Essays on technological change and income distribution

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Guido Pialli

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Essays on Technological Change and Income Distribution

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SUMMARY

Over the last several decades, there has been extensive evidence of the rise in income inequality in advanced economies. First, the empirical evidence documented a decrease in the share of labour. Second, income dispersion among individuals increased, pulled by the rise in the share of income accrued by the individuals in the upper tail of the income distribution and the wage divergence between high-skilled and lower-skilled workers. The empirical and theoretical literature has extensively analysed the role of technological change behind these trends, concluding that the recent advances in technological change are both capital-and skilled- biased.

This work adds to this debate by analysing the relationship between technological change and income distribution using the tools provided by the economics of knowledge. The recent advances in the economics of knowledge have inspired a vivid debate among economic professionals, but the implications for income distribution have often been neglected. In this work, the intrinsic characteristics of the innovation process and their implications for the functional and personal income distributions are analysed.

Advanced economies experienced a radical change from an industrial economy to a knowledge economy. The main hypothesis of this work is that the direction of technological change has become increasingly knowledge-intensive. The knowledge economy is characterized by the systematic generation of knowledge as input and its exploitation as output. However, the transition towards greater knowledge centrality has major implications for income distribution. The knowledge-intensive direction contrasts the classical view of the capital- and skilled-biased direction of technological change that was the primary explanation for the high levels of wage inequality during the last decades of the 20th century. On the other hand, over the most recent decades, the intensive use of knowledge in the production process has triggered different mechanisms that affect economic growth and income distribution.

The scope of the work is to shed light on and analyse the implications of the knowledge-intensive direction for income distribution. The work is articulated as follows.

First, I focused on the characteristics of the innovation process to articulate the hypothesis that when technological change is based on bottom-up processes exploiting and valorising workers' competence, the direction of technological change is labour- rather than- capital-biased. The econometric analysis based on a sample of European regions confirms that where the rate of technological change based upon subsequent and localized improvements is fast, the share of income going to

labour is higher. These results question the collective wisdom finding a generalized decline in the labour share of income due to capital-augmenting technological change.

Second, the existing contributions to the direction of technological change debate neglect the changes in the elasticity of substitution as an additional source of biased innovation. On the contrary, our results point to an increase in the elasticity of substitution over time within advanced economies. Therefore, the decline of the labour share may also be driven by institutional and market factors making labour more substitutable by capital.

Finally, the analysis of top income inequality and the growing disparities even within high-skill groups has been documented, but little effort has been provided to understand its causes. The work also attempts to explain the increasing wage dispersion, concentrated mainly among workers engaged in non-routine cognitive tasks, with the consequences of the increased demand for knowledge-based services. Therefore, the results in this chapter support previous descriptive evidence of the rising top income shares due to scale-based phenomena in knowledge-based sectors.

Finally, the findings' relevance, policy implications, and avenues for future research are discussed in the last section.

Chapter 1.

Introduction

Society and academics experienced an emerging debate about the determinants and consequences of the high levels of income inequality achieved by advanced economies over the last several decades (Aghion et al., 2019; Hartman et al., 2017; Milanovic, 2016; Piketty, 2014; Piketty and Saez, 2014; Ranaldi and Milanovic, 2022).

Empirical evidence for the 20th century has shed light on several stylized facts. First, while between-country inequality dominated in the middle of the last century, income inequality rose within countries in the second part of the 20th century but fell between advanced and emerging economies (Ravallion, 2018; Van Zanden et al., 2014). The increased levels of globalization in factor and product markets and in the rate of technological change contributed to levelling off between-country inequality (Antonelli and Gehringer, 2017; Risso and Sanchez-Carrera, 2019). However, globalization in factor markets is among the causes of the rise in within-country inequality by creating disparities between creative and manual labour, the so-called polarization of the labour markets (Autor, Dorn and Hanson, 2015).

Second, income inequality is split into functional inequality, which regards the income distribution between capital and labour, and personal inequality, which is related to the income dispersion among individuals. Furthermore, personal income inequality may be decomposed into wage and rent inequality. While wage inequality emerged during the 1980s, rent inequality deriving from the uneven distribution of wealth already existed at the beginning of the century (Piketty, 2014; Piketty and Zucman, 2014). The empirical literature has highlighted both the decrease in the labour share of income in advanced economies (Dao, Das and Kozcan, 2019; Elsby, Hobijn and Sahin, 2013; Karabarbounis and Neiman, 2014) and the rise in wage inequality between skilled-creative and unskilled-routine labour (Acemoglu and Autor, 2011; Goldin and Katz, 2010).

The empirical literature has identified technological change as responsible for the decreased labour share and the increased income disparities among individuals (Bassanini and Manfredi, 2014; Bentolila and Saint-Paul, 2003; Van Reenen, 2011). Specifically, technological change has been mainly detrimental for individuals placed on the lower end of the skill and wage distribution. The adverse effects of technological change on inequality and unemployment have received much interest since the origins of the Political Economy as a discipline (Babbage, 1835; Ricardo, 1821). Therefore, the transition to the knowledge and Information and Communication Technology (ICT) economy has been considered a potential major explanation for the recent surge in income inequality.

The economic literature has analysed in depth the intrinsic heterogeneous characteristics of technological change and its direction. Empirical evidence for the US and Europe confirmed the Skill-Biased Technological Change (SBTC) effect of new technologies that increased wage inequality between skilled and unskilled workers (Berman, Bound and Machin, 1998; Goldin and Katz, 2010). The SBTC hypothesis, at the beginning of the 21st century, was complemented by the Routine-Biased Technological Change (RBTC), which focused on the effects of the systematic use of new ICT technologies, complementing non-routine tasks, in creating polarization of the labour markets (Autor and Dorn, 2013; Autor, Levy and Murnane, 2003).

The close timely correlation between the observed decline of the labour share and the emergence of the skill-biased technological change has prompted the collective hypothesis that the capital-intensive direction of technological change is also skilled-biased. However, the SBTC hypothesis does not clarify whether the skill-intensive direction of technological change is labour- or capital-biased. The empirical literature has emphasized for long the capital- and skilled-bias direction of technological change triggered by the complementarity between skilled labour and physical capital and reduction in the capital user costs (Griliches, 1969; Karabarbounis and Neiman, 2014; Zeira, 1998). According to this view, skilled workers are required to operate with new sophisticated machinery (Krusell et al., 2000).

At the same time, much consensus has emerged, since the 1980s, on the capital-biased direction of technological change due to the advancements in ICTs (Autor and Salomons, 2018; O'Mahony, Vecchi and Venturini, 2021; Perugini, Vecchi and Venturini, 2017). However, deeper analyses based on the tools provided by the economics of knowledge suggest that the direction of technological change can be both labour-biased and skilled-intensive (Acemoglu, 2002, 2003, 2015; Antonelli and Feder, 2020; Consoli et al., 2021), triggered by localized technological change based on the workforce's competence and existing learning processes (Atkinson and Stiglitz, 1969; David, 1975).

The significant changes that have occurred in the last several decades regarding the mechanisms of knowledge generation and governance question the legitimacy of the capital-intensive direction of technological change result. On the contrary, advanced economies are increasingly characterized by a knowledge-intensive direction, favoured by new intangible assets that provide advanced economies with a cheaper input than fixed capital and labour. As a result, the abundance of knowledge in advanced countries provided a strong stimulus to the introduction of technologies that are knowledge-intensive and tangible-capital saving (Antonelli, 2019; Antonelli, Orsatti e Pialli, 2022b; Haskel and Westlake, 2018; Mohnen, Polder and van Leeuwen, 2018).

Concerning the functional distribution of income, the elusive foundation of the skilled-and capital-biased direction of technological change is rooted in the systematic use of the CES production function in analysing the direction of technological change. Indeed, in a CES framework, the assessments of the direction of technological change, which can be labour-or capital-biased, are based on the value of the elasticity of substitution between production factors. Its value is not estimated but directly inferred from the results of the empirical analysis (Bassanini and Manfredi, 2014; Damiani, Pompei and Ricci, 2020; Perugini, Vecchi and Venturini, 2017). A negative effect of technological change on labour share implies an elasticity higher than unity, meaning that labour and capital are substitutes.

The use of the CES has three major limitations for the assessments of the direction of technological change. First, while the hypothesis of capital heterogeneity has been considered from the empirical literature (O'Mahony, Vecchi and Venturini, 2021), the possibility of labour heterogeneity is often overlooked, with the consequence that one cannot measure the elasticities of substitution between capital and different categories of workers. Second, the CES setting infers the direction of technological change from the value assumed by the elasticity of substitution, but at the cost of keeping constant the output elasticities, which might be endogenous in the production function (Acemoglu, 2002, 2003). Third, the CES does not consider that technological change and other economic factors may directly affect the elasticity of substitution.

The second major pitfall of the SBTC literature is that it is less convincing in explaining the wage inequality in the upper tail of the skill and wage distributions. Lemieux (2006a, 2006b) shows that within-group inequality increases along with skill level, suggesting that the marginal returns to education are increasing. Moreover, the increase in income inequality has been strongly driven by the surge in top income inequality. The emergence of new professions and sectors based on scale-based phenomena may trigger superstar economies that benefit considerably top talented workers (Kaplan and Rauh, 2010, 2013). Wage inequality during the 20th century has long been dominated by the wage divergence between skilled and unskilled workers (Goldin and Katz, 1998, 2010). On the contrary, wage inequality, in the last two decades, seems to be characterised by high wage dispersion among high-skilled and non-routine workers (Kim and Sakamoto, 2008; Van der Velde, 2020).

Again, the tools provided by the economics of knowledge help to shed light on the rising upper-tail and within-group income inequality. The limited exhaustibility of knowledge implies that knowledge is not subject to the wear and tear suffered by standard economic goods (Le Bas and Scellato, 2014). This implies that the accumulation of knowledge and human capital of high-skilled individuals can be recombined and leveraged over time. The application of their knowledge in scale-based sectors such as finance, knowledge-intensive business services and professional services generates economies of superstars in which wage dispersion also increases among high-skilled non-routine workers (Rosen, 1981).

This thesis aims to extend and enrich the analysis of technological change and income inequality by addressing the limitations of the current empirical literature. Specifically, the thesis focuses on the new knowledge-intensive direction of technological change and its implications for both functional and personal income distributions. First, I propose the hypothesis that the skill-biased effect of technological change is also compatible with a knowledge-intensive and capital-saving direction of technological change (Antonelli, Orsatti and Pialli, 2022b). Second, I implement this hypothesis by relying on the recent advances of technological change based on the knowledge content of technological change and the direction of technological change based on augmenting the factor inputs that are more abundant locally (Antonelli, Orsatti and Pialli, 2022a). The work is articulated into three main chapters, each analysing a specific topic.

Chapter 2 analyses the determinants of the labour share across European regional labour markets. The chapter hypothesizes that technological change is labour-biased in the presence of localized and bottom-up technological change. When technological change relies on bottom-up processes, the direction of technological change valorises the learning processes of the workforce. At the same time, the rigidity of local labour markets and the lower unemployment rates strengthen the bargaining power of labour, inducing technological change directed to make more intensive use of labour, the most abundant and expensive production input. The empirical analysis is based on 171 NUTS-2 regions observed between 1999 and 2015. The results of the econometric analysis show a positive effect of technological change on the regional labour share, using total patent applications as a proxy for incremental and localized technological change. Moreover, the rigidity of the local labour markets, as proxied by the unemployment rate, suggests that greater bargaining power of labour is associated with a labour-biased direction.

Chapter 3 focuses on the role of the elasticity of substitution in the assessment of income distribution. Indeed, the role of the elasticity of substitution has often been overlooked by the previous literature. We focus on its role as an alternative source of biased innovation along with the changes in factor intensities and factor-augmenting technical change. First, we construct a relationship between the capital share, capital intensity and the elasticity of substitution. The elasticity of substitution is thus endogenous, as it changes with the capital intensity and capital share. Then, using a nine countries sample observed between 1950 and 2017, we estimate the elasticity of substitution from this relationship and, using a rolling window analysis, find that the elasticity is unstable across different subsamples. Specifically, we highlight the increase in the estimated elasticity in the most recent rolling window subsamples. Then, we estimate with a non-linear least squares estimator the elasticity before and after a turning year around which the data show a decrease in the labour share. The results of our estimations confirm the increase in the elasticity of substitution estimated both without and with labour-augmenting technical change. Therefore, we show that, in the assessments of the income distribution, the increase in the elasticity of substitution should also be considered.

Chapter 4 examines the relationship between technological change and personal income distribution. Precisely, it focuses on the consequences of the rising employment rate in knowledge-based services as a source of increasing income inequality in the US. Advanced economies experienced a transition from a manufacturing-based economy to a knowledge- and service-based economy. As a result, the employment rates in knowledge-based services such as finance, Knowledge-Intensive Business Services (KIBS) and both professional and business-related services have increased steadily since the last decades of the 20th century. The chapter empirically analyses the impact of this transition on wage inequality across 201 cities in the US for the period 1980-2010. Moreover, the other novelty of the chapter is also to focus on wage inequality within non-routine cognitive occupations. The results show that the demand for knowledge-intensive services positively and significantly affects both overall wage inequality and wage inequality within non-routine cognitive occupations.

Finally, chapter 5 discusses and summarizes the conclusions.

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Chapter 2.

The labour-biased direction of technological change across European regional labour markets

ABSTRACT

The labour share exhibits substantial variance across European regional labour markets. In some regions, the labour share has increased, while in others, it decreased sharply. This paper analyses the characteristics of technological change and internal labour markets as the main determinants of the evolution in labour share. Specifically, it advances the hypothesis that when substantial rigidity characterizes labour markets, and technological change is localized and based on bottom-up learning processes, the direction of technological change is labour-biased. The empirical analysis performed on a sample of 171 European regions observed for the period 1999-2015 confirms the theoretical hypotheses.

2.1. Introduction

A sizable literature confirms the large variability of the labour share of income over the recent decades. This trend conflicts with the 'stylized facts' of growth economics that treated factor income shares as constant in the long run (Kaldor, 1961; Solow, 1956). There is considerable consensus that the labour share has declined since the 1980s in the US and most European countries. The slowdown of the labour share is only a part of a global phenomenon of increasing levels of income inequality and labour market polarization (Atkinson, Piketty and Saez, 2011; Dosi and Mohnen, 2019; Goos, Manning and Salomons, 2014; Michaels, Natraj and Van Reenen, 2014; Tridico, 2018).

The analysis of the functional distribution of income has been a widely debated topic since the origins of the Political Economy as a discipline (Ricardo, 1821). The empirical interest in this topic has focused much on its consequences on economic growth and its causes. Post-Keynesian economics has long emphasized the merits of wage-led regimes for long-term productivity and effective demand (Bhaduri and Marglin, 1990; Stockhammer and Onaran, 2013). The analysis of the direction of technological change has received much interest along the lines paved by Marx and Hicks, which were incorporated into the induced technological change tradition (Ruttan, 1997). However, less empirical attention has been given to the characteristics of the innovation process, whether bottom-up or top-down, in driving the wage share.

There is broad consensus on the negative effect of technological change on labour share. At least since the influential contribution of Bentolila and Saint-Paul (2003), most studies have shown that the direction of technological change has become capital-biased in the 1980s (Bassanini and Manfredi, 2014; Hutchinson and Persyn, 2012; Karabarbounis and Neiman, 2014; Perugini, Vecchi and Venturini, 2017).

This paper delves into the determinants of labour share across European regions. It hypothesizes that the transition toward a knowledge-intensive economy induces a labour-biased, not capital-biased, direction of technological change. For this purpose, I propose an interpretative framework based on the notion of localized and bottom-up technological change. According to this framework, I argue that the localized technological change, exploiting bottom-up processes based on the accumulation of tacit knowledge and the valorisation of existing learning processes grounded on workers' competence, induces a labour-biased direction and increases the labour share of income.

The skill-biased effect of technological change has received much empirical support as an explanation for the increased wage inequality in advanced economies (Autor, Katz and Kearney, 2008; Goldin and Katz, 2010). However, the skill-biased literature is silent on the effects of technological change on income distribution between capital and labour. The different modes of knowledge production determine whether a skill-biased technology is *also* capital-biased, reducing the labour share, or capital-saving, resulting in an increase in the share of income paid to labour.

Since the contribution of Griliches (1969), a broad consensus has emerged on the capital-skill complementarity of technological change and the evidence that a skill-biased technology is conducive to a capital-intensive direction of technological change, triggered by the steady decline of the cost of capital over that of labour (Karabarbounis and Neiman, 2014; Zeira, 1998). On the contrary, the empirical analysis of this paper suggests that when technological change is localized and based on bottom-up learning processes, the direction of technological change is labour-biased.

The transition from a manufacturing to a knowledge-intensive economy has represented an unprecedented change in the advanced economies in the last decades. As the economy shifted from a manufacturing and capital-intensive economy to a new knowledge economy, technological change was no longer directed to fixed capital. On the contrary, it valorised learning processes, tacit knowledge and qualified labour competence. Indeed, several works suggest that the workforce now commands the technological knowledge used as input in the production process (Antonelli and Feder, 2020).

The paper examines the implications of this framework by exploiting variation within European regions. Technological change is far from being neutral at the regional level, and its direction exhibits substantial variance depending on the characteristics of local labour markets (Antonelli and Quatraro, 2013). European labour markets are heterogeneous in their levels of rigidity, with large consequences on the wage-bargaining process. The variance of the knowledge generation process at the European level and the different dynamics of internal labour markets constitute a fertile field for studying the relationship between technological change and income inequality (Lee and Rodriguez-Pose, 2013; Lee, Sissons and Jones, 2016; Pinheiro et al., 2022). However, this stream of research has received little attention from the empirical literature.

The empirical analysis is based on a sample of 171 NUTS-2 (Nomenclature des Unités Territoriales Statistiques) regions belonging to ten countries of the Euro Area, observed between 1999 and 2015. The results of the econometric analysis, based on panel data estimation, Instrumental Variable (IV) analysis and several robustness checks, support the labour-biased direction of technological change.

The chapter is structured as follows. First, section 2.2 illustrates the interpretative framework. Then, section 2.3 presents the empirical methodology and provides some descriptive statistics. Finally, in section 2.4, I discuss the results, whereas section 2.5 summarizes the conclusions.

2.2. Theoretical background

2.2.1. Related literature

The generalized decline of the labour share within advanced economies has become a major preoccupation of empirical economists. Accordingly, a rich bundle of studies has focused on the negative implications caused by globalization in factor and product markets. Over the recent decades, the entry into international markets of advancing countries specialized in labour-intensive goods has changed labour costs in advanced economies. Moreover, the decline in transportation costs, the diffusion of ICT and the removal of the restrictions on capital mobility have encouraged firms in developed countries to relocate part of their production activities into emerging economies. As a result, the expansion of global value chains and the increased levels of financial and trade integration have substantially harmed workers in developed economies, especially those engaged in routine-intensive tasks within the manufacturing sector (Dao, Das and Koczan, 2019; Elsby, Hobijn and Sahin, 2013; Jayadev, 2007; Vom Lehn, 2018).

Other studies have focused on plausible determinants of this slowdown, such as: automation (Acemoglu and Restrepo, 2018); superstar firms (Autor et al., 2020); intangible assets (Koh, Santaeulàlia-Llopis and Zheng, 2020; O'Mahony, Vecchi and Venturini, 2021); financialization and capital mobility (Kohler, Guschanski and Stockhammer, 2019; Pariboni and Tridico, 2019); deregulation of product markets (Azmat, Manning and Van Reenen, 2012); demographic change (Schmidt and Vosen, 2013); liberalization of the labour markets and the falling bargaining power of labour (Ciminelli, Duval and Furceri, 2020; Damiani, Pompei and Ricci, 2020; Guschanski and Onaran, 2021).

Nonetheless, technological change is considered the primary explanation for the decline in labour share. Most of the literature has documented a negative effect of technological change on the labour share, assuming that a Constant Elasticity of Substitution (CES) technology characterizes the production process. This strand of literature (Bassanini and Manfredi, 2014; Bentolila and Saint-Paul, 2003; Blanchard, 1997; Hutchinson and Persyin, 2012; Perugini, Vecchi and Venturini, 2017) presumes that as long as markets are competitive and technological change is labour-augmenting, the labour share is in a one-to-one relationship with the capital-output ratio. This relationship is defined as the SK schedule. The slope of this curve depends upon the elasticity of substitution since a value above unity signals a negative relationship between capital intensity and labour share. In contrast, a value below unity suggests that labour and capital complement each other in the production process. The empirical evidence showed that technological change negatively affects the labour share, implying an elasticity of substitution between capital and labour above unity. However, this argument contrasts with several stylised facts.

First, most empirical contributions estimate the aggregate and micro-level substitution elasticity values as lower than unity (Antràs, 2004; Chirinko, 2008; Chirinko and Mallick, 2017). Knoblach, Roessler and Zwerschke (2020) perform a meta-regression analysis showing that the US long-run elasticity of substitution is within the range 0.45 to 0.87.

Second, Cette, Koehl and Philippon (2019, 2020) have challenged the shared wisdom of a secular downturn in the labour share since they do not observe any structural decline when they explore alternative starting periods of the empirical analysis and address several biases in the wage share's measurement.[1] Similar findings have been produced for Italy (Torrini, 2015).

Third, even though the price of technological equipment has sharply declined, the capital share of income has remained unchanged, suggesting that several offsetting mechanisms are at work. The rise in automation may indeed reduce employment and the labour share. However, emerging labour-intensive tasks may counteract this opposing force and increase wage and employment levels (Acemoglu and Restrepo, 2018).

2.2.2. Interpretative framework

The transition from fixed capital and capital-intensive technologies to knowledge-intensive technologies characterizes the new knowledge economy. The emergence of the new knowledge economy has paralleled the decline of the manufacturing sector and the large corporation as the mechanisms for generating and exploiting knowledge (Charles, Hurst and Schwartz, 2019; Kristal and Cohen, 2017). As a result, the activities of knowledge generations and exploitations are no longer vertically integrated into big corporations but distributed horizontally and outsourced to new entities specialized in providing knowledge as a service, such as small knowledge-intensive firms and universities (Arora, Belenzon,

[1] Specifically, Cette et al. (2019, 2020) show that empirical evidence on labour share decline has three fallacies. First, taking the period of a wage push, which is only a temporary phenomenon, as the initial period in the empirical analysis, leads to overestimating the labour share decline. Second, the standard measurement assumes that the self-employed earn the same wage as the employees. However, for self-employed is difficult to distinguish between capital and labour income. Third, the real estate sector overestimates capital gains, but this does not correspond to fixed capital used by the firms.

Patacconi, 2018). In this scenario, Knowledge-Intensive Business Service (KIBS) firms are emerging as the locus of knowledge-intensive services provided to large corporations (Corrocher and Cusmano, 2014; Wessel, 2013).

The advancement in ICTs has triggered a radical structural change that made the tradability of knowledge as an economic good more practical. In particular, ICTs facilitate the codification of tacit knowledge in digitalized products and bring in skilled workers in the production process (Cirillo et al., 2021). Moreover, the easier tradability of knowledge as a good and service has prompted the emergence of small knowledge-intensive firms and universities as the main disseminators of basic research (Narula, 2004).

The new mechanisms of governance and generation of knowledge have substantially reshaped the production processes of advanced economies. At the same time, there is extensive literature showing the effects of technological change on wage inequality, based on the so-called Skill-Biased Technological Change (SBTC) effect of new technologies (Berman, Bound and Griliches, 1994; Dunne et al., 2004; Machin and Van Reenen, 1998). The SBTC literature has been recently complemented by the Routine-Biased Technological Change (RBTC) hypothesis (Autor, Levy and Murnane, 2003; Goos and Manning, 2007). The latter theory argues that the systematic and pervasive use of new ICTs largely benefits workers engaged in non-routine and cognitive tasks, while detrimental to workers performing routine non-manual tasks. The ultimate effect of the new technologies is the polarization of the labour market, in which the routinized workforce in the middle of the wage distribution is the most damaged.

However, less attention has been paid to assessing the determinants of income distribution between capital and labour. Indeed, the SBTC and RBTC theories do not clarify whether the direction of technological change is labour-or capital-biased. The consensus emerged around the capital-skill complementarity hypothesis (Griliches, 1969) led mainstream economics to consider that both high wages and skilled labour are associated with a capital-intensive direction (Zeira, 1998). Yet, the new knowledge economy is characterised by both a skilled and a labour-intensive direction of technological change (Acemoglu, 2015; Antonelli and Feder, 2020).

This paper advances the hypothesis that the direction of technological change is labour-biased when knowledge generation is a bottom-up process based on the use and valorisation of existing learning methods possessed by the workforce. Historically, two theories have faced each other in explaining technological change direction and rate. The first is the induced theory of innovation, which relies upon the Hicksian reinterpretation of the hypothesis developed by Karl Marx (Ruttan, 1997). This theory argues that the changes in factor prices stir the direction of technological change (Brugger and Gehrke, 2017). Specifically, technological change is directed to replace the factors of production that are relatively more expensive. Hicks (1932: 124-125) wrote:

> A change in relative prices of the factors of production is itself a spur to invention, and to invention of a particular kind – directed to economizing the use of a factor which has become more expensive.

Recently, the theory has received renewed interest in labour economics to investigate the causes behind the rise in the wage differential between skilled and unskilled workers while the supply of skilled workers kept increasing (Acemoglu, 1998, 2002). Acemoglu (2002, 2003, 2015) has placed novel attention on the endogenous direction of technological change by distinguishing a price effect, according to which firms are incentivized to develop technologies that use the most expensive factor, and a market-size effect that induces firms to bias the direction of technological change toward the use of the factor that is relatively more abundant. As long as the elasticity of substitution between factor inputs is sufficiently high, the market-size effect dominates the price effect, and the more abundant factor is also rewarded the more.

The contribution of Acemoglu has allowed reconciling and partially blending the induced tradition with the localized technological change approach based upon Atkinson and Stiglitz's (1969) and David's (1975) works. The localized technological change framework shares the essential background of the induced theory, as factor prices are the determinants of the introduction of innovations. However, the LTC hypothesizes that any increase in factor costs cannot be adjusted solely by changes in factor intensity, as substantial rigidity and irreversibility characterize labour input. As a result, faced with the irreversibility of the production factors, firms exploit the existing bottom-up processes based on labour's utilization and introduce capital-saving and labour-biased technological change.

The localized and bottom-up approach matches the application of efficiency wages. According to the efficiency wage theory, (large) firms pay higher unit wages to deter workers' shirking and foster their commitment to the existing learning processes (Akerlof and Yellen, 1986; Shapiro and Stiglitz, 1984). Therefore, the generation of technological change is bounded by the space of techniques in use and by the irreversibility of the production inputs, especially in the manufacturing sector, where the usual income distribution process based on wage premiums earned by workers in large firms continues to apply (Berlingieri, Calligaris and Criscuolo, 2018; Leonardi, 2007). As a result, firms react by exploiting internal competence and learning processes when they face substantial irreversibility of the production inputs. When substantial rigidity characterizes the labour markets and switching costs deter the shift toward a different capital-labour ratio, the response of the economies is to bias the direction of technological change toward the most expensive factor (Antonelli and Quatraro, 2013; David, 1975).

Indeed, further technological advancements are growingly shaped by the conditions of the local labour markets. The labour market reforms launched in the 1990s across European countries made labour input more flexible and sensitive to the changes in local labour markets (Kampelmann et al., 2018; Michie and Sheenan, 2003). Moreover, the resurrection of the wage curve across European regions (i.e., the negative relationship between wages and unemployment) has made local nominal wages more sensitive to fluctuations in the unemployment rate and conditions of the internal labour markets (Ammermüller et al., 2010; Devicienti, Maida and Pacelli, 2008). Therefore, the lower the unemployment rate, the stronger the wage bargaining power of the workers and, hence, the higher the efficiency wages. In regions where the unemployment rate is high, trade unions are weaker and less able to contrast the substitution of capital for labour. A higher unemployment rate is associated with a lower worker's bargaining power and a greater tendency to a capital-biased direction of technological change.

The economics of innovation has much focused on the limited exhaustibility of knowledge. This property implies that knowledge is not subject to the wear suffered by standard economic goods. Indeed, knowledge can be reused continually as an input in developing further technological knowledge. The knowledge generation process can be interpreted as a recombinant process in which technological knowledge is generated by recombining existing pieces of knowledge (Weitzman, 1996, 1998).

Technological change is localized and recombines the knowledge base developed internally and exploits the existing processes of learning by doing, learning by using and learning by interacting (Antonelli, Krafft and Quatraro, 2010; Jensen et al., 2007). Implementing the LTC, firms exploit the internal corridor of the techniques they know, using the same factor intensity, but bias the direction of technological change toward labour, the factor input that is more abundant and profitable (Acemoglu, 2015).

The competitive pressure produced by globalization in both factor and product markets has weakened the competitive advantage of advanced economies, which rely not merely upon the augmentation of capital intensity but more on the exploitation of knowledge as an input. While knowledge-intensive services have displaced the manufacturing economy, the workforce's competence and routinary skills continue to be essential to the production process (Consoli et al., 2021).

Moreover, the increasing specialization of know-how and the accumulation of tacit skills allow the middle-skilled and routine workforce to play a crucial role exploited by the firms (Piva, Grilli and Rossi-Lamastra, 2011).

The notion of technological change as a bottom-up process, as opposed to top-down, is central to understanding this argument. The bottom-up localized process is a reaction to the substantial irreversibility of the production inputs and exploits the competence and tacit knowledge based on the existing learning processes. On the contrary, the top-down process is science-based and exploits the specialized competence of high-skilled workers, who, in turn, appropriate a large share of knowledge rents (Antonelli and Tubiana, 2020). As a result, the top-down generation of technological change is more likely to be associated with worker segmentation and a capital-biased direction.

A bottom-up model of technological change is based on the implementation of incremental innovations and 'downstream' localized improvements. Incremental innovations characterize gradual and subsequent improvements of existing technologies, as opposed to radical and breakthrough technological change. These activities include solutions to removing production bottlenecks and enhancing product designs, improving communication between production segments and reinforcing feedback transmissions in user-producer interactions (Antonelli and Gehringer, 2019; Rosenberg, 1976; Rosenberg and Steinmuller, 2013). The tacit knowledge of a routine and specialized workforce trained by work-based learning and apprenticeship is the primary driver of these incremental modifications (Grinza and Quatraro, 2019; Lewis, 2020). Knowledge interactions supported by the ICT infrastructure enable to transmit and access the tacit component of knowledge. Even though the new ICTs have strongly increased the codification of technological knowledge, it remains a tacit and irreducible tacit component that can be transmitted only through workers' interactions and learning mechanisms (Cowan, David and Foray, 2000; Cowan and Foray, 1997). In fact, incremental innovations often arise from the on-work experience and learning-by-doing activities of technicians involved in operation and maintenance of existing processes and machines.

