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The Impact of Innovation on Wage Inequality

João Patrício Esteves Coelho

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THE IMPACT OF INNOVATION ON WAGE INEQUALITY

João Patricio Esteves Coelho

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Prof. Dr. Óscar Afonso

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Abstract

Innovation is widely regarded as a key driver of long-term economic growth, productivity, and competitiveness. However, its distributive consequences have become increasingly contested, particularly in relation to wage inequality. While theoretical frameworks such as skill-biased technological change and Schumpeterian creative destruction predict that innovation tends to widen income disparities, empirical evidence across different countries, sectors, and periods has been heterogeneous. This dissertation addresses this gap by systematically reviewing and quantitatively synthesising existing research through a meta-analysis of empirical studies on the impact of innovation on wage inequality. The analysis combines results from a wide range of studies across both developed and developing economies, encompassing diverse measures of innovation (including R&D expenditure, patent activity, and firm-level innovation) and inequality (such as wage dispersion, skill premium, and intra-firm wage gaps). Overall, the findings indicate that there is an average positive yet statistically insignificant effect of innovation on wage inequality, particularly in advanced economies and in innovation-intensive sectors and regions. The results also indicate that the reported effect of innovation on wage inequality is highly sensitive to methodological and contextual factors. In particular, the exclusion of highly innovative regions amplifies the observed effect, pointing to greater disruption in less innovative areas with weaker absorptive capacity. By contrast, when innovation is modelled with a temporal lag, its effect on wage inequality diminishes, consistent with the idea that initial wage disparities may narrow over time as technologies diffuse and labour markets adjust. The dissertation contributes to the literature by synthesising fragmented evidence, identifying the factors behind heterogeneous results, and clarifying when innovation worsens or reduces wage inequality.

Keywords: Innovation, Meta-analysis; Wage inequality.

JEL Codes: L26, O30, O40, O50.

Resumo

A inovação é amplamente reconhecida como um motor essencial do crescimento económico, da produtividade e da competitividade. Contudo, as suas consequências permanecem alvo de grande debate, sobretudo no que respeita à desigualdade salarial. Ao passo que a literatura teórica associada ao *skill-biased technological change* e à destruição criativa Schumpeteriana prevê que a inovação tende a acentuar as disparidades de rendimento, a evidência empírica tem revelado resultados heterogéneos entre países, setores e períodos. Esta dissertação procura clarificar esta relação através da realização de uma meta-análise dos estudos empíricos sobre o impacto da inovação na desigualdade salarial. A análise incide sobre os resultados de diversos estudos em economias desenvolvidas e em desenvolvimento, abrangendo distintas medidas de inovação (intensidade de I&D, patentes e inovação empresarial) e de desigualdade (tais como dispersão salarial ou *skill-premium*). Os resultados mostram que, em média, a inovação tem um impacto positivo, mas estatisticamente insignificante, sobre a desigualdade salarial. No entanto, a análise de variáveis moderadoras evidencia que este impacto depende de fatores metodológicos e contextuais. Em particular, a exclusão de regiões altamente inovadoras tende a amplificar os efeitos observados, sugerindo uma maior disrupção em áreas menos inovadoras e com menor capacidade de absorção. Em contrapartida, quando a inovação é considerada com um desfasamento temporal, o seu efeito tende a atenuar-se, o que é consistente com a hipótese de que disparidades salariais iniciais podem diminuir à medida que as tecnologias se difundem e os mercados de trabalho se ajustam. A dissertação contribui para a literatura ao integrar evidência fragmentada, identificar os principais fatores que explicam a heterogeneidade dos resultados e clarificar as condições em que a inovação agrava ou reduz a desigualdade salarial.

Palavras-Chave: Inovação, Meta-analise; Desigualdade salarial.

JEL Codes: L26, O30, O40, O50.

