wage inequality: here we discuss estimation outcomes for a RIF-OLS applied to the Gini coefficient (as a robustness check, we use also the P90/P10 ratio, see Table A.3.4 in Appendix).

Compared to Clerks, an increase in both the share of higher and lower skilled occupations significantly worsens inequality. As expected, as the share of Managers increases and strengthens over time, the effect is stronger for both men and women, while the effect associated with an increased share of Elementary occupations is quite stable.

Going back to theoretical explanations, the SBTC (Autor et al., 2003b; Katz and Murphy, 1992) predicts an increase in wage inequality at the top and decreasing wage inequality at the bottom of the distribution driven by the complementarity/substitutability nexus between technologies (capital) and skills (mostly proxied by educational attainment). Thus, occupational upgrading and higher inequality at the top of the wage distribution - where more educated workers are more likely to be employed - should be expected. On the contrary, occupations at the bottom should decrease and not being significant in explaining wage inequality. In Goldin and Katz's (2008) words, if the demand for skills is racing ahead of supply, then there will be an increase in wage inequality due to skill-bias. Our findings only partially coincide with the SBTC's. Indeed, we observe that compared to Clerks, an increase in the share of high skilled occupations – Managers and Professionals – significantly worsen inequality. For example, a 1% increase in the share of male (female) professionals contributes to a 0.46% (0.45%) increase in the Gini coefficient in 2007.[25]

However, contrary to the SBTC main prediction, we also find that an expansion of bottom occupations leads to higher wage inequality. This latter evidence can be explained by a polarizing pattern – in accordance with the RBTC – or by a significant downgrading in both employment and wage structures. In the case of Italy, this last mechanism seems to better explain the occupational and inequality distributions as the expansion of bottom occupations is higher than the increase in the top ones (see Figure A.3.2 in the Appendix). This downgrading trend is incompatible with both SBTC and RBTC predictions.

Furthermore, in terms of education, we observe higher Gini coefficients because of an increase in the share of highly educated workers (irrespective of gender), in line with SBTC theory. However, the magnitude is decreasing over time, suggesting that education may not be the unique and/or most important factor in shaping wage inequalities. Like Basso (2019), we fail to identify the SBTC as the main factor explaining the increase in wage inequality, which is mostly determined by changes at the

[25] 0.46% obtained as: (0.123/0.267)*0.01, where the numerator is the associated coefficient and the denominator the mean RIF for Men in 2007.

bottom of the income distribution.

Such changes at the bottom are mostly driven by the labour market institutions embodied in the dynamics of non-standard work arrangements, with the persistent increase in both the use of part-time and temporary contracts over time. Such stronger concentration of precarious occupational forms at the bottom of the wage distribution is inequality enhancing. More in details, in 2007 an increase of 1% in the share of women in part-time work led to a 0.40% increase in the Gini coefficient (0.60% for men). Similarly, an increase of 1% in the share of temporary contracts contributed to a 0.25% increase in wage inequality (0.37% for men).

Table 3.1: RIF Gini coefficient by gender over time

	2007		2017	
Gini	Women	Men	Women	Men
Occupations: ref. Clerks				
Legislators & Managers	0.253***	0.184***	0.419***	0.240***
Professionals	0.131***	0.123***	0.129***	0.099***
Technicians & Associate Prof.	0.016	0.028**	0.010	0.019
Service Workers	0.074***	0.034**	0.055***	-0.003
Skilled agricultural	0.140*	0.046	-0.023	0.026
Craft & related trade workers	0.057***	0.019*	0.083***	-0.022
Machine operators	0.020	-0.018*	0.014	-0.041***
Elementary occupations	0.109***	0.057***	0.107***	0.043**
Sectors: ref. Wholesale & Retail				
Primary	0.096**	0.084***	0.096**	0.048*
Mining, Manufacturing, Utilities	0.040***	0.003	0.007	-0.008
Construction	0.045	0.014	0.001	0.009
Accommodation	0.075***	-0.010	0.039**	0.033
Transport, store & communications	0.050*	-0.010	0.015	-0.021
Financial intermediation	0.126***	0.099***	0.158***	0.047
Real estate & business activities	0.069***	-0.024	0.034*	-0.000
Public Adm & social security	0.013	-0.055***	0.003	-0.059***
Education	-0.042**	-0.106***	-0.110***	-0.144***
Health	-0.040*	0.015	0.034*	0.014
Other social services	0.091***	-0.011	0.063***	0.015
Education: ref. Lower secondary				
<= Primary	-0.012	0.009	0.019	0.065***
Upper secondary	0.010	0.014*	-0.017*	0.005
Post II non-III	-0.000	0.009	-0.025	0.008
Tertiary	0.051***	0.109***	0.024	0.061***
Contract type: ref. Full-time				
Part-Time	0.114***	0.160***	0.080***	0.143***

Labor exp.	0.001*	0.000	0.000	0.000
Contract length: ref. Temporary				
Permanent	-0.073***	-0.100***	-0.086***	-0.092***
Macro-area: ref. North-West				
South & Islands	0.040***	0.021**	0.035***	0.028***
North-East	-0.010	-0.007	-0.019*	-0.026***
Centre	0.005	0.008	0.011	0.008
Constant	0.201***	0.297***	0.270***	0.332***
R-squared	0.177	0.165	0.159	0.144
N	6276	7786	6678	7462
Mean RIF-Gini	0.287	0.267	0.298	0.29

Note: the Mean-RIF refers to the mean of our RIF outcome. In this case it is the Gini coefficient. For example, 0.287 is the Gini coefficient for women in year 2007.

Overall, our results cannot fully support the SBTC and RBTC predictions both in terms of occupational and educational estimates, while the role of proxies for labour market institutions suggests a potential pivotal role in shaping the wage distribution and its dynamics. As previously anticipated, the continuous expansion of alternative work-arrangements and its impact on production structure and wage dynamics may be a more relevant theoretical explanation compared to the SBTC and RBTC predictions.

However, this evidence is not sufficient to truly understand the real mechanisms behind the wage inequality dynamics. The subsequent complementary and necessary step to test the relevance of SBTC/RBTC and institutional factors is the Oaxaca decomposition whose outcomes will be discussed in the next section.

3.5.3 RIF-Oaxaca decomposition

The last part of our analysis focuses on the main drivers of change in income inequality by means of the Gini decomposition, through which it is possible to distinguish between the endowment characteristics and unexplained (wage) coefficients effects. For this purpose, we follow Firpo et al.'s contribution (2009, 2018) to estimate Equation (6), discussed in Section 3.3.3. Given that the Gini coefficient is a low-dynamic index, the most convenient approach is to evaluate the change over the extreme points of the selected decade, 2007-2017. To be concise, we present only aggregate results for the main variables, i.e., summing up all the coefficients of different categories (for example, the occupation effect is the sum of all occupation categories).[26]

Lastly, we use the same variables specified in our model for the reweighting approach according to which the counterfactual consists of reweighting the characteristics in 2007 with the ones in 2017 (or equivalently, the 2007 characteristics with the 2017 returns).

The decomposition for log wage differences between 90p and 10p, 90p and 50p, 50p and 10p, as well as for the Gini coefficient is reported in Table 3.2, while Figure 3.5 presents the log wage differences at each percentile.

Table 3.2: Oaxaca-RIF decomposition by gender

	Women				Men			
	90-10	50-10	90-50	Gini	90-10	50-10	90-50	Gini
Total Change	0.072*	0.097***	-0.025	1.111*	0.208***	0.207***	0.001	2.276***
Total Explained	0.139***	0.050**	0.088***	3.543***	0.158***	0.088***	0.069***	2.197***
Total Unexplained	-0.067	0.046	-0.113***	-2.432***	0.050	0.119***	-0.068***	0.079
Specification error	0.024	0.013	0.010	0.282	0.007	-0.006	0.014	-0.067
Reweighting error	-0.026	-0.012	-0.014	-0.61*	-0.017	-0.015	-0.003	-0.218
Explained								
Occupation	0.060***	0.017*	0.043***	1.551***	0.041***	0.020***	0.021***	0.689***
Sector	0.006	-0.004	0.010**	0.407***	0.008	0.011	-0.003	0.094
Education	0.013	0.003	0.009*	0.576***	0.021**	-0.003	0.025***	0.579***
Part-time	0.020***	0.011***	0.009***	0.401***	0.037***	0.032***	0.005***	0.415***
Labour experience	0.006	0.003	0.003	0.183**	-0.001	-0.004	0.003*	-0.007
Temporary	0.008***	0.005**	0.003***	0.127***	0.045***	0.040***	0.005***	0.524***
Regions	0.002	0.001	0.001	0.016	-0.002*	-0.001*	-0.001	-0.029*
Unexplained								
Occupation	-0.023	0.026	-0.114*	-0.215	-0.012	0.013	-0.025	-1.764
Sector	-0.297**	0.032	-0.093	-3.403*	0.106	0.079	0.027	-0.349
Education	-0.136	0.027	0.021	-1.973	0.049	0.089	-0.039	0.145
Part-time	-0.080**	-0.027*	-0.006	-0.535	-0.022	-0.021	-0.002	0.012
Labour experience	-0.114	0.035	0.032	-0.950	-0.034	-0.048	0.014	-0.046
Temporary	0.010	-0.067	0.029	-0.720	-0.038	0.027	-0.07	-0.199
Regions	-0.073	0.018	-0.030	-0.451	-0.018	0.001	-0.018	-0.278
Constant	0.671**	-0.030	0.062	6.424*	0.036	-0.007	0.043	2.775

[26] In this case we rely on the same reference base used for the RIF-OLS. This process does not affect our estimates of total differences, total explained effects and unexplained effects.

We can confirm that both the 90-10 and 50-10 gap increased over time, signalling that the bottom 10^{th} clearly lags behind. On the contrary, the dynamic of the distance between the median and the top end is irrelevant. Because of the fall in the bottom end of the distribution, the Gini coefficient also increases by 2.3 points between 2007 and 2017.

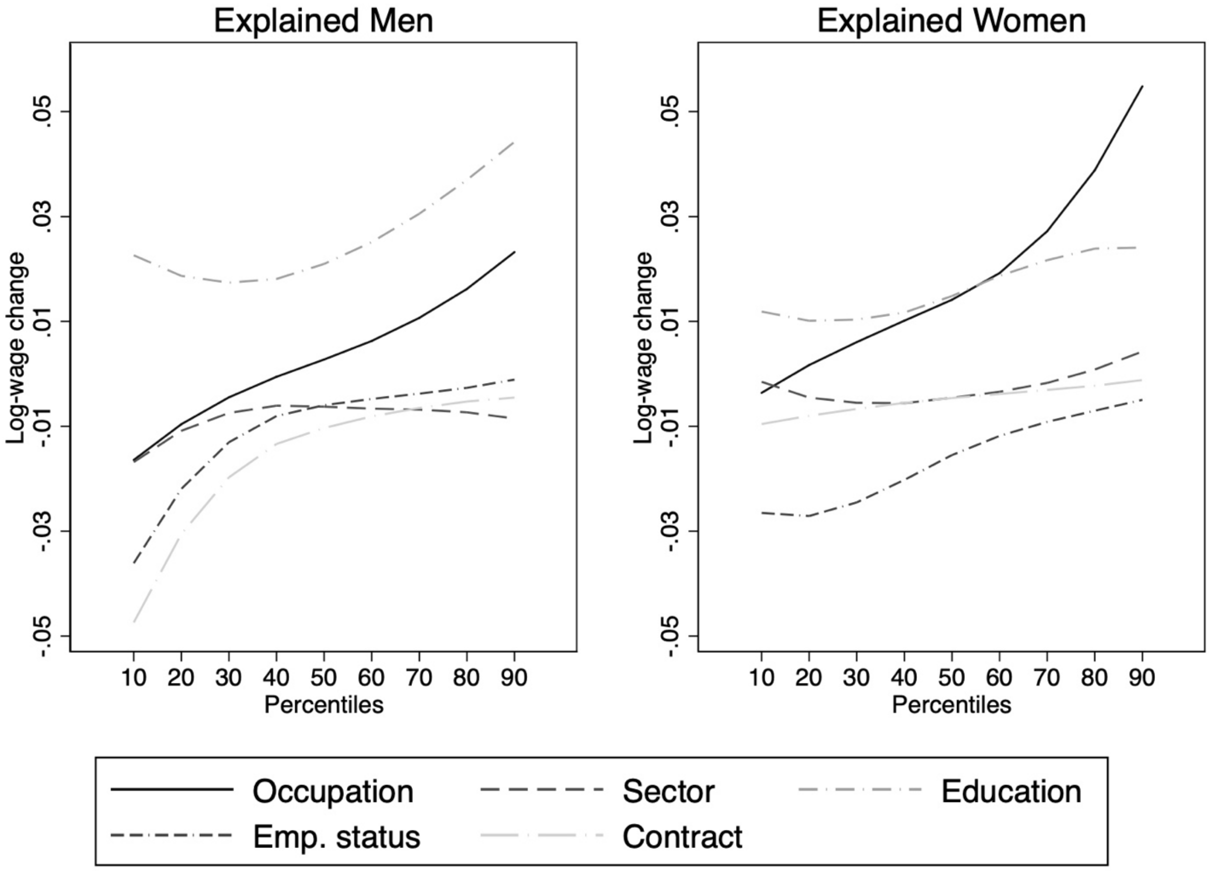
The composition effect, i.e., the differences in log wage due to differences in characteristics, explains most of the change during the decade, and specifically the 90-10 distance (76% for men and 193% for women), while it tends to be about the half in the 50-10 gap.

The decomposition analysis points to changes in the occupational structure and labour market institutions as the main factors in explaining changes across percentiles (**Errore. L'origine riferimento non è stata trovata.**), and specifically the 90-10 and 50-10 gap. More in details, for male workers in temporary jobs, changes in the occupational structure and working part time explain around 22%, 18% and 20%, respectively, of the total log wage difference between the 90^{th} and the 10^{th} percentiles. However, differently from men, the difference among women is mostly explained by occupations, and to a less extent by part-time and temporary employment. This is coherent with the gendered structure of occupations, with women employed mostly at the extremes of the occupational distribution.

The 50-10 wage difference for men is mostly determined by contractual arrangements, and to a lesser extent by the occupation of employment. The results for women are similar to the 90-10 difference.

Figure 3.5 presents graphically the results in Table 3.2. Each point along a selected line represents the log-wage change at each percentile due to the selected covariate. Therefore, if we consider the 90-10 gap for men in temporary employment (0.045 in Table 3.2), we should take the difference between the point estimate at 90^{th} percentile (-0.0047) and the point estimate at the bottom 10^{th} (-0.0499) on the ‘Contract’ curve.

Figure 3.5: Detailed explained effects by gender



Source: authors' elaboration on EU-SILC data

The analysis for the Gini coefficient confirms these results. Changes in the occupational structure account for the highest share in explaining the increase in wage inequality, with the effect for women being stronger. Although the role of education is marginal in explaining the 90-10 and 50-10 gap for men (and even non-significant for women), it turns to be comparable with part-time effects in the case of Gini decomposition. However, the combined effects of part-time and temporary characteristics – i.e., our proxies for labour market institutions – outweighs the role of education for both men and women. Lastly, the coefficient effects are generally not significant, and are reported in the bottom part of Table 3.2.

Overall, we confirm the hints provided by the static analysis in Section 3.5.1 and 3.5.2, with occupational structure and labour market institution proxies being the most important determinants in explaining the wage inequality over time, contrary to the main predictions of the SBTC theory.

3.6 Conclusions

In this paper we do not infer any causal effects, but we investigate the main structural contributions to wage inequality dynamics in Italy between 2007 and 2017. Starting from some stylised facts concerning the Italian labour market – a sharp increase in the share of temporary contracts, involuntary part-time work, working poor and the increase in low-added-value occupations – we firstly review the main reforms that directly affected the labour market. Following a discussion of these reforms, which are the key ingredients of the neoliberal and European recipes for the economy, we discuss the current literature on how Italy stands regarding occupational changes i.e., whether the Italian labour market has downgraded, upgraded, or polarised.