The production process assumes traits typical of an O-ring production function (Kremer, 1993), in which production at a particular stage depends upon the previous steps' success in a continuum of interrelated interactions. Therefore, technological imbalances among production phases generate supply-side constraints that guide the direction of technological change (Harada, 2014). The roles of 'useful knowledge' and blue-collar standard workers in complementing scientific knowledge are key factors for the subsequent improvements of new incremental innovations (Mokyr, 2005; Rosenberg, 1976).

The bottom-up process based on the development of downstream and incremental innovations represents a more inclusive knowledge generation process blending scientific and technical knowledge with practical experience incorporated in routine activities. Indeed, manual and standard labour may possess problem-solving capabilities to manage incremental and experimental-based improvements flowing to the management (Bradley, Kim and Tian, 2017). Therefore, when technological change is incremental and bottom-up, all workers are expected to contribute to the knowledge generation process, augmenting the share of income paid to labour.

In sum, the main hypotheses of this paper are:

i) the direction of technological change is labour-biased when technological change is localized and based on the exploitation of bottom-up processes.

ii) the more local labour markets are characterized by rigidity and the application of efficiency wages, the stronger the region's localized technological change reaction, and, hence, the greater the bias of technological change toward labour.

2.3. Empirical model

2.3.1. Econometric model

The empirical analysis tests the hypotheses developed in the previous section. The empirical specification draws on the model of Bentolila and Saint-Paul (2003) who derived the so-called SK schedule. However, the empirical analysis of this paper is not based on a specific production function, but it assumes a general multiplicative relationship between the labour share LS and the capital-output ratio $k = \frac{K}{Y}$ (Arif, 2021; Gonzalez and Trivin, 2016): [2]

$$LS = f(k)^{a} \tag{1}$$

Taking the logarithms of both sides produces a linear relationship between the log of the labour share and the log of the capital-output ratio. The sign of the relationship would tell us whether labour and capital are complements, therefore implying a positive relationship between LS and k, or substitutes, if the relationship is negative. This framework also

[2] The standard literature assumes a CES production function with a constant elasticity of substitution. However, this framework departs from the case of a variable elasticity of substitution. Indeed, recent research has shown a changing elasticity of substitution in advanced economies (Koesler and Schymura, 2015), contributing to the hypothesis that technological change may directly affect the degree of substitutability among production inputs (Sala and Trivín, 2018).

allows departures from equilibrium conditions in factor and product markets. In this setting, the labour share is measured empirically as the ratio between employees' compensation and GDP but does not represent necessarily the output elasticity of labour at the regional level, which is equal to the labour share when applying the Euler theorem in a Cobb-Douglas production function (Antonelli and Quatraro, 2013). Therefore, it assesses whether technological change and workers' bargaining power contribute to enlarging or depressing the wage share, above or below the (theoretical) output elasticity of labour. A positive (negative) relationship between technological change and the labour share implies that the direction of technological change is labour-biased (capital-biased), using the terminology adopted by Acemoglu (2002, 2003, 2015).

Therefore, the empirical analysis estimates the relationship between the labour share, technological change and the dynamics of internal labour markets. To this purpose, I estimate the following equation:

$$\mathrm{LS_{it}} = \alpha_0 + \alpha_1 \ln\left(\frac{K_{it-1}}{Y_{it-1}}\right) + \alpha_2 \ln(TECH_{it-1}) + \boldsymbol{X'}_{it-1}\alpha_3 + \varphi_i + \delta_t + \epsilon_{it} \tag{2}$$

where LS_{it} is the labour share of income in region i at time t, expressed as the logarithm of the ratio between the compensation of employees and the regional GDP; $\frac{K_{it-1}}{Y_{it-1}}$ is the capital-output ratio in region i at time $t-1$ expressed as the ratio between the capital stock and GDP; $TECH_{it-1}$ represents the technological change in region i at time $t-1$. The terms ϕ_i and δ_t are region and time fixed effects, respectively. The first captures time-invariant unobservable heterogeneity across regions, derived from local labour market asymmetries and different absorption capabilities; the second controls for business cycle effects hitting all regions simultaneously. Finally, the term ϵ_{it} is the idiosyncratic error term that captures unobserved factors at the NUTS-2 level.

The main variable of interest is technological change. In line with the theoretical analysis, the aim is to identify the conditions under which technological change is localized and based on bottom-up processes. For this purpose, I exploit information contained in patent data to develop a measure that accounts for the number of incremental innovations introduced at the regional level. Incremental innovations, as opposed to radical innovations, should represent a better proxy for that part of technological change based on the development of downstream and localized improvements exerting a positive effect on the wage share. Precisely, I exploit the radicalness measure proposed by Squicciarini, Dernis and Criscuolo (2013) to distinguish between incremental and radical innovations. As explained in the following section, this operationalization allows testing the effect of the type of technological change more likely to exploit workers' competence and learning processes.

The vector $\boldsymbol{X'}$ includes a range of additional factors that may affect the dependent variable.[3] First, to measure the dynamics across local labour markets, the unemployment rate is included. Indeed, the level of unemployment measures the extent to which trade unions may exert their effects on workers' bargaining and increase the rigidity of local labour markets. The lower the unemployment rate, the higher the workers' wages and the stronger the irreversibility of production factors providing incentives to firms to bias technological change toward labour (Antonelli and Quatraro, 2013; Dünhaupt, 2017; Pariboni and Tridico, 2019). Second, the estimation model includes the share of manufacturing employment over the total employment, as regions in which the manufacturing share is larger should be characterized by stronger workers' protection, higher efficiency wages and larger employment of blue-collar workers (Gould, 2019).

Finally, the analysis also includes the GDP growth rate to control for the counter-cyclical behaviour of the wage share during recession periods, as prices are more flexible than wages in the short-run (Stockhammer, 2017), and the population density to account for the role of agglomeration economies. Indeed, a vast body of empirical literature showed that areas where labour markets are more concentrated pay higher wages and display greater productivity levels, driven by the sorting and selection of high-talented workers, agglomeration externalities and firm concentration (Boschma, Eriksson and Lidgren, 2014; Boschma and Frenken, 2011; Duranton and Puga, 2004; Moretti, 2010). To net out unobservable heterogeneity, I apply the panel data fixed-effect estimator to equation (2).[4] All covariates are taken in (natural) logs and lagged by one year to soften reverse causality problems.[5] All the regression specifications compute autocorrelation and heteroskedasticity robust standard errors obtained with the Newey-West variance estimator, following Aghion et al. (2019).

Finally, section 2.4.3 presents the results of an Instrumental Variable strategy addressing endogeneity issues raised by technological change in equation (2).

[3] It is worth noticing that a few regions have zero patents in specific years. Therefore, taking the natural logarithm of those cases would remove such observations. For this reason, I follow Aghion et al. (2019), and I replace the natural logarithm of patent applications with zero while adding a binary variable equal to one and zero otherwise when patent applications are zero. This binary variable is added in every specification but never shown in the estimation results.

[4] Standard panel unit root tests that account for cross-sectional dependence (Im, Pesaran and Shin, 2003) indicate that labour share and the explanatory variables, including technological change, are stationary variables. Therefore, one may be confident in estimating equation (2) in levels.

[5] Tables A.1 and A.2 in Appendix A describe the variables and their summary statistics, respectively. Table A.3 shows the correlation matrix.

2.3.2. Data description

The empirical analysis is executed by using data from several sources. To construct time-series data at the regional level for economic aggregates, I rely upon the Cambridge Econometric European Regional Database[6] and Eurostat repositories. The other source is the OECD RegPat (OECD RegPat, 2020) database, from which information on patent applications at the European level is gathered. Due to data constraints, the econometric analysis is based on a sample of 171 NUTS-2 regions belonging to 10 countries in the European area: Austria, Denmark, Germany, Finland, France, Italy, Netherlands, Spain, Sweden and the United Kingdom. The period of observation ranges from 1999 to 2015.

I compute the labour share as the ratio between compensation of employees ($w_{it}L_{it}$) at current prices and the Gross Domestic Product (GDP_{it}) at current prices. However, I am not provided with data on capital stock to calculate the capital-output ratio in equation (2). Therefore, I apply the perpetual inventory method to gross fixed capital formation data at constant prices, which are available. Specifically, the capital stock series is constructed according to the following dynamic equation:

$$K_{it} = (1 - \delta)K_{it-1} + I_{it} \tag{3}$$

where I_t is the gross fixed capital formation in region i at time t and δ is the depreciation rate. I assume that capital constantly depreciates over time within each region with a rate of 6% for all regions. These assumptions, however, turn out to be relatively safe as long as I include region-specific fixed effects and time fixed effects in the regression. An estimate of the initial value of the series is required. To this end, I use the entire series of investment data available in Cambridge Econometrics (1980-2015) and, assuming that capital accumulation before 1999 follows equation (3), the capital stock in 1998 may be approximated as:

$$K_{i1998} = \frac{I_{i1999}}{g_i + \delta} \tag{4}$$

where g_i is the region-specific average annual growth rate of gross fixed capital formation in each region i along the period 1980-2015.

[6] Specifically, the data are accessed through ARDECO, the Annual Regional Database of the European Commission's Directorate General for Regional and Urban Policy, maintained and updated by the Joint Research Centre.

I extract patent data from OECD RegPat, which contains patent applications submitted to the European Patent Office (EPO) and linked to administrative regions according to the postal code of the applicants or the inventors.[7] I assign patent applications to NUTS-2 regions according to the applicant's address,[8] by following the standard procedure of fractional counting.[9] I allocate patents over time by considering the priority year of the application, which is the date of the first filing, considered the closest date to the original invention.

I exploit information on patent data to construct a measure of incremental innovations. Following Consoli et al. (2021), I distinguish between incremental and radical innovations using the radicalness index built by Squicciarini, Dernis and Criscuolo (2013). A patent is considered radical whether it "builds upon differential technical paradigms from the one in which it is applied". Therefore, the more a patent differentiates from its contributing innovations, the more radical it is (Briggs and Buehler, 2018; Castaldi, Frenken and Los, 2015). The radicalness index is a continuous variable ranging from 0 to 1, with values approaching 1 indicating a more radical innovation. I identify patents as incremental as whether they fall under the 97% percentile of the distribution in terms of radicalness by patent cohort defined relative to the filing year and technology field based on the Schmoch classification (Schmoch, 2008).[10] I then divide patent applications for incremental innovations, Pat, by the number of employees, L, in each region i at time t.

It is worth mentioning that using patents as a proxy for technology suffers from several drawbacks. First, patent applications capture only a subset of the whole range of technological knowledge generated as an output since not all inventions are patented. Indeed, innovation returns can be appropriated using other protecting tools, for example through secrecy. Moreover, the use of patents may be at odds with perfect competition assumptions since patent applications are mainly concentrated in a few economic entities that may also exploit patents to block competitors and erect barriers to entry (Blind, Cremers and Mueller, 2009). On the other hand, they represent one of the few indicators for regional technological capabilities, widely used by established literature since they capture differences across regions in technological capabilities related to their productivity levels (Acs, Anselin and Varga, 2002; Boschma, Balland and

[7] I analyse only patent applications regardless of whether or not the patent has been granted. This choice is motivated by the fact that only a few patents are granted, and the granting process is time-consuming and lasts, on average, four or five years. Therefore, granted patents are less helpful for studying the flow of potential inventions. Indeed, most regional literature uses patent applications to proxy for technological efforts.

[8] In Appendix A, I show that the results are robust to assign patents based on the inventors' location.

[9] The fractionalized counting assignment implies that patents with multiple owners located in different regions are assigned to a given region for a fraction equal to the applicants' share in that region over the total number of applicants.

[10] Section 2.4.3 shows that the analysis is robust by considering different thresholds to define patents as incremental or radical. Moreover, I also test the robustness of the results using an alternative measure based on the breakthrough index still developed by Squicciarini, Dernis and Criscuolo (2013).

Kogler, 2015). Nonetheless, section 2.4.3 shows that technological change has a positive impact on the labour share even when measured by the Total Factor Productivity (TFP).

Moreover, patent citations may have limitations as indicator of knowledge flows and technological quality, too. First, the examiner always decides which citations to include in the patent document. Therefore, many citations, especially from the US patent office, are of low quality (Michel and Bettels, 2001). However, this concern is mitigated by considering only patent applications made to the EPO, in which the examination process delivers patent citations that are considered of better quality than those contained in USPTO patent documents (Breschi and Lissoni, 2009).

Therefore, it must be acknowledged that patents may capture only a part of all technological innovations. Similarly, the citations received by such innovations may represent an imperfect measure of research quality. Yet, the count of patent citations provides one of the most accurate measures of technological quality, mainly when targeted to discriminate between high- and low-quality patents (Gay and Le Bas, 2005).

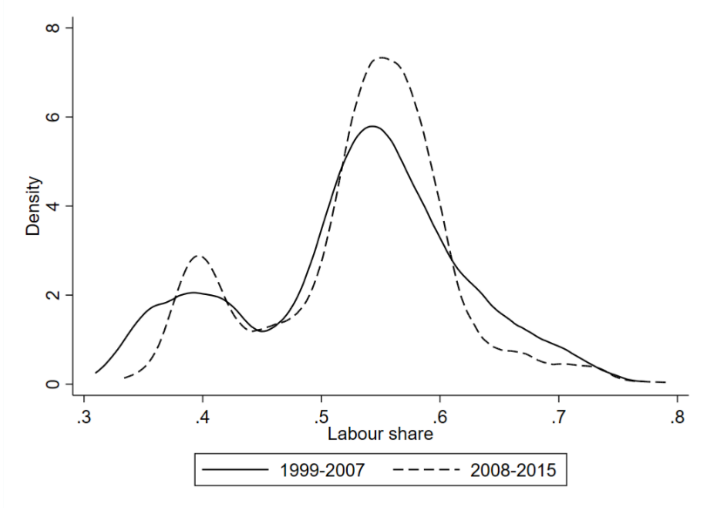
Finally, I extract the unemployment rate (defined as the number of unemployed persons between the ages of 16 and 74 divided by the labour force) and the population density (number of persons per square kilometre) from Eurostat. The manufacturing share is computed as the share of employment in manufacturing industries over total employment, retrieved from Cambridge Econometrics, while the GDP growth rate is equal to the logarithmic difference between t and $t-1$ of the GDP at current prices.

2.4. Empirical evidence

2.4.1. Descriptive evidence

To better understand cross-regional differences in the sample, I first look at the distribution of the labour share across regions. Figure 2.1 presents the Kernel density estimation for the distribution of the labour share across NUTS-2 regions.

Figure 2.1. Epanechnikov Kernel density estimation for the distribution of the labour share



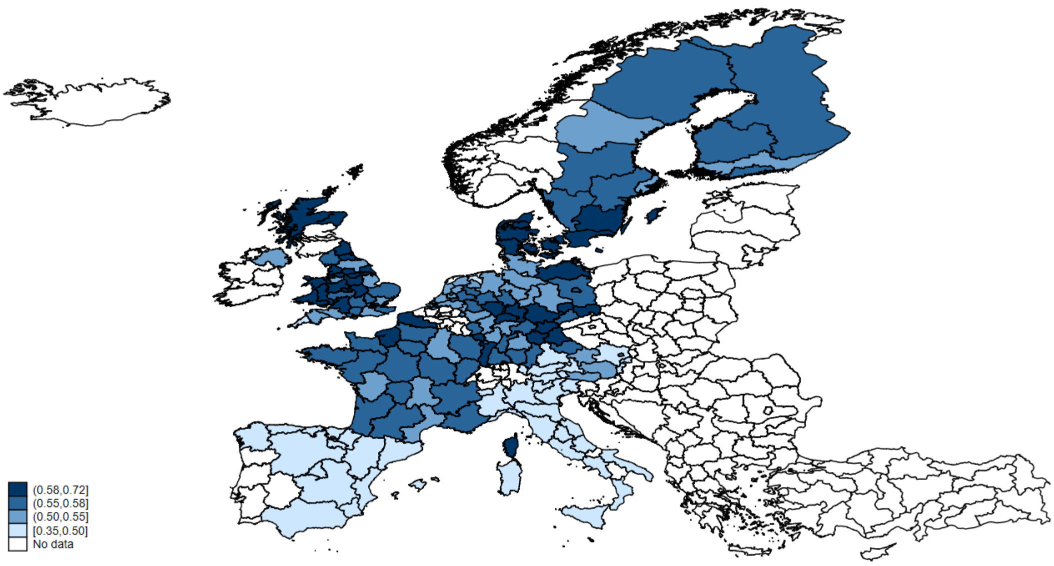
The figure splits the sample into two periods. The continuous line indicates the 1999-2007 period, while the dashed line refers to 2008-2015. The comparison between the two curves clearly shows that the distribution has changed over time. Specifically, it indicates that the distribution has become more polarized, suggesting the presence of two clubs of regions, one that adopts labour-biased technologies and the other that develops capital-biased technological change.

Figure 2.2a shows the spatial distribution of the value assumed by the labour share across NUTS-2 regions after dividing it into four quartiles. Higher labour share values characterize regions in the dark. The map shows two clusters of regions that display an opposite direction of technological change. Low levels of labour share characterize the Italian and Spanish regions, where the production process is carried out with capital-biased technologies. On the other hand, northern regions appear to have a labour-biased direction. This pattern can be detected in the centre of Germany, most of the UK regions, Denmark and some regions in France. These regions display high values of the labour share, which supposedly reflect a greater propensity towards introducing labour-biased innovations.

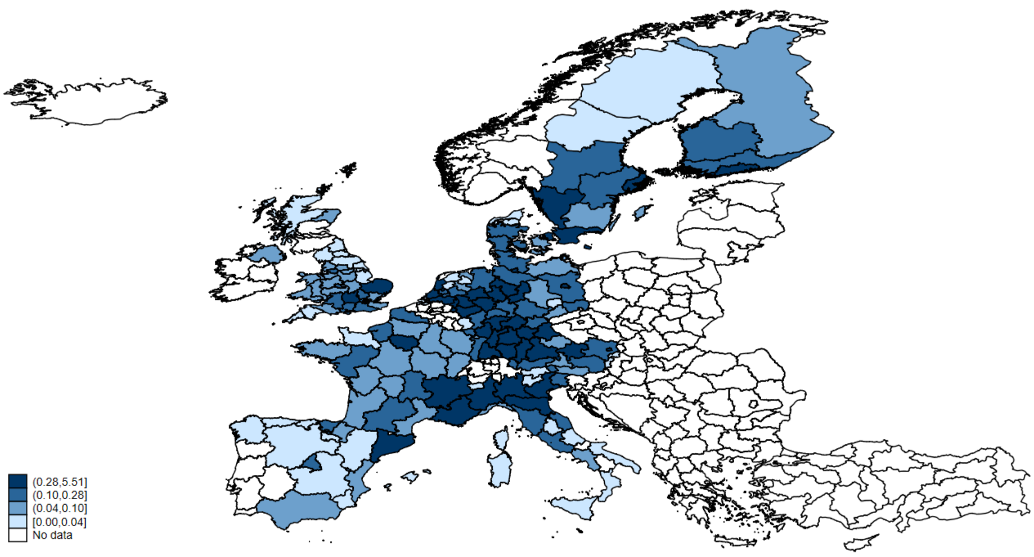
Much cross-regional variance can also be appreciated for the number of patent applications per 1000 workers, as shown in figure 2.2b. The distribution of patent applications shows a high degree of within-country variance, with a significant concentration of innovative activity in northern Italy, the centre of Germany, the south of the UK and southern Scandinavian regions. Although a clear geographical polarization does not seem to emerge, we can detect a relatively high cross-sectional spatial correlation between the levels of labour share and patents from this preliminary evidence.

Figure 2.2. Distribution of the labour share and patent applications across NUTS-2 regions

a) Distribution of the labour share across NUTS-2 regions

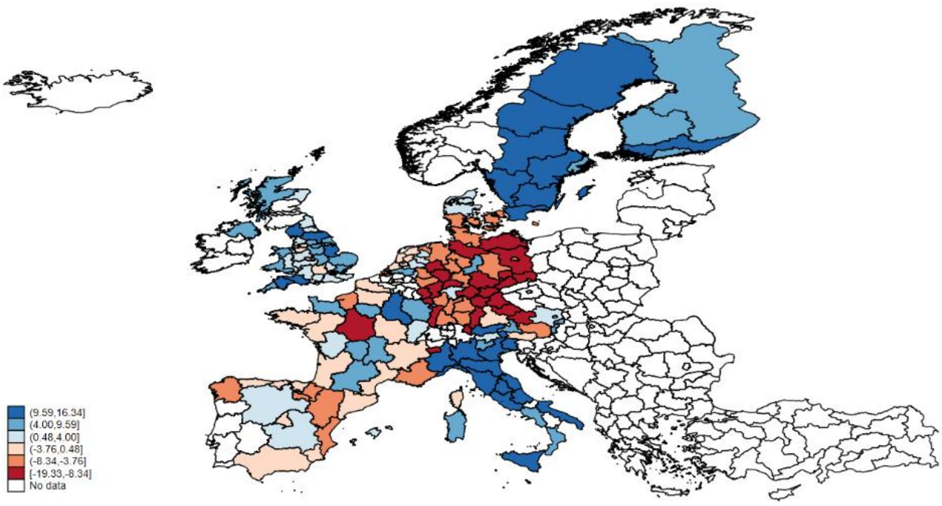


b) Distribution of patent applications per 1000 workers across NUTS-2 regions



Finally, figure 2.3 draws attention to the differences across regions in the percentage change of the labour share over the period 1999-2015. Red colours represent areas where the labour share has declined over time, whereas blue areas are the places where it has increased. The graph confirms the substantial heterogeneity in labour share across countries and regions over the period considered. The labour share has sharply increased in the Italian and Scandinavian regions, then increased modestly in the UK and some regions in France, whereas it strongly declined in Germany and eastern Spain. Nonetheless, even if the empirical analysis focuses on the unadjusted labour share (hence, it excludes self-employed) and the employees' compensation, the figures partially confirm the statistical evidence brought by Cette, Koehl and Philippon (2019, 2020), Pariboni and Tridico (2019), and Torrini (2015), pointing to an increase in the labour share in Italy and France since the end of the last century, and a decrease in Germany. However, the regional analysis unveils several within-country patterns. Precisely, the change in the labour share in France and Spain is highly heterogeneous, wherein some regions show a sharp decline in the wage share and others in which the bargaining power of labour has resisted.

Figure 2.3. Percentage change in the labour share across NUTS-2 regions over 1999-2015



2.4.2 Baseline results

This section presents the results of the econometric analysis regarding the relationship between labour share, technological change and the dynamics of local labour markets. Table 2.1 reports the results for equation 2. I introduce regressors gradually to detect spurious correlations among variables.

Column (1) shows the results of a baseline specification in which the capital-output ratio and technological change are the only covariates. The capital-output ratio and patents are positively related to the labour share ($p<0.01$). These results confirm the findings that capital and labour are complements (Chirinko, 2008) and highlight, differently from the previous literature (Bassanini and Manfredi, 2014; Bentolila and Saint-Paul, 2003; O'Mahony, Vecchi and Venturini, 2021), that the direction of technological change is labour-biased.

Column (2) includes the unemployment rate, which enters with a negative sign, and its coefficient comes to be statistically significant (p<0.01). The negative effect of the unemployment rate confirms hypothesis (ii) that a stronger bargaining power and higher efficiency wages are labour-enhancing. When the unemployment rate is low, the bargaining power of labour strengthens, and, hence, the wage share increases (Dünhaupt, 2017; Pariboni and Tridico, 2019). In column (3), the manufacturing employment share is added, showing a positive but not statistically significant coefficient. Finally, column (4) offers the results when the baseline specification is enriched with the GDP growth rate and the population density. The growth rate of GDP exerts a negative and statistically significant effect on the labour share (p<0.01), whereas the population density coefficient is positive and statistically significant (p<0.01). As highlighted in the previous section, the negative impact of the GDP growth rate confirms that prices are more flexible than wages in the short-term (Kohler, Guschanski and Stockhammer, 2019). In contrast, a denser population is associated with agglomeration economies and wage externalities that positively affect the share of income paid to labour (Kampelmann et al., 2018).

The preliminary evidence in Table 2.1 confirms the complementarity between labour and capital and the positive effect of technological change on the labour share, confirming hypothesis (i). Moreover, the stronger the bargaining power of labour and, as expected, the larger its share of total income, supporting hypothesis (ii).

Table 2.1. Baseline results - Fixed effects estimation

	(1)	(2)	(3)	(4)
ln (K_{it-1}/Y_{it-1})	0.129*** (0.024)	0.245*** (0.024)	0.250*** (0.025)	0.159*** (0.027)
ln (Pat_{it-1}/L_{it-1})	0.019*** (0.004)	0.019*** (0.004)	0.018*** (0.004)	0.015*** (0.004)
ln $(Unempl_{it-1})$		-0.067*** (0.005)	-0.065*** (0.005)	-0.081*** (0.005)
ln (Man_{it-1}/L_{it-1})			0.035 (0.026)	0.092*** (0.025)
ln (GDP_{it-1}/GDP_{it-2})				-0.260*** (0.043)
ln $(PopDensity_{it-1})$				0.466*** (0.058)
Region fixed effects	Yes	Yes	Yes	Yes

Year fixed effects	Yes	Yes	Yes	Yes
Observations	2544	2544	2544	2544
R^2	0.086	0.183	0.185	0.233
Number of regions	171	171	171	171

Notes: The dependent variable is the log of the labour share. The model is estimated with the fixed-effects panel data estimator. Autocorrelation and heteroskedasticity robust standard errors using the Newey–West variance estimator are presented in parentheses.
**** p<0.01, ** p<0.05, * p<0.1*

I conduct additional estimates to check the robustness of the measure of technological change based on the count of incremental innovations. Specifically, I first test whether the results hold by considering incremental patents as those falling behind the 99% or the 90% percentiles of the radicalness distribution, respectively. Moreover, I also use as an alternative variable the number of patents not figuring as breakthrough innovations, according to the index constructed by Squicciarini, Dernis and Criscuolo (2013). The index of breakthrough innovations is again a binary variable taking value equal to one if the patent is on the top 1% in terms of forward citations received in its cohort defined relative to the filing year and technology class. The results of these additional estimates are reported in Table A.4. Columns (1) and (2) consider incremental patents falling behind the 90% and 99% of the radicalness index distribution, respectively, whereas column (3) excludes breakthrough innovations as defined above. The results basically replicate those of Table 2.1, namely that technological change positively impacts the labour share, and its coefficient turns out statistically significant at the highest confidence level (p<0.01).

2.4.3. Additional results

Instrumental Variable estimation

This section enriches the baseline results found in section 2.4.2 with additional specifications to address some potential limitations of the main empirical analysis. First, even though the analysis controls for region fixed effects and considers one year lag between the dependent variable and the controls, one may not rule out completely the endogeneity of technological change in equation (2). The short time dimension of the data prevents the use of dynamic panel techniques suitable for macroeconomic data dealing with both endogeneity and cross-sectional dependence across units (Eberhardt and Presbitero, 2015).

For this reason, I adopt a novel instrumental variable (IV) strategy that endogenizes the number of incremental patent applications in each region. The instrument is based on a shift-share or Bartik instrument (Bartik, 1991), recently adopted by several studies at the sub-national level exploiting local industry composition (Charles, Hurst and Schwartz, 2019; Gould, 2019). Precisely, I exploit the information in patent documents extracted from the OECD RegPat database to assign each patent to the eight macro-technology classes based on the WIPO scheme measured at the 1-digit IPC code.[11] Then, I construct the shift-share instrument as follows:

$$\widehat{IncremPatents}_{ict} = \sum_{j=1}^{J} \mu_{jic1999} * \left(P_{jct} - P_{jc1999}\right) \tag{5}$$

where the predicted level of incremental patents $\widehat{IncremPatents}_{ict}$ in region i, country c and time t is given by the initial share $\mu_{jic1999}$ of patents in 1999 in the technology class j in region i and country c, multiplied by a shift term that calculates the difference of patent applications P in the technology class j in country c (excluding the patents in region i) at time t from the same variable in the initial period. The IV is based on the idea that a national change in a certain technology class affects more the regions in which this class was largely concentrated in the initial period, compared to other areas in the country. Moreover, the exclusion restriction is likely to be satisfied since the national change in a specific technology class may be considered exogenous to unobserved local factors influencing a region's functional distribution of income over time (Gould, 2019; Mazzolari and Ragusa, 2013).

Table 2.2 reports the results of the IV strategy. Almost all the variables maintain their sign in this specification. The capital-output ratio still exerts a positive and statistically significant effect on the labour share. In contrast, the unemployment level and the GDP growth rate negatively impact the labour share. The most noticeable change is in the technological change. Its coefficient is still positive and statistically significant (p<0.01), but its impact is now also economically meaningful. According to the estimates across columns (1)-(4) of Table 2.2, a 1% increase in incremental patent applications conduces to an increase of the labour share within the range 0.33 to 0.39%.[12] The F-statistics based on the Kleibergen-Paap test confirm that the instrument has high predictive power, as they fall above the accepted threshold of 10 and the critical values of Stock and Yogo (2005). For the other variables, we cannot rule out completely

[11] The eight classes are: Human necessities; Performing operations, transporting; Chemistry, metallurgy; Textiles, paper; Fixed construction; Mechanical engineering, lighting, heating, weapons, blasting; Physics; Electricity.

[12] One of the possible reasons behind the larger IV estimates compared to OLS is that the latest estimate the average treatment effect, while the IV regression estimates the local average treatment effect, which may be larger for a subset of regions in the sample.

the possibility of endogeneity, especially for the unemployment rate, which could be impacted directly by the labour share, implying reverse causality. Therefore, their coefficients must be interpreted as purely correlational, even though the negative correlation between the level of unemployment and the labour share seems robust.