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1. Introduction

Innovation has become one of the most important drivers of economic growth, productivity improvements, and long-term competitiveness. By reshaping industries, firms, and labour markets, it plays a decisive role in how modern economies evolve and respond to global challenges (Aghion & Howitt, 1992; Romer, 1990). At the same time, wage inequality has gained increasing attention over the past decades, as many economies have experienced a sharp rise in income dispersion, particularly between high-skilled and low-skilled workers(Acemoglu, 2008; Goldin & Katz, 2007). The coexistence of rapid innovation and widening inequality has raised critical questions regarding how the benefits of technological progress are distributed and whether they reach society in an equitable way.

The relationship between innovation and wage inequality has been widely studied, but results remain fragmented and often contradictory. On the one hand, theories such as skill-biased technological change (SBTC) suggest that innovation raises the relative demand for skilled labour, thereby increasing the wage premium of educated workers and contributing to inequality(Autor et al., 1998; Machin & Reenen, 1998). On the other hand, several scholars highlight that under certain institutional settings, innovation can create opportunities for inclusive growth by raising productivity, generating employment, and fostering wage convergence (Aghion et al., 2017; Law et al., 2020). This diversity of perspectives demonstrates both the complexity of the innovation/inequality nexus and the absence of a comprehensive synthesis that can reconcile theoretical predictions with empirical findings.

The main objective of this dissertation is to examine the impact of innovation on wage inequality by systematically reviewing and synthesising the existing empirical evidence. To achieve this, a meta-analysis is conducted on a wide range of studies that have estimated the effect of innovation on wage dispersion. This method allows for the integration of diverse results, the estimation of an overall effect size, and the identification of factors that may explain heterogeneity across studies (Stanley et al., 2008). By doing so, the dissertation provides a more general and reliable assessment of whether, and under what conditions, innovation exacerbates or mitigates wage inequality. The contributions of this work are threefold. First, it provides a systematic review of the theoretical and empirical literature on innovation and wage inequality, highlighting both classical and contemporary perspectives. Second, it applies meta-analytical tools to quantitatively synthesise existing findings, thus improving the robustness of conclusions in a field where individual studies often diverge.

Third, it contributes to the policy debate by identifying the conditions under which innovation is more likely to generate inequality and those in which it may support more inclusive development.

The structure of the dissertation is organised as follows. Chapter 2 presents the literature review, divided into theoretical and empirical perspectives. Chapter 3 introduces the methodology, focusing on the principles and procedures of meta-analysis and the process of data collection. Chapter 4 provides the descriptive analysis and estimation of the overall effect of innovation on wage inequality and addresses the issue of publication bias. Chapter 5 develops meta-regression models to explain the heterogeneity across studies. Finally, Chapter 6 concludes with the main findings, their theoretical and policy implications, and suggestions for future research.

2. Literature review

The relationship between innovation, economic growth, and wage inequality has attracted extensive attention in economic theory and policy debates. Far from being a neutral process, innovation constitutes a transformative force whose consequences extend well beyond productivity and competitiveness. To shed the light and deepen the knowledge on this topic, this dissertation starts by first resuming the theoretical mechanisms through which innovation influences wage structures, including creative destruction, skill-biased technological change, and the role of institutions and globalisation. Then we examine the empirical evidence to understand how these mechanisms manifest in practice across different countries, periods, and sectors, and assess the magnitude and direction of the effects. This structure provides a comprehensive framework, beginning with the theoretical foundations and then turning to the empirical evidence that tests and refines the conceptual insights.

2.1. The impact of innovation on wage inequality - theoretical mechanisms

Innovation has long stood at the forefront of economic inquiry, emerging as one of the key drivers of productivity, competitiveness and sustained economic development. As a multidimensional and complex phenomenon (Fragkandreas, 2022) encompassing the implementation of novel or significantly improved products, processes, organisational methods or marketing techniques(Organisation for Economic Cooperation and Development, 2005), innovation has become deeply embedded in contemporary growth theory. It has repeatedly been recognised as a core engine of national economies and an essential determinant of long-term prosperity (Aghion & Howitt, 1992; Cirera & Martins-Neto, 2023; Dinopoulos & Segerstrom, 1999; Romer, 1990). The intricate ways through which innovation shapes other economic variables remains, however, a subject of ongoing debate, particularly in respect to labour markets, wage setting dynamics, and the evolution of income distribution between different groups of workers. The relationship between innovation and wage inequality represents an important topic in economic theory, one that has evolved considerably over time as new mechanisms have emerged, and empirical evidence has deepened (Acemoglu, 2008; Afonso, 2006; Aghion et al., 2017; Kirzner, 1999; Van Reenen, 2011).