Although the existing literature is contradictory, we observe clear wage (and occupational) downgrading over the decade between 2007-2017, with the bottom 10% the most penalised, suffering a wage loss (in real terms) of about 20%, compared to 6% for the top 90%. This wage compression is coherent with the expansion of low-added-value occupations – elementary occupations and service workers – at the bottom of the wage distribution. Consequently, in the 2007-2017 decade, we observe an increase in wage inequality (+2pp in the Gini coefficient).

To answer the research question about the determinants of the increase in wage inequality, we follow Firpo, Fortin and Lemieux (2009, 2018), and use RIF-OLS (unconditional quantile regressions) together with Oaxaca decomposition. In this way we are able to firstly verify the effects of our main predictors on different percentiles and on the measure of overall inequality and then identify the main determinants behind inequality changes over time.

This exercise reveals that the top occupations (managers and professionals) experience positive monotonic returns on labour incomes for both male and female workers. Conversely, the expansion of middle to low occupations such as elementary workers and service workers has a strong negative association with the log wages at the bottom 10%. These results imply an inequality-enhancing effect that can be mostly explained by occupational downgrading, which is incompatible with both SBTC and RBTC predictions. Furthermore, in terms of education, we observe higher Gini coefficients as a consequence of an increase in the share of highly educated workers (irrespective of gender). However, these results are only partially coherent with SBTC, as the magnitude is decreasing over time, suggesting that education may not be the unique and/or most important factor in shaping wage inequalities.

Therefore, other theoretical mechanisms – mostly related to the labour market institutional changes – may better fit the Italian case. Indeed, the continuous expansion of non-standard work arrangements i.e., part-time and temporary contracts, reduce the workers' bargaining power and leads the employers to focus on costs-compression, which may result in occupational and wage downgrading. Coherent with this strand of literature, our findings confirm that labour market institutions matter and are the main driver of changes in labour income, especially at the bottom of the distribution. Indeed, in line with the existing literature (Naticchioni et al., 2016; Raitano and Fana, 2019; Rosolia and Torrini, 2016; etc.), both part-time arrangements and temporary contracts have strong depressing effects on log wages, especially at the bottom of the distribution, thus determining a strong rise in inequality. The generalised negative effect on wages induced by non-standard contractual arrangements is not gender neutral. For instance, men lose more compared to women, which also means that the associated reduction in the gender wage gap hides a generalised impoverishment of the labour force, not an improvement in living conditions for female workers.

The complementary results from the Oaxaca-Blinder decomposition reveal two important messages. First, looking at both the Gini coefficient and log wage differences at different points of the distribution, differences in characteristics explain most of the increases in wage inequality. Secondly, and more importantly, changes in the occupational structure are the main source of the widening log wage difference between the 90th and the 10th percentile (as well as for increasing Gini coefficient), with a stronger effect for women. As noted by Firpo, Fortin and Lemieux (2018), this result confirms that increasing attention must be given to the role of occupational tasks and their impact on wage distribution. Moreover, contractual arrangements, i.e., temporary vs permanent contracts and part-time vs full-time, play roles that are just as important as determinants of wage inequality, especially for men.

Education levels explain changes in the log wage differences only in a residual fashion, limited to men, while they account more for the increase in the Gini coefficient i.e., a higher share of workers with higher education significantly contributes to explain the increase in the Gini coefficient. However, the combined effects of part-time and temporary characteristics outweigh the role of education for both men and women.

All in all, our results seem to confirm more the "heterodox" approach to labour market inequality, seen as the combined result of both occupational and institutional changes.

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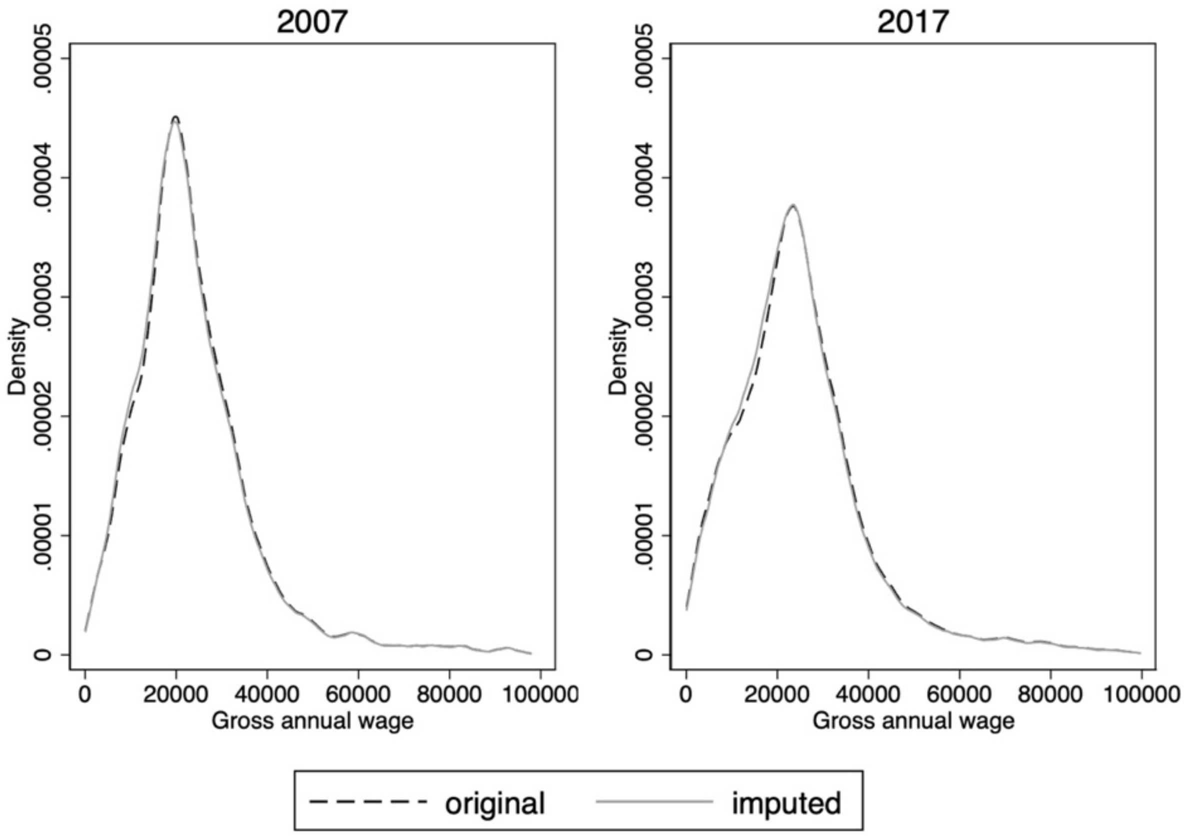
3. Appendix

Table A.3.1: employment distribution by main variable over time

	2007	2011	2014	2017
Occupation				
Legislators & Managers	1.8	2.4	1.3	1.4
Professionals	10.2	14.7	15.5	16.5
Technicians & Associate Prof.	23	16.8	16.7	17.6
Clerks	14.9	16.7	16	14.8
Service Workers	11.3	15.5	16.1	16.7
Skilled agricultural workers	1	0.8	0.9	0.9
Craft & related trade workers	15.7	14.3	15.3	13.2
Machine operators	11.6	7.6	6.9	7.1
Elementary occupations	10.5	11.2	11.3	11.8
Total	100	100	100	100
Sector				
Primary	2.6	2.6	2.1	3.1
Mining, Manufacturing, Utilities supply	26.8	24.1	24.1	22.6
Construction	7	6.3	5.8	6.7
Wholesale & Retail	10.9	12.6	11.8	11.6
Accomodation	3.1	4.9	4.7	5.3
Transport storage & communication	5.8	7.7	7.6	7.9
Financial intermediation	3.4	3.7	3.6	3.3
Real estate & business activity	6	7.8	8.5	8.7
Public Adm & social security	8.2	7.8	6.6	6.3
Education	9.7	8.7	8.9	9.4
Health	8.1	8.6	8.9	9.1
Other soc. Services	8.5	5.2	7.4	6
Total	100	100	100	100
Contract length				

Part-time		12	15.9	16.1	15
Full-time		88	84.1	83.9	85
	Total	100	100	100	100
Contract type					
Temporary		13.3	13.9	14.4	16.6
Permanent		86.7	86.1	85.6	83.4
	Total	100	100	100	100
Gender					
Female		43.3	44.7	45.6	45.4
Male		56.7	55.3	54.4	54.6
	Total	100	100	100	100

Figure A.3.1: Original and imputed wage distributions in 2007 and 2017.



Note: the Gini coefficient computed on the original distribution in 2007 is 0.305 and 0.307 with the imputation. In 2017 these values are 0,338 vs 0.335.

Table A.3.2: Annual gross income – percentiles and ratios

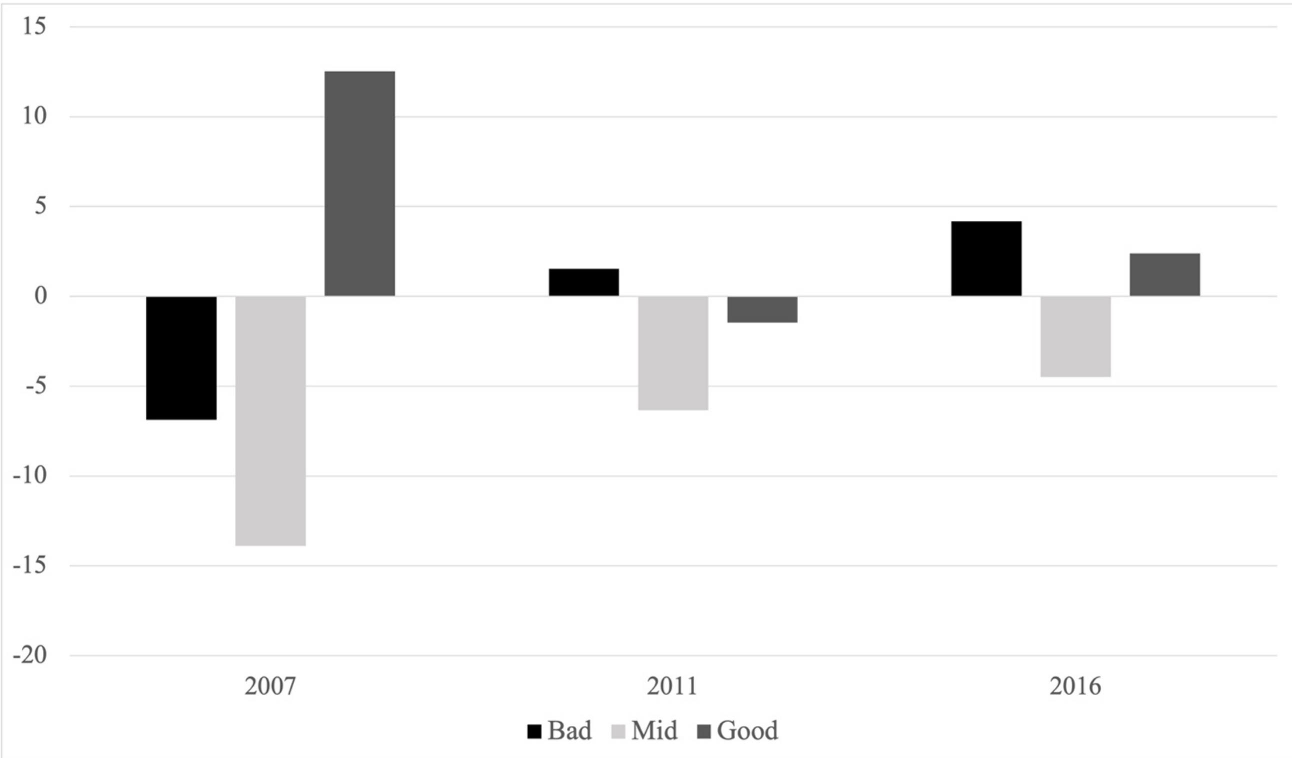
	p10	p50	p90	p90/p10	p90/p50	p50/p10
2007	10,997	24,155	43,001	3.91	1.78	2.20
2011	9,114	23,755	42,614	4.68	1.79	2.61
2014	9,028	23,396	41,674	4.62	1.78	2.59
2017	8,798	22,863	40,739	4.63	1.78	2.60

Table A.3.3: Summary statistics (%)

	2007			2011			2014			2017		
decile	*p10*	*p50*	*p90*	*p10*	*p50*	*p90*	*p10*	*p50*	*p90*	*p10*	*p50*	*p90*
Occupation												
Legislators & Managers	0.8	0.9	1.4	0.5	0.7	2.3	0.6	0.3	1.5	1	0.6	0.8
Professionals	4.7	5.0	18.1	6.8	9.6	26	7.6	8.8	27.2	9	9.9	23.5
Technicians & Associate Prof.	14.7	19.7	35.8	7.5	14.8	28.9	8.2	14.1	26.7	10.7	16.5	26.4
Clerks	12	15.8	15.9	10.4	20.1	18.6	10.7	22.8	17.4	9.6	18.5	18.7
Service Workers	20.4	11.8	7.2	27.3	16.4	7.3	27.7	16	7.6	27.6	17.1	10
Skilled agricultural workers	3.1	0.9	0.2	2.2	1.1	0	2.6	1.2	0	1.7	1.2	0.2
Craft & related trade workers	13.9	20.5	8.7	12.3	18.7	8.8	13.5	19.8	10.6	10.8	17.8	8.8
Machine operators	5.8	15.5	10.3	4.5	9.2	6.3	3.6	8.3	7	4	7.8	7.9
Elementary occupations	24.6	10.1	2.4	29.2	9.6	1.8	25.5	8.8	2	25.7	10.4	3.6
Total	100	100	100	100	100	100	100	100	100	100	100	100
Sector												
Primary	10.6	1.8	0.7	9.1	1.5	0.9	6.7	1.3	0.5	7.6	2.2	1.2
Mining, Manufacturing, Utilities supply	16	33	23.5	14.8	24.6	24.6	12.5	25.9	28.1	15.1	24.1	26
Construction	5.7	8.9	2.9	6.7	7.9	2.3	5.2	7.3	2.7	5.7	8.4	3.8
Wholesale & Retail	11.6	13.7	5	16.1	17.2	7.3	11.4	16.5	6.6	11.7	13.2	8
Accomodation	9.7	3.1	0.9	12.3	4	0.9	13.4	4	1.2	12.3	5.2	1.5
Transport storage & communication	2.7	4.6	7.2	3.8	6.7	12	4.2	6.6	10.6	4.5	6.4	11.5
Financial intermediation	1.4	1.7	6	1.2	1.1	6.4	1.3	1.4	6.1	1.9	1.3	5.8
Real estate & business activity	8.2	5.2	4.4	10.2	7.6	5.1	13.6	8.7	5.5	13	7.1	5.9
Public Adm & social security	4.9	5.6	16.2	3.2	7.6	14.2	1.3	7.2	15.6	1.6	6.9	12.3
Education	5.4	10.6	18.3	5.3	9.3	15.2	5.6	8.8	13.6	6.2	9.6	13.3
Health	4.9	7	11.8	5.3	9.1	7.8	6.9	9	6.9	6.3	10.9	8.6