Table 2.2. Instrumental variable regression

	(1)	(2)	(3)	(4)
ln (K_{it-1}/Y_{it-1})	0.118**	0.239***	0.223***	0.177***
	(0.054)	(0.048)	(0.052)	(0.059)
ln (Pat_{it-1}/L_{it-1})	0.393***	0.334***	0.357***	0.376***
	(0.072)	(0.062)	(0.070)	(0.083)
ln $(Unempl_{it-1})$		-0.069***	-0.076***	-0.079***
		(0.009)	(0.010)	(0.011)
ln (Man_{it-1}/L_{it-1})			-0.098*	-0.096
			(0.054)	(0.067)
ln (GDP_{it-1}/GDP_{it-2})				-0.321***
				(0.109)
ln $(PopDensity_{it-1})$				0.086
				(0.168)
Region fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	2544	2544	2544	2544
Number of regions	171	171	171	171
F-stat	30.90	31.86	28.29	22.97

Notes: The dependent variable is the log of the labour share. The model is estimated with the 2SLS estimator. Autocorrelation and heteroskedasticity robust standard errors using the Newey–West variance estimator are presented in parentheses.
**** p<0.01, ** p<0.05, * p<0.1*

The same specifications of Table 2.2 are estimated when patents are assigned to regions according to the inventor's address instead of the applicant's address. Table A.5 reports the results of this specification, which largely confirms the previous findings.

Further specifications

Another potential concern of the empirical analysis regards the cross-sectional dependence across units. Indeed, the results of standard tests for detecting cross-sectional dependence reject the null of weak cross-sectional dependence across units, suggesting that cross-units dependence is an issue for the empirical analysis.[13] For these reasons, Table A.6 in the Appendix A estimates equation (2) with the Driscool and Kraay (1998) covariance matrix estimator that produces standard errors robust to disturbances that are heteroskedastic, autocorrelated and cross-sectionally dependent across units, showing that the precision of the estimates is not meaningfully reduced.

Given the regional nature of the dataset, cross-sectional dependence is likely due to the spatial correlation across panel units. Spatial econometrics techniques are now extensively used in the regional literature to solve this econometric issue. The idea is that observed entities are influenced by neighbouring regions, and this similarity decays as the distance among units increases (Le Sage and Pace, 2009). As shown in the previous section, regions characterized by high levels of labour share are often located close to each other.

One of the common problems in spatial econometrics is choosing the most suitable model among those proposed by the spatial econometric literature. For these reasons, I run several tests for model specification following the procedure theorized by LeSage and Pace (2009) and implemented in Stata by Belotti, Hughes and Mortari (2017). The procedure suggests estimating a Spatial Durbin Model (SDM) and testing against the alternative specifications, such as the Spatial Autoregressive (SAR) model and the Spatial Error Model (SEM), which are both nested within the SDM. The results of the tests suggest that the SDM is the most suitable model in this context. For this reason, the empirical analysis shows the results only of the SDM. The model uses a contiguity matrix W normalized by row, whose entries take value one when two regions share a common border and zero otherwise. The diagonal entries are conventionally set to zero, whereas each row is normalized to sum to unity. The contiguity matrix is the standard specification used in the literature (LeSage and Pace, 2009).

Table 2.3 reports the results of the SDM estimates. Since the implementation of panel data spatial econometric techniques requires a balanced dataset, I use the employment rate in place of the unemployment rate in the estimation, as the latter contains some missing values for some region-year cells. Moreover, the population density is excluded from the analysis for the same motives. The Table reports the results of the independent variables and their spatially lagged coefficients in the rows below. Table 2.3 confirms the estimation results obtained with the FE and IV estimators. Technological change and the capital-output ratio are positively related to the labour share, and their coefficients are statistically significant at the conventional levels. The employment rate is positive and statistically significant (p<0.01), complementing the findings

[13] Specifically, the Pesaran test for cross-sectional dependence is implemented (Pesaran, 2015).

for the unemployment rate. Moreover, as expected, the labour share of a region has positive feedback effects on neighbouring regions, as indicated by the positive and statistically significant coefficient of the spatially lagged labour share in row 6. Regarding the independent variables, only shocks in the employment rate show statistically significant effects on the neighbouring regions.

Table 2.3. Spatial Durbin model

	(1)	(2)	(3)	(4)
ln (K_{it-1}/Y_{it-1})	0.115***	0.200***	0.215***	0.198***
	(0.035)	(0.036)	(0.034)	(0.035)
ln (Pat_{it-1}/L_{it-1})	0.017**	0.017**	0.014**	0.015**
	(0.007)	(0.007)	(0.006)	(0.006)
ln $(EmplRate_{it-1})$		0.449***	0.388***	0.387***
		(0.057)	(0.055)	(0.055)
ln (Man_{it-1}/L_{it-1})			0.119***	0.112***
			(0.040)	(0.039)
ln (GDP_{it-1}/GDP_{it-2})				-0.162***
				(0.053)
$W * LS_{it}$	0.387***	0.426***	0.423***	0.422***
	(0.045)	(0.042)	(0.041)	(0.041)
W * ln (K_{it-1}/Y_{it-1})	0.000	-0.047	-0.187	-0.033
	(0.070)	(0.079)	(0.073)	(0.076)
W * ln (Pat_{it-1}/L_{it-1})	0.002	0.005	0.003	0.003
	(0.008)	(0.007)	(0.007)	(0.007)
W * ln $(EmplRate_{it-1})$		-0.308***	-0.310***	0.328***
		(0.112)	(0.010)	(0.997)
W * ln (Man_{it-1}/L_{it-1})			0.022	0.028
			(0.054)	(0.054)
W * ln (GDP_{it-1}/GDP_{it-2})				-0.026
				(0.080)
Region fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	2580	2580	2580	2580
Number of regions	172	172	172	172

Notes: The dependent variable is the log of the labour share. Spatial Durbin model. Standard errors clustered at the NUTS-2 level are presented in parentheses.
**** p<0.01, ** p<0.05, * p<0.1*

As an additional robustness test and to reinforce the validity of the results presented, I also run the estimates by considering alternative variables to proxy for technological change. Table A.7 in the Appendix A shows the results of these tests. First, in column (1), I consider overall patent applications instead of using only incremental patents. In column (2), I weigh patent applications by the number of forward citations received within three years. Therefore, I also evaluate the quality of technological change, rather than only its quantity. Column (3) shows the estimates when a standard Total Factor Productivity (TFP) measure is used. The TFP represents the part of the overall output, the residual, not accounted for by the contribution of the standard factor inputs, and represents an (imperfect) measure of technological change. Nonetheless, its estimate may compare the results of this analysis with the findings of the related literature, which has employed standard TFP to measure (capital-augmenting) technological change (Bassanini and Manfredi, 2014; Damiani, Pompei and Ricci, 2020; Perugini, Vecchi and Venturini, 2017).

Table A.7 shows that technological change, when measured by these different proxies, continues to exert a positive and statistically significant impact (with a $p<0.01$ across all the columns (1)-(3) of Table A.7) on the labour share. Even though these variables may be endogenous in the estimation, their positive correlation with the labour share supports the previous findings that technological change is labour-biased, marking a clear detachment from the extant empirical literature.

Finally, as an additional robustness check, Table A.8 presents results on estimating equation (2) with a system GMM estimator (Blundell and Bond, 1998), which uses the lagged values of the endogenous explanatory variables as instruments. Table A.8 confirms the overall findings, proving that greater technological change and a higher rigidity in labour markets are positively related to the labour share.

2.5. Conclusions

In the new knowledge economy, the direction of technological change can be labour-biased under specific circumstances. This paper advances the hypothesis that when technological change is based on bottom-up and localized learning processes, the direction of technological change is labour-biased.

The assessments of the transition to a new knowledge economy helps frame the implementation in regional markets of the localized technological change. Firms base their competitive advantage no longer on fixed and tangible capital. On the contrary, they take advantage of learning by doing, learning by using and learning by interacting, made possible by the workforce’s skills. Firms are incentivized to retain the existing techniques through valorising the current internal competence based upon tacit knowledge owned by the workforce.

The dynamics of this interpretative framework presume a positive direction of technological change on the labour share, in contrast to the hypothesis of a secular decline of the labour share due to a capital-intensive direction of technological change and the steady reduction in the cost of capital put forward by an established stream of research. Instead, the theoretical framework proposed in this chapter emphasizes the heterogeneity in the labour share by arguing that technological change can be labour-biased under some circumstances, shaped by the local labour market conditions. Consequently, the induced hypothesis that firms substitute capital for labour when the cost of labour is relatively higher is valid only for less innovative regions. Instead, regions with a strong innovative capacity based on the implementation of incremental innovations are able to protect the worker’s bargaining power and increase the wage share.

The econometric analysis confirms that more innovative European regions have a greater labour share, especially when factor markets are rigid and constitute an incentive to develop labour-biased techniques. Furthermore, a novel Instrumental Variable strategy and spatial econometric techniques confirm that the results are robust after taking into account econometric issues raised by the endogeneity of technological change in the labour share equation and spatial dependence across regions.

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Appendix A

Table A.1. Main variables description

Variable	Description	Source
$\mathrm{LS}_{\mathrm{it}}$	Natural log of the labour share, defined as the ratio between compensation of employees and GDP.	Author’s elaboration on Cambridge Econometrics.
$\ln\left(K_{it}/Y_{it}\right)$	Natural log of the capital-output ratio.	Author’s elaboration on Cambridge Econometrics.
$\ln\left(Pat_{it}/L_{it}\right)$	Natural log of the number of patent applications for incremental innovations per 1000 workers.	Author’s elaboration on OECD RegPat and Cambridge Econometrics.
$\ln\left(Unempl_{it}\right)$	Natural log of the unemployment rate.	Eurostat.
$\ln\left(Man_{it}/L_{it}\right)$	Natural log of the ratio between manufacturing employment and total employment.	Author’s elaboration on Cambridge Econometrics.
$\ln\left(GDP_{it}/GDP_{it-1}\right)$	Growth rate of GDP.	Author’s elaboration on Cambridge Econometrics.
$\ln\left(PopDensity_{it}\right)$	Natural log of the population density, defined as number of persons per square kilometres.	Eurostat.

Table A.2. Descriptive statistics

Variable	Mean	Std. Dev.	Min	Max
$\mathrm{LS}_{\mathrm{it}}$	-0.6589	0.1645	-1.1711	-0.2315
$\ln\left(K_{it}/Y_{it}\right)$	1.1023	0.2345	0.2307	2.3203
$\ln\left(Pat_{it}/L_{it}\right)$	4.965	1.1007	0	7.7166
$\ln\left(Unempl_{it}\right)$	1.9174	0.5045	0.1823	3.5891
$\ln\left(Man_{it}/L_{it}\right)$	-1.9179	0.4108	-4.5514	-1.18
$\ln\left(GDP_{it}/GDP_{it-1}\right)$	0.0092	0.0287	-0.1271	0.2651
$\ln\left(PopDensity_{it}\right)$	5.179	1.1844	1.1939	9.3083

Table A.3. Correlation matrix

Variable	1	2	3	4	5	6	7
1. LS_{it}	1						
2. ln (K_{it}/Y_{it})	-0.2141	1					
3. ln (Pat_{it}/L_{it})	0.3029	-0.1751	1				
4. ln $(Unempl_{it})$	-0.2128	0.3199	-0.4436	1			
5. ln (Man_{it}/L_{it})	-0.0714	0.2376	0.2640	-0.1783	1		
6. ln (GDP_{it}/GDP_{it-1})	0.0413	-0.0967	0.0582	-0.1236	0.0738	1	
7. ln $(PopDensity_{it})$	0.1059	-0.3613	0.2001	-0.0595	-0.3219	-0.0060	1

Table A.4. Fixed effects estimation – Alternative definitions of incremental innovations

	(1) 90% Radicalness threshold	(2) 99% Radicalness threshold	(3) Excluding Breakthrough innovations
ln (K_{it-1}/Y_{it-1})	0.159***	0.159***	0.159***
	(0.027)	(0.027)	(0.027)
ln (Pat_{it-1}/L_{it-1})	0.015***	0.014***	0.014***
	(0.004)	(0.004)	(0.004)
ln $(Unempl_{it-1})$	-0.081***	-0.081***	-0.081***
	(0.005)	(0.005)	(0.005)
ln (Man_{it-1}/L_{it-1})	0.091***	0.092***	0.092***
	(0.025)	(0.025)	(0.025)
ln (GDP_{it-1}/GDP_{it-2})	-0.259***	-0.260***	-0.260***
	(0.043)	(0.043)	(0.043)
ln $(PopDensity_{it-1})$	0.465***	0.467***	0.467***
	(0.057)	(0.058)	(0.058)
Region fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	2544	2544	2544
R^2	0.234	0.233	0.233
Number of regions	171	171	171

Notes: The dependent variable is the log of the labour share. The model is estimated with the fixed-effects panel data estimator. Autocorrelation and heteroskedasticity robust standard errors using the Newey–West variance estimator are presented in parentheses.
**** p<0.01, ** p<0.05, * p<0.1*

Table A.5. Instrumental variable regression – Inventors' address

	(1)	(2)	(3)	(4)
ln (K_{it-1}/Y_{it-1})	0.073*	0.220***	0.197***	0.169***
	(0.041)	(0.035)	(0.038)	(0.043)
ln (Pat_{it-1}/L_{it-1})	0.302***	0.248***	0.272***	0.296***
	(0.043)	(0.036)	(0.041)	(0.051)
ln $(Unempl_{it-1})$		-0.079***	-0.090***	-0.092***
		(0.008)	(0.009)	(0.009)
ln (Man_{it-1}/L_{it-1})			-0.133***	-0.153***
			(0.044)	(0.058)
ln (GDP_{it-1}/GDP_{it-2})				-0.320***
				(0.087)
ln $(PopDensity_{it-1})$				-0.049
				(0.149)
Region fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	2544	2544	2544	2544
Number of regions	171	171	171	171
F-stat	60.62	64.63	59.99	48.30

Notes: The dependent variable is the log of the labour share. The model is estimated with the 2SLS estimator. Autocorrelation and heteroskedasticity robust standard errors using the Newey–West variance estimator are presented in parentheses.
**** p<0.01, ** p<0.05, * p<0.1*

Table A.6. Fixed effects estimation - Driscool-Kraay estimator

	(1)	(2)	(3)	(4)
ln (K_{it-1}/Y_{it-1})	0.129**	0.245***	0.250***	0.157***
	(0.059)	(0.034)	(0.040)	(0.030)
ln (Pat_{it-1}/L_{it-1})	0.019**	0.019***	0.018***	0.015***
	(0.008)	(0.007)	(0.006)	(0.005)
ln $(Unempl_{it-1})$		-0.067***	-0.065***	-0.077***
		(0.012)	(0.014)	(0.012)
ln (Man_{it-1}/L_{it-1})			0.035	0.087
			(0.064)	(0.077)
ln (GDP_{it-1}/GDP_{it-2})				-0.218*
				(0.115)
ln $(PopDensity_{it-1})$				0.479***
				(0.151)
Region fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	2544	2544	2544	2544
R^2	0.086	0.183	0.185	0.229
Number of regions	171	171	171	171

Notes: The dependent variable is the log of the labour share. The model is estimated with the fixed-effects panel data estimator. Driscoll-Kraay standard errors presented in parentheses.
**** p<0.01, ** p<0.05, * p<0.1*

Table A.7. Fixed effects estimation – Alternative definitions of technological change

	(1) Total patent applications	(2) Patents weighted by citations	(3) Total Factor Productivity
$\ln\,(K_{it-1}/Y_{it-1})$	0.157***	0.155***	0.054***
	(0.027)	(0.027)	(0.018)
$\mathrm{Tech.\,Change_{it-1}}$	0.015***	0.006***	0.094***
	(0.004)	(0.002)	(0.003)
$\ln\,(Unempl_{it-1})$	-0.077***	-0.077***	-0.042***
	(0.005)	(0.005)	(0.004)
$\ln\,(Man_{it-1}/L_{it-1})$	0.087***	0.088***	0.046***
	(0.026)	(0.025)	(0.018)
$\ln\,(GDP_{it-1}/GDP_{it-2})$	-0.218***	-0.221***	0.017
	(0.050)	(0.050)	(0.040)
$\ln\,(PopDensity_{it-1})$	0.479***	0.471***	0.268***
	(0.057)	(0.057)	(0.037)
Region fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	2544	2544	2544
R^2	0.229	0.229	0.540
Number of regions	171	171	171

Notes: The dependent variable is the log of the labour share. The model is estimated with the fixed-effects panel data estimator. Technological change is proxied by total patent applications in column (1), patents weighted by citations within three years in column (2) and total factor productivity in column (3). Autocorrelation and heteroskedasticity robust standard errors using the Newey–West variance estimator are presented in parentheses.
**** p<0.01, ** p<0.05, * p<0.1*

Table A.8. Baseline results - System GMM estimator

	(1)
ln (LS_{it-1})	0.803***
	(0.058)
ln (K_{it}/Y_{it})	0.059
	(0.043)
ln (Pat_{it}/L_{it})	0.060**
	(0.025)
ln $(Unempl_{it})$	-0.072***
	(0.010)
ln (Man_{it}/L_{it})	-0.085**
	(0.041)
ln (GDP_{it}/GDP_{it-1})	-0.539***
	(0.068)
ln $(PopDensity_{it})$	0.019
	(0.020)
Observations	2567
Number of regions	171
AR(1)	-6.38
AR(2)	-0.47
Hansen test	70.13

Notes: The dependent variable is the log of the labour share. The model is estimated with the GMM-SYS estimator. Robust standard errors presented in parentheses.
**** p<0.01, ** p<0.05, * p<0.1*

Chapter 3.

The increase in the elasticity of substitution between capital and labour: a cross-country investigation[14]

[14] This chapter is co-authored with Samule Ialenti. The authors acknowledge the Università di Torino e Collegio Carlo Alberto local research funds.

ABSTRACT

The economics literature emphasizes the importance of the elasticity of substitution between capital and labour in several economic contexts. However, analyses of the effect of the elasticity of substitution on the direction of technological change is often overlooked. Most assessments of the direction of technological change rely on a Constant Elasticity of Substitution (CES) production framework. This strand of empirical work considers the elasticity of substitution between capital and labour as a deep and fixed parameter. In this article, we show that the change in the elasticity of substitution that has occurred in recent decades might be an alternative source of change of factor income shares rather than factor-augmenting technological change. We construct a theoretical environment in which the elasticity of substitution is determined endogenously by the capital share and capital intensity. Rolling window estimates show that the elasticity of substitution in nine OECD economies observed between 1950 and 2017 was not constant and that, in fact, in the latter half of the 1970s, the elasticity of substitution increased.

3.1. Introduction

Based on the Cobb-Douglas-Kaldor paradigm, which predicts that factor income shares are constant (Cobb and Douglas, 1928; Kaldor, 1961), growth economics has long regarded technological change as neutral (Solow, 1957; Young, 1995). However, the historical evidence shows that technological change exhibits substantial variance, which can be capital- or labour-biased (Allen, 2011; Antonelli and Feder, 2021; Young, 2010). Income distribution analyses reveal a new trend, starting in the mid-1970s, towards increasing levels of income inequality and a reduction in the labour share of income in most of the advanced economies (Atkinson, Piketty and Saez, 2011; Piketty, 2014; Ranaldi and Milanovic, 2022). The documented reduction in the share of labour has renewed interest in studying the direction of technological change.

This article aims to contribute, theoretically and empirically, to debate on the direction of technological change, by examining the role of the elasticity of substitution between capital and labour. Theoretically, we propose a new method to estimate the elasticity of substitution for a CES (Constant Elasticity of Substitution) production function and assess its legitimacy as an assumption for studying the income distribution. Empirically, we find that, over the last 70 years, the elasticity of substitution has not been constant and, for a selected group of countries, it has increased.

The elasticity of substitution is a crucial parameter shaping economic growth and the income distribution. Several studies show a positive relationship between the elasticity of substitution and the level and rate of economic growth (De la Grandville, 1989; Federici and Saltari, 2016; Klump and De la Grandville, 2000; Mallick, 2012; Palivos and Karagiannis, 2010).[15] Also, the elasticity of substitution between capital and labour is important for: the sensitivity of capital formation to interest rate changes (Chirinko, 2002); returns to production factors in an open economy (Jones and Ruffin, 2008); dynamics of hours worked in response to technology shocks (Cantore et al., 2014; Cantore, Ferroni and Leòn-Ledesma, 2017); structural change and sectoral transformation (Alvarez-Cuadrado, Van Longe and Poschke, 2017); income distribution and the direction of technological change (Acemoglu, 2002, 2003; Caselli, 2005; Piketty, 2014).

Using a dataset of nine OECD countries observed between 1950 and 2017, we obtain the following results. First, using the intuition in Sato (1967), by generalizing a class of production functions based on a linear elasticity of substitution, we derive a relationship between the capital share, capital intensity[16] and the elasticity of substitution that subsumes the most common constant returns to scale production functions. We assume that the technology is CES and use a Non-Linear

[15] In particular, the *de La Grandville hypothesis* states that economic growth rates and income per capita levels increase as the elasticity of substitution between capital and labour increases.

[16] In the rest of the paper, we use capital intensity and capital abundance interchangeably to refer to the capital-labour ratio.

Least Squares (NLLS) method to estimate the elasticity of substitution for each country. Finally, our rolling window analysis (Zivot and Wang, 2006), allows us to assess the stability of the elasticity of substitution during the period considered. Our estimation results show that the elasticity of substitution is unstable across different subsamples, suggesting that the elasticity of substitution has changed and, more specifically, increased between 1950 and 2017.

Second, our empirical evidence shows that the decline in the share of labour started at the end of the 1970s. We hypothesize that this decline in the share of labour was concomitant with a change in the degree of substitutability between capital and labour. Specifically, taking 1979 as the turning point, we use a non-linear estimation method to estimate the elasticity in a CES production function before and after the turning point; we find that the elasticity increased everywhere, following the same trend as the capital share.

Our article contributes to several literature streams. First, it adds to the literature on the decline in the share of labour observed since the 1980s. Most studies that focus on the relationship between the functional distribution of income and technological change, rely on a CES production function and find a negative effect of various proxies for technological change on the labour share across different dimensions and contexts. This suggests that, since the 1980s, the direction of technological change has become capital-biased (Bentolila and Saint-Paul, 2003; Damiani, Pompei and Ricci, 2020; Karabarbounis and Neiman, 2014; O'Mahony, Vecchi and Venturini, 2021; Perugini, Vecchi and Venturini, 2017). In our study, the elasticity of substitution is allowed to differ from the unitary Cobb-Douglas assumption. The CES framework provides implications about the direction of technological change, based on the value of the elasticity of substitution, which is considered fixed over time.

However, the aforementioned studies neglect changes in the elasticity of substitution. Indeed, the CES theoretical setting does not distinguish between biased innovations, in the form of changes to either factor-augmenting parameters or the elasticity of substitution (Zuleta, 2016). In contrast, our paper shows that the elasticity of substitution has increased over time. In this respect, our article is more in line with the strand of the macroeconomics literature, which considers the elasticity of substitution to be a variable function of the institutional and economic factors and as contributing to shaping the relationship between the direction of technological change and factor income shares (Antony, 2010; Sala and Trivin, 2018). Our paper contributes to this debate by showing that, in assessments of the income distribution, the change (specifically, the increase) in the elasticity of substitution should also be considered.

Second, our theoretical model is connected strongly to the literature on factor-saving innovation (Peretto and Seaeter, 2006, 2013; Zuleta, 2008). In these models, the elasticity of substitution is endogenous and is related to output elasticities and capital intensity. When the capital abundance is sufficiently large, an increase in the elasticity of substitution between capital and labour is consistent with a capital-biased direction of technological change (Zuleta, 2016). Indeed, our results are in line with recent empirical contributions that show an increase in the elasticity of substitution over recent decades (Knoblach, Roessler and Zwerschke, 2020; Knoblach and Stöckl, 2020; Ziesemer, 2021).

The rest of the chapter is organized as follows. Section 3.2 summarizes the theoretical debate on the elasticity of substitution and the production function. It introduces our theoretical environment and tests the stability of the elasticity of substitution in a CES framework. The findings in Section 3.3 show how the elasticity of substitution has increased over the last seven decades. Section 3.4 concludes the paper.

3.2. Theoretical model and a test of the constant elasticity of substitution assumption

3.2.1. Theoretical background

The economics of innovation has invested huge effort into identifying the determinants of the endogenous rate and direction of technological change. In particular, the theory of induced technological change, based on the initial analyses conducted by Marx and Hicks, has for long emphasized the role of factor prices in triggering technological change (Drandakis and Phelps, 1966; Kennedy, 1964; Samuelson, 1965). The empirical evidence shows that the direction of technological change was mostly capital-intensive during the 20th century before turning to energy-saving as a result of the steady decline in the prices of energy (Karabarbounis and Neiman, 2014; Newell, Jaffe and Stavins, 1999).

The induced technological change approach has been adopted, also, to study biased and factor-saving innovation. A seminal contribution from Zeira (1998), investigates the introduction of technological innovations, based on the price and profitability of factor inputs, and provides evidence of the capital- and skilled-biased direction of technological change as a determinant of productivity differences across countries. Other contributions to biased technological change include Acemoglu (2002, 2003, 2015) and Boldrin and Levine (2002). In 2006, Peretto and Seater introduced a model of factor-saving innovation in which markets are non-competitive and savings rates are exogenous. Zuleta (2008) proposed an endogenous growth model with factor-saving innovation, Cobb-Douglas technology and competitive markets. Both Peretto and Seater (2006) and Zuleta (2008) show that technological change is both labour-saving and capital-using. Peretto and Seater (2013) theorized about perpetual growth and factor-eliminating technological change, in which the shares of reproducible factors (physical capital and skilled labour) increase and the shares of non-reproducible factors (unskilled labour) reduce. Similarly, using a model of perpetual growth with automation, Nomaler and Verspagen (2020) show through simulations that, as automation spreads rapidly, the wage share of income captures a negligible share of total income despite the increase in absolute wages.

At the same time, theoretical works on factor-saving innovation treat the elasticity of substitution as shaped endogenously by the capital intensity and output elasticities of factor inputs. In a model with endogenous output elasticities, capital-abundant countries face stronger incentives to develop capital-intensive technologies (Antonelli, 2016). At the same time, the elasticity of substitution is a function, also, of capital abundance (Zuleta, 2008, 2016). As a result, an increase in capital abundance is consistent with a long-run increase in the elasticity of substitution and both the capital-using and labour-saving direction of technological change.[17]

In an empirical context, the variability of factor income shares has been explained by several phenomena: i) globalization of factor and product markets and offshoring (Dao, Das and Koczan, 2019; Elsby, Hobijn and Sahin, 2014); ii) automation and task inputs (Acemoglu and Restrepo, 2018; Vom Lehn, 2018); iii) superstar effects and intangible assets (Autor et al., 2020; Koh, Santaeulalàlia-Lopis and Zheng, 2020; O'Mahony, Vecchi and Venturini, 2020); and iv) financialization and the reduced bargaining power of labour (Damiani, Pompei and Ricci, 2020; Pariboni and Tridico, 2019; Stockhammer, 2017).

Moreover, there is abundant evidence showing that technological change has been capital-augmenting since the 1980s and, in conjunction with capital intensity, it has had a negative impact on the labour share, implying that the elasticity of substitution between capital and labour lies above unity[18] (Bassanini and Manfredi, 2014; Bentolila and Saint-Paul, 2003; Hutchinson and Persyn, 2012; Karabarbounis and Neiman, 2014; O'Mahony, Vecchi and Venturini, 2021).

Nevertheless, this collective wisdom, renamed "accumulation theory", has attracted some criticism. Cette, Koehl and Philippon (2019, 2020) show that adjusting for some measurement issues in the computation of the wage share leads to the conclusion that the declining pattern is not ubiquitous and that, rather, there is much heterogeneity across countries.

[17] The capital-intensive direction of technological change in capital-abundant countries is consistent, also, with the finding that richer countries are characterized by greater output elasticity of capital (Durlauf and Johnson, 1995).

[18] This literature abstracts from time-dimension considerations. Indeed, according to Klump, McAdam and Willman's (2007, 2008) estimates, capital-augmenting technological change may be a merely transitory phenomenon. Klump McAdam and Willman's results support Acemoglu's (2002, 2003) theoretical model, which demonstrates that technological change should be labour-augmenting only in the long-run and that capital-augmenting technical change is transitory.

Antonelli and Feder (2020, 2021) confirm the significant heterogeneity in labour share dynamics and argue that, in the new knowledge economy, the direction of technological change is labour-biased and conducive to higher total factor productivity growth.

The proponents of accumulation theory and CES technology, argue that the capital share increases with capital-augmenting technological change and capital intensity, implying that the elasticity of substitution is greater than 1. The use of CES technology has implications for the direction of technological change since it focuses on the value of the elasticity of substitution between capital and labour. Accumulation theory implies that the elasticity of substitution lies above unity and, hence, there is a substantial degree of substitutability between capital and labour.

However, although estimates of the elasticity of substitution differ, depending on the data used, the chosen functional form[19] and the level of analysis, few studies find values above 1 for the elasticity of substitution. Studies exploiting cross-country variability tend to estimate elasticities of substitution above unity (Duffy and Papageorgiou, 2000; Karabarbounis and Neiman, 2014; Masanjala and Papageorgiu, 2004; Piketty, 2014; Piketty and Zucman, 2014). However, most work at the micro or industry level, or studies using time series data for single countries find an elasticity of substitution below 1. Early studies by Arrow et al. (1961) and David and van de Klundert (1965) estimated respective elasticities of substitution for the US of 0.57 and 0.32. More recently, Antràs (2004), who in his econometric specification allows for biased technological change, estimated an elasticity for the US private sector within the range 0.3 to 0.9. Chirinko's (2008) review of previous findings suggests an elasticity of substitution within the range 0.4 to 0.6 and Mallick (2012) found that the average elasticity of substitution for a sample of 90 countries was 0.34. Young (2013) uses industry data for the US economy and concludes that the elasticity of substitution is below unity while the meta-regression analysis in Knoblach, Roessler and Zwerschke (2020) suggests a long-run elasticity of substitution for the US within the range 0.45 to 0.87.

Also, by definition, the CES framework prevents changes over time in the values assumed by the elasticity of substitution. The evolution of factor income shares is explained by the value of the elasticity of substitution, but does not consider it changes. As the literature on factor-saving innovation demonstrates, the elasticity of substitution can alter the capital-labour ratio and, therefore, represents biased innovation (Zuleta, 2008, 2016).

[19] In particular, how technological change is modelled affects has a substantial effect on the estimates of the elasticity of substitution. For example, Antràs (2004) shows that omitting biased technological change drives the estimates towards unity. In general, assuming Hicks-neutral technological change, tends to overestimate the elasticity of substitution values.