At the heart of the classical literature lies Joseph Schumpeter's (1947) proposition that innovation constitutes a process of creative destruction. Under this paradigm, innovation replaces the old with the new, unsettling previously stable structures through the introduction

of novel technologies and organisational formations. This process, although inherently growth enhancing, is not neutral regarding distributional outcomes: while creating new opportunities for entrepreneurs and skilled workers, it simultaneously renders obsolete certain forms of capital and low-skilled labour. Early conceptualisations thus placed innovation as an inherently disruptive force with ambiguous equity implications, recognising that benefits tend to accrue disproportionately to those actors most capable of seizing new technological opportunities. Schumpeter's insights were subsequently elaborated by Romer (1990), Aghion and Howitt (1992) and other proponents of endogenous growth theory, who formalised the notion that technological change is both a product and a determinant of economic progress. These models positioned innovation-led technological change at the centre of growth, highlighting the pivotal role of research and development, human capital formation, and institutional frameworks. Innovation becomes both a cause and a consequence of growth, an engine whose benefits are amplified over time through positive spillovers, learning effects, and increasing returns. Yet as innovation became conceptualised as a continuous driver of structural change, questions began to arise regarding its broader societal consequences most notably in the distribution of wages.

While endogenous growth theory offered a powerful framework for understanding the macroeconomic benefits of innovation, it also raised questions about distribution. If innovation disproportionately rewards those with the ability to generate or utilise new knowledge, typically skilled workers and capital owners, then it may also exacerbate wage inequality. As empirical evidence mounted through the 1980s and 1990s, the notion that technological progress might be "skill-biased" gained traction. This gave rise to the skill-biased technological change (SBTC) hypothesis, which posits that innovation increases demand for high-skilled labour while reducing demand for low-skilled, especially in routine occupations. Technological change was rapidly identified as a key suspect in explaining rising dispersion of wages across workers with different skills and educational attainments. The seminal works of Machin and Van Reenen (1998) and Autor et al. (1998) contributed significantly to the development of the skill-biased technological change (SBTC) hypothesis, arguing that technological innovations tend to disproportionately complement skilled labour whilst substituting for routine or low-skilled labour. Technologies such as computing, automation, and digitalisation were found to increase the relative productivity of high-skilled workers, notably those engaged in cognitive and non-routine tasks, thereby augmenting demand for skilled labour, bidding up their wages, and widening the wage gap vis-à-vis the

less skilled. Under this framework, innovation is not merely correlated with inequality: it actively drives inequality by reshaping the structure of production in ways that favour certain types of labour. Afonso (2006) later refined the SBTC framework, demonstrating its persistence in the absence of scale effects, thus reinforcing the robustness of the theoretical linkage.

Beyond SBTC, scholars began to investigate alternative channels through which innovation might amplify inequality. One such mechanism centres on the growing role of "superstar firms" and winner-takes-most dynamics in innovation-intensive sectors. As argued by Aghion et al (2019), firms that succeed in innovation races gain dominant market positions, which allow them to capture a disproportionate share of economic rents and pay exceptionally high wages to a small segment of elite workers. These firms also tend to exhibit lower labour share of income, as capital-intensive production and intellectual property allow them to scale without proportionally increasing employment. These dynamic shifts the distribution of income away from labour in general, and especially from routine and middle-wage occupations. Relatedly, Helpman et al. (2010) argued that global trade and technological progress can jointly increase wage inequality within countries, particularly when innovation is concentrated in high-productivity firms that employ relatively few workers. In this framework, innovation does not just raise the skill premium it creates structural asymmetries in wage-setting power and labour market bargaining.