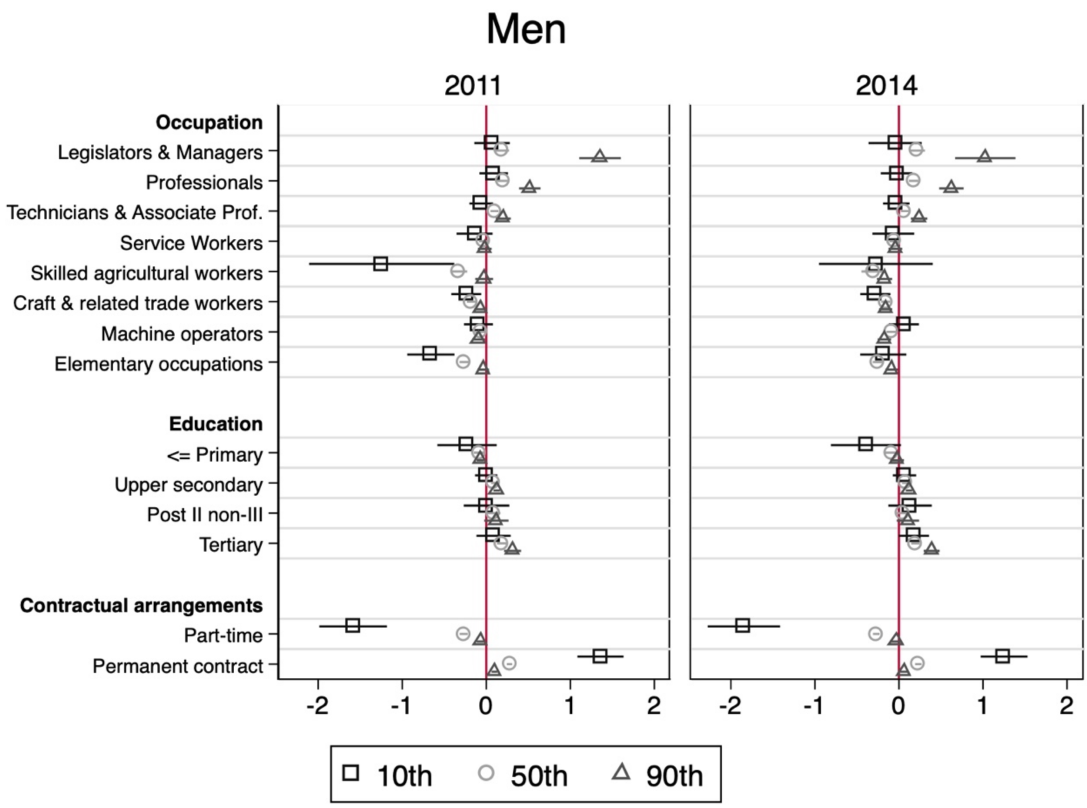
Other soc. Services	18.9	4.8	3.3	12.1	3.2	3	17.9	3.1	2.5	14.2	4.7	2.1
Total	100	100	100	100	100	100	100	100	100	100	100	100
Gender												
Female	67.5	42.4	36.7	63.3	45.3	34.8	63	47.1	35.4	61.2	48.4	32.8
Male	32.5	57.6	63.3	36.7	54.7	65.2	37	52.9	64.6	38.8	51.6	67.2
Total	100	100	100	100	100	100	100	100	100	100	100	100
Contract type												
Part-time	49.8	4.9	1.6	47.6	7.6	2.1	48.7	9.7	1.6	39.2	7.6	1.9
Full-time	50.2	95.1	98.4	52.4	92.4	97.9	51.3	91.4	98	60.8	92.4	98.1
Total	100	100	100	100	100	100	100	100	100	100	100	100
Contract length												
Temporary	47.6	9.9	3.6	48.4	119	1.5	47.8	9.7	1.6	42.7	13.9	2.1
Permanent	52.4	90.1	96.4	53.6	89	98.5	52.2	90.3	98.4	57.3	86.1	97.9
Total	100	100	100	100	100	100	100	100	100	100	100	100

Figure A.3.2: Employment share (%) by terciles of job – bad, mid, good jobs



Note: estimates based on Labour Force Survey data following job approach presented in H*urely et al. (2019)*

Figure A.3.3: RIF estimates at 10th, 50th and 90th by gender in 2011 and 2014.



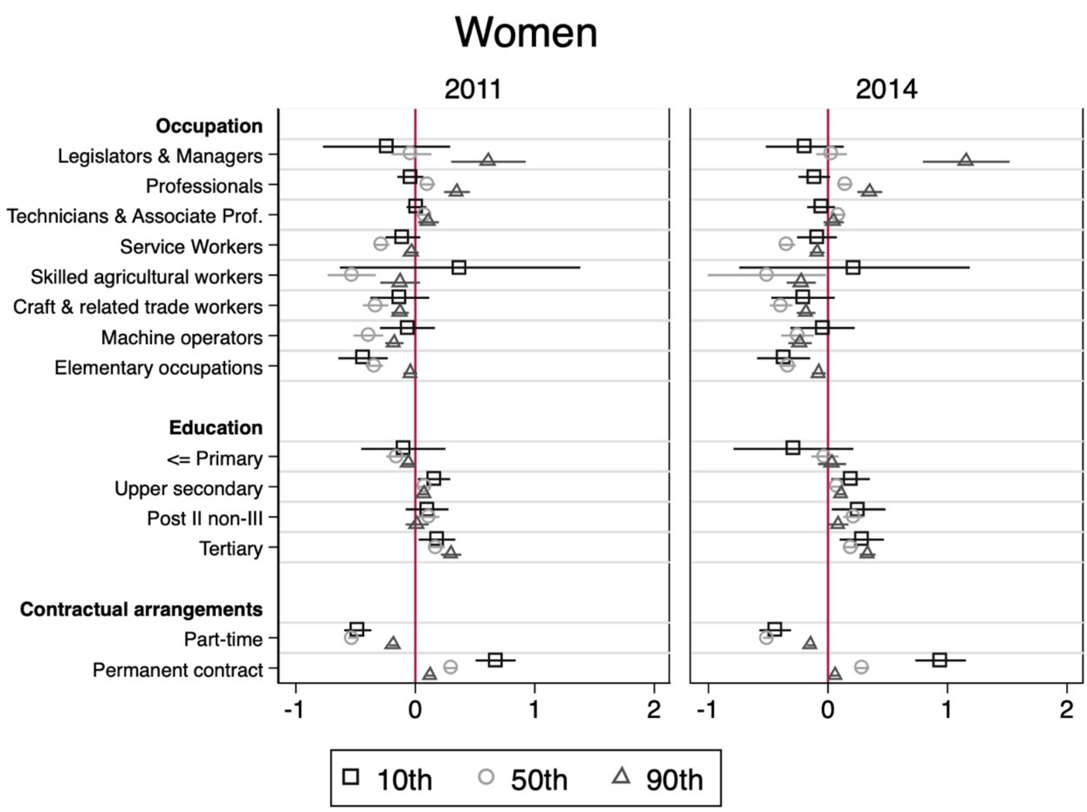


Table A.3.4: RIF Gini estimates by gender for 2011 and 2014

	2011		2014	
Gini	Women	Men	Women	Men
Occupations: ref. Clerks				
Legislators & Managers	0.217***	0.287***	0.333***	0.235***
Professionals	0.085***	0.091***	0.121***	0.124***
Technicians & Associate Prof.	0.019	0.035***	-0.002	0.041***
Service Workers	0.055***	0.027*	0.047***	0.028*
Skilled agricultural	0.012	0.162***	0.005	0.072*
Craft & related trade workers	0.017	0.038***	0.023	0.014
Machine operators	0.009	0.008	-0.015	-0.023*
Elementary occupations	0.112***	0.086***	0.090***	0.054***
Sectors: ref. Wholesale & Retail				
Primary	0.127***	0.076***	0.149***	0.088***
Mining, Manufacturing, Utilities	0.039**	-0.015	0.041**	-0.013
Construction	0.041	0.016	0.030	0.038**
Accommodation	0.057***	0.055**	0.103***	0.037*
Transport, store & communications	0.032	-0.008	0.033	-0.010
Financial intermediation	0.121***	0.097***	0.163***	0.042
Real estate & business activities	0.028*	0.013	0.054***	0.011
Public Adm & social security	-0.005	-0.053***	-0.021	-0.082***
Education	-0.089***	-0.106***	-0.111***	-0.110***
Health	0.002	0.019	0.037*	-0.015
Other social services	0.060***	0.032	0.094***	0.032
Education: ref. Lower secondary				
<= Primary	0.017	0.037*	0.032	0.036
Upper secondary	-0.012	0.016*	-0.002	0.006
Post II non-III	-0.014	0.027	-0.025	0.000
Tertiary	0.040***	0.045***	0.036**	0.033**
Contract type: ref. Full-time				
Part-Time	0.108***	0.189***	0.099***	0.211***
Labor exp.	0.000	-0.001	0.000	-0.000
Contract length: ref. Temporary				
Permanent	-0.084***	-0.142***	-0.116***	-0.134***
Macro-area: ref. North-West				
South & Islands	0.048***	0.03***	0.053***	0.035***
North-East	-0.012	-0.006	-0.021*	-0.017*
Centre	0.021*	0.016	0.018	0.007
Constant	0.262***	0.343***	0.271***	0.339***
R-squared	0.198	0.233	0.212	0.216

N	5696	6493	5776	6343
Mean RIF-Gini	0.303	0.277	0.306	0.279

Table A.3.5: RIF P90-P10 coefficient by years and gender

P90/P10 ratio	2007		2011		2014		2017	
	Women	Men	Women	Men	Women	Men	Women	Men
Occupation: ref. Clerks								
Legislators & Managers	1.294	2.103***	4.114***	5.513***	6.240***	4.597***	4.519***	5.177***
Professionals	2.072***	1.795***	1.855***	1.826***	2.151***	2.794***	2.028***	2.561***
Technicians & Associate Prof.	0.288	0.597**	0.467	1.141***	0.493	1.164**	0.884*	1.043**
Service Workers	0.884*	0.664	0.382	0.560	0.031	0.107	1.251**	0.287
Skilled agricultural workers	4.269	0.095	-2.499	5.549**	-2.081	0.451	-3.089	1.047
Craft & related trade workers	0.333	0.031	0.064	0.788	0.150	0.536	1.269	-0.788
Machine operators	-0.096	-0.717***	-0.493	0.029	-0.857	-0.999*	-0.357	-1.420***
Elementary occupations	2.170***	0.792*	2.020***	2.845***	1.415*	0.435	2.287***	1.853**
Sectors: ref. Wholesale&Retail								
Primary	4.396***	2.775***	4.454***	4.033***	6.958**	5.617***	3.450*	3.094***
Mining, Manufacturing, Utilities supply	1.328***	-0.122	0.526	-0.620	0.631	-0.252	0.162	0.691
Construction	1.151	0.050	0.998	0.784	0.359	1.144	0.872	0.553
Accommodation	2.707***	-0.685	1.411	2.528*	3.509***	1.474	0.585	1.338
Transport storage & communication	1.351*	-0.112	1.123	-0.134	0.658	0.366	0.965	0.229
Financial intermediation	3.354***	2.047***	3.302***	2.587***	3.865***	1.323*	3.113***	1.972**
Real estate & business activity	1.580***	-0.608	0.356	-0.259	0.632	0.350	0.720	0.396
Public Adm & social security	1.161**	-1.283***	-0.157	-1.062*	-0.343	-1.828***	0.066	-1.096*
Education	-0.018	-2.313***	-1.984***	-3.037***	-1.878**	-2.687***	-1.474***	-2.937***
Health	0.697*	-0.645	-0.749	0.031	0.460	-0.199	-0.066	-0.294
Other soc. services	2.584***	-0.283	2.055**	1.626	1.719**	2.212	1.365*	1.492
Education: ref. Lower Secondary								
<= Primary	-0.003	-0.037	0.244	0.727	1.529	1.607	-0.390	3.170**
Upper secondary	-0.098	0.232	-0.443	0.545	-0.386	0.231	-0.807*	0.035
Post II non-III	-0.134	0.356	-0.429	0.504	-0.827	-0.114	-0.551	0.943
Tertiary	0.370	1.409***	0.498	0.952	0.180	0.900*	0.120	1.492**
WorkingHours: ref. FullTime								
Employed PT	2.640***	4.960***	1.575***	6.913***	1.436***	7.848***	0.949**	4.804***
Experience	0.007	-0.002	0.005	-0.029	-0.013	0.006	-0.011	0.000
Contract: ref. Temporary								
Permanent	-2.210***	-2.968***	-2.816***	-5.750***	-4.204***	-5.132***	-2.750***	-3.206***

Macroarea: ref. NorthWest								
Sud & Isole	1.498***	0.550**	1.579***	1.145***	2.323***	1.527***	1.143**	1.120**
Nord-est	0.001	-0.077	-0.239	-0.117	-0.439	-0.390	-0.195	-1.018**
Centro	0.564**	0.106	0.400	0.274	0.486	0.053	0.335	0.165
Constant	2.855***	5.293***	5.085***	7.663***	6.313***	6.547***	5.266***	5.135***
R-squared	0.142	0.146	0.106	0.174	0.134	0.183	0.074	0.112
N	6276.000	7786.000	5696.000	6493.000	5776.000	6343.000	6678.000	7462.000

Figure A.3.4: Total differences, total explained and unexplained of the log-wage decomposition by gender