Another stream of research, which started with Hildebrand and Liu's (1965) contribution, models the elasticity of substitution as a function of the capital-labour ratio. This has resulted in the study of a class of production functions - the so-called VES (Variable Elasticity of Substitution) production functions - in which the elasticity of substitution is variable (Kadiyala, 1972; Revankar, 1971). Several empirical studies show that the VES production function provides a better fit than the CES (Kazi, 1980; Lu and Fletcher, 1968; Sato and Hoffman, 1968). Karagiannis, Palivos and Papageorgiou (2005) analyse a basic Solow growth model with a VES and show that the model exhibits unbounded endogenous growth without technological progress.[20]

The relationship between the changes in the elasticity of substitution and technological change was highlighted by Hicks (1932), who speculated about potential channels enabling such changes to the elasticity of substitution. In a multi-sector economy, the elasticity of substitution can change as the result of: i) intra-sectoral substitution of production methods; ii) technological innovations that augment these methods; and iii) inter-sectoral substitution of commodities endowed with different factor intensities.

The shortcomings of the empirical literature that finds a decline in the share of labour due to capital-augmenting technological change based on the CES environment, call for more effort to analyse the role of the elasticity of substitution in explaining the empirical facts. Our approach aims to evaluate the appropriateness of the CES production technology for studying factor income shares, starting from a theoretical background where the elasticity of substitution is a function of the capital intensity and capital share.

3.2.2. Theoretical model

We start with the definition of the elasticity of substitution. We outline the mathematical model and develop the methodology used to assess whether the constant elasticity of substitution approximates the behaviour displayed by the economy. The concept of the elasticity of substitution dates back to the seminal contributions made by Hicks (1932) in *Theory of Wages* and Robinson (1933) in *The Economics of Imperfect Competition*. Hicks (1932: 117) defined the elasticity of substitution as:

[20] Other contributions have developed other classes of production functions based on a changing elasticity of substitution (Antony, 2010; Growiec and Muck, 2020).

> a measure of the ease with which the varying factor can be substituted for others. If the same quantity of the factor is required to give a unit of the product, in any circumstances whatever, then its elasticity of substitution is zero. If all the factors employed are for practical purposes identical, so that the varying factor can be substituted for any co-operating factor without any trouble at all, then the elasticity of substitution is infinite. The case where the elasticity of substitution is unity can only be defined in words by saying that in this case (initially, before any consequential changes in the supply of other factors takes place) the increase in one factor will raise the marginal product of all the other factors taken together in the same proportion as the total product is raised.

Hicks was interested in the effect of capital accumulation, which he understood as economic progress, on the distribution of factor incomes. In his setting, he considers a neoclassical production function $Y = F(K, L)$ in which output Y is produced with the contribution of capital K and labour L. As a result, we can define the elasticity of substitution as:

$$\sigma_{K,L} = \frac{\partial (K/L)(w/r)}{\partial (w/r)(K/L)} \tag{1}$$

where w and r are, respectively, the average wage rate and the real interest rate.[21] The assumption that a Cobb-Douglas technology governs the production process implies that income shares are constant in early neoclassical growth models. If this is so, the labour share $sh(\mathrm{L}) = wL/Y$ would imply a linear relationship between the output per labour y and the wage rate w. However, Arrow et al. (1961) tested the following logarithmic relationship:

$$\log(Y/L) = \log a + b * \log w \tag{2}$$

and showed that the slope b of the linear relationship was equal to the elasticity of substitution between labour and capital, and found that, in most industries, the coefficient b differed significantly from zero and was below unity. Based on this relationship, they constructed the well-known CES production function, which assumes constant elasticity of substitution between capital and labour alongside and across any isoquant of the production function.[22] Thus, the CES has become a

[21] Notice that the formulation in (1) is not Hicks's original formulation; it is an adapted version of Robinson (1933), which assumes perfect competition in factor and product markets. Hicks later proved that definition in the second edition of *Theory of Wages*.

[22] See Arrow et al. (1961: 229-230) for the mathematical steps to obtain the CES production function from Equation (2).

fundamental economic analysis tool and, following Arrow et al.'s (1961) original formulation, which did not introduce a factor-augmenting technological change parameter, can be expressed as follows:

$$Y = C\left[\delta K^{\frac{\sigma-1}{\sigma}} + (1-\delta)L^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \tag{3}$$

where δ and $1-\delta$ are the normalized factor cost shares and C is a normalization constant. The CES specification corresponds to the Cobb-Douglas case when $\sigma = 1$.

On the other hand, the CES production function with labour-augmenting technical change can be expressed as follows:

$$Y = C\left[\delta K^{\frac{\sigma-1}{\sigma}} + (1-\delta)(AL)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \tag{4}$$

where A represents labour-augmenting technological change.

Our theoretical analysis draws on De La Grandville (2009), who show that, for any homogeneous production function of degree 1 (the economy is characterized by constant returns to scale), the elasticity of substitution between K and L can be expressed as a functional relationship of the capital-labour ratio k:[23]

$$\sigma_{K,L} = \sigma(k) = -\frac{f'(k)[f(k) - kf'(k)]}{kf(k)f''(k)} \tag{5}$$

where $f(k) = y = Y/L = F(K/L, 1)$. Sato (1967) shows that the previous equation can be rewritten using the fact that $\theta \equiv \theta(k) = f'(k)k/f(k)$, where θ is the capital share.[24] In perfect competition, $f'(k)$ is equal to the real interest rate, so the elasticity of substitution is determined endogenously by the changes to capital accumulation or relative factor prices. Therefore, we have:[25]

[23] Similar proofs are provided in Sato and Hoffman (1968) and Burmeister and Dobell (1970).

[24] Notice that $\theta \equiv (\partial F(K,L)/\partial K)K/F(K,L) = f'(k)k/f(k)$ given that $f'(k) = \partial F(K,L)/\partial K$.

[25] The mathematical steps to obtain Equation (6) from Equation (5) are provided in the Appendix B, section B.1.

$$\sigma_{K,L} = \sigma(k) = \frac{\theta(1-\theta)}{\theta(1-\theta) - k\theta'} \tag{6}$$

where θ' is the first derivative of the capital share θ.

The elasticity of substitution is constant if $\sigma(k) = \sigma \; \forall \; k$ for $k > 0$. Sato (1967) shows how to derive an explicit form of the production function from a linear elasticity of substitution $\sigma(k) = a + bk$. Instead, we specify a functional form for the elasticity of substitution $\sigma_{K,L}$ that covers the most relevant cases of the neoclassical production function:

$$\sigma(k) = \alpha k^{\beta} \tag{7}$$

Equation (7) covers all the standard production functions in the economic literature and a class of production functions in which the elasticity of substitution depends on the capital-labour ratio. The chosen functional form is not crucial for the succeeding steps or for the estimation methodology used in Section 3.2.3. However, the multiplicative relationship presented in (7) highlights that, in principle, we can recover different production functions depending on the values of α and β.

Therefore, we can derive the different production functions $F(K, L)$:

1. $\alpha = 0$: Leontief production function
2. $\beta = 0$ and $\alpha = 1$: Cobb-Douglas production function
3. $\beta \to +\infty$ and/or $\alpha \to \infty$: Linear production function
4. $\beta = 0$ and $\alpha \in (0; 1) \cup (1; +\infty)$: CES production function
5. otherwise: the elasticity of substitution depends on the capital-labour ratio with a multiplicative form.

Then, by equating (7) to the relation defined in (6), we obtain that:

$$\sigma_{K,L} = \frac{\theta(1-\theta)}{\theta(1-\theta) - k\theta'} = \alpha k^{\beta} \tag{8}$$

This provides a general relationship between the capital share and the capital-labour ratio.

Hence, our method enables us to derive estimates for the elasticity of substitution relying merely on its definition, assuming that the economy has a constant returns to scale technology. Rearranging the terms in Equation (8), we obtain a Bernoulli differential equation of degree 2:

$$\theta' = \left(k^{-1} - \frac{1}{\alpha}k^{-\beta-1}\right)\theta - \left(k^{-1} - \frac{1}{\alpha}k^{-\beta-1}\right)\theta^2 \tag{9}$$

Supposing that $\beta \neq 0$ and $\alpha \neq 0$, the general solution to the Bernoulli differential equation is given by:

$$\theta = \frac{1}{1 + ck^{-1}e^{-(k^{-\beta}/\alpha\beta)}} \tag{10}$$

which shows a relationship in which the elasticity of substitution is not constant, but is a function of k. The term c is the integration constant.

At this point, we want to test the assumption that a CES production function is suited to the description of the capital share and capital intensity dynamics. Therefore, in Equation (10), we assume that the technology is CES and we estimate the elasticity of substitution. In a second step, we test the stability of the estimated parameter using a rolling window analysis methodology, as explained below.

We assume that the elasticity of substitution is constant by imposing β=0. We define $1/p \equiv \alpha$ with $p \in (-\infty; 1]$. The solution to the differential equation defined in Equation (9), with the restrictions imposed, is:

$$\theta = \frac{1}{1 + ck^{-p}} \tag{11}$$

where $c > 0$ is an integration constant.

Notice that the result obtained in equation (11) does not depend on the functional form defined in equation (7). For our purposes, $\sigma = \alpha$ can be substituted in equation (8) and then the resulting Bernoulli equation can be solved as before. The result can be generalized as follows.

Proposition 1. For a homogeneous production function of degree 1, the elasticity of substitution between K and L does not depend on the capital/labour ratio k, that is, it is constant if and only if the share of capital in total income can be expressed as

$$\theta = \frac{1}{1+ck^{-p}}$$

with $c > 0$ and $p \in (-\infty; 1]$

Proof. 'The "if" part is proved by what we said earlier. In the case of the "only if" part, assume that the capital share can be expressed as before. By applying the definition, we obtain that:

$$\sigma(k) = \frac{\theta[1-\theta]}{\theta[1-\theta]-k\theta'}$$

and note that the result is $\sigma(k) = \sigma = 1/(1-p)$, which is the elasticity of substitution for a general CES production function.'

Therefore, our exercise is aimed at obtaining estimates for a constant elasticity of substitution in Equation (11) using a NLLS estimator. In the second step, we assess empirically whether the elasticity of substitution can be considered constant during the period.

Before introducing the econometric procedure to understand whether or not the elasticity of substitution is constant over time, we specify some aspects of the relationship defined in Equation (11). Following Sato and Hoffman (1968), starting from the relationship between θ and $f(k)$, we know that:

$$f(k) = Be^{\int [\theta/k]dk} \tag{12}$$

where $B > 0$ is an integration constant.

Thus, Equation (12), from which we can derive θ/k, can be integrated as follows:

$$\frac{\theta}{k} = \frac{1}{k + ck^{-p+1}} \rightarrow \int \frac{1}{k + ck^{-p+1}} dk = \frac{\log(c + k^p)}{p} + \epsilon \tag{13}$$

where ϵ is a constant that we can be set to zero without loss of generality. We solve Equation (12) by using this result and obtain:

$$f(k) = B[c + k^p]^{\frac{1}{p}} \tag{14}$$

which is a CES production function expressed in efficiency units. Equation (14) captures the nature of parameters c and B. While B can be considered the normalization constant (which can incorporate a neutral technological progress parameter), c can be interpreted as labour-augmenting technical change. We can apply analogous reasoning to consideration of a Cobb Douglas production function, which has a unitary elasticity of substitution. By integrating the resulting function and solving as before, we obtain:

$$f(k) = B(c + 1)k^{\frac{1}{c+1}} \tag{15}$$

where $1/(c + 1) \in (0; 1)$ because $c > 0$. Here, $B(1 + c)$ is a technological progress parameter. The above two examples suggest that, if we assume a constant elasticity of substitution, that is, we assume that the elasticity of substitution is not a function of the capital per worker, the resulting aggregate production function is a constant returns to scale production function with labour-augmenting technical change.

3.2.3. Econometric evidence

Econometric methodology

In this section, we assess whether we can assume theoretically a constant elasticity of substitution environment to analyse the determinants of the evolution of the capital share. To do this, we conduct a rolling window analysis of the estimates of the elasticity of substitution obtained in Equation (11).

Rolling window analysis of a time series model is a tool often used in financial econometrics to evaluate model stability over time (see Zivot and Wang, 2006). In particular, it detects whether the model's parameters are constant. The underlying logic is that it allows estimation of a certain parameter in rolling window samples of fixed size, over the entire sample. If the parameter is constant over time, the estimates over different rolling sub-samples should not differ. If the parameter estimates across different rolling sub-samples show appreciable differences, we can conclude that the parameter is unstable over time.

The procedure can be summarized in the steps below:

1. let T be the number of observations;
2. let N be the number of *rolling sub-samples*;
3. choosing the number m of observations in each rolling sub-sample (we must keep this number constant during the analysis), from which $N = T - m + 1$;
4. now we have a set of rolling sub-samples $n = (n_1, \dots, n_j, \dots, n_N)$, such that, for each observation $x_t,\ t \in (1;T)$, and it is true that:

$$\begin{cases} x_{n_1} = x_1, \dots, x_m \\ \dots \\ x_{n_j} = x_j, \dots, x_{m+j-1} \\ \dots \\ x_{n_N} = x_N, \dots, x_T \end{cases}$$

5. now, estimating the parameters c and p in Equation (11) for each rolling sub-sample $n_j,\ j \in (1;N)$, to obtain N estimates of the parameter.

This method assesses the stability over time of the parameter p. If the results of the rolling window analysis shows a clear variation in the estimates of the different sub-samples, then the assumption of a stable elasticity of substitution pattern is rejected, which would lead us to conclude that the elasticity of substitution displays dynamic behaviour.

Our analysis is based on a sample of nine countries observed between 1950 and 2017. We assume that the number of observations in each subsample is $m = 50$, which gives us $N = 19$ rolling sub-samples. To estimate the parameter p, we apply the NLLS estimator to Equation (11), since the non-linearity of this functional form can be treated using appropriate algorithms. The standard errors are those obtained by the standard NLLS procedure.

The following subsection describes the data used to perform the econometric analysis and provides descriptive evidence for our sample.

Data and descriptive evidence

The estimation model requires data on capital services and factor income shares. We retrieve these data from the Penn World Table (PWT), version 9.1 (Feenstra et al., 2015). The PWT is a rich and extensively used database that contains information on accounting data for outputs, inputs and productivity at country level. The PWT version 9.1, covers 182 countries between 1950 and 2017. We use data on capital stock at 2011 constant national prices, number of individuals involved and share of labour compensation in GDP at current national prices. Labour compensation includes both employee and self-employed compensation. The labour income of self-employed is not directly observable, since it could include remuneration from both capital and labour. To allocate labour compensation for self-employed, Feenstra et al. (2015) use a country-specific "best estimate" approach, based on four adjustments to self-employed incomes.[26]

Since we assume constant returns to scale, the capital share θ is computed as a residual:

$$\theta = 1 - (1 - \theta) \tag{16}$$

where $1 - \theta$ is the labour share. We acknowledge some limitations of our empirical analysis, especially regarding the assumption of constant returns to scale and the well-known problems associated with computation of labour compensation, from which the capital share is derived as a residual. However, these assumptions are used frequently in the empirical literature. Moreover, the widespread use of PWT data in cross-country analysis encouraged us to adopt this approach.

Our analysis is aimed a obtaining a long-run perspective and, so, covers the period 1950 to 2017. However, since for most countries, income shares are assumed to be constant before 1980 (Feenstra et al., 2015), we limit our analysis to nine OECD economies, for which data on labour compensation are available and measured more accurrately and observed from 1950 to 2017.[27]

[26] The first two methods of adjustment rely on mixed-income, which is capital and labour income combined. The third assumes that self-employed individuals earn the same wage rates as employees. The fourth uses agricultural value added, since most self-employed work in the agricultural sector.

[27] The countries included in the analysis are Australia, Canada, Finland, France, Italy, Japan, Netherlands, Sweden and the US.

Figure 3.1 shows the evolution of the share of capital compensation over GDP, obtained in Equation (16), for the sample considered. To emphasize country-specific short-run variations over time, each graph is based on a different scale according to the value of θ,. It can be seen that the capital share increased over the last 40 years, for all the countries considered, albeit at different rates. For example, in France, Italy, Japan and Canada, the capital share shows a sudden jump around the 1980s, while in the US, Australia and Sweden there was a steady increase, starting in the 1970s.

Figure 3.1. Share of capital compensation over GDP

Table 3.1 provides descriptive statistics for the entire sample and shows that the sample is heterogeneous in terms of factor income shares and capital intensity.

Table 3.1. Descriptive statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
$1-\theta$	612	0.633	0.058	0.499	0.770

θ	612	0.367	0.058	0.229	0.501
K/L	612	247,859	113,162	19,183	525,924

Source: PWT and authors' elaborations. θ and 1 - θ are, respectively, the shares of labour and capital compensations of GDP at current national prices. K/L is the capital-labour ratio. Capital stock is in millions of 2011 $, and labour input is expressed in millions of persons engaged.

Econometric results

Here, we present and discuss the results of the NLLS estimations and the rolling window analysis. The estimated value of the elasticity of substitution σ is based on the estimate of p, given that $\sigma = 1/(1-p)$. We present the standard errors for the estimates of the parameter p.[28] Table 3.2 presents the results of the NLLS estimation of Equation (11) for the parameters c and p, for the countries under scrutiny.

The estimation coefficients of the parameter p, which is the parameter of interest, behave as expected and have low standard errors. The findings indicate, also, that the elasticity of substitution σ is above unity, in all cases, over the entire period. The estimates of the elasticity of substitution range from 1.076 for Japan to 1.764 for Netherlands with the estimated elasticity of substitution of the US at 1.159.

The estimation coefficients of the parameter c should be treated with caution since they vary widely (e.g., Canada, Australia and Netherlands present very high estimated values for c compared to the other countries in the sample). Misspecification of capital intensity may cause substantial bias on the results obtained from a growth accounting framework and, in principle, may apply to our case (Sturgill and Zuleta, 2017; Zuleta, 2012). As described in Section 3.2.2, the term c is the integration constant from the solution to the Bernoulli equation. Therefore, our results are not sensitive to the unit of measurement of capital intensity. Indeed, the integration constant c includes potential errors in the measurement of capital intensity, of the form described in Zuleta (2012).

The results suggest that the capital share is rising in countries with a degree of substitutability between capital and labour above unity and, hence, would seem to support the accumulation view. Figure 3.2 plots the log of factor income shares against the log of the capital-labour ratio. The graphs show a positive relationship between these two variables for all the countries in our sample, albeit with some non-linearities. Therefore, the increase in the capital share over the labour share is related to the increase in the capital-labour ratio, implying an elasticity of substitution above unity (Bentolila and Saint-

[28] We can use σ in the estimated equation, obtaining the standard errors for its estimates directly. However, given that the relationship of interest is a non-linear one and the NLLS method is based on an optimisation algorithm, to simplify the numerical method, we prefer to retain p. Since studying p means studying σ, this choice is not crucial for our interpretation.

Paul, 2003; Karabarbounis and Neiman, 2014; Piketty, 2014). Our finding of an elasticity of substitution above unity across all the countries studied is in line with the accumulation view.

Figure 3.2. Relationship between the factor income shares ratio (in logs) and capital intensity (in logs)

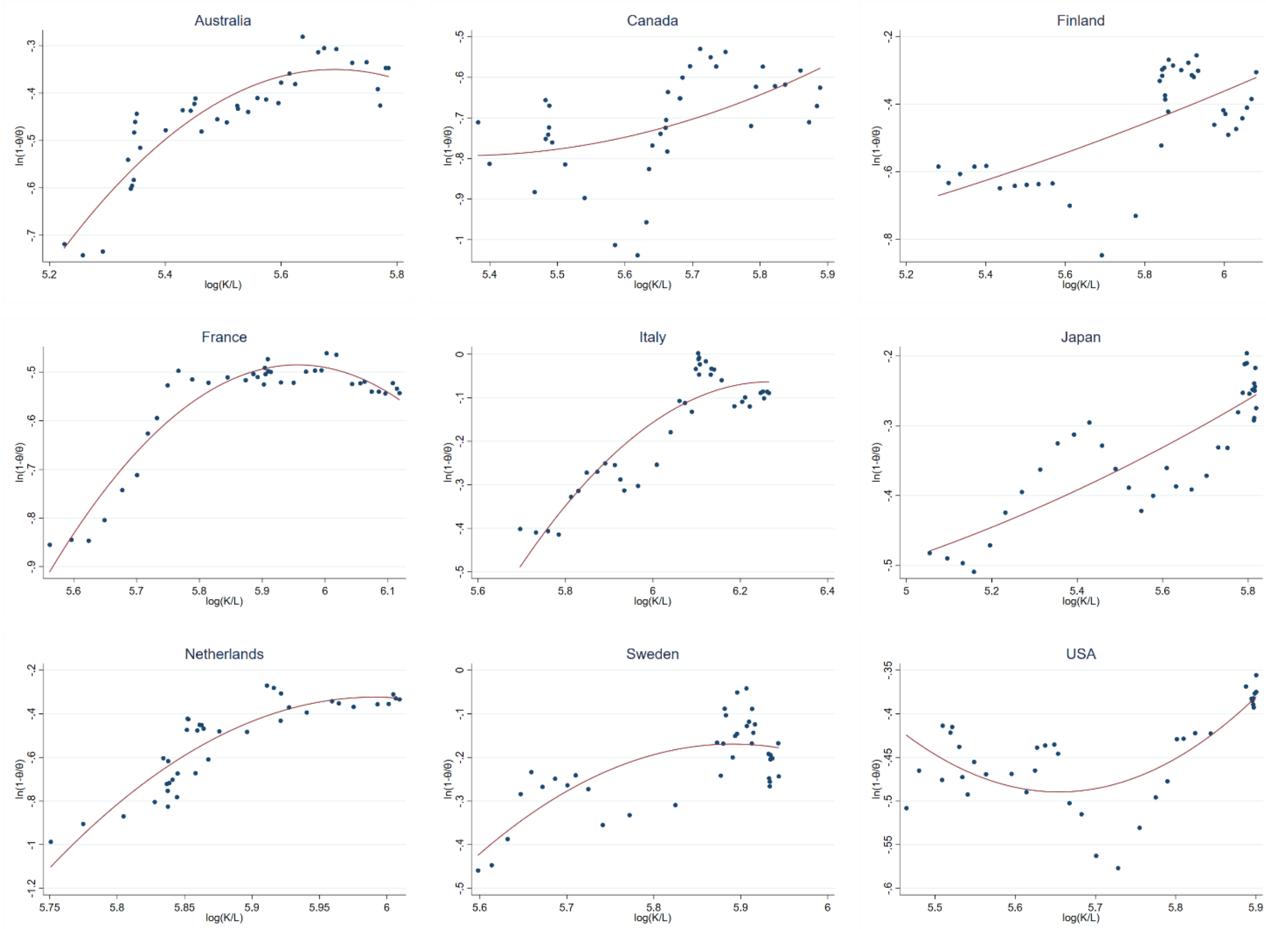


Table 3.2. Results of the NLLS estimations

		c	p	σ
US	Estimate	8.769	0.137	1.159
	Std. Error	1.470	0.014	Na
SW	Estimate	35.705	0.267	1.364
	Std. Error	10.922	0.026	Na
NL	Estimate	375.714	0.433	1.764
	Std. Error	140.639	0.031	Na
AU	Estimate	83.538	0.320	1.470
	Std. Error	21.966	0.022	Na
CA	Estimate	250.587	0.386	1.628
	Std. Error	78.420	0.026	Na

FN	Estimate	12.310	0.164	1.196
	Std. Error	2.645	0.018	Na
JP	Estimate	3.350	0.071	1.076
	Std. Error	0.268	0.007	Na
FR	Estimate	12.994	0.159	1.189
	Std. Error	2.798	0.018	Na
IT	Estimate	6.980	0.140	1.163
	Std. Error	1.006	0.012	Na

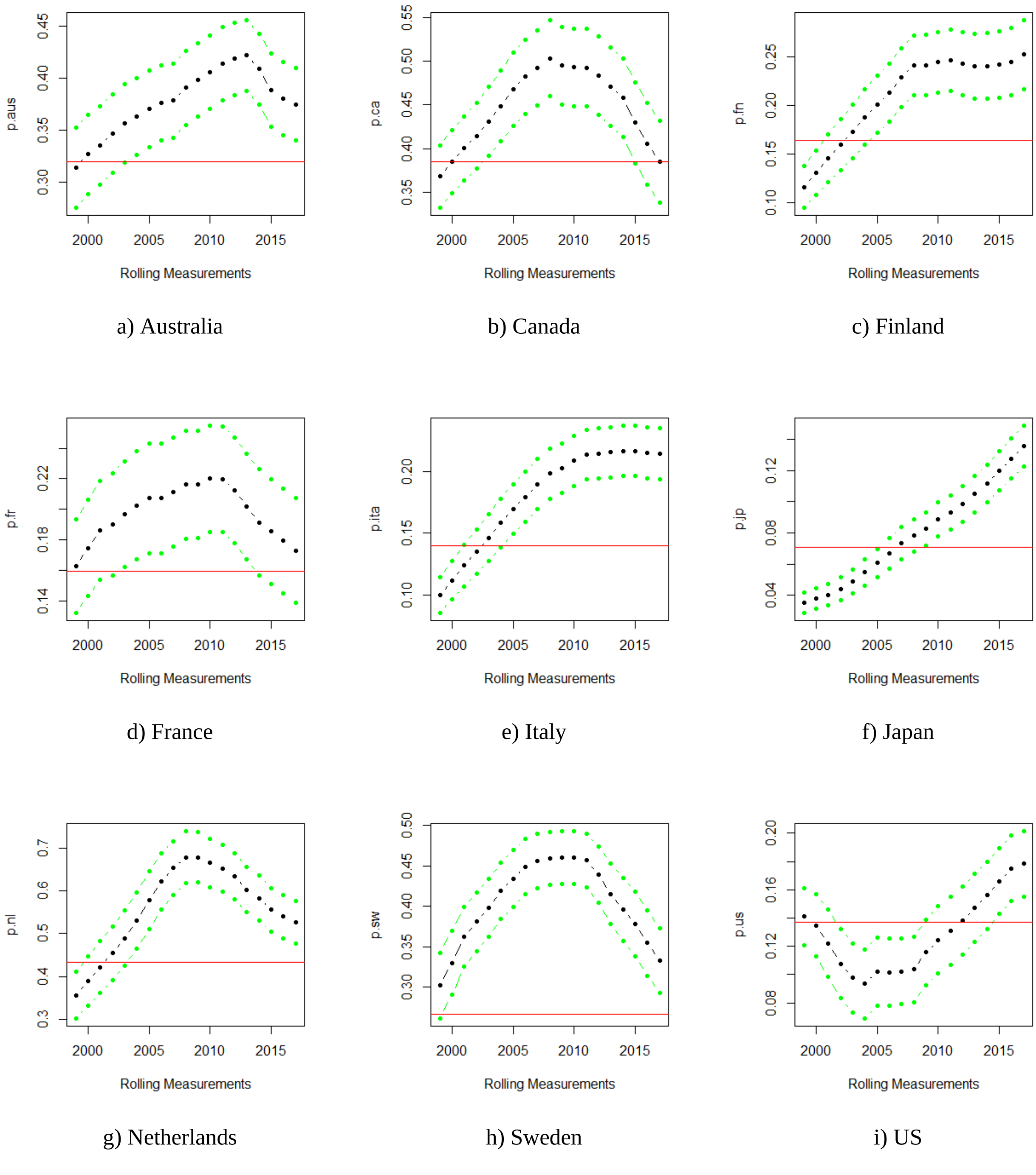
Figure 3.3 displays the results of the rolling window analysis performed on the estimates in Table 3.2. The black points represent the estimates of p for the 19 rolling sub-samples; the green points are the values of $p \pm s.e.$ ("*s.e.*" = standard errors) and show the boundaries around which the estimates oscillate; the red line represents the estimates of p using the entire sample in Table 3.2. The x-axes represent the end year of each sub-sample.

The estimates of p vary substantially across the rolling sub-samples, indicating that the elasticity of substitution is unstable. Moreover, the standard errors obtained suggest that the estimates are accurate. Since $m = 50$ implies a consistent sub-sample length, the constancy of the elasticity of substitution (represented by the parameter p) would seem to be rejected. The results of the estimates are presented in the Appendix B, Table B.1.

The higher estimated values for the elasticity of substitution in the recent subsamples seem to indicate an increase in the elasticity of substitution (Cantore, Ferroni and Leon-Ledesma, 2017). Although it is not possible to derive an accurate timing of the increase using this methodology, the exercise clearly rejects the stability of the estimates of parameter p, suggesting that the elasticity of substitution changed and, broadly, increased between 1950 and 2017.

The increase in the elasticity of substitution questions the validity of the accumulation view, which predicts constant elasticity over the period. In contrast, our results suggest that the capital-biased direction is triggered, also, by an increase in the elasticity of substitution which made labour more substitutable with capital. Therefore, the increase in the elasticity of substitution may a biased innovation additional to capital-augmenting technical change (Zuleta, 2008, 2016).

Figure 3.3. Rolling window analysis



a) Australia b) Canada c) Finland

d) France e) Italy f) Japan

g) Netherlands h) Sweden i) US

3.3. The change in the elasticity of substitution

This section elaborates the previous results by providing evidence of an increase in the elasticity of substitution over time, within each country (Knoblach and Stöckl, 2020). Among the potential causes of the change in the degree of substitutability between capital and labour, the literature suggests the openness to international trade (Sala and Trivin, 2018), the extent of government intervention (Mallick, 2012) and labour market regulations (De la Grandville, 2009). However, the aim in this section is not to discuss the determinants of the change in the elasticity of substitution, but only to highlight its increase.

Consistent with the results in Section 3.2, we hypothesize that, in line with recent empirical evidence, the elasticity of substitution has increased (Kemnitz and Knoblach, 2020; Knoblach and Stöckl, 2020; Ziesemer, 2021).

The empirical literature suggests that, in most advanced economies, the labour share started to decline between the late 1970s and the early 1980s. The findings in Section 3.2 show that the elasticity of substitution increased in that period, suggesting that the start of the decline in the share of labour may have coincided with a change in the elasticity of substitution, which is consistent with our proposed theoretical framework. For these reasons, by choosing 1979 as a cut-off year, we can hypothesize that the value of the elasticity of substitution was higher after the cut-off.[29]

We estimate the elasticity of substitution for two different periods, before and after the cut-off year $\tilde{t} = 1979$. The original CES function developed by Arrow et al. (1961) did not contain any form of factor-augmenting technical change. However, at least since Hahn and Matthews's (1964) contribution, the empirical literature assumes that labour-augmenting technical change is necessary to replicate the stylized facts of growth. Moreover, the results in Klump, McAdam and Willman (2007, 2008) indicate that only labour-augmenting technical change is relevant in the long-run, with capital-augmenting technical change, at most, a transitory phenomenon (Acemoglu, 2002, 2003). Indeed, several studies find negative growth rates for the capital-augmenting parameter and highlight the difficulties associated with its measurement (Antràs, 2004; Leon-Ledesma, McAdam and Willman, 2010).