In parallel, alternative mechanisms emerged to describe how innovation may reinforce inequality via more complex economic channels. Dinopoulos and Segerstrom (1999) introduced a Schumpeterian model of trade protection, linking innovation to international competition and relative wages. In their view, the diffusion of innovation is not uniformly beneficial: countries and firms that innovate escape competition and enjoy transient monopoly rents, allowing them to pay higher wages to limited pools of skilled labour. This creates a divergence in earnings trajectories both within and between countries. Galindo and Méndez-Picazo (2013) similarly framed entrepreneurship and innovation as complementary forces that universally enhance economic growth, whilst noting the propensity for technological entrepreneurs to accumulate disproportionate rewards relative to other factor owners. The literature increasingly suggested that innovation acts as a sorting mechanism, enabling those with entrepreneurial skill, education, and access to capital to capture outsized gains, while leaving less advantaged workers more vulnerable to displacement.

Further advancements in theoretical engagement underscored the interaction between innovation, globalisation, and labour market institutions. Allen (2020) examined the historic interplay between wages, technological change, and globalisation, highlighting how open economies enabled the rewards of innovation to flow upward and outward in increasingly globalised production systems. This transformation reshaped labour demand, intensifying international wage competition for routine, offshorable jobs, while reinforcing the returns of innovation for knowledge-intensive, high-skilled workers embedded in advanced production networks. Salverda and Mayhew (2009) further linked capitalist dynamics to wage inequality, arguing that the structural asymmetries inherent in capitalist systems exacerbated by continual waves of innovation facilitated the concentration of economic power and wage-setting capacities among upper-tier firms and workers. Meanwhile, Capello et al. (2024) showed that the emergence of the digital service economy has further deepened wage disparities between and within regions, as innovation-driven growth tends to cluster in particular territories where skilled labour, investment capital, and high-value firms agglomerate. This leads to a geography of inequality, where certain regions become innovation winners and others lag behind. The agglomeration effects associated with innovation thus deepen territorial disparities in income and employment prospects. These insights complement those of Ghosh and Wang (2009) who, though focusing on foreign direct investment, emphasised the role of institutional and structural factors in determining how innovation-related capital inflows affect income distribution. Innovation is not inherently inclusive it magnifies differences between those with the capacity to absorb and benefit from it, and those without.

By the early twenty-first century, theoretical discourse had converged around the premise that innovation exerts a fundamental and multifaceted influence on wage inequality. The mechanisms span creative destruction, monopsonistic rents, entrepreneurial dynamics, international integration, and above all, the skill bias embedded in modern technological change. Though innovation stimulates aggregate economic growth and productivity gains, its benefits are unevenly distributed not only across skill groups but also across regions, industries, and occupations. Those endowed with scarce skills complementary to new technologies, or with strategic control over innovative capabilities, accrue disproportionately large wage gains. Conversely, workers whose activities are most susceptible to automation and technological substitution often face stagnating or declining relative wages (Katz & Murphy, 1992).

A growing strand of literature has also emphasised the role of digital platforms and algorithmic technologies in shaping modern labour markets. While not always framed in traditional innovation terms, these technologies represent a continuation of the innovation-inequality nexus. Platform firms, often innovation-intensive and data-driven, structure labour relations in ways that reduce employment protections, compress wages, and shift risks onto workers. This development has raised concerns about a new phase of technologically driven inequality, where innovation leads not to empowerment and mobility but to fragmentation and insecurity, particularly for low and mid-skilled workers. Although this theme is more prominent in recent empirical studies, it builds on theoretical insights regarding how innovation can undermine traditional wage-setting norms and institutions. Thus, innovation plays a central role to innovation in shaping the contemporary trajectory of wage inequality, a relationship that continues to evolve as emerging technologies from artificial intelligence to advanced digital platforms alter the economic landscape (Afonso et al., 2023; Dawid & Neugart, 2023; Rajeshwari et al., 2024; Upreti & Sridhar, 2024; Xin & Ye, 2024).