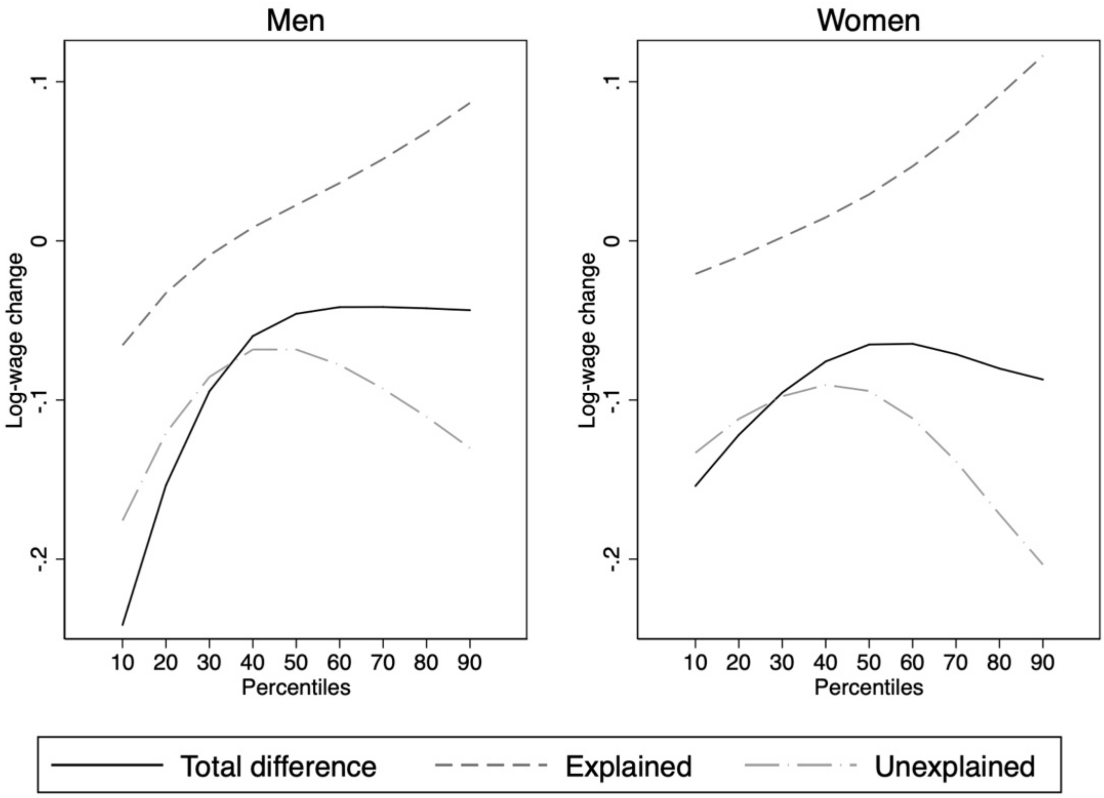
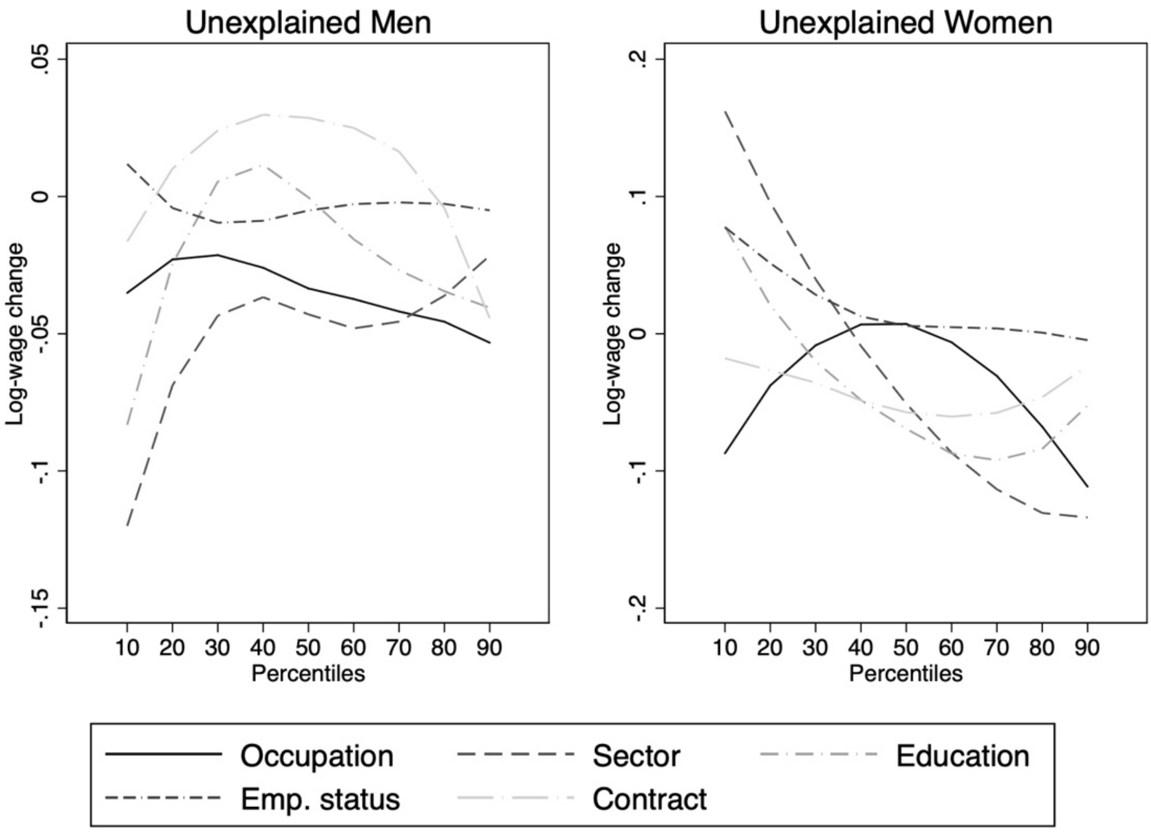


Figure A.3.5: Detailed unexplained covariates by gender



Source: authors' elaboration on EU-SILC data

4. Social Class origin and income variations among degree holders: evidence from Italy

Abstract

The role of educational attainment in intergenerational social mobility has been widely discussed in the sociological literature, but mostly in its vertical dimension. There is much less work on the role of the horizontal dimension of education, the one defined by fields of studies within educational levels. This paper investigates the role of educational fields in the intergenerational transmission of advantage among Italian university graduates, and if the impact of social origins on the wages they earn in the first occupation varies by different fields of studies.

Using a large sample of Italian university graduates, we test whether graduates' class of origin is stronger in "soft fields"—like humanities, economics, social sciences, and law—than in "hard" ones—engineering, architecture, sciences, medicine. We observe that individuals with a privileged background who graduated in economics & statistics, law, and other social sciences earn around 3-4% higher wages than their socially less advantaged counterpart. The cases of the humanities and medicine represent important exceptions in the role that the class origin plays within the soft and hard fields, respectively.

Keywords: social class direct effect; horizontal education; wage heterogeneity.

4.1 Introduction

The role of educational attainment is widely discussed in the sociological literature on social stratification and mobility. There exist competing theories about how the vertical dimension of educational attainment, manifesting in different levels, affects the intergenerational transmission of inequalities, using the so-called (O)rigin-(E)ducation-(D)estination triangle[27]. The discussion focuses on whether such vertical dimension of education is or is not a "great equalizer" (Bernardi and Ballarino, 2016; Bukodi et al., 2016; Fiel, 2020; Torche, 2011; etc.).

According to the modernization-theory (e.g., Bell, 1972; Blau and Duncan, 1967; Treiman, 1970; Treiman and Terrell, 1975), as the economy develops and new and more technologies are required by the production system, the demand for high-skilled workers will increase. This functionalist argument sees the "democratization" – i.e., expansion – of education, and specifically of secondary and tertiary education, as a key levelling mechanism in advanced societies. Because of such democratization, the O-E path should weaken (and the E-D path would be strengthened), as all resources, and especially human, need to be more efficiently developed/employed whichever their location in the class structure. Therefore, according to the modernization theory, class disadvantages would cease to be transmitted via education (Breen et al., 2009), as its mediating power increases over time in more advanced societies, leading to a decrease in the total effect of social origin on destination.

However, Erikson and Goldthorpe (1992) did not find any increased social fluidity (freer intergenerational movements up and down the social hierarchy) over time across industrial and post-industrial societies. Other, more recent evidence also suggests that education is not a great-equalizer, and that social origins still play a significant role on individuals' destinations and outcomes (Bernardi and Ballarino, 2016; Bernardi and Gil-Hernández, 2021; Fiel, 2020; Gugushvili et al., 2017; Laurison and Friedman, 2016; Torche, 2011; etc.). Studies in Italy (Barone (2009); Esping-Andersen and Wagner (2012); Raitano and Vona, (2015)), the UK (Bukodi et al., 2021; Bukodi et al. (2016) and Bukodi and Goldthorpe (2013), or Sweden (Erikson, 2016), show that this is due to

[27] It is the most popular tool for studying social class mobility: it places the (vertical) dimension of education between the direct path from class of origin and the destination outcome.

a constant and persistent inequality of educational opportunity. Furthermore, other mechanisms like unobserved characteristics linked to the social background (e.g., personality traits, cognitive skills) and/or labour market imperfections (e.g., employers' discrimination and/or social networks) may weaken the mediating power of educational attainment.
Yet, the evidence is inconclusive, as other studies do find a decrease in the role played by social origins on educational attainment (e.g., Marks, 2014).

Could this conflicting evidence about the mediating role of education on the transmission of inequalities be due to the role be that another, more horizontal dimension of education, has on such transmission? By the horizontal dimension it is typically meant the existence of fields or areas of study within each educational level, but especially at the mid and higher levels, which are associated with different outcomes. Depending on the strength and sign of the association between social class of origin and fields of studies, the horizontal dimension could then have different effects on the destination outcome. If individuals' social backgrounds influenced the choices they make of fields of studies, and if such fields led to differently desirable outcomes, then inequalities could be transmitted via this horizontal dimension. Conversely, if such association between class of origin and field of study did not exist, as some evidence appears to suggest (Jackson et al., 2008), inequalities could not be transmitted through the choice of fields of study even if these were associated with alternative outcomes.

But would the absence of an association between class of origin and fields of study mean that the latter do not play any role in the transmission of inequality? In this paper, we consider the possibility that fields of study may still play such a key role by moderating the effect of social class on destinations, instead of by mediating its transmission through the choice of fields. Our focus is not on inequalities in educational attainment (in particular, in the choice of fields of study) but in how the economic outcomes of the individuals choosing some fields instead of others on a meritocratic basis may still depend on their class of origin. This moderating role of fields of studies in the association between social class and destinations might help explain the inconclusive evidence on the role of education in reducing social inequalities even in the presence of strong processes of educational expansion and democratization.

Our main research questions are: does the impact of social origin on first-occupation wages vary according to the field of study chosen by high-degree holders in Italy? If so, which may be the factors accounting for these variations? To our knowledge, this is the first paper attempting to evaluate the degree of intergenerational social mobility in Italy considering the role of the horizontal dimension of education in the OED triangle, and the first to assess alternative explanations for the interaction effects between class of origin and fields of study on wages. The paper is structured as follows. It firstly reviews the available theoretical arguments and empirical evidence on the role of the horizontal dimension of education in the transmission of inequalities. Secondly, it discusses the possible sources of any differences in the impact of class of origin on destinations according to field of studies, from which several research hypotheses are raised. Next, we introduce the data and the methodology adopted in the study and provide some preliminary descriptive evidence on the relationship between class of origin, fields of study, and wages. It follows the presentation of the main results of the study. The paper concludes with a discussion of its main findings.

4.2 Horizontal education and the intergenerational transmission of inequalities

Following Shavit and Blossfeld (1993) contribution on the "persistent inequality", a significant theoretical debate emerged. Raftery and Hout (1993) introduced the concept of "Maximally Maintained Inequality" (MMI). According to them, the inequality of education may persist even in the presence of strong educational expansion if the "saturation point" by which the upper and middle classes occupy the top spots has not been achieved, due to the parents and children of these classes mobilizing their higher available resources – financial, cultural, and social – to monopolize the best educational outcomes. At any given level of educational expansion there are fixed numbers of available top-educational spots, which are firstly occupied by the privileged classes. The available spots for the children of the other classes may vary over time depending on the demand from the high-classes and/or the number of available spots. Therefore, according to the MMI, if the demand for these spots is higher than the available educational offer, we will still observe persistent educational inequalities and an effect of social origin on the labour market. On the contrary, if the enrolment rates at higher levels are higher than the demand, we may observe a lowering of educational inequalities.

Lucas (2001) revised the MMI theory and introduced the "Effectively Maintained Inequality" (EMI) argument. Contrary to the MMI thesis, Lucas' theory implies that once the privileged classes' demand for the highest spots is saturated at a given level of education (quantity), they may still obtain further educational advantages, especially related to its quality, but also by adding further, higher levels, which can result in persisting inequalities, contrary to the MMI prediction.

One important mechanism for effectively maintaining inequalities consists of parents influencing the choice of educational fields within the same educational level, when these fields are associated with alternative returns.

The existing evidence about how educational fields affect the intergenerational transmission of inequality is limited. Triventi et al., (2017) focused on the origin-educational field association in Italy. They observed partial evidence for the Effectively Maintained Inequality theory, with social origin playing a significant role in children's choice of fields like medicine and law that could be associated with better outcomes, but the overall strength of such association was quite low. Vvan de Werfhorst (2002) observed that in the Netherlands children tend to choose the educational field that is more closely related to the social class of their parents and that once educational fields are introduced in the OED triangle, the DESO (direct effect of social origins on children's destinations, the one net of the attained level of educational) becomes smaller. However, a subsequent and more comprehensive study by Jackson et al. (2008) on the effects of educational fields on the intergenerational transmission of social inequality in European countries (UK, Germany, Netherlands and France), concluded that there are not any relevant effects of educational fields on the OED triangle; the mediating power of education does not increase once the fields of studies are added, and the direct effect of social origin remains basically unchanged. They argue that the main reason behind this evidence is the lack of a significant association between social class of origin and fields of studies. These findings partly refute Lucas' EMI theory, at least that part in which the differences in the quality of education attached to different fields play a key role.

That educational fields do not play any additional mediating role in the OED triangle does not mean that they may not moderate the impact of the class of origin on destinations, strengthening it in some cases. As mentioned in the introduction, the social class of origin may have negligible (or even negative) effects in some fields but provide a further direct advantage in others. Following this argument, Hansen (2001) observed that in Norway the graduates with a privileged background had an income advantage if they graduated in fields like humanities, economics, law and social sciences. These fields are often labelled "soft-fields" (Biglan, 1973). Similarly, Laurison and Friedman (2016) found supporting evidence for the moderating effect of fields of study in the UK. Individuals with a high-class background had a boosting-income effect in high-status occupations – professionals and managers – in the fields of medicine, law, and economics. Valuable as they are, these studies do not consider which factors may account for this interaction effect.

4.3 Interaction effects on wages of social origins and fields of studies

What is the reason for the interaction effects between social class of origin and field of studies on destination, and more specifically, on wages? Why should individuals with the same level of education and field of study, but different social background, earn different wages?

According to the standard marginal theory, the economic rewards should be linked to the productive capacity of each production input. It follows that the wages should reflect the productivity of each worker. Since the marginal productivity is not easily observable, it is common to link it to individuals' educational qualifications. The proponents of the human capital theory (Becker, 1964; Mincer, 1958) argue that, as individuals rationally plan their educational investments, they expect to increase their productivity and, in turn, their economic rewards. Educational qualifications are thus defined as a guarantee/warrant of a given level of productivity.

In this classical view, employers have no role in defining workers' productivity. In the alternative screening and signalling theory (Dobbs et al., 2008; Spence, 1973; Stiglitz, 1975) both employers and employees' rational behaviours are considered. As in the human capital classical theory, in the signalling theory employers cannot observe the productive capacity of the workers they want to hire, so they sign the work contracts with limited information. In making their hiring decision, employers rely on workers' educational qualifications, not as a guarantee of productive capacity, but as a means to sort and screen potential candidates based on their *potential* abilities and adequacy to fulfil the job requirements. Educational qualifications are not deterministically linked to productivity – as argued by the human capital theory – but rather signal to the employers, workers' potential productivity. It follows that workers do not value education as an investment per se, but as a tool with which to signal their potential productive value. It could be argued, in line with the screening-signalling theory, that workers' signalling power varies across different fields of studies.

Biglan (1973) distinguished fields of studies according to Kuhn (1962) definition of a paradigm, and more specifically, to whether or not "a body of theory is subscribed to by all members of the field". Paradigmatic fields are those characterized by a high consensus about the content and methods of the field. Biglan (1973) found that paradigmatic fields mostly encompass "hard fields" like physics, mathematics, engineering, and all natural sciences. In non-paradigmatic fields graduates are often required to display a more general type of skills than graduates from the hard fields. Signalling the potential productivity of a worker with such skills may be difficult, or employers may find it hard to evaluate it. On the contrary, workers in "hard" fields may better signal their potential productivity to the employers and their adequacy to their specialised requirements. Because of soft fields' lower signalling power, employers may rely on additional sources of information when hiring workers in these fields. A common and important source of information on individuals' productivity is their social class of origin, since higher backgrounds provide workers with economic, cultural, and social resources that may be useful at work (Goldthorpe, 2014; Jackson et al., 2005). Therefore, our first hypothesis (H1) states that *fields of study will moderate the impact of social origin on wages, which should be stronger in non-paradigmatic fields of studies.*

Charles and Grusky (2004) argued that the labour market is characterized by high vertical and horizontal gender segregation both in the demand and supply-side of the labour market. In the demand side, there is employers' discrimination against women; in the supply side, the internalized preferences and self-evaluation that guide women's investments decisions. Both create "occupational ghettos" along vertical and horizontal lines of differentiation. According to the authors, *gender essentialism* imbues horizontal segregation, fostered by cultural and institutional stereotypes, which lead to consider women as being more valuable in some sectors – the ones filled by women – like nurturing or education – and less in others. On the vertical dimension, a *male primacy* conception explains why men are perceived to be worthier than women in high-power positions. Reskin (2000) relied on social cognition theory to explain the roots of such gender discrimination in the labour market: women's categorization and the consequent application of stereotypes about what they can do explain such discriminatory behaviour. Kaufman (2002) combined gender stereotyping with the queuing theory for filling job vacancies (Thurow, 1976). Employers rank candidates along a queue and rely on categorizations (and attached stereotypes) to select the best candidates. Gender categorizations and stereotypes act as proxies to judge the fit for the vacant job, i.e., whether women are appropriate for it. In loose labour markets employers select their best preferences – typically white men – for the highest ranked jobs, but in tight labour markets the discriminated groups may have access to the high-ranked jobs, and segregation decreases. In these tight markets, or more generally in fields and occupations where a discriminated group has a higher chance of being hired, women in the queue may rely on additional sources of individual signalling – like their social origin class – to reduce over-simplifications and biases about their productivity induced by patriarchal categorizations and stereotyping, which apply equally to all women. In patriarchal societies, women's personal worth may be at least partly established by their father's. Consequently, our second alternative hypothesis (H2) is that *employers rely more on father's class to evaluate candidates' potential productivity in female-dominated fields.*

In addition to these two main competing hypotheses, we contemplate other possible reasons for the presence of an interaction effect between social class of origin and field of studies on workers' wages. Two of them, have to do with the characteristics of the occupations filled by the workers in different fields. One hypothesis (H3) is that there may be *stronger inter-generational processes of occupational inheritance in well-established, traditional fields than in more recently developed fields that are less likely to have been chosen by parents in the past.* While access to all fields may have been democratized, the individuals from the upper classes could count more on their fathers' mentoring and advice in fields where occupations are more established , helping them achieve higher positions and rewards. Another hypothesis (H4) is that the *fields vary in their degree of vertical, occupational differentiation. Such vertical differentiation may crystallize into different sub-levels of education (e.g., 3-years vs 5 or 6-year degrees), or simply in larger numbers of occupations with alternative levels of specialization or* *decision-making within each field.* This hypothesis simply extends the well-established association between social origins, educational attainment, and work rewards (see above) to within the fields of study. In a sense, it argues that what appears to be a horizontal dimension of education is indeed vertically structured in fine-graded echelons within broad levels of education.