For these reasons, we estimate the CES, amplified by labour-augmenting technical change. In addition, to be in line with Arrow et al.'s (1961) original formulation and allow comparison with the labour-augmenting estimates, we report estimates of the CES production function in the absence of factor-augmenting technical change.

To estimate the elasticity of substitution for the overall period (1950-2017) and for the two subperiods (1950-1979 and 1980-2017), we assume a specific functional form for labour augmenting technological progress, following Kastrup et al.

[29] Analogous to Federici and Saltari (2016), we implement a simple Chow breakpoint test to confirm the structural break for each country. We experimented with alternative thresholds, such as years 1978, 1980 and 1981 and the results did not change.

(2022), Klump, McAdam and Willman (2007, 2008), McAdam and Willman (2013) and Stewart and Li (2018), based on application of the Box-Cox transformation. We assume that the CES production function takes the following form:

$$\tilde{y}_{\mathrm{t}} = \left[\tilde{\pi}\tilde{k}_t^{p_t} + g_t(1-\tilde{\pi})\right]^{\frac{1}{p_t}} \tag{17}$$

where:

$$g_t = e^{G_t} \tag{18}$$

and,

$$G_t = \frac{\gamma}{\lambda} t_0 \left[\left(\frac{t}{t_0}\right)^{\lambda} - 1\right] \tag{19}$$

Notice that $g_t(t_0) = 1$. The parameter λ determines the functional form for technological progress, while γ is a parameter of the intensity of technological progress at the normalization time t_0. To simplify the analysis, we set $\lambda = 1$, and obtain a linear function of G_t, i.e., $G_t = \gamma(t - t_0)$, which depends on the normalized discrete time $t - t_0$.

The variables $\tilde{y}_t$ and $\tilde{k}_t$ and the parameters $\tilde{\pi}_1$ and $\tilde{\pi}_2$ are normalized.[30] We also estimate the CES without the factor-augmenting form. The CES without labour-augmenting technical change can be expressed as follows:

$$\tilde{y}_{\mathrm{t}} = \left[\tilde{\pi}\tilde{k}_t^{p_t} + (1-\tilde{\pi})\right]^{\frac{1}{p_t}} \tag{20}$$

We use a non-linear method to estimate the CES production function. Most studies rely on some form of linearisation to estimate the CES. The Kmenta (1967) approximation is used frequently in the literature. In the simple case of a two-factor CES, the Kmenta linear approximation coincides with the Translog linear approximation, proposed by Berndt and Christensen (1973).[31] However, the Kmenta approximation may not perform well if the elasticity of substitution departs

[30] Normalization of the variables is fundamental when estimating a CES production function. De la Grandville (2009) makes it clear that normalization follows directly from the derivation of the CES production function; however, while from a pure theoretical view point, every year can be chosen as the normalization year, from an econometric perspective, it is useful to consider the mean values of GDP and capital per worker. Following Leon-Ledesma et al. (2010), we use the geometric mean since there is a strong time-dependency path in both the considered variables. Thus, we impose $\tilde{y} \equiv y/\bar{y}$, $\tilde{k} \equiv k/\bar{k}$, $\tilde{\pi}_1 \equiv \pi_1/\bar{\pi}_1$ and $\tilde{\pi}_2 \equiv \pi_2/\bar{\pi}_2$.

[31] The Kmenta approximation generates the linear function:

$$\log\tilde{y}_t = \beta_0 + \beta_1\log\tilde{k}_t + \beta_2(\log\tilde{k}_t)^2$$

from unity. In other words, the Kmenta approximation works well if the production function is close to a Cobb-Douglas, but its estimates become unreliable if the elasticity of substitution is either very high or very low (Thursby and Lovell, 1978).

For these reasons, and in line with Koesler and Schymura (2015), we implement a NLLS estimation procedure. We set constraints on the behaviours of our parameters ($\tilde{\pi} \in (0;1)$ and $p \in (0;-\infty)$) and estimate Equations (17) and (20) using the L-BFGS-B algorithm (Byrd et al., 1995).

Therefore, we test whether the value of the elasticity of substitution is higher after 1979. We show the results without and, then, with labour-augmenting technical change. Table 3.3 presents the results of the estimates without labour-augmenting technical change; it shows the estimated elasticity of substitution for the overall period of observation (1950-2017), and the first (1950-1979) and the second (1980-2017) subperiod. We also provide the standard errors of the estimates. Following Vinod (2016), we adopt a maximum entropy time series bootstrap to estimate the standard errors. Using this procedure, we replace the classic bootstrap standard error measure proposed by Efron and Tibshirani (1993) by a more robust measure of dispersion, to control for possible outliers deriving from the optimization algorithm used. We follow the MAD measure proposed by Rousseeuw and Croux (1993), based on the median (med), which is expressed as follows:

$$MAD_{\widehat{\omega}} = med(|\widehat{\omega}_i - med(\widehat{\omega}_i)|) \tag{21}$$

where $\widehat{\omega}_i$ is the vector of the estimates of the parameters of interest in the i^{th} bootstrap sample. Our results are robust to the number of bootstrap resamplings equal to or higher than 500.

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where $\tilde{\pi} = \beta_1$ and $p = 2\beta_2/[\beta_1(1-\beta_1)]$.

Problems can arise in interpreting the estimated coefficient β_0 in the above equation; Leon-Ledesma et al. (2010) suggest treating it as an *integration constant*, i.e., $\beta_0 = \log\xi$, when it is true that $\bar{y} = \xi f(\bar{k})$, with $E[\xi] = 1$. The estimates of this constant are always very close to 1. The Appendix B, Table B.2, presents the results of the Kmenta method and explains, in depth, its limitations in the context of our analysis.

Table 3.3. Estimates of σ – No labour-augmenting technical change

Country	1950-2017	1950-1979	1980-2017
Australia	1.279 (0.332)	0.510 (0.162)	1.339 (0.147)
Canada	1.004 (0.115)	0.827 (0.090)	0.961 (0.036)
Finland	1.770 (0.612)	0.321 (0.365)	1.858 (0.200)
France	1.626 (0.456)	0.482 (0.330)	1.559 (0.171)
Italy	1.284 (0.134)	0.788 (0.071)	1.225 (0.058)
Japan	1.303 (0.095)	0.656 (0.023)	1.321 (0.061)
Netherlands	1.760 (1.295)	0.400 (0.293)	1.751 (0.207)
Sweden	1.284 (0.296)	0.386 (0.126)	1.392 (0.158)
USA	2.568 (1.255)	0.332 (0.079)	3.119 (0.765)

The estimation results confirm our conjectures. The elasticity of substitution is higher in all the countries after 1979. The standard errors appear acceptable and well below the estimation coefficients. It is interesting, also, that, when labour-augmenting technical change is not included, the elasticity of substitution passes from a value lower than 1 in the first period to a value higher than 1 in the second period, for all the countries analysed. Similar results were obtained by De la Grandville (2009), who analysed a sample of 16 OECD countries along the period 1966-1997 and found elasticities of substitution above unity in the second subperiod, 1982-1997, for all the countries considered.

Table 3.4 reports the estimates for the elasticity of substitution including the labour-augmenting technical change term. All show an elasticity of substitution of ∼0.83 for the period 1950 to 2017. In particular, the elasticity increased from ∼0.76 in the sub-period 1950-1979 to ∼0.83 in the second sub-period 1980-2017. The estimates are similar across countries: the explanation being that most variation in the CES estimation originates from the labour-augmenting technical change parameter, which varies widely across countries. The inclusion of labour-augmenting technical change in fact lowers the value of the elasticity of substitution quite dramatically. However, the results in Table 3.4 confirm the increase in the elasticity of substitution in the period under examination. These findings support recent evidence of an increase in the elasticity of substitution over the most recent decades (Kemnitz and Knoblach, 2020; Knoblach, Roessler and Zwerschke, 2020; Knoblach and Stöhl, 2020).

Table 3.4. Estimates of σ - Labour augmenting technical change included

Country	1950-2017	1950-1979	1980-2017
Australia	0.829 (0.0099)	0.759 (0.0024)	0.8298 (0.0049)
Canada	0.8298723 (0.016097312)	0.7603307 (0.006624677)	0.8298833 (0.002942757)
Finland	0.8299859 (0.032387234)	0.7571565 (0.080077537)	0.8296074 (0.002382117)
France	0.8299238 (0.027102347)	0.758955 (0.029406392)	0.8359686 (0.002920216)
Italy	0.8300517 (0.039047019)	0.7572221 (0.001082211)	0.8295923 (0.002618631)
Japan	0.8300604 (0.018256125)	0.7565086 (0.001173512)	0.8295149 (0.001029452)
Netherlands	0.8298883 (0.0013851636)	0.7590745 (0.0009882395)	0.8298375 (0.0027689621)
Sweden	0.8299162 (0.00004543444)	0.7577899 (0.0008564649)	0.8401196 (0.0009901728)
USA	0.8298433 (0.0024183658)	0.7595978 (0.0006505500)	0.8298404 (0.0009006302)

3.4. Conclusions and suggestions for further research

The present study aimed to highlight the role of the elasticity of substitution in the income distribution. Most empirical work focused on the functional distribution of income, relies on a CES production function that assumes a constant elasticity of substitution between capital and labour. In this context, the rise in the share of capital on income is explained by the capital-intensive direction of technological change combined with a fixed degree of substitutability between capital and labour above unity, during the period of observation. In this strand of the literature, the elasticity of substitution is considered a fixed and deep parameter that does not play any role.

However, we hypothesize that the elasticity of substitution might be a further element shaping the income distribution between capital and labour. An increase in the elasticity of substitution makes labour more substitutable and, therefore, reflects a lower share of labour in total income. Our findings can be summarized as follows.

First, we constructed a relationship between capital share, capital intensity and the elasticity of substitution using the theoretical advances in Sato (1967) and de La Grandville (2009). We obtained estimates of the elasticity of substitution, using a NNLS estimator, for our nine country sample, observed between 1950 and 2017. We found an estimated elasticity above unity, confirming the accumulation view of a capital-biased direction and an elasticity of substitution above unity. However, we conducted a rolling window analysis to assess the stability of the elasticity of substitution and found that the elasticity of substitution was not constant for all the countries considered. Specifically, the estimates obtained for the most recent rolling window sub-samples show that the elasticity of substitution has increased. These results indicate that the evolution of factor income shares is explained not only by changes in the factor-augmenting form but also by the increase in the elasticity of substitution.

We estimated the elasticity of substitution for a CES production function before and after 1979, which is around the cut-off year after which the labour share began to decline and the capital share started to increase. Estimating the CES without and with labour-augmenting technical change, we provided evidence of an increase in the elasticity of substitution for all the countries considered in our analysis. When labour-augmenting technical change is not included, the elasticity estimates pass from a value lower than unity in 1950-1979 to a value above 1 in 1979-2017. However, if labour-augmenting technical change is included, the estimates remain lower than unity over the entire period, but are higher after 1979 than before 1979.

Our paper adds to debate on the elasticity of substitution. We have demonstrated that more research is needed to capture the role of the factors underlying the evolution of the elasticity of substitution. In our framework, it would seem that the effect of technological change affects not just capital or labour, but also can change the degree to which factor inputs can be combined. In further research, we need to explore in more depth, the determinants of the change in the elasticity of substitution and disentangle the impact of economic and institutional factors on the elasticity of substitution, from the rate and direction of technological change.

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Appendix B

B.1. Derivation of Equation (6)

Equation (6) can be rephrased as:

$$\sigma = \frac{f(k) - kf'(k)}{-\frac{kf(k)f''(k)}{f'(k)}}$$

by multiplying both the numerator and the denumerator of the second term of the previous equation by $kf'(k)/f^2(k)$, we obtain:

$$\sigma = \frac{\frac{kf'(k)}{f(k)} - \frac{k^2(f'(k))^2}{f^2(k)}}{-\frac{k^2 f''(k)f(k)}{f^2(k)}} \, .$$

Considering the definition $\theta = kf'(k)/f(k)$, the numerator of the right handside of the previous equation collapses to:

$$\theta(1-\theta)$$

Regarding the denumerator, by adding and subtracting the terms $kf'(k)/f(k)$ and $-k^2(f'(k))^2/f^2(k)$, we obtain:

$$\theta - \theta^2 - \frac{k[f'(k)f(k) + kf''(k)f(k) - k(f'(k))^2]}{f^2(k)}$$

where the third term is just $k\theta'$. Finally, we obtain:

$$\sigma = \frac{\theta(1-\theta)}{\theta(1-\theta) - k\theta'}$$

which is Equation (6).

Table B.1. Rolling window estimates for p and related standard errors

		SW	US	NL	AU	CA	FIN	JAP	FR	IT
1950-1999	estimate	0.302	0.141	0.356	0.314	0.368	0.116	0.035	0.163	0.100
	s.e.	0.041	0.020	0.054	0.038	0.035	0.021	0.006	0.031	0.014
1951-2000	estimate	0.330	0.135	0.389	0.327	0.385	0.131	0.038	0.174	0.112
	s.e.	0.040	0.022	0.057	0.038	0.036	0.023	0.007	0.032	0.016
1952-2001	estimate	0.362	0.122	0.422	0.336	0.400	0.146	0.040	0.186	0.124
	s.e.	0.037	0.024	0.060	0.038	0.037	0.025	0.007	0.033	0.017
1953-2002	estimate	0.381	0.108	0.454	0.347	0.415	0.159	0.044	0.190	0.135
	s.e.	0.036	0.025	0.062	0.038	0.038	0.026	0.007	0.035	0.018
1954-2003	estimate	0.398	0.098	0.489	0.357	0.431	0.173	0.049	0.197	0.146
	s.e.	0.036	0.025	0.064	0.037	0.039	0.028	0.008	0.035	0.019
1955-2004	estimate	0.419	0.093	0.531	0.363	0.449	0.188	0.055	0.202	0.158
	s.e.	0.035	0.024	0.066	0.037	0.041	0.029	0.008	0.036	0.020
1956-2005	estimate	0.434	0.102	0.578	0.371	0.468	0.201	0.061	0.207	0.170
	s.e.	0.035	0.023	0.067	0.036	0.042	0.030	0.009	0.036	0.020
1957-2006	estimate	0.449	0.102	0.623	0.376	0.482	0.213	0.067	0.207	0.180
	s.e.	0.034	0.023	0.066	0.036	0.043	0.030	0.010	0.035	0.020
1958-2007	estimate	0.456	0.102	0.653	0.379	0.492	0.229	0.073	0.211	0.190
	s.e.	0.033	0.024	0.063	0.035	0.043	0.031	0.010	0.036	0.021
1959-2008	estimate	0.459	0.104	0.679	0.391	0.503	0.242	0.078	0.216	0.199
	s.e.	0.033	0.023	0.061	0.035	0.043	0.031	0.010	0.035	0.020
1960-2009	estimate	0.460	0.116	0.679	0.398	0.495	0.242	0.083	0.216	0.203
	s.e.	0.033	0.023	0.059	0.035	0.044	0.031	0.011	0.035	0.020
1961-2010	estimate	0.460	0.124	0.666	0.406	0.493	0.245	0.088	0.220	0.209
	s.e.	0.032	0.024	0.057	0.035	0.044	0.031	0.011	0.035	0.020
1962-2011	estimate	0.456	0.131	0.653	0.414	0.493	0.247	0.093	0.220	0.214
	s.e.	0.033	0.024	0.055	0.035	0.044	0.032	0.011	0.035	0.020
1963-2012	estimate	0.439	0.138	0.634	0.419	0.483	0.243	0.098	0.212	0.214
	s.e.	0.035	0.024	0.054	0.035	0.045	0.033	0.011	0.035	0.020
1964-2013	estimate	0.415	0.147	0.603	0.422	0.471	0.241	0.105	0.202	0.216
	s.e.	0.037	0.024	0.053	0.034	0.045	0.033	0.012	0.035	0.020
1965-2014	estimate	0.396	0.156	0.583	0.409	0.458	0.241	0.112	0.191	0.217
	s.e.	0.039	0.024	0.053	0.034	0.045	0.033	0.012	0.035	0.020
1966-2015	estimate	0.378	0.166	0.555	0.388	0.430	0.243	0.120	0.185	0.217
	s.e.	0.040	0.023	0.051	0.035	0.046	0.034	0.012	0.035	0.021
1967-2016	estimate	0.354	0.175	0.540	0.380	0.405	0.245	0.127	0.179	0.216
	s.e.	0.040	0.023	0.051	0.035	0.047	0.035	0.013	0.034	0.021
1968-2017	estimate	0.333	0.178	0.526	0.375	0.385	0.253	0.136	0.173	0.215
	s.e.	0.040	0.023	0.050	0.035	0.047	0.036	0.013	0.034	0.021

Table B.2. Estimates of σ (Kmenta approximation)

Country		1950-2017 (σ)	1950-1979 (σ_1)	1980-2017 (σ_2)
Australia		0.360	0.120	-0.252
		$[0.314: 0.414]$	$[0.076: 0.167]$	$[-0.719: -0.070]$
Canada		0.398	0.158	-0.478
		$[0.366: 0.433]$	$[0.139: 0.179]$	$[-45587.89: 22542.73]$
Finland		0.755	0.545	-1.893
		$[0.633: 0.912]$	$[0.453: 0.659]$	$[-492174.8: 115251.6]$
France		0.248	0.201	0.286
		$[0.232: 0.266]$	$[0.193: 0.210]$	$[0.100: 0.518]$
Italy		0.364	0.433	0.183
		$[0.353: 0.375]$	$[0.386: 0.484]$	$[0.037: 0.309]$
Japan		0.585	0.372	0.241
		$[0.550: 0.623]$	$[0.348: 0.397]$	$[0.031: 0.436]$
Netherlands		0.224	0.921	-0.327
		$[0.199: 0.250]$	$[-2898.665: 3009.09]$	$[-1.615: -0.055]$
Sweden		0.747	0.311	-0.919
		$[0.633: 0.896]$	$[0.253: 0.380]$	$[-210017: 50951.67]$
USA		0.277	0.110	-0.130
		$[0.215: 0.363]$	$[0.087: 0.134]$	$[-0.429: -0.016]$

Notes: For the linear Kmenta approximation, we present the range in which the estimated elasticity of substitution may vary according to the standard errors of the estimated coefficients of the linear regression model representing the linear approximation. See Tables B.3-B.11 for the results of the linear estimation for each country.

It is straightforward to notice that the estimates obtained with the Kmenta linear approximation have to be refused. First of all, comparing the estimates obtained for the elasticity of substitution for the overall period (σ) with the ones obtained with the non-linear least square methodology, we can observe that the first are always lower than the unity, while the last are always higher than one. However, the range in which the Kmenta estimates for σ are allowed to vary according to the standard errors of the regression coefficients is sometimes large, compared to the standard errors of the non-linear estimates for the same parameter. Second, the most important thing to be noticed is the fact that the Kmenta estimates for the elasticity of substitution in the two different periods (σ_1 and σ_2) are not precise and often not comparable with theoretical assumptions (especially regarding the Kmenta estimates for σ_2, very often lower than zero, which is meaningless form a theoretical perspective). There can be several reasons for this particular behaviour. One can be the simple fact that there are no sufficient observations to perform a well-behaved regression (while the non-linear estimation procedure seems to be well behaved, and it is confirmed by the bootstrap analysis on the standard errors) so that estimates tend to be inconsistent.

Another possible cause of these results can be that, running a simple linear regression, we are not able to pose implicit constraints to the coefficients we want to estimate (the constraints that have to be assumed are non-trivial, given that we have an assumption about the behaviour of the parameters $\tilde{\pi}$ and p, but we estimate the vector of coefficients β; box-constrained least squares methods are not so developed in literature and present lots of problematic issues). The last explanation for this result is that the linear approximation around the unitary elasticity of substitution is not representative of the real data: the Kmenta approximation is a good linear representation of the CES production function if we assume that the elasticity of substitution is very close to the unity, which implicitly implies that it works well when we assume a production function not too different from the Cobb-Douglas one. In other words, the resulting estimates for the elasticity of substitution obtained with this linear approximation have to be very close to one to be credible, and we have seen that this is not the case.

Table B.3. Kmenta estimation for Australia (two subperiods)

	Dependent variable:		
	$\log y$ (1)	$\log y_{1950-1979}$ (2)	$\log y_{1980-2017}$ (3)
$\log k$	0.731 ***		
	(0.015)		
$(\log k)^2$	−0.175 ***		
	(0.032)		
$\log k_{1950-1979}$		0.300 ***	
		(0.112)	
$(\log k_{1950-1979})^2$		−0.764 ***	
		(0.162)	
$\log k_{1980-2017}$			1.197 ***
			(0.113)
$(\log k_{1980-2017})^2$			−0.586 ***
			(0.102)
Constant	0.042 ***	0.002	-0.058 **
	(0.011)	(0.017)	(0.028)
Observations	68	39	29
R^2	0.973	0.938	0.940
Adjusted R^2	0.972	0.934	0.935
Residual Std. Error	0.060 (df = 65)	0.057 (df = 36)	0.040 (df = 26)
F Statistic	1,154.939*** (df=2;65)	270.151*** (df = 2; 36)	202.562 *** (df = 2; 26)

Note: *p<0.1; **p<0.05; ***p<0.01

Table B.4. Kmenta estimation for Canada (two subperiods)

	Dependent variable:		
	$\log y$ (1)	$\log y_{1950-1979}$ (2)	$\log y_{1980-2017}$ (3)
$\log k$	0.569^{***}		
	(0.013)		
$(\log k)^2$	-0.185^{***}		
	(0.025)		
$\log k_{1950-1979}$		0.271^{***}	
		(0.033)	
$(\log k_{1950-1979})^2$		-0.523^{***}	
		(0.038)	
$\log k_{1980-2017}$			1.364^{***}
			(0.362)
$(\log k_{1980-2017})^2$			-0.766^{***}
			(0.286)
Constant	0.059^{***}	0.038^{***}	-0.171
	(0.011)	(0.007)	(0.102)
Observations	68	39	29
R^2	0.970	0.972	0.982
Adjusted R^2	0.969	0.970	0.980
Residual Std. Error	0.061 (df = 65)	0.036 (df = 36)	0.021 (df = 26)
F Statistic	1,035.167*** (df = 2; 65)	1,365.531*** (df = 2; 36)	32.604 *** (df = 2; 26)

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

Table B.5. Kmenta estimation for Finland (two subperiods)

	Dependent variable:		
	$\log y$ (1)	$\log y_{1950-1979}$ (2)	$\log y_{1980-2017}$ (3)
$\log k$	0.769 ***		
	(0.015)		
$(\log k)^2$	-0.029		
	(0.020)		
$\log k_{1950-1979}$		0.643 ***	
		(0.043)	
$(\log k_{1950-1979})^2$		-0.096 ***	
		(0.034)	
$\log k_{1980-2017}$			1.547 ***
			(0.485)
$(\log k_{1980-2017})^2$			-0.647 *
			(0.318)
Constant	0.018	-0.029 **	-0.153
	(0.016)	(0.011)	(0.169)
Observations	68	39	29
R^2	0.979	0.988	0.703
Adjusted R^2	0.978	0.987	0.681
Residual Std. Error	0.091 (df = 65)	0.049 (df = 36)	0.107 (df = 26)
F Statistic	1,506.124*** (df = 2; 65)	1,435.276*** (df = 2; 36)	30.837 *** (df = 2; 26)

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

Table B.6. Kmenta estimation for France (two subperiods)

	Dependent variable:		
	$\log y$ (1)	$\log y_{1950-1979}$ (2)	$\log y_{1980-2017}$ (3)
$\log k$	0.778 ***		
	(0.011)		
$(\log k)^2$	-0.261 ***		
	(0.015)		
$\log k_{1950-1979}$		0.506 ***	
		(0.025)	
$(\log k_{1950-1979})^2$		−0.495 ***	
		(0.026)	
$\log k_{1980-2017}$			0.712 ***
			(0.190)
$(\log k_{1980-2017})^2$			−0.256 *
			(0.140)
Constant	0.114 ***	0.070 ***	0.174 ***
	(0.010)	(0.005)	(0.047)
Observations	68	39	29
R^2	0.988	0.997	0.858
Adjusted R^2	0.988	0.997	0.847
Residual Std. Error	0.060 (df = 65)	0.023 (df = 36)	0.061 (df = 26)
F Statistic	2,662.948*** (df = 2; 65)	7,007.800*** (df = 2; 36)	78.483 *** (df = 2; 26)

Note: *p<0.1; **p<0.05; ***p<0.01

Table B.7. Kmenta estimation for Italy (two subperiods)

	Dependent variable:		
	$\log y$ (1)	$\log y_{1950-1979}$ (2)	$\log y_{1980-2017}$ (3)
$\log k$	0.706 ***		
	(0.006)		
$(\log k)^2$	-0.181 ***		
	(0.007)		
$\log k_{1950-1979}$		0.790 ***	
		(0.020)	
$(\log k_{1950-1979})^2$		-0.108 ***	
		(0.014)	
$\log k_{1980-2017}$			0.844 ***
			(0.127)
$(\log k_{1980-2017})^2$			-0.293 ***
			(0.067)
Constant	0.148 ***	0.137 ***	0.138 **
	(0.007)	(0.006)	(0.054)
Observations	68	39	29
R^2	0.996	0.998	0.884
Adjusted R^2	0.996	0.998	0.875
Residual Std. Error	0.042 (df = 65)	0.024 (df = 36)	0.042 (df = 26)
F Statistic	8,898.138*** (df = 2; 65)	10,877.40*** (df = 2; 36)	99.087 *** (df = 2; 26)

Note: *p<0.1; **p<0.05; ***p<0.01

Table B.8. Kmenta estimation for Japan (two subperiods)

	Dependent variable:		
	$\log y$ (1)	$\log y_{1950-1979}$ (2)	$\log y_{1980-2017}$ (3)
$\log k$	0.690 ***		
	(0.010)		
$(\log k)^2$	-0.076 ***		
	(0.010)		
$\log k_{1950-1979}$		0.446 ***	
		(0.032)	
$(\log k_{1950-1979})^2$		-0.208 ***	
		(0.019)	
$\log k_{1980-2017}$			0.840 ***
			(0.141)
$(\log k_{1980-2017})^2$			-0.211 ***
			(0.075)
Constant	0.096 ***	0.068 ***	0.119 *
	(0.016)	(0.013)	(0.062)
Observations	68	39	29
R^2	0.991	0.993	0.956
Adjusted R^2	0.991	0.993	0.953
Residual Std. Error	0.078 (df = 65)	0.059 (df = 36)	0.026 (df = 26)
F Statistic	3,786.260*** (df = 2; 65)	2,555.661*** (df = 2; 36)	284.208 *** (df = 2; 26)

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

Table B.9. Kmenta estimation for Netherlands (two subperiods)

	Dependent variable:		
	$\log y$ (1)	$\log y_{1950-1979}$ (2)	$\log y_{1980-2017}$ (3)
$\log k$	0.814 ***		
	(0.015)		
$(\log k)^2$	-0.262 ***		
	(0.022)		
$\log k_{1950-1979}$		0.975 ***	
		(0.043)	
$(\log k_{1950-1979})^2$		−0.001	
		(0.049)	
$\log k_{1980-2017}$			1.279 ***
			(0.193)
$(\log k_{1980-2017})^2$			−0.724 ***
			(0.162)
Constant	0.079 ***	0.053 ***	0.046
	(0.011)	(0.007)	(0.040)
Observations	68	39	29
R^2	0.978	0.994	0.855
Adjusted R^2	0.978	0.993	0.844
Residual Std. Error	0.068 (df = 65)	0.028 (df = 36)	0.073 (df = 26)
F Statistic	1,467.107*** (df = 2; 65)	2,862.435*** (df = 2; 36)	76.616 *** (df = 2; 26)

Note: *p<0.1; **p<0.05; ***p<0.01

Table B.10. Kmenta estimation for Sweden (two subperiods)

	Dependent variable:		
	$\log y$ (1)	$\log y_{1950-1979}$ (2)	$\log y_{1980-2017}$ (3)
$\log k$	0.706 ***		
	(0.015)		
$(\log k)^2$	-0.035		
	(0.023)		
$\log k_{1950-1979}$		0.406 ***	
		(0.067)	
$(\log k_{1950-1979})^2$		-0.266 ***	
		(0.063)	
$\log k_{1980-2017}$			1.416 ***
			(0.267)
$(\log k_{1980-2017})^2$			-0.614 ***
			(0.194)
Constant	0.015	-0.053 ***	-0.136
	(0.014)	(0.013)	(0.081)
Observations	68	39	29
R^2	0.973	0.972	0.830
Adjusted R^2	0.972	0.971	0.817
Residual Std. Error	0.080 (df = 65)	0.048 (df = 36)	0.084 (df = 26)
F Statistic	1,160.255*** (df = 2; 65)	634.897*** (df = 2; 36)	63.453 *** (df = 2; 26)

Note: *p<0.1; **p<0.05; ***p<0.01

Table B.11. Kmenta estimation for USA (two subperiods)

	Dependent variable:		
	$\log y$ (1)	$\log y_{1950-1979}$ (2)	$\log y_{1980-2017}$ (3)
$\log k$	0.868 ***		
	(0.015)		
$(\log k)^2$	−0.150 ***		
	(0.040)		
$\log k_{1950-1979}$		0.362 ***	
		(0.077)	
$(\log k_{1950-1979})^2$		−0.927 ***	
		(0.136)	
$\log k_{1980-2017}$			1.128 ***
			(0.104)
$(\log k_{1980-2017})^2$			−0.624 ***
			(0.149)
Constant	0.021 ***	−0.026 ***	0.023 *
	(0.008)	(0.009)	(0.014)
Observations	68	39	29
R^2	0.981	0.972	0.982
Adjusted R^2	0.981	0.970	0.980
Residual Std. Error	0.046 (df = 65)	0.036 (df = 36)	0.021 (df = 26)
F Statistic	1,715.141*** (df=2;65)	617.520*** (df = 2; 36)	704.759 *** (df = 2; 26)

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

Chapter 4.

The rise in knowledge-intensive services and wage inequality

ABSTRACT

Over the last several decades, advanced economies experienced a transition from a manufacturing-based to a service economy in which knowledge is central and more scalable compared to other sectors. This paper investigates the consequences of this change on wage inequality. The empirical analysis studies this hypothesis on a sample of US cities observed for the period between 1980 and 2010. The econometric model tests the relationship between the decadal change in wage inequality against the decadal change in knowledge-intensive services employment rate. The econometric analysis shows that services exert a positive and statistically significant impact on wage inequality within US cities that is robust to several specifications and econometric concerns.