Our final hypothesis (H5) states that other unobserved characteristics – such as motivation, personality traits or other cognitive and non-cognitive skills – may lead some individuals to self-select into the labour market. *If in addition to be differentially distributed across fields, these unobserved traits were also associated with graduates' social backgrounds, they could explain the difference in the association between the class of origin and wages across fields.*

4.4 Data & Methods

To answer the research question and test the hypothesis, we rely Scientific Use File called "Inserimento Professionale dei Laureati" released by the National Institute of Statistics of Italy (Istat) in 2011.The dataset contains a wide range of information on the educational curricula, working conditions, and family background of a large sample of university students who graduated in 2007. Working conditions are evaluated 4 years after the graduation. The whole population of graduates in 2007 was 300.338. To this population, a stratified random sampling design without replacement was applied. The primary strata were defined by the degree course - Master of Science and single-cycle degree vs. bachelor degree, which were further subdivided by University and gender, and, for bachelor degrees, by degree class. The final sample consists of 62,000 graduates in 2007. To this original sample, we apply different filters. Firstly, as the focus is on the first-entry wage of Italian graduates, we select only graduates who were working at the time of the interview (2011). Subsequently, due to reliability and comparability issues, we discard the self-employed. The reason is that, as it is well known, it is quite difficult to obtain reliable information of the income earned by these workers. Finally, we select only those cases for whom there is information on father's occupation i.e., we drop graduates with missing information about their social class of origin. At the end of this selection process, the total sample drops to 29,204 graduates.

As anticipated, our outcome variable is the (log) monthly net wage. Although this choice does not allow us to calculate a pure mobility index - or income-elasticity measure relating fathers' to children's incomes - it allows ranking graduates on an unambiguous scale measuring the returns they obtain from their work, to assess the impact of graduates' social origins on such ranking, and to identify the degree of transmitted inequality.

We now present our main predictors.

Social class of origin. Our main predictor is the social class of origin based on the father's occupation at the time of interview[28] . Occupation was measured with the 2-digit codes in the National Classification of Occupations, which is similar to the standard ISCO classification. We then derive a 7-class scheme defined in the following way:

Table 4.1: Social class definition

2-digit code	Content	Class
1.0-1.3	Higher managers, employers and legislators	Executives & Managers (1)
2.0-2.6	Higher professional occupations	(Traditional) professionals (2)
3.0-3.4	Lower technical professionals	Semi-professionals and technicians (3)
4.0-5.4	Administrative employees, clerks.	White-collar class (4)
6.0-6.5	Small employers & self-employed	Small employers & self-employed (5)
7.0-7.5	Semi-routine & skilled workers	Skilled and semi-skilled workers (6)
8.0-8.4	Routine & unskilled workers in all sectors	Unskilled workers (7)

In some analysis, the class of origin is further collapsed into a dummy variable indicating whether the graduate has a privileged class background (1 and 2) or not (any other class).

[28] The dominance principle cannot be applied as the mother occupational code is not available. Furthermore, we have excluded the armed forces.

Educational fields. The educational field variable is available in both 16- and 9-category specifications. We opted for the second, as the counts and corresponding statistical power in the 16-categories version were small in some fields. We excluded physical education from the analyses and merged engineering with architecture. Consequently, we ended up with the following seven fields of studies:

- Humanities – includes literature, languages, teaching, psychology
- Economics & statistics
- Social sciences – includes political science and sociology
- Natural Sciences – includes science, physics, chemical-pharmaceutical, geo-biology
- Law
- Engineering & architecture
- Medicine

Gender. Gender is coded binary, with men coded with a 0 and women with a 1.

Vertical differentiations within fields. As noted above, we also aim to assess the extent to which some fields are more differentiated along vertical lines than others. We consider two such possible sources of differentiation. The first is the type of program taken by the graduate – short-cycle, bachelor, Master degree. The second is the job he or she held four years after graduating, defined as a single cell in an occupation-sector matrix.[29]

Occupational inheritance. This is captured with a dummy variable indicating whether the individual has the same 2-digit Occupational Classification Code as his or her father.

Controls. To minimize bias due to the omission of unobservable characteristics (e.g., motivation, personality, or intelligence) our main solution is to introduce a rich set of "supply-side" controls related both to education and the labour market. Starting with the former, we take into account whether the graduate completed the degree within the

[29] The occupation is 1-digit occupational code of the respondent, while the sector is a 3-level variable (agricultural, industrial and service sector). So we have a 9x3 matrix, where all the cells with less than 30 observations have been deleted.

prescribed formal time[30] and the age at which he/she did it. We also control for the type of university attended (public or private, in interaction with the total average quality scores of each university, as shown in the Censis dataset [31]), for some argue that, at least in the case of Italy (Anelli 2020), enrolment in elite universities is associated with 55% higher returns. Other educational controls are the high-school final mark – which can eventually determine the type of University and/or the field of study subsequently attended – and the GPA final grade obtained in the higher degree. As for the labour market controls, we include a set of dummies measuring whether the respondent's employer pays social contributions, and the graduate's part-time vs. full-time, and permanent vs. temporary, employment status.

4.4.1 Methods

We apply a set of linear regression models (OLS) in which – using a stepwise approach – we assess how the direct effect of social origin (DESO) on log-income changes as educational fields and the controls are added to the models, and hence the extent to which fields can partially or fully mediate the origin association.

Next, we replicate the full-control OLS model adding an interaction term between the social origin variable (using the dummy version, for simplicity) and fields of studies, so as to test the first hypothesis on the higher signalling effect of hard fields. As a robustness check, we replicate this model with a more detailed version of the father-class variable[32].

To test the gender composition hypothesis, we compare the previous models with another one that adds an interaction effect between gender and the social origin dummy variable, and which considers the possibility that employers may rely on graduates' social backgrounds more heavily when they are female than males. If that were the case the interaction between fields of studies and social origin should weaken in the fields more heavily populated by women.

[30] The opposite would be to complete a bachelor degree in, for example, 4 years while the prescribed time is 3 years.

[31] The total average scores are based on different categories: services, scholarships, internationalization, web and infrastructures.

[32] We fit a multilevel model with random intercepts and random slopes by province of residence before starting university to test whether the origin effects vary also by geographical location. We do not find any significant geographical variation. Results are available upon request.

To test the remaining hypotheses about the possible reasons explaining the interaction between fields of studies and social origin, we run additional models adding, first, a dummy for occupational inheritance, and second, two variables capturing fields' vertical differentiation — the sub-level/type of degree within the field, and the occupation held four years after graduation (this one entered in the form of a fixed effects model).

Because there may still be other unobserved factors explaining the interaction effect between fields of study and class of origin (e.g., selection into employment due to unobserved characteristics linked to fields and social class), our final model re-estimates all the effects using Heckman's correction for selectivity.

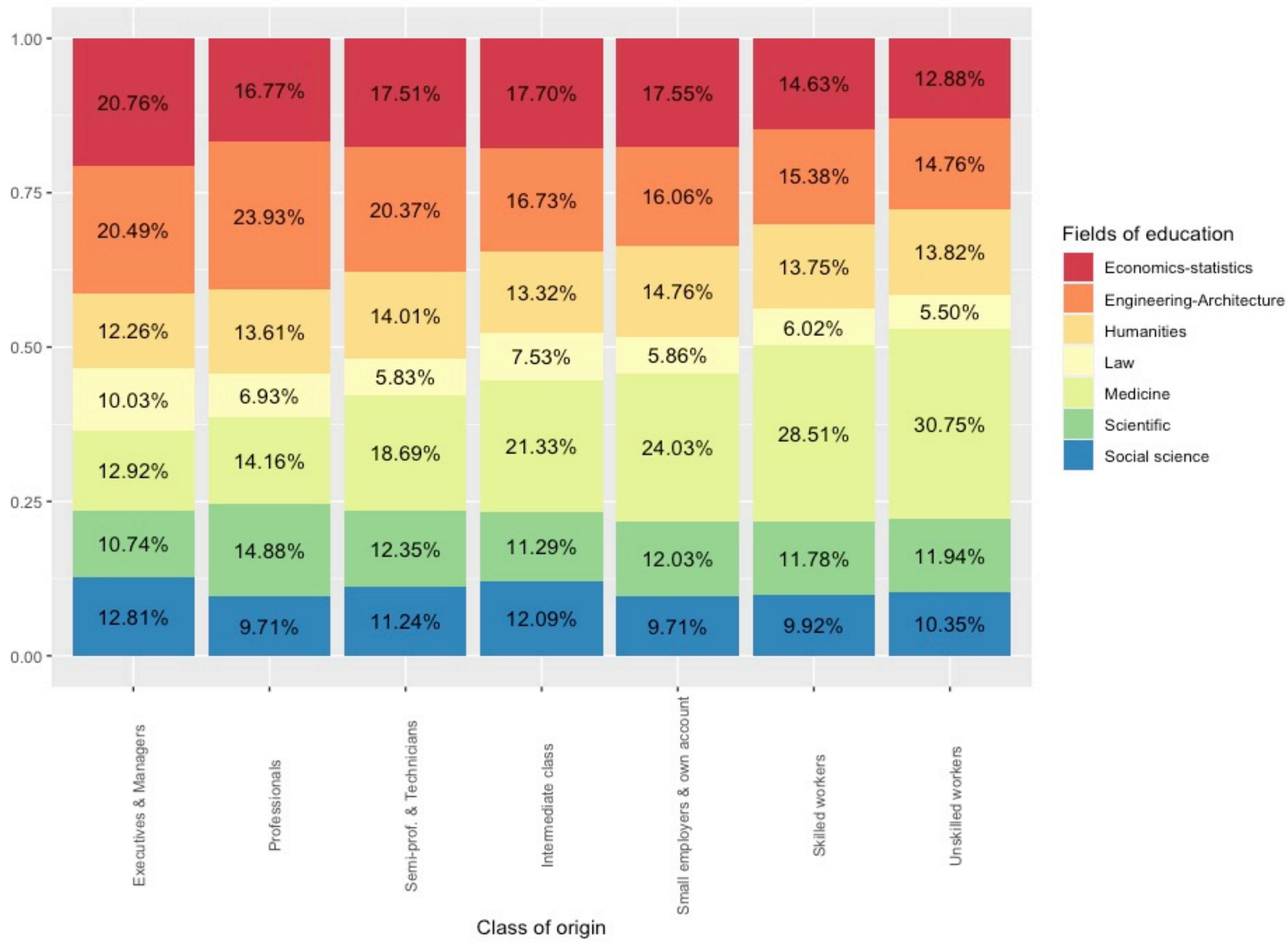
4.5 Summary statistics & Results

4.5.1 Summary statistics

The number of university graduates in Italy is among the lowest in Europe – 13.8% among the 15-64 aged population. This number reached a plateau in 2005, after the Bologna reform of 2001, staying at around 300,000 graduations per year (ANVUR, 2014), and signalling that the expansion of tertiary education had stalled. Barone (2009) argues that such stalling is the background for the observed persistent educational inequalities in educational attainment in Italy.

In Figure 4.1 we show some preliminary evidence on the association between class of origin and fields of studies for the entire sample (the figure hardly changes by gender).

Figure 4.1: Fields of studies by graduates' social class of origin



Source: own computation using the Istat micro-data

According to Figure 4.1, graduates with a service class background – executives & managers, and professionals – mostly choose the fields of economics-statistics and engineering-architecture. They also disproportionally choose the law field (10% of children of executives & managers compared to 5% of the unskilled workers). On the contrary, medicine is preferred field by graduates with a working-class background. In terms of overall gender composition, women are dominant in the humanities (more than 30%), medicine, and the social sciences. Instead, men are clustered in engineering-architecture (27%), economics-statistics, and the natural sciences (see Table A.4.3 in the Appendix).

While there is a statistically significant association between social class of origin and fields of studies – as the chi-square statistic reports[33] – its strength is very low (Cramer-

[33] Chi-square: 738.53, df=48, p-value: 0.000

V= 0.065). This is in accordance with Jackson et al. (2008), who found a very low association between origin and fields of studies, thus downplaying any mediating role of the horizontal dimension of education for transmitting inequalities.

In terms of average net-monthly wage by field of study, the humanities yield the lowest returns – as expected -, while the highest wages are observed in medicine, law, economics-statistics and engineering-architecture. A significant gender wage-gap of about 200 euros per month can be observed in all fields (men earn about 1,448€ while women earn 1,273€). This gap is preserved also within classes of origin.

4.5.2 Results

Table 4.2 reports a first set of stepwise linear models aimed at evaluating the mediating role of fields of study on the transmission of inequalities. In Model (1) father's class is the only predictor, while Model (2) adds graduates' educational fields. Model (3) adds all other the variables described above, which at this point are simply treated as controls.

Table 4.2: stepwise OLS models

	Dependent variable: Log Monthly-income		
	(1)	(2)	(3)
Father's occupation			
Exectutives and Managers	0.0628***	0.0584***	0.0457***
Professionals	0.0254**	0.0260**	0.0230**
Semi-prof. and Technicians	0.0103	0.0113	0.0155**
Small employers and own account	0.0110	0.0134	0.0208**
Skilled workers	0.00339	4.12e-05	-0.00163
Unskilled workers	0.0287*	0.0211	-0.000595
Fields of study			
Economics-statistics		0.248***	0.0842***
Social science		0.133***	0.0343***
Natural Sciences		0.162***	0.0603***
Law		0.211***	0.0694***
Engineering-Architecture		0.270***	0.0974***
Medicine		0.320***	0.137***
Women			-0.0925***
23-24 years			0.0254***
25-29			0.0741***
>30			0.151***
University ranking score			0.0114***
Private University			0.0686***
Private*Ranking			0.0291***
Graduate score			
91-100			-0.00125
101-105			0.00190
106-110			0.00444
110 cum laude			0.0291***
Graduate on time			0.0460***
High-school grade			0.00982***
Undeclared work			-0.194***
Permanent contract			0.116***
Part-time			-0.475***
Constant	7.109***	6.934***	6.900***
Observations	28,916	28,217	27,816
R2	0.002	0.116	0.500

Note: reference categories are: intermediate class, humanities field, men, aged 21-22, Public University, 66–90 degree grade, regular work, fixed-term contract, full-time contract.

$^{+}$*<0.1; * p<0.05; ** p<0.01; *** p<0.001*

Model (1) shows that compared to the children of white collar workers (the reference category) all other children earn higher wages, although the difference is significant only for the children of executive & managers, professionals, and unskilled workers (the children of executives & managers and of professionals earn around 6 and 2.5% higher net-monthly wages than the children of white collar workers). Model (2) shows that all fields yield higher returns than the humanities. The field with the highest returns is medicine, followed by engineering and architecture, and economics and statistics. (It must be born in mind that what are observed are differences in wages at the initial stages of graduates' careers and that they may change at later stages if the returns to experience vary by field.) A comparison of the coefficients for the association of the class of origin with wages in models (1) and (2) suggest that fields of study is not an effective mediator between the social origin class and wages. This is because of the very weak association between social origin and fields of studies, as shown before in the descriptive analyses, not because there are no differences across fields in their economic returns. The inclusion of further controls in Model 3 does not affect much the estimates for the class of origin, but it markedly decreases the differences in the fields' economic returns, suggesting that the choice of fields is much affected by graduates' socio-economic characteristics (age and gender), and by additional educational and labour market factors (grades, choice of university, length of program, and type of contract). The coefficients of all these controls on wages are in the expected direction: women have a wage penalty of around 9%; better grades and private and more prestigious universities grant higher log-wages: and having a full-time and a permanent contract is also associated with higher wages.

Although our findings suggest that educational fields do not act as mediators – in line with the results obtained by Jackson et al. (2008) – they may still interact with class of origin and provide an advantage in some fields to individuals in the upper classes. To evaluate this possibility and, more generally, to test the five hypotheses set up above, in Table 4.3 we rerun the models displayed in Table 2 using the same stepwise strategy, but now adding in Model (4) an interaction effect between educational fields and the simplified, dummy, version of class of origin, which distinguished the service class (executives, managers, and professionals) from all others[34]. Before interpreting these

[34] As a robustness check, we have run the same models using the full classification of the class of origin. The results, available upon request, provide more detail to the picture but do not change the main findings.

results, we run another model – Model (5), where we further add an interaction effect between gender and the dummy for class of origin, so as to test H2 and evaluate the extent to which any differences across fields detected in Model (4) in the effect of class of origin on wages can be explained by the higher value that such origins have for women and the concentration of women in some fields.

Table 4.3: OLS moderating effects – class of origin by fields of studies interactions

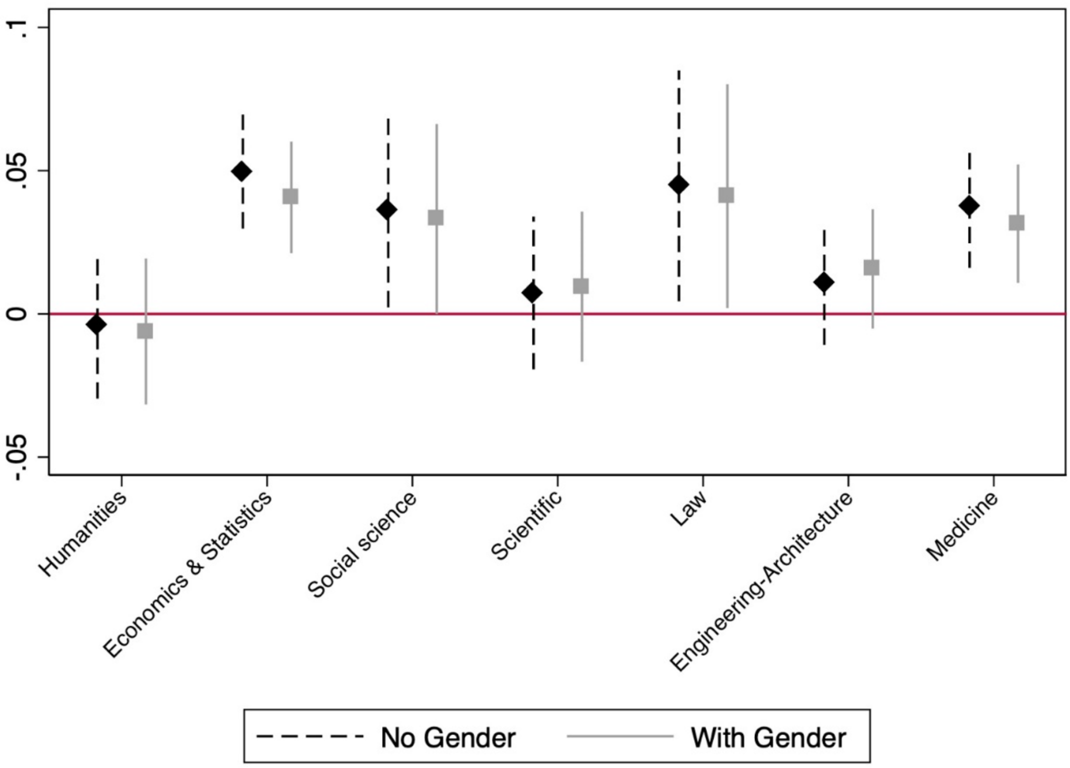
	Dependent variable: Log Monthly-income			
	(4)	(5)	(6)	(7)
High Class	-0.000491	-0.00341	-0.00384	-0.00879
Fields of studies				
Economics-statistics	0.0989***	0.0755***	0.0752***	0.0696***
Social-science	0.0407***	0.0266**	0.0264**	0.0304***
Natural Sciences	0.0866***	0.0578***	0.0579***	0.0459***
Law	0.0751***	0.0598***	0.0595***	0.0536***
Engineering-Architecture	0.147***	0.0949***	0.0949***	0.0607***
Medicine	0.135***	0.130***	0.130***	0.142***
High class*Economics-statistics	0.0543***	0.0458**	0.0464**	0.0427*
High class*Social-science	0.0415+	0.0402+	0.0406+	0.0350+
High class*Natural Sciences	0.0119	0.0150	0.0150	0.0134
High class*Law	0.0464+	0.0441+	0.0442+	0.0366
High class*Engineering-Architecture	0.0143	0.0187	0.0185	0.0179
High class*Medicine	0.0402*	0.0368*	0.0372*	0.0392*
23-24 years	0.0244***	0.0243***	0.0243***	0.00656
25-29	0.0761***	0.0730***	0.0730***	0.0336***
>30	0.157***	0.150***	0.150***	0.115***
Ranking-score	0.0109***	0.0117***	0.0117***	0.00960***
Private University	0.0686***	0.0688***	0.0687***	0.0608***
Private*Ranking	0.0320***	0.0270***	0.0270***	0.0251***
91-100	-0.00906	-0.00182	-0.00182	-0.00904
101-105	-0.0120	0.00123	0.00121	-0.0119
106-110	-0.0109	0.00347	0.00350	-0.0137+
110 cum laude	0.0155+	0.0290***	0.0290***	0.00110
On time	0.0465***	0.0458***	0.0458***	0.0327***
High-school grade	0.00366	0.00950***	0.00951***	0.00845***

Undeclered work	-0.191***	-0.192***	-0.192***	-0.191***
Permanent contract	0.119***	0.116***	0.116***	0.115***
Part-time	-0.488***	-0.476***	-0.476***	-0.462***
Women		0.0905***	-0.0904***	-0.0871***
Women*High class		-0.00492	-0.00503	-0.00346
Same occupation			0.00599	0.00800
Master of Science				0.0298***
Bachelor				-0.0260***
Jobs FE	No	No	No	Yes
Constant	6.939***	6.913***	6.913***	7.161***
Observations	27,816	27,816	27,816	27,722
R^2	0.485	0.499	0.499	0.516

*Note: $^{+}$<0.1; * p<0.05; ** p<0.01; *** p<0.001*

Figure 4.2 provides a summary view of the average marginal effects of having an origin in the service class in each field of study, before and after adding the interaction effect between gender and class of origin.

Figure 4.2: Average Marginal Effects of having a service class origin on the log-monthly net wage across fields of studies – with and without gender interacting with class of origin



To start with, Figure 4.2 shows that, indeed, the effect of social class on the log-wages varies considerably across fields of study. Graduates with a service class background have a wage-advantage – or boosting effect – of around 5 and 4%, respectively, in the fields of economics and law, and of around 3% in the social sciences and medicine fields. All "soft-fields", except the humanities, have the highest marginal effects, while all "hard-field", except medicine, have non-significant, close to zero estimates. H1 posited that such differences across fields would be due to variations in the content of work in each field and the consequent variations in the ability of their graduates to send an effective signal to prospective employers. This basic (and residual) interpretation holds (imperfectly) even after adding the interaction effect between gender and fields of studies, as the estimates for the interaction effect between class of origin and fields hardly change, thus refuting H2. The reason for this stability is *not* that fields do not differ in their gender composition, which they do – see Table A.4.3 in the Appendix – with women being under-represented in the hard fields, except in medicine, but in the lack of a significant interaction effect between gender and class of origin. [9]

In Model (6) of Table 4.3 above, we test whether the origin advantage observed in some fields operates through occupational inheritance, by adding a dummy for having the same occupation as the father's. The consequence of adding this variable on the estimates of the interaction effect between fields of study and class of origin is minimal, mainly due to occupational inheritance not providing any wage advantage. This result helps reject H3. In Model (7), we test if variations in the vertical differentiation within fields could explain the presence of an interaction effect between class of origin and fields of study, by adding two variables distinguishing graduates by the type of degree they obtained (3- or 5-year, or master) and the job they held four years after graduating. Once again, the interaction between fields of study and class of origin is unaffected in magnitude or significance (law is the only exception as it loses some statistical power), thus refuting H4.

All in all, the results confirm that the social origin effects vary by fields of study, with the "soft-fields" generally guaranteeing the highest class-advantage (with the exception of the humanities) compared to the "hard-fields" (with the exception of medicine), where

[9] Controlling for the type of degree and type of degree in interaction with social class of origin does not affect class of origin by fields interactions.

the class of origin does not provide any advantage. These coefficients do not depend on variations across fields in their gender composition (combined with a stronger effect of class of origin among women), and their degree of occupational inheritance and vertical differentiation, and hence we tentatively conclude that they may be related to variations in the content of work and graduates' capacity to send effective signals to employers about their potential performance in the job.

4.6 Heckman's correction

As anticipated, such results may be biased due to selection effects caused by key unobserved characteristics, like motivation, perseverance or other traits. These characteristics might explain both why we observe some individuals working four years after graduating (and hence, their wages) and the levels of their wages. In other words, these unobserved characteristics may determine whether an individual select into the labour market (employed) or remains unemployed. If these characteristics varied across the classes of origin (e.g., because the most determined to work were more likely to come from the lower classes, given the many filters they had to overcome to access higher education or their more pressing needs) and such variations did in turn vary by fields of study (e.g., with more committed students choosing the most difficult fields), they might explain why we observe an interaction effect between fields of study and class of origin (such that in the hard fields the effect of social class is smaller or nihil). To test this possibility, we apply a two-step Heckman (1976) correction for selectivity. The selection equation takes the form of a probit model predicting participation in the labour market i.e., being employed or not. The substantive equation is the full OLS Model (7) displayed above. To avoid relying only on distributional assumptions, we introduce an exclusion restriction in the form of an instrument influencing selection into employment but not the substantive equation in the second step. The chosen instrument is the provincial unemployment rate by gender at the time of graduation (2007). This unemployment rate may affect graduates' ability to access the labour market, and highlight the differential probabilities of being employed and earn higher wages of those who are more dedicated and determined (or have other unobserved characteristics). To be a valid instrument, the unemployment rate in 2007 should not be correlated with the wages in 2011, net of its effect on the rate of labour market participation. While there may be reasons to expect the rate of unemployment to directly affect the level of wages (e.g., neo-classical economists argue that it exists a unique natural unemployment rate at which there's no inflationary pressures and the labour market will be in equilibrium at this corresponding wage), its effects might be offset by other important forces, such as unions' bargaining power. We have taken a more practical stance, and decided to use the 2007 provincial rate of unemployment rate as an instrument due to its being weakly correlated with wages in 2011. [10]

Table 4.4 displays the estimates for the interaction effects on wages of having a high class social origin and choosing a particular field of study, after applying Heckman's correction (using maximum likelihood estimation techniques).

Table 4.4: Heckman's estimates

Substantive equation	
High class*Economics-statistics	0.028+
High class*Engineering-Architecture	0.005
High class*Law	0.037
High class*Medicine	0.091***
High class*Social-science	0.016
High class*Scientific	0.007
Men	0.080***
Educational controls	Yes
Labour market controls	Yes
Jobs Fixed Effects	Yes
Select equation	
Provincial unemployment rate in 2007	-0.028***
Lambda	-0.107***
Observations	44,634

Note: $^{+}$*<0.1; * p<0.05; ** p<0.01; *** p<0.001*

The lambda parameter summarizes the selectivity effect. The negative correlation between the error terms in the selection and the substantive equations suggests that, in the

[10] This holds both in terms of the simple raw Pearson correlation coefficient between unemployment rate and income in 2011 and in terms of a OLS regression where we control for the unemployment rate net of the predicted probabilities estimated from the Heckman 1st step.

absence of a correction for selection effects, the estimates might be biased, and that the unobserved characteristics that explain participation into the labour market are associated with lower wages. After computing the marginal effects from the estimates and after comparing them to the baseline model without correcting for selectivity (see Figure A.4.2 in the Appendix), we observe that they hardly change neither for the hard sciences, as wages continue to be unaffected by class of origin, nor for economics and law, as graduates with a privileged background still have a significant wage advantage of around 3%. In contrast, lower classes' disadvantage in the social sciences vanishes after the correction, signalling that it was possibly explained by the selection into this field of less individuals from the lower classes who feel stronger pressures to work and accept lower wages compared to their lower class counterparts in other fields. On the contrary, the wage boosting effects for graduates in medicine with high-class background increases to 9%. This may suggest that medicine graduates with a low social class background may have some unobserved characteristics positively associated with wages.

In sum, after applying selection effects, we still observe overall differences between the hard and soft fields, being class of origin more important in the latter. This confirms hypothesis H1, which posited that soft-fields confer mostly general skills with a low signalling power, so that employers have to rely on candidates' social backgrounds to sort them out and offer them wages in accordance to their skills and potential productivities. However, there are soft fields where such differences are not present, like in the humanities and the social sciences, and hard fields, like medicine, where the advantage of a privileged upbringing is very marked. These exceptions suggest that in these fields there may be additional skills that are valuable to employers but difficult to evaluate, and for which social class is a good proxy. In other words, the lower signalling power in the "soft-fields" seems to be a necessary but not a sufficient condition to explain wage differentials by class of origin. Note that this result is not due to our focusing on the early stages of the working career. Our robustness checks suggest that in some fields like the humanities the impact of social class is even stronger later in this career – see the robustness check section in the Appendix.

4.7 Conclusions

This paper aimed to provide new evidence on the role of the horizontal dimension of education in transmitting inequalities from parents to children and in thwarting social mobility. As argued, most of the literature focuses on the vertical dimension of education, i.e., on the level of education and on its mediating role between individuals' social origins and destinations. We argued that, by focusing just on this vertical dimension, we might neglect other more horizontal ways by which education can transmit social inequalities, namely through the fields of study. We argued that there are two ways in which fields could play this role – by differentially attracting individuals from alternative classes and helping them achieve different outcomes (mediating role), or by helping individuals with higher social backgrounds achieve better outcomes in some fields instead of in others (moderating role). The extent to which fields play the first role will depend – we argued – on the association between the social class of origin and educational fields, and between the latter and the destinations; the second, on the presence of interaction effects between the class of origin and fields of study. In this paper, we investigated the extent to which field of study plays a mediating or moderating role among Italy' university graduates, and which factors might explain such a moderating role.