4.1. Introduction

Over the last couple of decades, the economics literature has renewed the interest in income inequality (Milanovic, 2016; Piketty and Saez, 2003). The main explanation was the dramatic increase in within-country income inequality triggered by the surge in wage inequality at the end of the 1970s, mainly in Anglo-Saxon countries. In addition, a vast literature has documented increasing wage differentials between graduate and non-graduate workers. The canonical explanation was the increase in the relative demand for high-skilled workers owing to advancements in technological change (Berman, Bound and Griliches, 1994; Goldin and Katz, 2010; Katz and Murphy, 1992; Machin and Van Reenen, 1998).

Therefore, a strong consensus has been reached on the Skill-Biased Technological Change (SBTC) as the primary determinant of the increased demand for skills.[32] More recently, the Routine-Biased Technological Change (RBTC) hypothesis has offered a refined explanation for the increase in wage inequality, suggesting that new technologies favour high-skilled and low-skilled workers engaged in non-routine tasks while detrimental to routine medium-skilled workers (Autor, Katz and Kearney, 2006; Autor, Levy and Murnane, 2003). This mechanism has caused a polarization of the labour market. Alternative explanations for the increase in wage inequality, such as the rise of international trade and changes in institutional settings, have obtained scarce empirical and theoretical support.

The study of within-group wage inequality has received far less attention, even though the SBTC hypothesis cannot explain adequately the wage dispersion within the upper tail of the skill and wage distributions (Lemieux, 2008). Lemieux (2006b) proves that residual or within-group inequality has grown sharply among skilled workers and little among other education groups.

This article examines the determinants of wage inequality by exploiting cross-city[33] variation in the US between 1980 and 2010. The empirical analysis links deindustrialization and the rising demand for knowledge-intensive services to the 90-10 wage gap in US cities. While the transition from manufacturing to services has been discussed extensively in relation to economic growth and knowledge governance (Buera and Kaboski, 2012; Rodrik, 2016; Wood, 2006), its consequences for income inequality have been little analysed.

This paper tests the hypothesis that the increased demand for service activities favoured by the limited exhaustibility of knowledge and changing practices in the tradability of knowledge, that can now be exchanged and traded as a service, in

[32] See Acemoglu and Autor (2001) for an extensive literature review.

[33] This paper uses the terms cities and Metropolitan Statistical Areas (MSAs) interchangeably.

conjunction with the new knowledge-intensive direction of technological change, are the primary cause of the increase in wage inequality across US cities.

Advanced economies experienced deindustrialization with a sharp reduction in manufacturing. On the contrary, service-based sectors acquired a prominent role. The transition to the service economy has been fostered by the dissemination of new Information and Communication Technologies (ICTs), which have reshaped the generation and exploitation of knowledge as an economic good. Several studies documented the knowledge-intensive direction of technological change in the US labour market owing to an increased demand for workers performing non-routine and cognitive tasks (Autor and Dorn, 2013; Autor, Levy and Murnane, 2003; Goos and Manning, 2007). As a result, advanced economies have growingly remunerated knowledge embodied in human skills.

The notion of knowledge-intensive service economy refers to a broad range of service industries whose demand has increased steadily over the last decades. Among them are the finance sector, KIBS (Knowledge-Intensive Business Services), professional occupations, arts and entertainment, and business services. These sectors are characterized by a large share of workers engaged in non-routine cognitive tasks who experienced substantial growth in wage compensation. In these sectors, knowledge embodied in human skills may be diffused and traded as a service. For example, several studies show that the salaries paid to executives, financial professionals and professional-related workers are an important feature of growing wage inequality, explaining the rise in top income inequality (Bivens and Mishel, 2013; Kaplan and Rauh, 2010; Lindley and Machin, 2017). On the contrary, low-skilled labour is exposed to the decline of the manufacturing sector and the influx of low-skilled migration from labour-abundant countries (Autor et al., 2020; Gould, 2019; Ravaillon, 2018).

While the contribution of service workers to the increase in top income inequality has been documented, a formal test of such a relationship at the city level in the US has not been performed. Moreover, the other main novelty of the paper is to show that a large part of the increase in wage inequality is due to the rising wage dispersion within non-routine cognitive occupations. I argue that the rise in services may be equally responsible for such an increase. Indeed, the increased demand for service activities may have created fiercer competition for high-paying job positions and widened wage differentials among similarly highly qualified individuals.

The evidence of this paper shows that wage inequality has been driven mainly by wage inequality within non-routine cognitive occupations. Theoretical models on the jobs' task content predict that occupations characterized by non-routine, abstract, creative and cognitive tasks are more sensitive to differences in workers' skill levels compared to routine and manual-intensive occupations (Jung and Mercenier, 2014; Van der Velde, 2020). Routine and manual workers are more substitutable among each other. Therefore, substituting a routine worker with another routine one will likely have a negligible impact on productivity. On the contrary, productivity is more sensitive to substitution among non-routine workers, implying greater competition for such positions and a larger wage dispersion among them. Since knowledge-intensive services dispense a wage premium to workers in non-routine cognitive occupations, this explains the observed increase in wage inequality within this category.

As the main explanation of these dynamics, I rely on the superstar theory elaborated by Rosen (1981), who demonstrated that slight differences in talent among imperfect substitutable workers are associated with large remuneration differences, especially in those markets characterized by great scalability of talent. In other words, the bigger the market size, the larger the concentration of incomes accrued to the top workers in that market. Furthermore, the limited exhaustibility of knowledge, meaning that knowledge is not subject to the wear and tear experienced by other economic goods, implies that the most talented individuals can leverage their knowledge on a larger scale in the service industry, creating larger wage dispersion between the upper and the lower tails of the wage distribution (Jones and Kim, 2018; Kaplan and Rauh, 2010, 2013).

I find that the increased demand for these knowledge-intensive services has a positive and large effect on the overall city-level wage inequality. The results are robust to considering several confounding factors at the city level. The specification in levels estimates that the increase in knowledge-intensive services explains 28% of the increase in wage inequality between 1980 and 2010. Moreover, I test the effect of services on wage inequality within non-routine cognitive and routine manual occupations, respectively. Consistently with the model proposed, the effect of services is positive and statistically significant only for non-routine cognitive occupations.

The empirical analysis uses 1980, 1990, and 2000 census data and the 2010 American Community Survey (ACS). The econometric strategy compares the decadal change in the overall 90-10 wage inequality and the 90-10 inequality within non-routine cognitive occupations with the decadal change in the employment rate of workers employed in knowledge-based service industries. I augment this specification with time-varying city controls, year fixed effects, and region fixed effects. Estimating the model in first differences alleviates concerns derived from the possible existence of a spurious correlation between the changes in inequality and services; indeed, both variables trended upwards over the last several decades. Moreover, the results are robust across different specifications and several robustness checks. To lessen further endogeneity concerns, I also estimated the model with a two-stage least squares (2SLS) estimator using a Bartik-style instrument widely used by the related literature. The results of the 2SLS estimation confirm the OLS findings.

This paper contributes to several studies in economic geography studying wage inequality in the US at the sub-national level (Farinha et al., 2019; Florida and Mellander, 2016; Lee and Rodriguez-Pose, 2013; Lindley and Machin, 2014; Perez-Silva and Partridge, 2020). Most of these studies focused on the effect of various technological change or educational upgrading measures on inequality, generally finding that innovation and the share of creative labour increase income disparities. This paper departs from these contributions by studying the transition toward services as its major determinant. Indeed, no studies analysed the effect of the transition to services on wage inequality within US cities. Moreover, the analysis also examines wage inequality within non-routine cognitive occupations and takes care of several potential econometric concerns neglected by the previous empirical literature.

The chapter is organized as follows. Section 4.2 presents the theoretical background. Section 4.3 presents the data and the empirical model used. Section 4.4 presents the results and discusses their implications, addressing several potential concerns of the empirical analysis. Finally, Section 4.5 summarizes the conclusions.

4.2. Theoretical framework

4.2.1. The transition to the knowledge and service economy

The New Growth Theory has long emphasized the increasing returns at the system level derived from the non-appropriability of knowledge as an economic good (Romer, 1986, 1990). Due to its non-appropriable character, firm knowledge spills over to third parties that automatically benefit from knowledge externalities (Hall, Mairesse and Mohnen, 2010). However, the micro-econometric evidence showed substantial heterogeneity among firms in accessing and benefiting from external knowledge to increase productivity levels (Antonelli and Colombelli, 2015). Indeed, knowledge is transferable and tradable only to a limited extent. The limited transferability of knowledge implies that knowledge transmission between economic agents may be hindered by the inability of the perceiver to understand the content of the piece of knowledge received. Using knowledge as an economic good is thus costly, requiring substantial effort from its user (Cohen and Levinthal, 1990).

The limited tradability and transferability of knowledge are related to the nature and characteristics of information and the problems of its tradability. For example, the customer of a piece of information has a high ex-ante risk of buying a lemon. However, the vendor cannot reveal the information content before the transaction. As a result, the customer may take advantage of the information ex-post and exit the transaction without any payment (Stiglitz and Weiss, 1981). In recent decades, the large absorption costs observed in the US economy suggest that knowledge spillovers are not ubiquitous and, far greater, not free (Bloom et al., 2020; Jones, 2009).

The rise in ICTs has reshaped the generation, appropriability and transfer of knowledge in modern advanced economies. Knowledge cannot just be used as input embodied in tangible goods, but it may be traded as a good and service. New digital technologies support the search and selection of existing knowledge and its repeated use to generate new technological knowledge and produce other economic goods.

The advanced economies are characterized by a new trend away from manufacturing towards a new economy in which knowledge is central and highly valuable in the service sector (Capello, Lenzi and Panzera, 2022; Meliciani and Savona, 2013). Recent evidence from the US economy showed a dramatic decrease in employment in the manufacturing sector (Gould, 2019). On the other hand, the share of the service sector in total value added has grown rapidly and steadily (Buera and Kaboski, 2012). The implementation of ICTs helped services to access global markets and diffuse service-based products ubiquitously. Specifically, the clustering of business services in densely urban areas has expanded the market size reachable by these industries (Doloreux and Shearmur, 2012).

The reforms in Intellectual Property Rights (IPRs) supported the creation and development of the commercialisation of knowledge as a service and licensee (Arora, Fosfuri and Gambardella, 2001). The new market for knowledge takes place outside the firm's boundary and involves workers in services devoted to facilitating such transactions and providing customer assistance (Hagiu and Yoffie, 2013). Moreover, advances in ICTs favour the exchange of knowledge as a service in digital platforms by enhancing user-producer interactions and allow matching the goods offered by vendors with the customers' specific needs. In the new digital markets, vendors can provide direct assistance to the customers or users, facilitating the tradability and transferability of knowledge. On one side, vendors can effectively transmit knowledge as a service while keeping control of their property; on the other, customers can better select and access knowledge and receive direct assistance to understand its content.

The new globalization of factor and product markets, the openness to international financial markets and the enhanced tradability of knowledge triggered a radical change in the exploitation and appropriation of knowledge. The distribution of knowledge profits along the value chain in the global economy is profoundly transformed. Knowledge-intensive sectors appropriate an increasing share of profits derived from generating and exploiting knowledge. On the contrary, manufacturing has been increasingly exposed to the competition of low-wage and labour-abundant countries, leading to the outsourcing of manual and routine activities to industrializing countries (Timmer et., 2020; Avenyo, Konte and Mohnen, 2019). Therefore, profits from knowledge rents shifted upstream in the global value chains, concentrated in knowledge-intensive sectors, and favoured workers engaged in non-routine cognitive occupations (Autor, Dorn and Hanson, 2015).

Less understood is that the shift from manufacturing to knowledge-intensive services may substantially affect income inequality (Florida and Mellander, 2016; Van Reenen, 2011). The transition from manufacturing to the service and knowledge economy has profoundly transformed the production process with important consequences for the income distribution dynamics (Kollmeyer, 2018). Advanced economies have long performed the knowledge generation process in large corporations where standard and manual labour benefited from high unit wages and strong unionization rates. However, in recent decades, the levels of unionization declined in conjunction with the share of workers, employed in manufacturing industries, that benefited most from this redistribution system (Damiani, Pompei and Ricci, 2020; Mueller, Ouimet and Simintzi, 2017).

Knowledge generation activities have long been integrated into big corporations that could appropriate and share the rents from knowledge generation with all the workers. However, recent decades showed a growing decentralization of the knowledge creation process, with large shares of it performed extra-muros by research-intensive units, mainly small and knowledge-intensive firms and universities (Colombelli, Krafft and Vivarelli, 2016; Cowan and Zinovyeva, 2013). Modern corporations are increasingly outsourcing part of their knowledge inputs to external entities that provide and sell knowledge as a service. These entities based their advantage on employing a large share of high-skilled workers engaged in non-routine and intellectual activities.

The rise in services, due to the increased levels of tradability of knowledge, complements and reinforces the specialization of advanced economies in the generation and exploitation of technological knowledge engendering economic rents growingly redistributed to creative and scientific labour. Indeed, the firms' rents are reallocated more to high-skilled and top-hierarchy workers than standard and low-skilled workers, contributing to widening within-firm wage inequalities, especially where unions' power is weaker (Barth et al., 2012; Cirillo, Sostero and Tamagni, 2017).

The share of creative and skilled labour has increased, favoured by changes in the generation, governance and exploitation of knowledge as an economic good. Advanced economies, especially the US, have experienced a knowledge-intensive direction of technological change with substantial consequences for labour market inequality (Autor and Dorn, 2013; Autor, Levy and Murnane, 2003). Specifically, the knowledge-intensive direction has largely favoured workers engaged in non-routine and cognitive tasks and severely damaged workers performing manual and routine activities (Goos, Manning and Salomons, 2014; Vom Lehn, 2020).

The analysis of income inequality using tax return data showed that the dramatic increase in income inequality was driven by the increase in the share of income accrued by the top tail of the income distribution (Bivens and Mishel, 2013; Piketty and Saez, 2003). Specifically, the rise in inequality is associated with rent-shifting mechanisms prevalent among financial professionals, top executives, entertainment stars, lawyers and professional-related occupations (Essletzbichler, 2015; Kaplan and Rauh, 2013).

The rising financial sector has played an essential role in the explosion in top income inequality. The increase in pay among financial professionals has regarded hedge and private equity fund managers and managers of venture capital funds (Kaplan and Rauh, 2013). Venture capitalism has represented an important institutional innovation for the financing of innovation. Venture capitalists support the formation of new start-ups and the development of local entrepreneurship and raise equity funds to finance new investments and participate in the firm's successes. In addition, the growing practice of the takeover made by large firms of knowledge-intensive start-ups, contributed to capitalizing new knowledge as an intangible asset whose rewards are appropriated by venture capitalists.

Common explanations proposed to explain the increase in top income inequality included social norms, tax policies affecting the distribution of rents between employers and employees and increasing attention toward executive power (Piketty, 2014; Piketty and Saez, 2006; Piketty, Saez and Stantcheva, 2014). On the contrary, another view explained this trend with superstar mechanisms that favoured top talented workers in knowledge-scalable industries (Gabaix and Landier, 2008; Kaplan and Rauh, 2010, 2013). According to this view, the combination of scale-biased technical change and increasing returns to technology are conducive to rising concentration and accumulation of rents in the hands of a few individuals (Autor et al., 2020; Cortes and Tschopp, 2020).

The economics of superstar literature may provide valuable insights into understanding this mechanism. This theory originated with Rosen’s work (Rosen, 1981), which proved that slight differences in talent among imperfect substitutable workers engender large differences in remuneration among them. In other words, the function linking rewards to the quality or talent of the individual is convex. According to this analysis, information technologies allow some individuals to spread their service or talent to a broader portion of the market, widening wage differentials. The leading example is the invention of the compact disc. While before this invention, the top singers could reach an audience that was limited to the concert in which they performed, with the diffusion of the compact disc, the top singers could reach a much larger audience. As a result, the income differences between the top and the lower tails increase because the top singers can leverage their talent in a larger market. In other words, the market share accrued by the top talents increases along with their income (Krueger, 2005).

The new digital and intangible economy and the globalization of product markets have exacerbated this phenomenon, creating superstar effects observed across regions and firms and among workers within the same firm (Guellec and Paunov, 2017; Mueller, Ouimet and Simintzi, 2017). For example, Garicano and Rossi-Hansberg (2006) showed that digital technologies widen the span of control of supervisors over the employees and therefore favoured, more than proportionately, workers in the highest level of the hierarchy.

Therefore, the increase in inequality is strongly connected with the rising demand for workers employed in these scalable sectors, such as finance, professional and business services and entertainment. Here, the top workers usually receive wage compensations well above their marginal productivity and much larger than the rest of the individuals (Célérier and Vallée, 2019; Koenig, 2021; Krueger, 2005; Lindley and MacIntosh, 2017; Marin and Vona, 2022). The same mechanism applies to individuals employed in the Knowledge-Intensive Business Service (KIBS) sectors, such as legal, accounting, computer and scientific research services (Antonelli and Tubiana, 2020; Breau, Kogler and Bolton, 2014; Powell and Snellman, 2004).

Moreover, this mechanism can also explain why wage inequality increases among non-routine cognitive but not within routine occupations. Non-routine workers are imperfect substitutes because creativity in non-routine and intellectual jobs is much higher than in routine workers. Routine jobs leave little autonomy to the worker and do not stimulate her creativity (Frey and Osborne, 2017). This implies that manual workers are more substitutable among them than non-routine workers. Replacing a routine worker with another one is likely to exert a small impact on productivity.

On the contrary, creative workers are not perfect substitutes for each other, implying greater competition for these jobs and larger wage dispersion among non-routine workers. Indeed, Van der Velde (2020) has shown that the wage distribution among creative and non-routine occupations is sparser than among routine workers. Moreover, given the growing importance attributed to creative, social and interactive occupations and increased practices of knowledge flexibility and autonomy at the workplace, it is now clear that competition for such qualities has sped up and overcompensated for the value of knowledge activities (Deming, 2017, 2021).

As a result, productivity in knowledge-intensive sectors is more sensitive to differences among workers' skills (Jung and Mercenier, 2014). Since small differences among individuals may generate wide differences in productivity, the competition for such positions is greater. While recent literature has shown that the low-skill service occupations have benefited from a growing demand for home-production activities made by high-wage workers (Leonardi, 2015; Liu and Yang, 2021; Mazzolari and Ragusa, 2013), the rising demand for services may also have created more intense competition for non-routine cognitive workers, widening wage disparities between the top talented individuals in services and the rest of the economy.

4.2.2. Increasing returns to talent in the knowledge and service economy – A heuristic model

This section uses the tools provided by the economics of knowledge to articulate more formally how the transition to services may have exacerbated wage inequality. Specifically, the section analytically outlines how knowledge's non-exhaustible and scalable character is conducive to increasing individual returns to knowledge in knowledge-intensive services.

The cumulative and long-standing character of knowledge, which is not subject to the obsolescence experienced by other economic goods, implies that economic agents can reuse knowledge repeatedly to produce other goods and new technological knowledge (Mohnen and Hall, 2013). Within this context, knowledge is subject to limited exhaustibility and substantial extensibility. The generation of knowledge is thus a recombinant process in which past knowledge is an essential ingredient alongside current research activities (Weitzman, 1996, 1998). The extensible character of knowledge implies that the original blueprint can be used to produce a larger volume of output with decreasing marginal costs. Unlike other economic goods, knowledge is scalable to a large extent, and its reproduction costs do not increase with the quantity of output produced (Antonelli, Krafft and Quatraro, 2010; Krafft, Quatraro and Saviotti, 2014). Ultimately, knowledge extensibility allows the spread and smear of the amount of knowledge over the output produced. While the consequences of the limited exhaustibility and appropriability of knowledge have greatly affected the firm's performance, it is recently that mathematical economics has started to incorporate these notions into the individual income generation process.

It is well known that a Pareto distribution well approximates top income inequality in recent decades. Pareto distributions arise with the assumption that individual income grows exponentially with talent or experience (Jones, 2015; Jones and Kim, 2018). The individual returns' function strongly emphasizes the powerful effects of the limited exhaustibility and limited appropriability of knowledge at the individual level. From the human capital model developed by Becker (1964), it is clear that individuals postpone entry into the labour market and invest in accumulating knowledge to receive a higher wage. Hence, wage differentials reflect heterogeneous educational attainments among workers (Lemieux, 2006a).

The economics of science has highlighted the convexity in returns to individual knowledge. For example, the distribution of citations to scientific articles usually exhibits a non-normal behaviour and is highly skewed towards the most talented professors (Silverberg and Verspagen, 2007). At the same time, economic history has long found evidence of disproportional returns to a few inventors (Mokyr, 2016; Squicciarini and Voigtländer, 2015).

This theory predicts that the same dynamics of heterogeneous returns among individuals characterise the distribution within each quantile of the skill distribution. This implies that the motion of income inequality is fractal. For instance, income inequality among the 10% of the richest individuals is the same for the top 1%, the 0.1%, etc.

I sketch a simple model building on Jones (2015) and Jones and Kim (2018) to formalize more in detail the role of the limited exhaustibility of knowledge at the individual level. First, I assume that individuals are exponentially distributed across a certain variable k, which can proxy for the stock of knowledge or accumulated experience. Hence:

$$Pr[Knowledge > k] = e^{-\delta k} \quad (1)$$

where δ is the death rate among the individuals. This term represents the individual's probability of getting out of the list and is usually modelled as a creative destruction process. The limited exhaustibility of knowledge implies that individual income y may grow exponentially at some rate x with the form:

$$y(k) = e^{xk} \quad (2)$$

Therefore, by exploiting the property that if the log of income is exponential, then the level of income is characterized by a Pareto distribution,[34] we have:

$$Pr[Income > y] = y^{-\frac{\delta}{x}} \tag{3}$$

In this setting, the shape parameter of the Pareto distribution, which is linked to the inequality level, is equal to the inverse of the exponent above, $\frac{x}{\delta}$. Therefore, income inequality rises either because income possesses a higher return x to knowledge, or because there are some barriers to entry hampering creative destruction, resulting in a decrease of the death rate δ. The new evidence of the US suggest that the shape parameter of the Pareto distribution has increased over the recent decades (Saez and Zucman, 2020).

Therefore, the rising demand for knowledge-intensive services (and for workers performing such activities) may have substantially reshaped income distribution dynamics. The mechanism is that the returns to knowledge at the individual level are magnified in knowledge-based services, characterized by superstar and scalability mechanisms. Within these sectors, a few individuals benefit from the scalability of knowledge (i.e., talent) and the difference between the top and lower tails of the wage distribution enlarges. Analytically, this corresponds to an increase in parameter x in Equation (3), which is related to the shape of the Pareto distribution and, hence, to wage income inequality among individuals. Moreover, the model explains why one should observe increasing wage dispersion among non-routine workers, whose talent and contribution to productivity is more heterogeneously distributed within the population compared to routine workers (Cortes, 2016; Jung and Mercenier, 2014). For these reasons, one should observe greater levels of wage inequality, both overall and within non-routine cognitive occupations, in areas with larger employment rates in knowledge-based services.

4.3. Data and econometric model

4.3.1. Descriptive evidence

The data set combines US decennial census micro-data for 1980, 1990 and 2000 and the American Community Survey (ACS) for 2009, 2010 and 2011. The waves 2009, 2010 and 2011 are pooled together to form the 2010 period (Altonji,

[34] The reader may refer to Jones and Kim (2018) for the mathematical proof.

Kahn and Speer, 2014; Winters, 2014). All data are extracted from IPUMS (Ruggles et al., 2021).[35] The sample considers white, native-born men individuals between 25 and 55 years.[36] To compute wage inequality, the analysis is restricted to individuals who worked at least 30 hours per week and 40 weeks a year. Self-employed, unpaid family workers, residents in group quarters, such as prison and mental health institutions, and individuals belonging to the armed forces are dropped.

The dataset allows computing log hourly wages, defined as annual total wage income divided by the number of usual worked hours.[37] The empirical analysis uses the ratio between the 90th and the 10th percentiles of the log wage distribution as the main measure of wage inequality. Therefore, I compute both the overall 90-10 wage gap and the residual 90-10 wage gap. The inequality within the residual distribution studies the unexplained part of wage inequality. Therefore, this variable gives an overall picture of the spreading of wages after controlling for individual observable characteristics (Gould, 2019).

Residual wage inequality is obtained from the residuals of each annual regression in which the log of hourly wage is the dependent variable and workers' observable characteristics are the explanatory variables. Among the controls, I include six age dummies (25-29, 30-34, 35-39, 40-44, 45-49, 50-55), nine dummies for education and their interaction with the age dummies, 30 occupation dummies and 13 industry dummies. Occupation, industry and educational categories are made comparable by IPUMS and correspond, respectively, to variables *occ1990*, *ind1990* and *educ*. Then, the residual 90-10 is calculated as the ratio between the 90th and 10th percentiles of the log wage residuals distribution.

I compute wage inequality measures for non-routine cognitive and routine workers separately. To identifying non-routine cognitive and routine-manual workers, I use the classification proposed by Acemoglu and Autor (2011) and applied, among others, by Cortes (2016) and Shim and Yang (2018), based on the *occ* variable in IPUMS. Specifically, the classification distinguishes between non-routine cognitive and routine occupations as follows:

- Non-routine cognitive occupations: managers, professionals and technicians.

[35] Specifically, the samples extracted are the 1980 5% State, 1990 5% State, 2000 5% and the 1% sample for 2009, 2010 and 2011.

[36] Therefore, I abstract from gender, race and ethnicity issues.

[37] Specifically, the weekly wage is computed as the annual wage (variable *incwage*) divided by the annual weeks worked. The 2010 sample contains only interval data on weeks worked per year (40-47, 48-49 and 50-52). I use the 1980-2000 sample distribution to take each interval's median. Then, the hourly wage is computed by the ratio between the weekly wage and the usual hours worked per week. Wages are then deflated using the Consumer Price Index from the Bureau of Labour Statistics, with 2008 as the base year. Top coded earnings have been multiplied by 1.5, following Katz and Murphy (1992). Earnings are top coded at $75,000 in 1980, $140,000 in 1990, $175,000 in 2000 and $200,000 in 2010.

- Routine occupations: sales; office and administration; production, crafts, and repair; and operators, fabricators, and labourers.

Figure 4.1 shows the overall 90-10 wage inequality and the residual 90-10 wage inequality over time. The dashed line in Figure 4.1 reproduces the overall 90-10 wage differential. The overall 90-10 increased from 1.12 in 1980 to 1.43 in 2010. The solid line represents the residual 90-10. Obviously, the residual 90-10 is below the overall 90-10 but follows the same trend, increasing from 0.95 in 1980 to 1.16 in 2010, an increase of 0.21 log points.

Figure 4.1. Change in overall and residual wage inequality

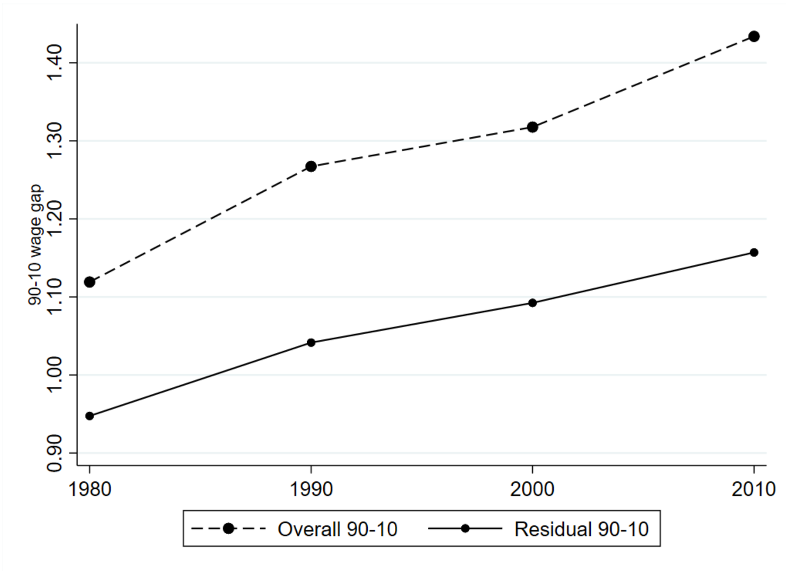
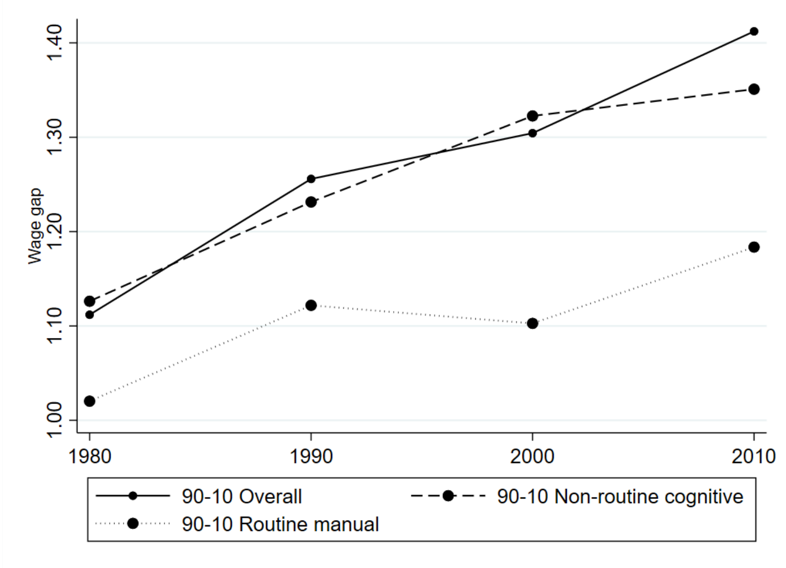


Figure C.1 in the Appendix C shows that the increase in wage inequality is concentrated at the top of the distribution. Indeed, the 90-50 wage gap was more than 40% higher in 2010 than in 1980, whereas the 50-10 gap rose but less intensively.

To focus on differences between non-routine and routine cognitive occupations, figure 4.2 shows the evolution of wage inequality overall and, then, for non-routine cognitive and routine manual occupations, separately. The graph shows that the pattern of wage inequality within non-routine cognitive occupations mimics closely the pattern of overall wage inequality. On the contrary, wage dispersion within routine occupations has increased less. Moreover, wage inequality within routine occupations is significantly lower than inequality within non-routine cognitive occupations along the period.

Figure 4.2. Change in overall, non-routine cognitive and routine manual wage inequality



The hypothesis is that the increased demand for services (and, so, for workers performing them) is responsible for a large part of the increase in wage inequality, especially among non-routine cognitive occupations. I include among service-based sectors the following industries: communications, finance, business services, and professional-related services. Table 4.1 shows in detail their composition. I refer to these sectors also as knowledge-intensive service sectors. Indeed, figure C.2 in the Appendix shows that these subsectors had the largest shares of non-routine cognitive workers at the beginning of the period. Therefore, the production activity in the sectors is strongly knowledge-intensive. The share of non-routine cognitive occupations in 1980 was 0.36 for Information and Communication, 0.46 in finance, 0.32 in business services, 0.5 in entertainment and recreation and 0.78 in professional related services.

Table 4.1. Knowledge-intensive service sector composition, according to the variable *ind1990* in IPUMS

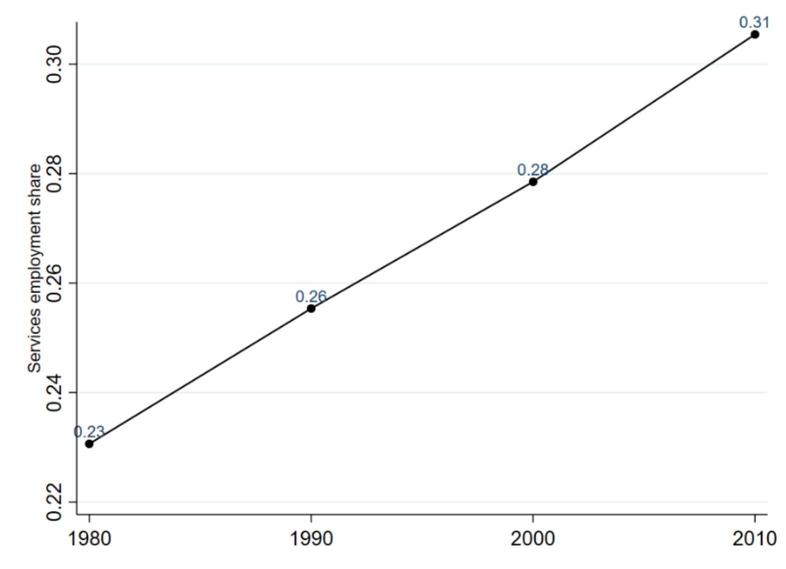
Ind1990 code	Definition
440-442: Communications	Radio and television broadcasting and cable; Telephone communications; Telegraph and miscellaneous communications services.
700-712 Finance, insurance and real estate	Banking, Savings institutions, including credit unions; Credit agencies; Security, commodity brokerage, and investment companies; Insurance; Real estate, including real estate-insurance offices

721-741 Business services	Advertising, Services to dwellings and other buildings; Personnel supply services; Computer and data processing services; Detective and protective services; Business services
800-810 Entertainment	Entertainment and recreation services
812-893 Professional and related services	Offices and clinics of physicians; Offices and clinics of dentists; Offices and clinics of chiropractors; Offices and clinics of optometrists; Offices and clinics of health practitioners; Hospitals; Health services; Legal Services, Elementary and secondary schools; Colleges and universities; Vocational schools; Libraries; Educational services; Job training and vocational rehabilitation services; Museums, art galleries, and zoos; Labor unions; Religious organizations; Membership organizations; Engineering, architectural, and surveying services; Accounting, auditing, and bookkeeping services; Research, development, and testing services; Management and public relations services.

Moreover, as Figure C.3 in the Appendix shows, these sectors also experience the fastest growth in real wages. For example, real wages in finance increased by 74% between 1980 and 2010, 41% in professional and related services, 30% in business services and 20% in information and communication. On the contrary, the growth of real wages in the other sectors was slower.

To provide evidence of the growth of the employment rate in these sectors, figure 4.3 shows the change in the percentage of US workers employed full-time in the knowledge-intensive service sector. The pattern shows the same steady increase as wage inequality, suggesting that the two trends are correlated. Specifically, the services employment rate increased from 0.23 in 1980 to 0.31 in 2010.

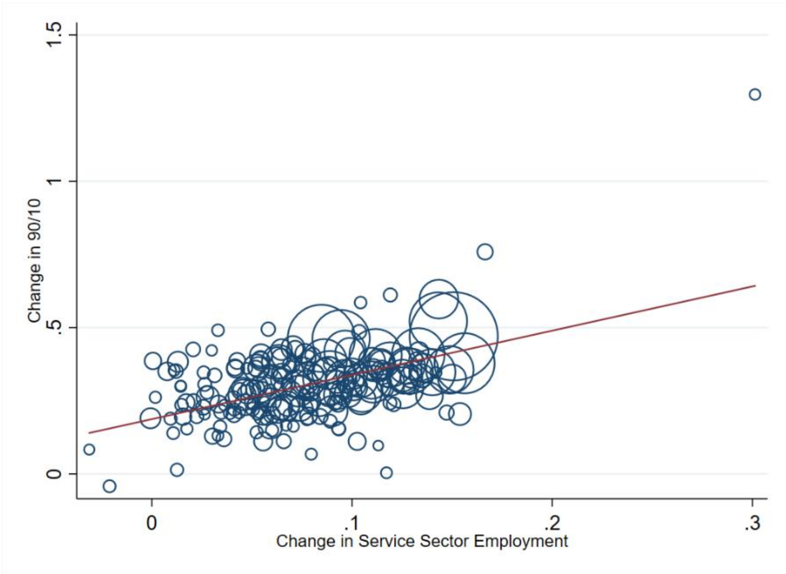
Figure 4.3. Change in the knowledge-intensive service sector employment rate



The rest of the section provides initial evidence of the link between graduate wage inequality and services rise by exploiting US cross-city variation. Specifically, the main empirical analysis uses panel data for 201 consistently defined MSAs observed in 1980, 1990, 2000 and 2010. Therefore, following existing studies (Consoli et al., 2021; Gould, 2019; Liu and Yang, 2021; Mazzolari and Ragusa, 2013), I consider an MSA as a proxy for local labour markets. A metropolitan area defines a city's large urban core and the surrounding population with a high degree of integration with the core. For this analysis, I follow Mazzolari and Ragusa (2013) and Gould (2019) by selecting only those cities identified consistently throughout the sample period.

Finally, figure 4.4 plots the 90-10 wage gap change against the knowledge-intensive services employment rate change between 1980 and 2010. The graph shows a considerably positive effect of the change in the service sector on the change in wage inequality. Moreover, the most populated cities mainly drive the change, as the largest circles are located very close to the fitted line.

Figure 4.4. Change of the 90/10 wage gap against the change in the knowledge-based services employment rate between 1980 and 2010



Notes: Cities are weighted by population size in 1980.

4.3.2. Econometric models

The empirical strategy exploits variation across cities and over time by estimating the following first-difference model of the relationship between decadal changes in inequality and services:

$$\Delta Ineq_{it} = \beta_0 + \beta_1 \Delta KnowlServ_{it} + \beta_2 \Delta \boldsymbol{X'}_{it} + \delta_t + e_{it} \tag{4}$$

where $\Delta Ineq_{it}$is the change of the 90-10 wage inequality in city i between the three decades 1980-1990, 1990-200 and 2000-2010; $\Delta KnowlServ_{it}$ denotes the change, in each decade, of the share of graduate full-time and full-year workers employed in knowledge-intensive service sectors in city i, $\Delta \boldsymbol{X'}$ is a vector of time-varying city characteristics and δ_t are time fixed effects. The error term e_{it} captures unobserved shocks at the city level. Equation (1) is estimated by Ordinary Least Squares (OLS) with standard errors clustered at the city level to adjust for heteroskedasticity and autocorrelation within cities. Each regression is weighted by the city population in the initial period 1980 to correct for different sampling sizes across the US subpopulations (Gould, 2019, 2021).[38] The estimation is conducted on 201 consistently defined

[38] Table C.7 in Appendix C shows that the estimates for services are unaffected if the model is estimated without weighting observations (Solon, Haider and Wooldridge, 2015).

Metropolitan Statistical Areas, for a total of 603 observations. Descriptive statistics and pairwise correlations among variables are shown in Tables C.1 and C.2 in the Appendix, respectively.

The empirical strategy tests the differential decadal change in inequality against the decadal change of employment in service sectors. A first-difference model alleviates concerns arising from a possible spurious correlation between the change in knowledge-intensive services and inequality. Indeed, both inequality and knowledge-intensive services trended upwards in the period between 1980 and 2010. By taking first-differences, city fixed effects are netted out. To address other possible confounding factors, I show that the results are robust by including control variables at the city level measured as decadal changes or in levels at the beginning of the period. The vector $\boldsymbol{X'}$ includes controls for age composition, such as the percentages of workers between 25-34 and 35-44 years (individuals between 45-55 years is the omitted category), the unemployment rate to deal with city-specific business cycle effects and the share of college workers to control for educational composition. Furthermore, in a more demanding specification, I also include region fixed-effects that, in this setting, correspond to region-specific linear time trends that may affect the evolution of wage inequality.[39]

As a further validation of the relationship between inequality and services, I also estimate Equation (4) in levels. In this case, I test the relationship between the level of wage inequality against the employment rate in knowledge-intensive services. In this case, I can control for city-specific linear time trends capturing any other potential increasing variable that is correlated both with inequality and services (such as technology, automation, trade, etc.). As shown in section 4.4, the robustness of the main results to using this specification reinforces the argument that a spurious relationship between knowledge-intensive services and inequality is unlikely.

The second model tests the effect of knowledge-intensive services on inequality within non-routine cognitive occupations. For this purpose, analogously to Equation (4), I estimate the following model:

$$\Delta NonRoutineCognIneq_{it} = \lambda_0 + \lambda_1 \Delta KnowlServ_{it} + \lambda_2 \Delta \boldsymbol{X'}_{it} + \delta_t + \epsilon_{it} \tag{5}$$

where $\Delta NonRoutineCognIneq_{it}$ is the change of the 90-10 wage inequality among workers in non-routine cognitive occupations in city i between the three decades 1980-1990, 1990-2000 and 2000-2010; $\Delta KnowlServ_{it}$ denotes the change

[39] Specifically, the regions correspond to the following nine divisions: New England, Middle Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain, and Pacific Division.

in each decade of the share of full-time and full-year workers employed in service sectors in city i. The $\boldsymbol{X'}_{it}$ contains the same controls as in Equation (1). Standard errors are clustered at the city level and each regression is weighted by the city population in 1980.

To address further endogeneity problems, I also implement an Instrumental Variable (IV) analysis based on the use of a Bartik-style instrument (Bartik, 1991; Faggio and Overman, 2014; Van Dijk, 2017). Following Lee and Clarke (2019), the instrument is computed using the predicted employment growth in knowledge-intensive services based on the initial share of services over the total economy in 1980 and the national growth rates (excluding the city in question) in the following period. Precisely, the instrument is computed as follows:

$$\frac{\widehat{KnowlServ_{it}}}{Empl_{it}} = \frac{KnowlServ_{i1980}}{Empl_{i1980}} \times \frac{KnowlServ_{Nt} - KnowlServ_{Nt-1}}{KnowlServ_{Nt-1}} \quad (6)$$

where $\frac{KnowlServ_{i1980}}{Empl_{i1980}}$ is the employment rate in knowledge-intensive services in city i in 1980 and the $KnowlServ_{Nt}$ is the national growth in employed workers in the knowledge-intensive services nationally at time t, net of workers in city i. The idea behind the instrument is that a national change (net of workers in city i) in service industries will influence the local supply of services only through the initial share within each city. Nonetheless, the national change in the employment rate of services is considered exogenous to other unobserved local factors influencing wage inequality (Faggio and Overman, 2014; Lee and Clarke, 2019).

4.4. Results

4.4.1. Main results

Table 4.2 shows the results from estimating equation (4) by OLS. Columns (1) and (2) represent the bivariate relationship between wage inequality and services without and with year fixed effects, respectively, and without any controls at all. The coefficient for the decadal change in the percentage of workers employed in knowledge-intensive services is positive and statistically significant in both specifications (p<0.01). Column (3) adds controls for the decadal changes in age composition, share of college workers and unemployed workers. The coefficient of interest is unaffected by the inclusion of these city-level contemporaneous shifts. Column (4) includes additional potential confounding factors. First, I include the decadal change in the average log wage. Indeed, one may argue that wage inequality may have increased more in cities where the mean wage has grown more, reflecting a correlation between average income and inequality. Second, I add the change in manufacturing employment. Perhaps, it may be the decline of the manufacturing sector that has increased wage inequality. As a matter of fact, services and manufacturing have displayed opposite trends in the past decades. Against these arguments, column (4) shows that the change in services is robust to including these controls. Column (5) estimates a more demanding specification in which region fixed effects are included. In this setting, region fixed effects control for regions-specific linear time trends that may affect the evolution of wage inequality. The coefficient of interest slightly reduces but remains statistically significant (p<0.01). In column (6), I control for the initial values of the control variables instead of their decadal changes. I also include the initial level of residual inequality (in 1980) to control for the mean reversion effects of the dependent variable (Mazzolari and Ragusa, 2013; Michaels, Natraj and Van Reenen, 2014). I find that the coefficient of interest is robust to this specification. Finally, column (7) shows the results of the IV estimation, in which services are instrumented with the Bartik-style instrument. The coefficient of services increases in magnitude and remains statistically significant at the conventional levels (p<0.01). Across specifications (1)-(6), I find that a one percentage point increase in the percentage of workers employed in knowledge-intensive service sectors is associated with an increase of the 90-10 wage inequality in the range of 0.913 to 1.250 percentage points.

Table 4.2. Cross-city regressions of decadal change in wage inequality and decadal change in knowledge-intensive services

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	OLS	OLS	OLS	OLS	OLS	IV
ΔKnowlServ	1.139***	1.134***	1.250***	1.043***	0.913***	1.045***	2.468***
	(0.206)	(0.186)	(0.229)	(0.231)	(0.252)	(0.189)	(0.470)
ΔAge 25-34			-0.258	-0.197	-0.215		-0.253*
			(0.177)	(0.172)	(0.158)		(0.151)
ΔAge 35-44			0.258	0.173	0.147		0.136
			(0.229)	(0.193)	(0.185)		(0.228)
ΔCollege			-0.252	0.174	0.235		-0.942***
			(0.165)	(0.160)	(0.171)		(0.313)
ΔUnempl rate			0.155	0.102	-0.083		-0.152
			(0.283)	(0.291)	(0.255)		(0.255)
ΔAverage log wage				-0.276***	-0.380***		
				(0.068)	(0.080)		
ΔManufacturing				-0.093	-0.115		
				(0.139)	(0.151)		
Age 25-34$_{1980}$						-0.120	
						(0.105)	
Age 35-44$_{1980}$						0.137	
						(0.155)	
College$_{1980}$						0.156***	
						(0.051)	
Unempl rate$_{1980}$						0.356*	
						(0.188)	

$Inequality_{1980}$						-0.082***	
						(0.025)	
10-year fixed effects		Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects					Yes	Yes	Yes
Observations	603	603	603	603	603	603	603
Number of cities	201	201	201	201	201	201	201
F-stat							140.89

Notes: The analysis is performed on three periods (1980-1990, 1990-2000 and 2000-2010) and 201 MSAs. The dependent variable is the decadal change in the 90-10 wage gap. The estimation model is indicated in the column head. Standard errors clustered at the city level are in parentheses. Regressions are weighted by city population in 1980.
*** *p<0.01*, ** *p<0.05*, * *p<0.1.*

Table C.3 in Appendix C shows the results from estimating Equation (4) in levels. Therefore, it estimates wage inequality in the years 1980-1990-2000 and 2010 against the employment rate in services in the same years. Column (1) represents a baseline specification without any controls at all. Column (2) augments the specification with year and city fixed effects. Column (3) adds other time-varying control variables (i.e., age composition, share of college workers and unemployment rate). Column (4) adds the manufacturing share and the average log wage. Finally, Column (5) shows a more demanding specification where city-specific linear time trends are included. Therefore, the analysis controls for any other possible confounding trend specific to a city correlated with both knowledge-intensive services and inequality. The coefficient for knowledge-intensive services reduces but remains statistically significant at 95%. Furthermore, the coefficient for knowledge-intensive services is statistically significant across all the specifications and sizable in magnitude. Its coefficient in the specification in Column 3 is 1.028. Since the service sector employment share has increased by 0.08 percentage points over the period 1980-2010, its predicted impact on wage inequality within the college group is of 0.08 log points. This increase represents 26% of the increase in wage inequality shown in Figure 1. Tables C.4 and C.5 also show that the results are robust by using the standard deviation of wages and the coefficient of variation as alternative proxies for the dispersion of wages within the city. Indeed, the coefficient of services remains positive and statistically significant at the highest level of confidence across all the specifications.

The Appendix also presents the results for other models estimated with the first-difference specification with standard errors clustered at the state rather than the city level (Table C.6), no weighting (Table C.7), using weekly wages rather than hourly wages (Table C.8) and residual rather than overall wage inequality (Table C.9). The latter check confirms that the rise of knowledge-intensive services is related to the unexplained component of wage inequality, which nets out individual observable characteristics. Finally, Table C.10 studies the relationship between services and inequality for different time periods. Specifically, Column (1) restricts the analysis to the period 1990-2010, considering the change between 1990 and 2000 and 2000 and 2010. Column (2) considers the period 1980-2000, thus studying the changes between 1980 and 1990 and 1990 and 2000. Column (3) shows the results from estimating the decadal change in inequality against the decadal change in services measured in the previous decade. Finally, Column (4) estimates a long difference model where the change in inequality between 1980 and 2010 is regressed against the change in services between 1980 and 2010. All models include changes in city control variables and region fixed effects. Again, the coefficient of services is positive and statistically significant at the highest level of confidence across all the specifications.

Furthermore, one additional caveat arises from the definition of the unit of analysis. As a matter of fact, MSAs are not representative of the whole US population because they exclude rural areas. Moreover, they are not consistently delineated over time; hence, some units are lost during the observation period. For these reasons, I also implement the analysis at the state level. I estimated the same model as in Equation (4), including a control for the decadal change in the number of patent applications per million inhabitants (Aghion et al., 2019); the population density to control for agglomeration economies (Duranton and Puga, 2004); the capital tax gain and the house price index, to account for state-specific price and taxation effects that may drive the sorting of workers into selected areas (Moretti, 2013; Neffke et al., 2018).[40] Results are shown in Table 4.3.

Columns (1) and (2), Table 4.3, report the estimates of the relationship between the decadal change in wage inequality and the decadal change in knowledge-intensive services without and with year fixed-effects, respectively. The estimation coefficient is positive and statistically significant ($p<0.01$), confirming the results obtained at the city level. Column (3) adds to the estimation the share of workers between 25 and 34 years, the share of workers between 35 and 44 years, college workers and the unemployment rate; all controls are measured as decadal changes. In Column (4), we measure control variables based on their initial value (1980) and introduce the dependent variable's initial value. Column (5) introduces additional regressors, i.e., the decadal changes in density, house price index, capital tax gain, share of manufacturing and patent applications per inhabitant. From Column (4), I also include Census 9 regions dummies to control for region-specific effects. The estimation coefficient for the change in knowledge-intensive services remains positive and statistically significant across all specifications. Overall, the overall results at the state level essentially confirm and support the findings of the city analysis. Moreover, columns (6) and (7) use as dependent variables the

[40] The number of patent applications is accessed through *PatentsView*, which collects granted patent applied to the USPTO. Patent applications are then allocated to US states according to the inventor's address and are expressed as non-integer numbers according to the sum of each inventor State proportion in a given patent. The population density and the maximum tax gain on capital rents are from Aghion et al. (2019). The house price index is retrieved from Bogin et al. (2019).

decadal change in the share of income going to the top 1% and the top 0.5%, using data from Frank (2009). Therefore, it is reassuring for the analysis that the change in services is positively related to top income inequality. Consistently with the superstar economics literature, the greater scalability in knowledge-intensive services is likely to lead individuals working in these sectors to reach the upper tail of the income distribution.

Table 4.3. Cross-state regressions of decadal change in inequality and decadal change in knowledge-intensive services

	(1) 90-10 WageGap	(2) 90-10 WageGap	(3) 90-10 WageGap	(4) 90-10 WageGap	(5) 90-10 WageGap	(6) Top1%	(7) Top0.5%
ΔKnowlServ	0.839*	1.299***	2.549***	1.417***	1.691***	0.518*	0.523**
	(0.436)	(0.420)	(0.569)	(0.389)	(0.380)	(0.296)	(0.259)
ΔAge 25-34			-0.678***		-0.273	-0.366*	-0.355**
			(0.223)		(0.198)	(0.191)	(0.167)
ΔAge 35-44			0.211		0.309	-0.272	-0.253
			(0.303)		(0.237)	(0.186)	(0.174)
ΔCollege			-1.602***		-1.059***	0.261	0.207
			(0.399)		(0.294)	(0.317)	(0.272)
ΔUnempl rate			-0.007***		-0.012***	-0.007**	-0.007***
			(0.003)		(0.003)	(0.003)	(0.002)
Age 25-34$_{1980}$				0.150			
				(0.189)			
Age 35-44$_{1980}$				-0.129			
				(0.358)			
College$_{1980}$				0.192**			
				(0.083)			
Unempl rate$_{1980}$				0.005***			
				(0.002)			
Inequality$_{1980}$				-0.121***			
				(0.043)			
ΔPopDensity					0.000	0.000*	0.000**
					(0.000)	(0.000)	(0.000)
ΔHPI					-0.001***	-0.000**	-0.000**
					(0.000)	(0.000)	(0.000)
ΔTaxGain					0.003	-0.004**	-0.004**
					(0.003)	(0.002)	(0.002)
ΔManufacturing					-0.125	-0.224	-0.197
					(0.188)	(0.139)	(0.132)
ΔPatents					0.000**	0.000**	0.000**
					(0.000)	(0.000)	(0.000)
10-year fixed effects		Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects					Yes	Yes	Yes
Observations	144	144	144	144	144	144	144
Number of states	48	48	48	48	48	48	48

Notes: The analysis is performed on three periods (1980-1990, 1990-2000 and 2000-2010) and 48 States. The dependent variable is the decadal change in the 90-10 wage gap in columns (1)-(5), the top 1% income inequality in column (6) and the top 0.5% income inequality in column (7). Models estimated by OLS. Standard errors clustered at the state level are in parentheses. Regressions are weighted by state population in 1980.

4.4.2. Inequality within non-routine cognitive occupations

I proceed by estimating Equation (5) in which the decadal change in inequality among non-routine cognitive occupations is regressed on the decadal change in services. Table 4.4 display the results. The estimates mimic those obtained in Table 4.2. Column (1) shows a baseline specification without year fixed effects and any controls at all. Columns (2) and (3) include year fixed effects and other time-varying controls, respectively. Column (4) adds the decadal changes in the average log wage and manufacturing share. Column (5) looks at inequality within routine occupations. Finally, column (6) implements the IV strategy for non-routine cognitive occupations. The coefficient for the change in knowledge-intensive services is positively related to the change in inequality within non-routine cognitive occupations across all the specifications. Therefore, it is robust to the inclusion of year fixed-effects, time-varying controls and region fixed-effects. These results support the theoretical model, showing that the rise in knowledge-intensive services strongly increases wage inequality among workers in non-routine cognitive occupations. On the contrary, the decadal change in services exerts an impact on inequality within routine occupations that is not statistically different from zero at the standard confidence levels. Therefore, these results support the hypothesis that wage inequality originated from greater wage disparity among workers competing for non-routine cognitive positions.

Table 4.4. Cross-city regressions of decadal change in wage inequality based on occupational tasks and decadal change in knowledge-intensive services

	(1) Non-routine cognitive OLS	(2) Non-routine cognitive OLS	(3) Non-routine cognitive OLS	(4) Non-routine cognitive OLS	(5) Routine cognitive OLS	(6) Non-routine cognitive IV
ΔKnowlServ	1.173***	1.099***	1.320***	1.131***	0.427	2.378***
	(0.282)	(0.264)	(0.317)	(0.364)	(0.277)	(0.626)
ΔAge 25-34			-0.118	-0.134	-0.086	-0.179
			(0.239)	(0.230)	(0.212)	(0.207)
ΔAge 35-44			0.118	0.058	0.156	-0.008
			(0.244)	(0.240)	(0.278)	(0.270)
ΔCollege			-0.307	-0.118	-0.106	-1.019***
			(0.218)	(0.263)	(0.244)	(0.387)
ΔUnempl rate			-0.238	-0.484	-0.527	-0.621*
			(0.411)	(0.374)	(0.458)	(0.357)
ΔAverage log wage				-0.231**	-0.547***	
				(0.091)	(0.095)	
ΔManufacturing				0.065	-0.308**	

				(0.227)	(0.151)	
10-year fixed effects		Yes	Yes	Yes	Yes	Yes
Region fixed effects					Yes	Yes
Observations	603	603	603	603	603	603
Number of cities	201	201	201	201	201	201

Notes: The analysis is performed on three periods (1980-1990, 1990-2000 and 2000-2010) and 201 MSAs. The dependent variable is the decadal change in the 90-10 wage gap within the occupations indicated in the column head. The estimation model is indicated in the column head. Standard errors clustered at the city level are in parentheses. Regressions are weighted by city population in 1980.
*** *p<0.01*, ** *p<0.05*, * *p<0.1*.

To support this latter hypothesis, I turn to an individual level analysis to assess whether non-routine cognitive occupations are more remunerated in knowledge-intensive services than other sectors in the economy. I pool data from 1980, 1990, 2000, and 2010, and focus on the individual log hourly wage. This specification allows to include individual demographic characteristics and considering the variation of individual wages within cities by including city fixed effects. The estimation model is the following:

$$w_{ict} = \alpha + \beta_1 NonRoutCogn_{ict} + \beta_2 KnowlServ_{ict} + \phi_1 \ (KnowlServ_{ict} \times NonRoutCogn_{ict}) \ + \boldsymbol{X}'_{ict}\delta + \mu_c + \mu_t + e_{ict} \tag{7}$$

The dependent variable w_{ict} is the log of the hourly wage for individual i living in city c at time t; $\boldsymbol{X}'_{ict}$ is a vector of individual characteristics and the terms μ_c and μ_t are city and time fixed effects, respectively. The term e_{ict} is the error term capturing unobserved individual characteristics. The coefficient of interest is that of the interaction between the dummy variable $KnowlServ_{ict}$, taking value one if the individual works in a knowledge-intensive service sector, and the dummy indicating whether the worker is employed in a non-routine cognitive occupation $NonRoutCogn_{ict}$. Therefore, this variable should indicate whether non-routine cognitive occupations earn a wage premium by working in services, conditional on workers' characteristics.[41]

Table 4.5 reports the results from estimating equation (7) by OLS. The main result shown in the table is that the wage premium of non-routine cognitive workers in services is statistically significant when controlling for individual characteristics. The estimates in Table 4.5 confirm that non-routine cognitive occupations benefit from a wage premium of 13% when applying their skills to a knowledge-intensive sector.

[41]The set of controls used in the individual wage equation is indicated in the notes to Table 4.5.

Table 4.5. Individual wage analysis for the wage premium of non-routine cognitive workers in knowledge-intensive services

	(1) Log (hourly wage)
Services	-0.414***
	(0.046)
NonRoutineCognitive	0.036***
	(0.006)
NonRoutineCognitive x Services	0.130***
	(0.005)
City fixed effects	Yes
Year fixed effects	Yes
Individual characteristics	Yes
R-squared	0.381

Notes: The analysis is performed at the individual level. The number of observations is 2,240,156. The dependent variable is the log of the hourly wage. OLS estimation. Individual characteristics include nine education dummies, 5 age dummies and their interaction with education dummies, 2-digit industry dummies, 30 occupation dummies, a dummy for marital status and a dummy for living in an urban area. Standard errors clustered at the city level are in parentheses.
**** p<0.01, ** p<0.05, * p<0.1*

4.5. Conclusions

This article aims to fill a gap in the empirical analysis by investigating the rise of the knowledge-intensive services as a potential determinant for the rise in wage inequality experienced by the US over the last decades.

The US have experienced a profound transformation from a manufacturing-based economy to a knowledge-intensive economy in which service activities acquired a key role. However, the rise in services with high content of knowledge embedded in creative and skilled labour may have increased income inequality.

The change in the tradability and exploitation of knowledge has reshaped the income distribution of the rents generated from using knowledge. This change has radical effects on: i) the tradability of knowledge that can be now traded as a good and service favoured by the systematic use in ICT technologies enabling better screening, selection and exploitation of knowledge; ii) the dismissal of the large corporation and its dynamics of income distribution based on the participation of all the workers to the redistribution of rent profits; iii) the change toward a knowledge-intensive direction in production tasks requiring creative and skilled labour specialized in non-routine cognitive activities; iv) the increase in the share of profits going upstream in the value chain and favouring cognitive-based occupation with the consequent outsourcing of manufacturing-based activities in labour-abundant countries.

This transition has generated substantial consequences for the income distribution process. Individuals working in sectors based on knowledge-intensive activities and specialized in trading knowledge as a service have experienced the fastest growth in real wages. The literature studying income and wealth inequality has identified the rise in workers in professional occupations, financial professionals, KIBS and business services as the main drivers of the sharp increase in income inequality over the last several decades.

The New Growth Theory has much emphasized the limited appropriability of knowledge as a source of knowledge spillovers for increasing returns at the system level. However, the New Growth Theory has not provided a convincing explanation for the differences in productivity among heterogeneous systems. However, it is now evident that the limited exhaustibility of knowledge may generate increasing returns at the individual level from the use of knowledge (Jones, 2015; Jones and Kim, 2018). Specifically, individuals can exploit increasing returns to knowledge in those sectors in which the talent and knowledge offered by the individuals is scalable and can be leveraged over a large market size. The ultimate consequence is an increase of wage dispersion among heterogeneous individuals given by the returns to their knowledge.

We test these hypotheses in the US context by exploiting cross-city variation for the period between 1980 and 2010. The results show that knowledge-intensive services had a strong and positive effect on wage inequality within cities. The results are robust after accounting for other possible confounding factors, related city-specific time trends, endogeneity concerns and several robustness checks of the model specification. Moreover, consistently with the theoretical analysis, we found that the impact of services is greater on individuals within non-routine cognitive occupations and has no effects of wage dispersion within the group of routine-manual workers.