To identify these factors, we first relied on signalling theory (Dobbs et al., 2008; Spence, 1973; Stiglitz, 1975), which argues that educational qualifications are workers' means to signal their potential skills and knowledge to their prospective employers. If this signalling-power was smaller in some fields, employers might rely on workers' class of origin to figure out their potential productivities.

Using Biglan (1973) classification of fields of studies, we distinguished between "soft-fields" – characterized by a lack of general consensus on the substance and work methods to be applied at work – and "hard fields" – which on the contrary are well defined in terms of contents and methodologies. "Soft-fields" are more likely to be characterized by more general or less specialized sets of skills and competencies and, therefore, by a lower signalling-power regarding potential productivities. Thus, our first hypothesis was that in such "soft" fields, the information on social origins helped prospective employers sort out graduates' potential productivities, and adapt their wage offers accordingly.

We then proposed various alternative hypotheses. First, we combined the gender stereotypes (Reskin (2000) and queuing theories (Kaufman, 2002) to explore whether women's productivities were more strongly estimated by employers from their social class of origin than men's, leading to a stronger effect of family background on wages in female-dominated fields. Subsequently, we investigated whether the interaction effect between class of origin and field study on wages might be due to a higher occupational inheritance in some fields than in others. Next, we explored if the interaction effect could be due to a higher vertical – educational and occupational – differentiation in some fields. Finally, we tested whether the horizontal-educational effect could be entirely explained by differential self-selection into employment across fields of individuals with some unobserved characteristics.

Our analyses detected a very weak, non-significant association between social origin and educational fields, confirming the results from previous studies (Jackson et al., (2008) on the non-mediating role of the horizontal dimension of education in transmitting social inequalities. In contrast, we observed that the significant direct effect of social origins on the log monthly wage at entry jobs – which all in all guaranteed around 4% higher wages to Italian graduates from the service class – differed across fields. In other words, while social class of origin does not directly influence the choice of educational fields – in contrast with the predictions of the Effectively Maintained Inequality theory (Lucas, 2001) – it can influence the monthly wage differently by interacting with fields of studies.

Consistent with our first hypothesis, we found that the origin effect varies by fields of studies and tends to be stronger in the "soft-fields", while it is close to zero in most "hard fields". Specifically, an individual who graduated in economics-statistics or in law with a privileged background had around 4% higher net-monthly wages compared to their peers with a lower class of origin. Similar results were observed for political science and medicine, where the class-advantage was of around 3%.

These estimates were quite stable even after controlling for a gender-class interaction effect, for occupational inheritance and for vertical and other differentiations within fields (e.g., occupations fixed-effects). Such stability provides sufficient evidence to reject the hypothesis that class effects in some fields are due to the over-representation of women in some of them and employers' general discrimination against women, and/or that the effects mostly operate through occupational differentiations. Additional robustness checks assessing the intergenerational income elasticity on a different Italian sample confirmed the validity of our first hypothesis of a class-premium in most "soft-fields". And while the Heckman's correction seemed to confirm the existence of a selection bias in these estimates, it did not alter our basic leaning in favour of the hypothesis of stronger class signals in "soft-fields".

In these fields the social class of origin appears to constitute an additional signal about graduates' potential productivity. Different mechanisms could possibly explain the advantage that graduates with a privileged background enjoy and exploit in these fields. It could be that a privileged background stands for traits or tacit knowledge and behaviours which are associated with higher productivities. For example, a graduate in economics with a father in the executives & managers class might have a higher command of language, higher presentation skills or a better idea of the "business-dynamics" compared to a same graduate with a working-class background. There is also room for demand side explanations – e.g., that employers in some fields have higher preferences for high-class graduates (Bourdieu, 1984), as shown by Jackson et al. (2005) for the UK, perhaps because of their own class background.

Our general conclusion must be qualified for the cases of the humanities and medicine, which represent important exceptions in the role that the class origin plays within the soft and hard fields, respectively. We found no relevant class effect in the humanities, and the strongest effect of class in medicine, especially after controlling for self-selection into employment. Several reasons could explain these anomalies. One could be the weight of the public and private sectors in the jobs typically held by graduates from both fields. It could be that class effects were minimized in the public sector – where many graduates in the humanities work as teachers – and exacerbated in the private one – where many medicine graduates work due to the weight of the private health sector in Italy (Annuario Statistico del Servizio Sanitario Nazionale, 2019; Buzelli and Boyce, 2021). Unfortunately, we were not able to assess the plausibility of this explanation, due to lack of data on the public, vs. private nature of the organizations where the graduates work. Nor could we assess if the size of the firms where the graduates work could account for differences across fields in the impact of their social backgrounds on wages, due to lack of information on this variable. It could be that high-class graduates find it easier because of their having greater social capital to work in large firms that pay higher wages (Laurison and Friedman, 2016). If large firms were more common in some fields than in others this could explain our observing a different effect of class of origin on wages in each. Another reason could be the differences in the audiences (students vs. patients) that are targeted by graduates in each field. If the practice of medicine was stratified by the social class of the patients more than the practice of teaching is stratified by the social characteristics of the students it educates, and if the social match between providers and recipients was key for achieving the desired outcomes in each activity, these factors might explain the higher role played by graduates' social backgrounds in medicine than in the humanities. Finally, there may be reasons related to the characteristics of the tasks to be performed by graduates in each field, beyond those defined by their soft or hard nature, that could explain the opposite impact of social class of origin in each. Abbott (1988) once described medicine as a technical profession in which there is much consensus about work contents and methods, but one in which the uncertainties surrounding a patient's diagnosis makes the colligation process by which patient's symptoms are defined as a case of an illness, an "art". Conversely, it has been argued that the general nature of educational tasks has been made increasingly concrete and standardized through high-stakes testing and scripted curricula (Au, 2011) .This implies that the logic distinguishing soft from hard fields based on the absence and presence, respectively, of a single scientific paradigm may be insufficient to classify a field as soft or hard. Alternatively, it may be that the operationalization of medicine and the humanities as hard and soft fields requires a revision, based on the changes experienced by their respective professions in the last decades, or on a crispier definition of single vs. multiple-paradigm disciplines.

Regardless of these limitations, we hope to have contributed to highlighting the importance of considering fields of study as a key factor moderating the effect of origins on destinations, and to assessing the plausibility of different explanations for why it plays this role.

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4. Appendix

Robustness check – interaction model with father detailed class

We report here the interaction effects of the full-control model using the detailed father class. This finer detail robustness shows that the Professional origin class is the one training the positive class-gap in medicine (compare to the working-class origin). The wage-gap in economics and law is driven by the Executives & Managers origin class. Controlling for jobs does not affect the interaction estimates. Therefore, we can conclude that the dummy approach is consistent.

Table A.4.1: Interactions between detailed father class and fields of studies, controlling for gender interaction, with and without job controls

	Log-wage	
Interactions	Without Jobs	With Jobs
Exec. & Mng*Economics	0.109***	0.099***
Exec. & Mng *Social Sciences	0.05	0.045
Exec. & Mng *Scientific	0.063	0.063
Exec. & Mng *Law	0.089*	0.076+
Exec. & Mng *Engineering-Arch.	0.052	0.054
Exec. & Mng *Medicine	0.037	0.041
Professionals*Economics	0.035	0.035
Professionals *Social Sciences	0.049	0.046
Professionals *Scientific	-0.000	0.004
Professionals *Law	0.007	0.004

Professionals * Engineering-Arch.	0.025	0.023
Professionals *Medicine	0.039*	0.041*
Technicians*Economics	0.022	0.020
Technicians * Social Sciences	0.007	0.009
Technicians *Scientific	0.000	0.006
Technicians *Law	0.004	0.003
Technicians * Engineering-Arch..	0.014	0.016
Technicians *Medicine	0.011	0.014
Small-empl.*Economics	0.01	0.006
Small-empl.* Social Sciences	-0.008	-0.013
Small-empl.*Scientific	0.023	0.027
Small-empl.*Law	-0.024	-0.023
Small-empl.* Engineering-Arch.	-0.002	-0.008
Small-empl.*Medicine	-0.020	-0.022
Skilled work*Economics	0.025	0.026
Skilled work* Social Sciences	0.016	0.01
Skilled work*Scientific	-0.006	-0.003
Skilled work*Law	-0.043	-0.037
Skilled work* Engineering-Arch.	0.03	0.03
Skilled work*Medicine	0.009	0.009
Unskilled*Economics	0.022	0.022
Unskilled* Social Sciences	0.085*	0.087*
Unskilled*Scientific	0.009	0.014
Unskilled*Law	0.068	0.085
Unskilled* Engineering-Arch.	0.049	0.048
Unskilled*Medicine	0.008	0.01

Note: reference intermediate class and humanities field;

*$^{+}$<0.1; * p<0.05; ** p<0.01; *** p<0.001*

Robustness check – effects later in career

The highly educated individuals have steeper wage-curves compared to the less-educated wage earners. This means that it is likely that we are underestimating the social origin interactive effects at the beginning of employment career.

To provide a more reasonable estimate and stronger evidence for our hypothesis, we replicate the analysis using a sample aged 30-50, where the career curve should be at its highest slope. For this purpose, we use the Survey on Household Income and Wealth microdata provided by the Bank of Italy. As the social origin occupational information are not sufficiently detailed to create a class-scheme, we apply the Two-sample Two-stage Least Squares (TS2SLS) to predict father's income. Björklund and Jäntti (1997) were the first to apply this method for the computation of the Intergenerational Income Elasticity (IGE).

The method makes use of two different samples. The first sample corresponds to the most recent respondents, providing (real) information about their fathers. For this purpose, we pool the last three most recent waves reporting such information – 2008, 2010 and 2012 [1] and select employed heads of households aged between 30 and 50.[2] The second sample represents the pseudo-fathers of the youngest respondents still aged between 30-50. Therefore, the pseudo-fathers are observed in the waves between 1977-1982, for a total sample of around 8,200 observations. In this sample it is necessary to have the same information provided by the respondents in the most recent waves, so we standardize across the two samples the definitions of occupations, education and sector. Together with age, these are the main predictors of a linear regression with pseudo-father net labour income as outcome.

We then use the estimated coefficients to predict the real father income using the information provided by the respondents in the most recent waves. In this way, we have labour income for both the respondents and the estimated labour income for their real

[1] SHIW is a rotating panel conducted every 2 years. Since 2014 information about father are less detailed and not sufficient for prediction purposes.

[2] Information about fathers is available for the household head only.

father and we can regress the first on the latter. The main downside of this approach consists in the likely upward inconsistency of the estimator. The sources of bias (Björklund and Jäntti, 1997; Bloise et al., 2021) refer to the incorrect prediction of the fathers' income and to the positive correlation existing between the predictors in the first-stage regression and the respondents/child income. Therefore, the first-equation specification is the one determining the type of bias in the TS2SLS estimator[3].

With these data, we now select the respondents with a tertiary education, for a total sample of around 1,000 observations and regress the (log) net labour income of respondents on the (log) net labour income of their fathers. We obtain an Intergenerational Income Elasticity (IGE) of 0.44, in line with the results obtained by Cannari and D'Alessio (2018) and Mocetti (2007).

However, this income elasticity can vary by the field of studies. Therefore, we replicate the interactive model of the baseline results adding an interaction between father labour income and the field of studies of the respondents[4]. We control for gender and jobs of the respondent.

The Table A.4.2 reports the average marginal effects of father income over the different fields (see Figure A.4.1 for the graphical representation of the interactions).

Table A.4.2: Average Marginal Effects of father income on the log-income of respondents by fields of studies

Fields	Average Marginal Effect	p-value
Math & Science	-0.01	0.967
Medicine	0.243	0.167
Engineering-Architecture	-0.01	0.948
Economics-Statistics	0.788	0.000***
Social Sciences	0.063	0.772

[3] Bloise et al. (2021) introduce an innovative approach based on machine-learning algorithm to minimize this bias.
[4] These have been adjusted to be as close as possible to the fields analysed in the baseline model, and are: Humanities, law, economics and statistics, social sciences, engineering and architecture, math and science, medicine.

Law	0.742	0.001***
Humanities	0.647	0.000***

Note: $^{+}$*<0.1; * p<0.05; ** p<0.01; *** p<0.001*

These estimates provide stronger support to our first hypothesis, as the labour income of the respondents tend to increase with the father income in fields like economics, humanities, law, and to a lower extent in medicine as well. Furthermore, they confirm our intuition of an underestimating origin effects at the entrance on the labour market, specifically in the case of those graduated in humanities.

Table A.4.3: gender composition in each field of study - percentages

Fields	Men	Women
Humanities	8.75	32.93
Economics-Statistics	18.90	14.17
Social sciences	13.96	15.23
Scientific	12.05	9.02
Law	5.73	4.92
Engineering-Architecture	31.51	8.09
Medicine	9.12	15.64

Figure A.4.1: Log-labour income predictions by field of studies

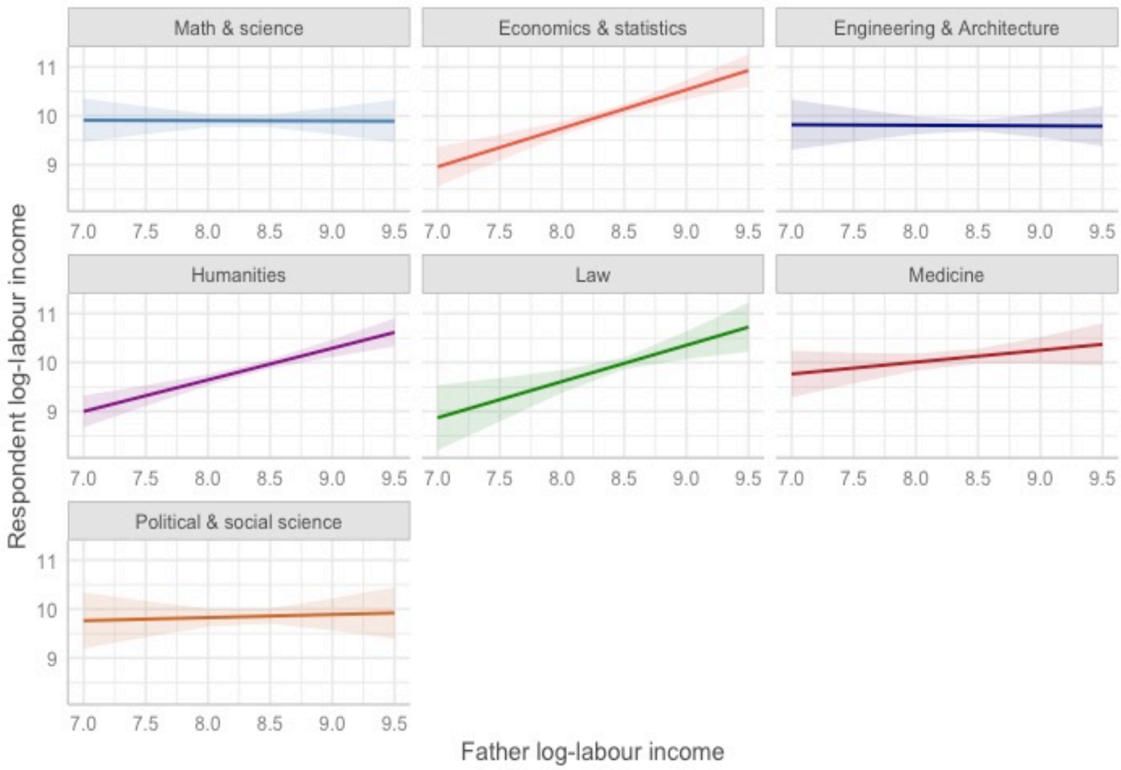
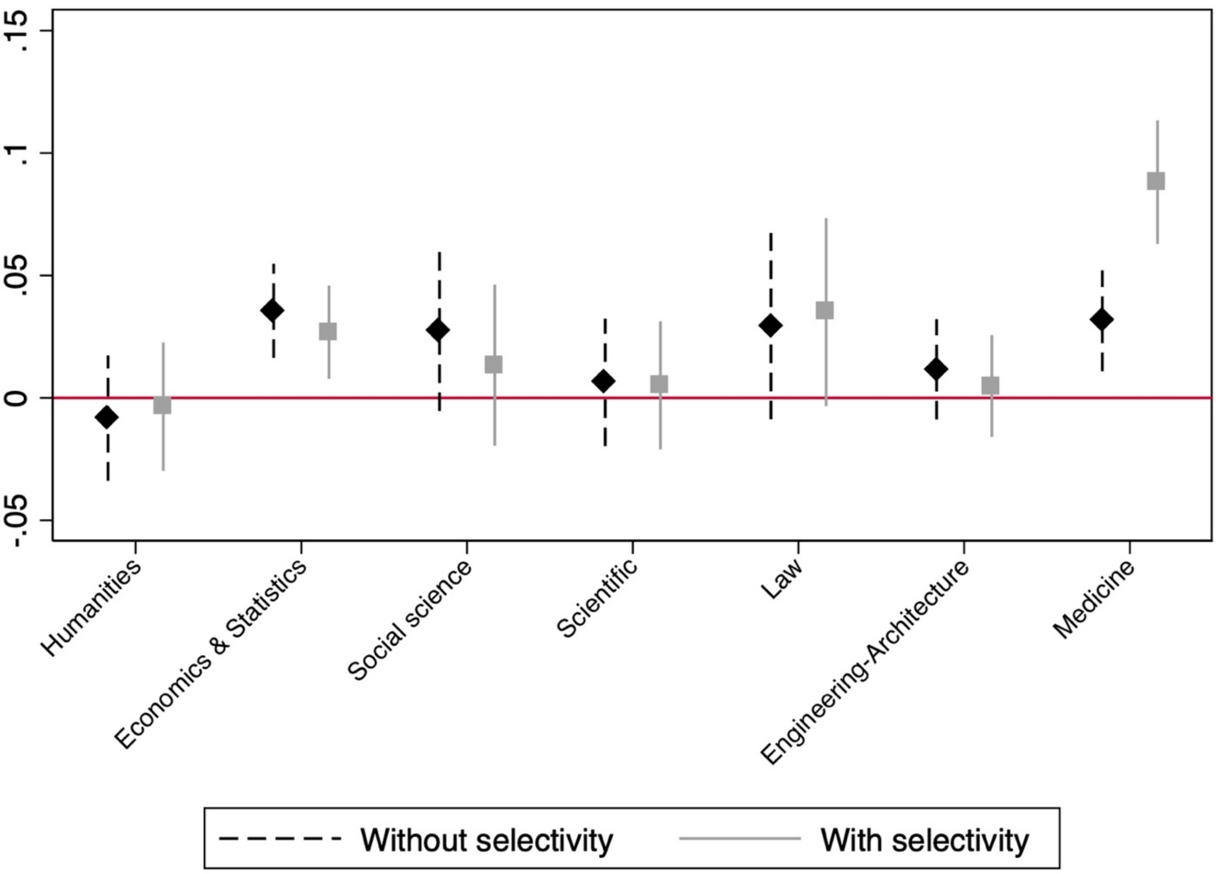


Figure A.4.2: Average Marginal Effects on linear predictions



5. General conclusions

The economic and political relevance of inequality has led to a flourishing literature about the possible main sources of income inequality, such as labour market structure and the welfare system. At the same time, the dominant liberal idea of “meritocracy” has been questioned, based on the relationship between outcome and opportunity inequalities; this may result in a pervasive loop where higher outcome inequality prevents the effective functioning of meritocracy, which in turn enhances income and/or wage inequality.

The main purpose of this thesis has been to investigate the institutional and individual-level mechanisms behind income inequality dynamics. Indeed, moving from a macro to a micro perspective is necessary when analysing outcomes that are shaped by the interconnections between the state and individuals.

It is historically and empirically demonstrated how different type of societies – i.e. institutional structures – are key in shaping the allocation of resources to citizens. Although it seems that advanced economies have converged to form common institutional frameworks – liberal democracies – they are still differentiated by country characteristics. This is the case, for example, in structuring cash-transfer welfare versus service-based welfare, which determine different trajectories in the evolution of budgets.

Different institutional settings have direct effects on shaping outcome distributions through distinct budget compositions. Therefore, it may be useful to understand in what directions these heterogeneous institutional changes over time may have affected the income inequalities.

However, the evolution in institutional structures, under both internal and external political pressures, directly shapes labour market structure. Furthermore, the availability (or not) of public services and/or cash transfers, and fiscal composition – i.e. internal fiscal policy – indirectly influence the individual labour supply. Therefore, the structural characteristics of the labour market, and in particular its occupational-sector structure, are inadequate in explaining the dynamics of income inequality. This means that we may expect different inequality patterns depending on the ways the labour market is structured i.e. whether it is more or less flexible, more or less precarious, and the presence or not of minimum wages or generous cash transfers, etc.

In addition, individual choices and characteristics, particularly educational choices and family background, can be pivotal in reproducing inequality. Individual and social class strategies can directly facilitate and transmit financial and network resources to the next generation, exacerbating outcome inequalities due to different returns in the labour market. Furthermore, these strategies can also affect the type of workers available on the labour market and, in turn, the occupational sector structure.

These mechanisms have been addressed throughout this dissertation, moving from a macro-descriptive perspective on the comparison across countries, to a more micro-detailed analysis on family dynamics within a single-country case study i.e. Italy.

Specifically, the first paper introduces a comparison across countries about the evolution of inequality between 2008 and 2017, focusing on the changes in the welfare systems in terms of in-kind benefits and cash transfers and on what the most relevant sources of income have been behind the rising trend in the Gini coefficient.

Subsequently, once it has been proved that labour market income – and wages in particular – still represent the largest source of income inequality, the second paper moves to the micro-level analysis, and focuses on individual workers' characteristics to investigate the labour market as the primary source of wage inequality. Indeed, the paper aims to identify the determinants of increasing wage inequality in Italy, testing the standard hypothesis of Skill Biased Technical Change.

Finally, the third and last paper introduces an additional potential mechanism behind the case of Italy, verifying whether class background can transmit additional advantages to Italian graduates and – above all – whether these advantages change across different fields of studies.

All together, these three papers examine inequality, going from a state-macro perspective to individual characteristics.

4.1 Re-assessing the role of welfare regimes

This first paper centres on disentangling the contribution of each income source to the evolution of income inequality, but with a specific focus on the sources that are directly under state control such as taxes, cash benefits and – above all – in-kind benefits. The paper attempts to consider the whole set of policy tools available to the welfare state. In-kind benefits are rarely discussed in public and academic debates about inequality, but the share of government expenditure devoted to public services has increased over time. Therefore, it is relevant from a policy perspective to understand how such services (social housing, healthcare, early years, primary, secondary and tertiary education) contribute to the evolution of income inequality compared to the more traditional cash transfers. In other words, to understand whether shifting from a cash-based welfare system toward a service-based one – or a more balanced share of both – is an effective strategy in terms of reducing inequality.

Using the scant literature that combines the distributional effects of in-kind benefits and types of cash transfers, together with all other income sources, elasticities of each income source were computed by means of a Gini coefficient decomposition. In this way, it was easier to interpret how a marginal change in a given income source affected the inequality index. Results showed – in line with existing research – that wages are the primary source of inequality, while taxes are the strongest redistributive tool, especially in the Scandinavian countries. Cash transfers and in-kind benefits, with a particular focus on healthcare and compulsory education, also have equalising effects: healthcare and compulsory education generally outperform all other measures in terms of inequality reduction except pension cash transfers.

I also show that, between 2008 and 2017, changes in the share of employee wages, taxes and cash transfers are the most relevant elements in determining the income inequality trend, while in-kind benefits have a minor role in explaining the evolution of Gini coefficient over the decade.

The paper concludes that, although the primary source of inequality lies in the labour market, a useful strategy to decrease it is to shape state intervention by developing a

more balanced combination of cash transfers – with particularly attention to non-contributory means-tested transfers - and in-kind benefits.
Increasing the share of non-contributory vs contributory cash programs seems to have beneficial effects in terms of reducing inequality, because the transfers towards the less advantaged (means-tested) are not in function of their contributions to them. Typically, those who contribute the least are concentrated at the bottom of the income distribution where discontinuous careers, precarious employment and discontinuity in contributory payments are more likely. In this situation, contributory means-tested transfers are redistributive only if – overall – the contributions are higher than the payments, and there exists a surplus to be redistributed to people who have contributed less. This condition is resolved by using non-contributory means-tested cash programmes.

4.2 Labour market dynamics in Italy

Following the evidence presented in the first paper, the second focuses on labour market structure to investigate the main determinants of wage inequality in a country characterised by relevant labour market reforms since the 1990s, and that is the only OECD country with lower average wages in 2020 than in 1990.

To do so, the paper assesses the role of job composition – occupational and sectorial changes – and "institutional" characteristics – proxied by contractual arrangements and working times – in explaining wage dynamics between 2007 and 2017. By means of a Recentred Influence Function regression and a Oaxaca decomposition, it has been possible to directly observe the effects of each element on measures of wage inequality such as the Gini coefficient and interquartile ratios, and to test whether the Skills Biased Technical Change or alternative theories grounded in the "institutional" characteristics of the labour market are relevant in explaining the Italian case.
The SBTC predicts wage inequality as a consequence of mismatches in labour demand and supply, where the demand for high-skilled workers races ahead of the labour supply. According to the SBTC, it follows that occupational upgrading should be observed. However, there is contrasting evidence, with the latest contributions highlighting a downgrading occupational structure. This paper aims to enter into this debate by providing new evidence based on recent econometric contributions.

Contrary to the SBTC predictions and in line with other existing evidence, results suggest that between 2007 and 2017 Italy experienced a clear wage downgrade, with the bottom 10% experiencing a fall in wages of about 20%. This drop is coherent with the expansion of low-added-value occupations at the bottom of the distribution i.e. downgrading, which led to inequality increasing by 2 Gini points. Indeed, the Oaxaca decomposition suggests that occupational changes – followed by more "institutional" elements in terms of contractual arrangements (part-time vs full-time and permanent vs temporary jobs) – are the main source of increasing wage inequality.

All in all, this paper stands with the "heterodox" strand of labour market inequality literature focused on the relevance of the combined effects of both occupational and institutional changes. In other words, distributive results are not exclusively market based i.e. the result of the labour demand and supply, but mostly depend on how labour market structure is shaped by institutional characteristics.

4.3 Intergenerational transmission

Finally, the last paper relates to the fact that Italy stands out as one of the most immobile countries, characterised by a strong correlation between income and opportunity inequality (the Great Gatsby curve). Unlike most contributions in the sociological and economic literature, this paper focuses on the horizontal dimension of education, i.e. fields of studies, in the intergenerational transmission of inequality among Italian university graduates, and whether the impact of social background on the first-occupation wage is heterogenous across different fields of studies. If the privileged social background of an individual directly and/or indirectly guarantees higher labour market returns through their choice of educational fields, then existing income inequality is transmitted to the next generation, breaking the meritocratic idea of education and the labour market. More simply, if social class is important in determining the horizontal educational choices of individuals, then the class effect is (partially) mediated by education, and inequality is transmitted via educational fields. Conversely, if social class is only weakly associated with fields of studies, the horizontal education choice may act as a moderating effect.

By means of OLS regressions and Heckman selection models, the paper tested to what extent the fields studied had a moderating effect i.e. whether the direct effect of social background is stronger in "soft fields" – such as humanities, economics, social sciences, or law – than in "hard" ones, like engineering, architecture, or sciences.
Different hypotheses might explain a possible heterogeneous effect of class background on fields of studies, for example, the lower signalling power about individual productivity in less specialised and less technical fields. Alternatively, social class may be particularly important in "soft fields" mostly chosen by women, due to employers' stronger misperceptions about their real value. An alternative view consists of the absence of any horizontal class effects due to the self-selection of the most motivated individuals from the lower classes, which would blur their differences compared to graduates from the upper classes.

The results provide evidence that supports the main hypothesis about lower signalling power: graduates with privileged backgrounds who study fields such as education, statistics, law and other social sciences enjoy a wage advantage of around 3-4%. These results – combined with the lack of mediating power of educational attainment – suggest that Italy is characterised by a strong intergenerational transmission of inequality, particularly in non-technical fields where social class may provide a stronger signal for sorting workers into jobs with alternative/higher returns. This is likely to result in further wage inequality. Therefore, it is not only the structure of the welfare state and of the labour market that constitutes a mechanism through which wage inequality is exacerbated, but also class structure.

4.4. Main limitations

It is clear that all research suffers from theoretical and/or empirical limitations. This dissertation is not an exception, and each paper contributing to it is subjected to some limits.

In the first paper, there are some important limitations due to data constraints related to the inclusion of the in-kind benefits. Indeed, it was not possible to quantify the costs of

access to services which are not completely free and may vary not only between countries, but also within each country. Similarly, an additional relevant assumption is the fact that public services are all delivered by public entities i.e. there is no private sector provision of them. These two elements may bias estimating the equalising effect of in-kind benefits, since both the costs of accessing the services and the private share of them should be discounted.
Furthermore, the results are dependent on the allocation method of the in-kind services. For example, the per capita expenditures for healthcare have been imputed to the individuals using their predicted probabilities of accessing the healthcare system, estimated by logistic regression. These probabilities are therefore strongly dependent on the definition of access to the healthcare system and on the model specification for predicting the corresponding probabilities.
All in all, such limitations are not likely to cause the main results and conclusions to be disregarded, but may affect how precise they are.

The second paper is missing a relevant theoretical component: the evolution of the Skilled Bias Technical Change theory. Specifically, to have a complete picture of what might drive wage inequality trends, it would be necessary to have an idea of what individual workers are doing and the monetary return associated with each of their tasks. Indeed, the Routine Biased Technical Change has evolved from the SBTC and relates wage differentials not to individual skills (education) but to the degree of routinisation of tasks performed in a given occupation. Therefore, to test all possible mechanisms of wage inequality, it would have been ideal to also have information about individual tasks performed. Unfortunately, Italy does not have such data at the worker level, making this analysis impossible. However, in a parallel study on France, Fana and Giangregorio (2021) apply the same methodology and observe that individual tasks are not the main determinants of wage inequality over the 2005-2016 decade; instead, labour market institutions in the form of contractual and work arrangements explain almost all variations in the inequality indexes. This may provide some evidence in support of the results obtained in this chapter.

Unlike the second paper, the third chapter is focused on a single point in time. In particular, the large sample of Italian graduates who graduated from university in 2007 and were surveyed in 2011. This means that this case is missing a dynamic perspective over time, which would be very informative about the trends of transmission of class advantage. For example, it seems reasonable that during economic downturns, the class effect may be stronger and may better protect graduates with privileged backgrounds, compared to their classmates with a less advantaged backgrounds. Furthermore, a dynamic perspective would have been useful for tracking how the class effect across fields of studies may have changed due to the Bologna Process. Unfortunately, the oldest survey data are only available by physically accessing the National Institute of Statistics premises in Rome. The pandemic situation has prevented physically accessing these data, and it was necessary to rely on files for scientific use. These were only available for the 2011, since in 2015 detailed information about class background were removed.

An additional limitation consists of the impossibility of distinguishing between the public and the private sector. This would have been relevant for those who graduated and began working in the health sector and might have contributed to the explanation of class advantage in the medical field.

Therefore, future research could focus on including a dynamic perspective to this kind of investigation about class advantages by field of studies.

To sum up, this dissertation has moved from a macro-descriptive perspective on income inequality to a micro-analysis of potential mechanisms behind the most relevant source of income inequality i.e. the labour market. Taken together, the three papers try to cover the most relevant sources and determinants of inequalities in outcome and opportunity. Nevertheless, further research is required to deal with the main limitations associated with this dissertation.