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Appendix C

Figures

Figure C.1. Change in the 90-10, 90-50 and 50-10 wage gap over time

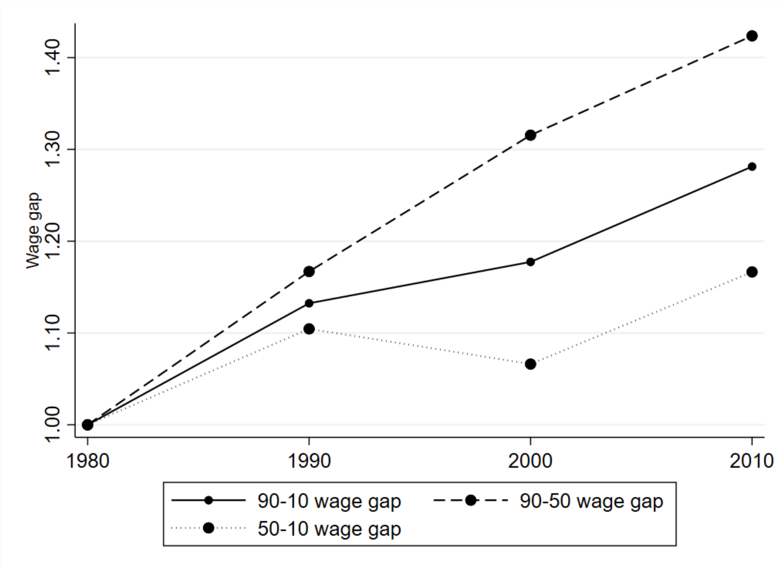


Figure C.2. Share of non-routine cognitive occupations across sectors

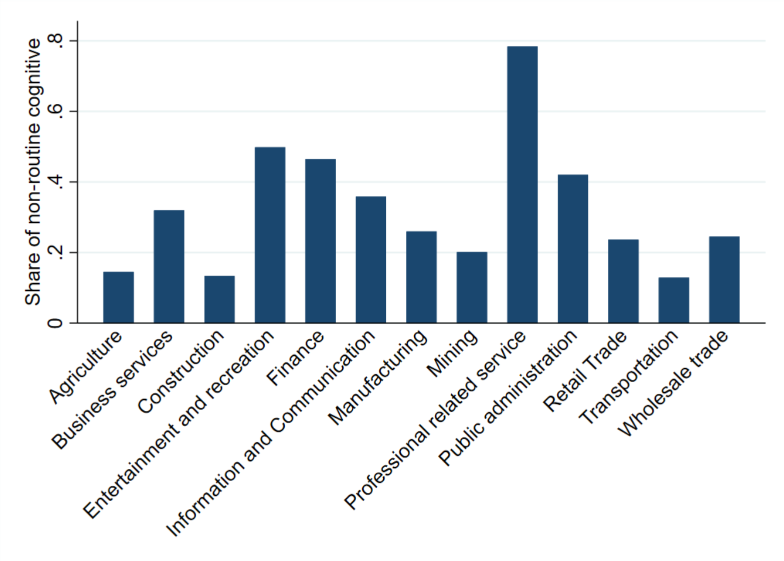
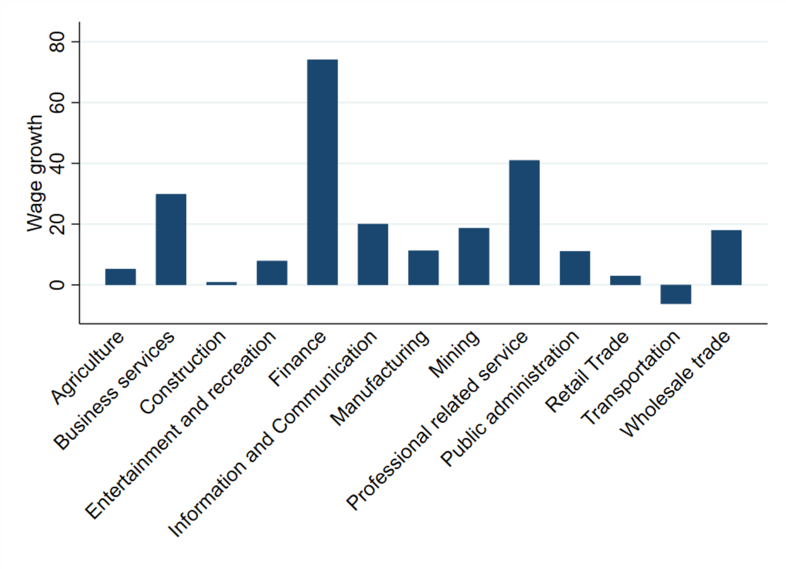


Figure C.3. Real wage growth across sectors



TABLES

Table C.1. Descriptive statistics

Census year: 1980

	N	Mean	Std. Dev.	Min	Max
90-10 wage gap	201	.947	.089	.715	1.201
%KnowlServ	201	.231	.053	.134	.392
%Age 25-34	201	.428	.033	.341	.534
%Age 35-44	201	.287	.016	.249	.335
%College	201	.258	.071	.125	.493
Unempl rate	201	.041	.021	.008	.175
%Manufacturing	201	.268	.119	.061	.553
Average log wage	201	3.133	.115	2.767	3.51

1990

	N	Mean	Std. Dev.	Min	Max
90-10 wage gap	201	1.041	.084	.851	1.419
%KnowlServ	201	.255	.057	.135	.414
%Age 25-34	201	.378	.027	.284	.484
%Age 35-44	201	.357	.02	.292	.425
%College	201	.273	.08	.133	.582
Unempl rate	201	.039	.013	.014	.081
%Manufacturing	201	.232	.097	.066	.508
Average log wage	201	3.064	.131	2.7	3.598

2000

	N	Mean	Std. Dev.	Min	Max
90-10 wage gap	201	1.092	.109	.877	2.179
%KnowlServ	201	.279	.066	.153	.551
%Age 25-34	201	.286	.03	.212	.423
%Age 35-44	201	.36	.018	.297	.417
%College	201	.286	.087	.121	.671
Unempl rate	201	.029	.01	.012	.064
%Manufacturing	201	.205	.091	.055	.518
Average log wage	201	3.082	.144	2.688	3.824

2010

	N	Mean	Std. Dev.	Min	Max
90-10 wage gap	201	1.157	.115	.929	2.081
%KnowlServ	201	.305	.071	.156	.617
%Age 25-34	201	.274	.035	.186	.424
%Age 35-44	201	.297	.018	.23	.353
%College	201	.313	.099	.139	.72
Unempl rate	201	.071	.023	.032	.174
%Manufacturing	201	.17	.077	.048	.47
Average log wage	201	3.069	.156	2.741	3.936

Table C.2. Correlation table

	1.	2.	3.	4.	5.	6.	7.	8.
1. 90-10 wage gap	1							
2. %KnowlServ	0.6171	1						
3. %Age 25-34	-0.5198	-0.2382	1					
4. %Age 35-44	0.1030	-0.0119	-0.2937	1				
5. %College	0.4121	0.8436	-0.0632	-0.0274	1			
6. Unempl rate	0.1662	-0.0026	-0.2468	-0.3874	-0.1492	1		
7. %Manufacturing	-0.6102	-0.6833	0.2333	0.0261	-0.3874	-0.0517	1	
8. Average log wage	0.0304	0.3238	0.1087	-0.0693	0.5720	-0.0701	0.1189	1

Table C.3. Cross-city regressions of wage inequality and knowledge-intensive services - Levels

	(1)	(2)	(3)	(4)	(5)
%KnowlServ	1.298***	0.906***	1.028***	0.708***	0.545**
	(0.077)	(0.207)	(0.243)	(0.237)	(0.251)
%Age 25-34			-0.126	-0.184	0.146
			(0.150)	(0.133)	(0.104)
%Age 35-44			0.218	0.123	0.065
			(0.197)	(0.168)	(0.075)
%College			-0.133	-0.123	-0.110
			(0.150)	(0.174)	(0.174)
Unempl rate			-0.135	-0.142	-0.449**
			(0.244)	(0.224)	(0.186)
%Manufacturing				-0.510***	-0.321**
				(0.104)	(0.156)
Average log wage				0.072	-0.214***
				(0.065)	(0.058)
Year FE		Yes	Yes	Yes	
City FE		Yes	Yes	Yes	Yes
City FE x Trend					Yes
Observations	804	804	804	804	804
Number of cities	201	201	201	201	201

Notes: The analysis is performed on four years (1980, 1990, 2000 and 2010) and 201 MSAs. The dependent variable is the 90-10 wage gap. Standard errors clustered at the city level are in parentheses. Regressions are weighted by city population in 1980.
**** p<0.01, ** p<0.05, * p<0.1.*

Table C.4. Cross-city regressions of wage inequality and knowledge-intensive services – Levels and standard deviation as a measure of wage inequality

	(1)	(2)	(3)	(4)	(5)
%KnowlServ	0.877***	0.738***	0.543***	0.487***	0.464***
	(0.033)	(0.095)	(0.109)	(0.110)	(0.163)
%Age 25-34			-0.171**	-0.182***	-0.194***
			(0.066)	(0.063)	(0.051)
%Age 35-44			-0.062	-0.056	-0.106**
			(0.091)	(0.084)	(0.046)
%College			0.227***	0.178**	-0.032
			(0.069)	(0.079)	(0.105)
Unempl rate			0.159	0.154	-0.185*
			(0.116)	(0.112)	(0.098)
%Manufacturing				-0.090*	-0.119
				(0.050)	(0.111)
Average log wage				0.048*	-0.012
				(0.029)	(0.035)
Year FE		Yes	Yes	Yes	
City FE		Yes	Yes	Yes	Yes
City FE x Trend					Yes
Observations	804	804	804	804	804
Number of cities	201	201	201	201	201

Notes: The analysis is performed on four years (1980, 1990, 2000 and 2010) and 201 MSAs. The dependent variable is the standard deviation of wages. Standard errors clustered at the city level are in parentheses. Regressions are weighted by city population in 1980.
**** p<0.01, ** p<0.05, * p<0.1.*

Table C.5. Cross-city regressions of wage inequality and knowledge-intensive services – Levels and coefficient of variation as a measure of wage inequality

	(1)	(2)	(3)	(4)	(5)
%KnowlServ	0.223***	0.144***	0.153***	0.140***	0.138***
	(0.011)	(0.024)	(0.034)	(0.031)	(0.049)
%Age 25-34			-0.049***	-0.051***	-0.063***
			(0.019)	(0.018)	(0.015)
%Age 35-44			0.020	-0.015	-0.032**
			(0.031)	(0.024)	(0.014)
%College			-0.014	0.057**	-0.001
			(0.022)	(0.022)	(0.032)
Unempl rate			0.042	0.047	-0.046
			(0.031)	(0.031)	(0.030)
%Manufacturing				-0.020	-0.033
				(0.014)	(0.034)
Average log wage				-0.046***	-0.059***
				(0.008)	(0.010)
Year FE		Yes	Yes	Yes	
City FE		Yes	Yes	Yes	Yes
City FE x Trend					Yes
Observations	804	804	804	804	804
Number of cities	201	201	201	201	201

Notes: The analysis is performed on four years (1980, 1990, 2000 and 2010) and 201 MSAs. The dependent variable is the coefficient of variation of wages. Standard errors clustered at the city level are in parentheses. Regressions are weighted by city population in 1980.
**** p<0.01, ** p<0.05, * p<0.1.*

Table C.6. Cross-city regressions of decadal change in wage inequality and decadal change in knowledge-intensive services – Standard errors clustered at the state level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	OLS	OLS	OLS	OLS	OLS	IV
ΔKnowlServ	1.139***	1.134***	1.250***	1.043***	0.913***	1.045***	2.468***
	(0.204)	(0.234)	(0.294)	(0.313)	(0.303)	(0.208)	(0.517)
ΔAge 25-34			-0.258	-0.197	-0.215		-0.253
			(0.215)	(0.210)	(0.204)		(0.177)
ΔAge 35-44			0.258	0.173	0.147		0.136
			(0.227)	(0.198)	(0.198)		(0.233)
ΔCollege			-0.252	0.174	0.235		-0.942***
			(0.163)	(0.185)	(0.168)		(0.324)
ΔUnempl rate			0.155	0.102	-0.083		-0.152
			(0.445)	(0.468)	(0.378)		(0.334)
ΔAverage log wage				-0.276***	-0.380***		
				(0.056)	(0.079)		
ΔManufacturing				-0.093	-0.115		
				(0.102)	(0.119)		
Age 25-34$_{1980}$						-0.120	
						(0.081)	
Age 35-44$_{1980}$						0.137	
						(0.176)	
College$_{1980}$						0.156***	
						(0.028)	
Unempl rate$_{1980}$						0.356*	
						(0.206)	
Inequality$_{1980}$						-0.082***	
						(0.028)	
10-year fixed effects		Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects					Yes	Yes	Yes
Observations	603	603	603	603	603	603	603
Number of cities	201	201	201	201	201	201	201
F-stat							172.51

Notes: The analysis is performed on three periods (1980-1990, 1990-2000 and 2000-2010) and 201 MSAs. The dependent variable is the decadal change in the 90-10 wage gap. The estimation model is indicated in the column head. Standard errors clustered at the state level are in parentheses. Regressions are weighted by city population in 1980.
**** p<0.01, ** p<0.05, * p<0.1.*

Table C.7. Cross-city regressions of decadal change in wage inequality and decadal change in knowledge-intensive services – No weighting

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	OLS	OLS	OLS	OLS	OLS	IV
ΔKnowlServ	1.117***	1.068***	0.942***	0.833**	0.850**	0.989***	1.783***
	(0.298)	(0.314)	(0.306)	(0.368)	(0.401)	(0.267)	(0.475)
ΔAge 25-34			-0.568***	-0.537***	-0.516***		-0.487***
			(0.154)	(0.159)	(0.163)		(0.155)
ΔAge 35-44			-0.003	-0.009	-0.004		-0.013
			(0.226)	(0.227)	(0.227)		(0.229)
ΔCollege			0.066	0.242	0.243		-0.383*
			(0.154)	(0.208)	(0.220)		(0.220)
ΔUnempl rate			-0.084	-0.084	-0.096		-0.168
			(0.206)	(0.209)	(0.210)		(0.215)
ΔAverage log wage				-0.145	-0.167		
				(0.117)	(0.126)		
ΔManufacturing				-0.067	-0.033		
				(0.101)	(0.116)		
Age 25-34$_{1980}$						-0.271	
						(0.179)	
Age 35-44$_{1980}$						0.021	
						(0.200)	
College$_{1980}$						0.201**	
						(0.085)	
Unempl rate$_{1980}$						0.278**	
						(0.136)	
Inequality$_{1980}$						-0.084***	
						(0.031)	
10-year fixed effects		Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects					Yes	Yes	Yes
Observations	603	603	603	603	603	603	603
Number of cities	201	201	201	201	201	201	201
F-stat							209.56

Notes: The analysis is performed on three periods (1980-1990, 1990-2000 and 2000-2010) and 201 MSAs. The dependent variable is the decadal change in the 90-10 wage gap. The estimation model is indicated in the column head. Standard errors clustered at the city level are in parentheses.
**** p<0.01, ** p<0.05, * p<0.1.*

Table C.8. Cross-city regressions of decadal change in wage inequality and decadal change in knowledge-intensive services – Weekly wages

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	OLS	OLS	OLS	OLS	OLS	IV
ΔKnowlServ	1.278***	1.255***	1.286***	1.023***	0.782***	1.126***	2.480***
	(0.228)	(0.209)	(0.259)	(0.245)	(0.271)	(0.220)	(0.561)
ΔAge 25-34			-0.217	-0.158	-0.180		-0.206
			(0.203)	(0.198)	(0.175)		(0.178)
ΔAge 35-44			0.332	0.230	0.201		0.223
			(0.249)	(0.202)	(0.189)		(0.246)
ΔCollege			-0.112	0.369**	0.500***		-0.787**
			(0.184)	(0.181)	(0.190)		(0.374)
ΔUnempl rate			0.004	-0.056	-0.310		-0.341
			(0.368)	(0.375)	(0.334)		(0.335)
ΔAverage log wage				-0.305***	-0.441***		
				(0.073)	(0.090)		
ΔManufacturing				-0.153	-0.241		
				(0.162)	(0.173)		
Age 25-34$_{1980}$						-0.156	
						(0.134)	
Age 35-44$_{1980}$						0.072	
						(0.185)	
College$_{1980}$						0.192***	
						(0.060)	
Unempl rate$_{1980}$						0.391*	
						(0.211)	
Inequality$_{1980}$						-0.069**	
						(0.030)	
10-year fixed effects		Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects					Yes	Yes	Yes
Observations	603	603	603	603	603	603	603
Number of cities	201	201	201	201	201	201	201
F-stat							140.89

Notes: The analysis is performed on three periods (1980-1990, 1990-2000 and 2000-2010) and 201 MSAs. The dependent variable is the decadal change in the 90-10 wage gap. The estimation model is indicated in the column head. Standard errors clustered at the city level are in parentheses. Regressions are weighted by city population in 1980.
**** p<0.01, ** p<0.05, * p<0.1.*

Table C.9. Cross-city regressions of decadal change in wage inequality and decadal change in knowledge-intensive services – Residual wage inequality

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	OLS	OLS	OLS	OLS	OLS	IV
ΔKnowlServ	0.826***	0.791***	1.027***	0.750***	0.684***	0.710***	1.495***
	(0.175)	(0.174)	(0.206)	(0.215)	(0.206)	(0.156)	(0.273)
ΔAge 25-34			0.008	-0.033	-0.034		0.012
			(0.115)	(0.115)	(0.105)		(0.102)
ΔAge 35-44			0.284*	0.212	0.205		0.246
			(0.167)	(0.151)	(0.143)		(0.160)
ΔCollege			-0.312**	-0.144	-0.115		-0.616***
			(0.123)	(0.126)	(0.131)		(0.176)
ΔUnempl rate			-0.383*	-0.405**	-0.537***		-0.529***
			(0.204)	(0.205)	(0.180)		(0.179)
ΔAverage log wage				-0.066	-0.145**		
				(0.051)	(0.057)		
ΔManufacturing				-0.352***	-0.337***		
				(0.090)	(0.093)		
Age 25-34$_{1980}$						-0.179**	
						(0.089)	
Age 35-44$_{1980}$						0.111	
						(0.135)	
College$_{1980}$						0.124***	
						(0.040)	
Unempl rate$_{1980}$						0.250*	
						(0.135)	
Inequality$_{1980}$						-0.070***	
						(0.021)	
10-year fixed effects		Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects					Yes	Yes	Yes
Observations	603	603	603	603	603	603	603
Number of cities	201	201	201	201	201	201	201
F-stat							140.89

Notes: The analysis is performed on three periods (1980-1990, 1990-2000 and 2000-2010) and 201 MSAs. The dependent variable is the decadal change in the 90-10 residual wage gap. The estimation model is indicated in the column head. Standard errors clustered at the city level are in parentheses. Regressions are weighted by city population in 1980.
**** p<0.01, ** p<0.05, * p<0.1.*

Table C.10. Cross-city regressions of decadal change in wage inequality and decadal change in knowledge-intensive services – Different time periods

	(1) 1990-2010 Period	(2) 1980-2000 Period	(3) 10-year lagged services	(4) Long differences- change 1980-2010
ΔKnowlServ	0.659**	1.143***	0.532***	0.969***
	(0.274)	(0.282)	(0.133)	(0.364)
ΔAge 25-34	-0.310*	-0.550***	-0.364*	0.295
	(0.187)	(0.181)	(0.188)	(0.347)
ΔAge 35-44	0.177	-0.025	0.145	0.940***
	(0.201)	(0.206)	(0.194)	(0.267)
ΔCollege	0.412*	0.170	0.730***	0.600
	(0.209)	(0.206)	(0.158)	(0.373)
ΔUnempl rate	0.142	0.156	0.105	0.652**
	(0.256)	(0.339)	(0.260)	(0.313)
ΔAverage log wage	-0.085	-0.440***	-0.106	-0.254**
	(0.105)	(0.084)	(0.107)	(0.117)
ΔManufacturing	0.164	-0.242	-0.167	-0.244
	(0.158)	(0.147)	(0.153)	(0.153)
10-year fixed effects	Yes	Yes	Yes	
Region fixed effects	Yes	Yes	Yes	Yes
Obs.	402	402	402	201
R-squared	0.394	0.550	0.405	0.477

Notes: The column head indicates the model used. The analysis is performed on 201 MSAs. The dependent variable is the decadal change in the 90-10 residual wage gap. Standard errors clustered at the city level are in parentheses. Regressions are weighted by city population in 1980.
*** *p<0.01*, ** *p<0.05*, * *p<0.1.*

Chapter 5.

Conclusion

This dissertation intended to contribute to technological change and the income inequality debate. The general trend in income inequality has raised preoccupation among economists. Higher levels of income inequality may have substantial implications for the general society. For example, higher income inequality may erode trust (Graafland and Lous, 2019), reduce pro-social behaviours (Hijzen and Gould, 2016), and have negative socioeconomic aspects in terms of physical and mental health, segregation and democracy (Buonanno and Vargas, 2019; Ferrer-i-Carbonell and Ramos, 2014; Stiglitz, 2012; Wilkinson and Pickett, 2016). Therefore, it is undeniable that understanding the causes of income inequality is crucial to implement appropriate policy measures.

The economic literature has focused on technological change's characteristics to explain the income inequality increase. As a result, great attention has been given to the implications of technological change for workers based on different skill levels. The results of these empirical analyses showed that new information and communication technologies complement skilled workers, contributing to enlarging the wage gap with respect to unskilled workers (Berman, Bound and Machin, 1998; Dunne et al., 2004; June, Murphy and Pierce, 1993). At the same time, recent contributions showed a decrease in labour share and identified capital-biased technological change as the main driver of this decline (Bassanini and Manfredi, 2012; Karabarbounis and Neiman, 2014; Hutchinson and Persyn, 2012).

Hence, the theoretical and empirical literature has often associated the capital-intensive direction with the skill-biased effect of new technologies, due to the complementarity between capital and skilled labour. The empirical association between the decline of the labour share and the skill-biased technological change hypothesis led to the collective wisdom that a capital-intensive direction of technological change is also skilled-biased (Karabarbounis and Neiman, 2014; Zeira, 1998). Nonetheless, the systematic use of the CES production function has shifted the attention from the changes in the output elasticities to explain the direction of technological change to the value assumed by the elasticity of substitution. The difficulties associated with estimating the elasticity of substitution and the wide variety of results obtained across different samples and dimensions make it difficult to reconcile the results of the empirical analysis with the theoretical assumptions. The usual approach is to draw implications of the elasticity of substitution from the results of the empirical analysis (Bassanini and Manfredi, 2012; Perugini, Vecchi and Venturini, 2017). The capital-biased effect of technological change should imply an elasticity of substitution above unity, whereas most studies obtain an elasticity of substitution below one (Chirinko, 2008; Knoblach and Stockl, 2020).

The contribution of this work was to complement and challenge the literature on technological change and income inequality based on the skill-biased- and capital-biased- effect of technological change. The skill-intensive direction may be compatible with either a capital-intensive direction due to the need for skilled workers to use new machinery or a labour - and knowledge-intensive direction that can also be capital-saving. This work supported the latter interpretation by providing evidence of the knowledge-and labour-intensive direction of technological change and the limitations of the CES theoretical setting to study the direction of technological change. Then, the implications for personal income inequality of the knowledge-intensive direction are analysed extensively.

Chapter 2 analysed the implication of the knowledge-intensive direction for income distribution between capital and labour. The econometric analysis based on a sample of 171 NUTS-2 European regions showed that a greater labour share of income characterized more innovative regions. Therefore, technological change proxied by the number of patent applications is related to a labour-biased direction of technological change. I explained this fact with the localized and bottom-up technological change approach, according to which the development of technological change is based on the localized improvements of new technologies based on the workforce's competence.

In Chapter 3, we contrasted the current theoretical literature on the analysis of income distribution based on the systematic use of the CES production function. The CES is a standard macroeconomic tool with the advantage of being a flexible, functional form and allowing the value of the elasticity of substitution to differ from unity. Therefore, the assessments of the direction of technological change are based on studying the value of the elasticity of substitution and estimating the factor-augmenting parameters. In our work, we showed that the assumption of a constant elasticity of substitution must be rejected for a sample of nine advanced economies observed between 1950 and 2017. Instead, we documented that the elasticity of substitution has increased in the last several decades. Moreover, the increase in the elasticity of substitution was evident as the sample was split at the end of the 1970s when the labour share started to decline and the capital share increased. Therefore, relying on the literature on factor-saving innovation, we argued that the increase in the elasticity of substitution might be an alternative source of change in factor income shares.

Finally, the SBTC is silent on the effects of technological change on the upper tail of the skill and wage distribution. While ample empirical evidence existed on the effect of the SBTC on wage inequality between high-skilled and unskilled individuals, wage dispersion among non-routine cognitive workers has been little analysed. Chapter 4 proposed that the increasing demand for knowledge-based services, such as finance, KIBS, and business and related professional services, is associated with greater wage inequality overall and within non-routine cognitive occupations. The theoretical hypothesis behind these results is based on the greater scalability of knowledge in these sectors, which favours the emergence of superstar effects and widens wage inequality between the top and the rest of the wage distribution.

This dissertation questioned the current understanding of the SBTC hypothesis as capital-intensive and labour-saving. Indeed, it articulated and tested the hypothesis that the direction of technological change is now knowledge-intensive and associated with a labour-biased direction. The results confirmed that knowledge-intensive activities are skill-biased and that skilled labour is a necessary and key input to the production of new technological knowledge. Moreover, the empirical analysis suggested that, for the generation of technological knowledge, skilled labour is the key input in a production process with low levels of capital intensity. Moreover, the empirical work provided an additional challenge to the capital-biased direction by questioning the legitimacy of the CES production function as a tool to explain the direction of technological change. Indeed, we showed that the increase in the share of capital had been largely driven by an increase in the elasticity of substitution between capital and labour.

Therefore, this dissertation aimed to provide a fresh understanding of the relationship between technological change and inequality that the empirical literature has often neglected. Particularly, it provides three elements of novelty in the literature:

1. The direction of technological change is labour-biased at the European regional level, in contrast with most recent literature showing a capital-biased direction of technological change. The main explanation is the localized introduction of technological change based on the systematic exploitation of the factor inputs that are more abundant locally.
2. The change in factor income shares might also be explained by the changes in the elasticity of substitution between capital and labour. Specifically, our results showed that the increase in the elasticity of substitution driven by institutional and economic factors made labour more easily substitutable with capital.
3. The greater scalability of knowledge in most recent decades is magnified in knowledge-based services where superstar effects widened individual wage inequality. Therefore, the increased demand for workers in knowledge-based services has exacerbated inequality along the entire wage distribution and within non-routine cognitive workers.

This work also presents several limitations. First, the lack of consistent micro-data at the European regional level prevents the researcher from analysing the heterogeneous effects of the localized introduction of technological change on labour input. While the functional distribution of income analysis focuses only on the relationship between capital and labour, whether the share of income going to skilled and unskilled workers followed or not the same trend might be a promising avenue for further research.

Second, the existing literature has not considered the analysis of the dynamics of the elasticity of substitution between capital and labour. While our work highlighted the change and, precisely, the increase in the elasticity of substitution as additional biased innovation, the determinants behind the increase in the elasticity of substitution deserve to be investigated (Knoblach and Stöckl, 2020). In particular, an interesting avenue for future research might be to disentangle the effects of institutional factors from the effects of economic factors in shaping the evolution of the elasticity of substitution. Moreover, the availability of data on income shares at the country level for a longer period could allow us to extend the dataset to other advanced countries, including developing countries.

Finally, within-group inequality accounted for a large part of the increase in wage inequality in the last several decades. Moreover, evidence has been provided for the increase in within-group wage inequality, especially among high-skilled workers (Autor, Katz and Kearney, 2008; Lemieux, 2006). Nonetheless, the empirical literature lacks assessments of the causes of the increase in wage inequality within the upper tail of the skill and wage distribution. In Chapter 4 of the thesis, I analysed and tested a specific mechanism, the rise in knowledge-based services. While the city dimension creates sources of variation that can be exploited in the empirical analysis, the use of employer-employee datasets might provide more detailed insights into the relationships between knowledge scalability, superstar effects, market concentration and individual wage inequality (Akerman et al., 2013; Song et al., 2019).

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Valorisation addendum

> In accordance with article 22.5 of the "Regulation governing the attainment of doctoral degrees at Maastricht University", this addendum discusses valorisation opportunities of the dissertation regarding "social and/or economic relevance" of the research results.

The dissertation explores the impact of technological change on income distribution from various perspectives. The findings of this work have not only academic relevance but also implications for society and policymakers. Income inequality is detrimental to the general society for several reasons. Greater levels of income inequality are associated with lower trust, higher levels of crime and social unrest, as well as health and psychological issues. Therefore, contrasting income inequality should be at the top of the economic policy agenda. This dissertation offers several insights to address policy instruments to contrast income inequality.

First, the results of the first chapter show that the share of labour is larger where technological change is faster. The divergence across European regions in technological capabilities is well recognized, although additional efforts to favour convergence across regions in technological change are called for. In particular, the economics of innovation has offered a variety of policy tools to foster technological catch-up. The findings in this dissertation suggest that a greater level of technological change supported by appropriate measures should contribute to reducing the levels of functional inequality, increasing the share of income paid to labour.

Second, Chapter 3 shed light on a scenario that has been neglected by the policy agenda, the increase in how labour is made substitutable by capital. If the trend of the last decades is toward an increase in the elasticity of substitution, the economic agenda should closely investigate the phenomenon. As explained in Chapter 3, the change in the elasticity of substitution may be driven by economic and institutional factors related to international trade and labour markets. In particular, the degree of unionization and labour market regulations may represent significant institutional barriers that facilitate or hamper the substitution of labour by capital. The assessments of the variation of the elasticity of substitution across places and the causes behind the changes are therefore crucial to address this critical change of the recent decades.

Finally, Chapter 4 suggested that increasing attention should be given to the role of knowledge-based services in increasing income inequality. In these sectors, compensations are highly skewed towards top talented workers, and workers with these scarce talents command a wage premium with respect to other sectors. Policymakers should investigate in more detail whether the excess compensation mechanisms are related to superstar and market size mechanisms or to social norms that allow these workers to extract rents above their marginal productivity.

About the author

Guido Pialli was born in Cecina (LI), Italy, in 1993. He obtained a bachelor's degree in Economics from the University of Pisa and a master's degree in Economics from the Sant'Anna School of Advanced Studies and the University of Pisa. He started his PhD in Economics at the University of Torino, in co-tutelle with Maastricht University, in 2018. He successfully completed the first-year courses of the PhD program at the Collegio Carlo Alberto, Turin. His research interests lie in the broad area of the economics of knowledge and innovation but also include other fields of applied economics such as labour economics, firm dynamics and economic history. His doctoral dissertation was advised by Prof. Cristiano Antonelli and Prof. Pierre Mohnen. Since 2019, he has been one of the organizers of the Workshop in Innovation, Complexity and Knowledge (WICK), held in Collegio Carlo Alberto, Torino.

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