Although much of the theoretical literature emphasises the inequality-enhancing effects of innovation, it is also important to consider mechanisms through which technological change may reduce wage inequality. Endogenous growth models suggest that innovation-driven productivity growth can generate widespread income gains when accompanied by broad-based human capital development (Galor & Moav, 2000). In this perspective, technological progress raises the returns to ability and education, but when access to education expands, the benefits of innovation can diffuse across a wider share of the labour force, reducing skill premia over time. Goldin and Katz (2007) describe this process as a "race between education and technology," in which countries that successfully expand educational attainment manage to offset the inequality pressures of innovation.

Institutional frameworks may also condition innovation's effects on inequality. Theories of wage-setting regimes argue that collective bargaining and coordinated labour market institutions can ensure that productivity gains from innovation are more evenly distributed across workers (Chu et al., 2016; Freeman, 2007). In such contexts, innovation contributes to overall wage growth without widening intra-firm or inter-sectoral differentials. Similarly, innovation in labour-intensive sectors or in regions where absorptive capacity is high may create employment multipliers that benefit low- and medium-skilled workers, narrowing inequality (Lee & Clarke, 2019). Another mechanism is linked to the diffusion of innovation

across firms and regions. When new technologies spread beyond frontier firms and are adopted more broadly, they can raise the productivity of laggard firms and support wage convergence (Comin & Mestieri, 2018). Policies that promote inclusive innovation, such as subsidies for small and medium enterprises or incentives for regional development, may therefore transform innovation into a force for reducing disparities rather than deepening them.

2.2. The impact of innovation on wage inequality - empirical evidence

The empirical literature on the relationship between innovation and wage inequality has expanded significantly over the past three decades, reflecting the growing concern that technological progress, while boosting productivity and long-term growth, may also exacerbate income disparities within and across countries. Early contributions to this field were largely motivated by the observed polarisation of labour markets in advanced economies, where the growth of high- and low-wage jobs appeared to come at the expense of middle-wage employment. The foundational work of Goldin and Katz (2007), further reviewed by Acemoglu and Autor (2012), framed this empirical phenomenon as a "race between education and technology", in which the capacity of the labour force to adapt to innovation determines the distributional outcome. Their findings, primarily focused on the United States, showed that technological change was outpacing the accumulation of human capital, leading to a growing skill premium and rising wage inequality. This was interpreted as evidence for skill-biased technological change (SBTC), wherein new technologies complement skilled labour and substitute for unskilled workers.

Numerous empirical studies since then have confirmed and extended the SBTC hypothesis across countries and time periods. Card and DiNardo (2002), while acknowledging the influence of technology, also questioned the simplicity of SBTC narratives, noting that wage inequality trends could not be fully explained by education and skill differentials alone. In a broader international context, Esposito and Stehrer (2009) documented sector-specific skill-biased effects in transition economies, demonstrating that technological adoption led to increased wage dispersion, especially in tradable sectors. Similarly, Lemieux (2008) found strong evidence of rising wage inequality driven by demand-side changes, including technology, in OECD countries. Almeida and Afonso (2010) used panel data for 25 OECD countries and confirmed that both trade and SBTC contributed to

rising skill premia, although their relative weights varied across contexts. At the firm level, Black et al. (2004) analysed U.S. data to show that workplace innovation and technological upgrades were associated with increased wage inequality, particularly within firms. This was supported by more recent work by Miao et al. (2020), who examined Chinese listed firms and found that corporate innovation increased intra-firm wage inequality by raising wages at the top more than at the bottom. Similar within-firm dynamics were identified in the European context by Cirillo et al. (2017), who found that firms engaged in innovation tended to exhibit higher wage dispersion. This suggests that innovation may not only differentiate wages across sectors or occupations but also intensify inequality within individual organisations.

Several studies have investigated the spatial dimensions of innovation-induced inequality. Breau et al. (2014), using Canadian city-level data, demonstrated that urban areas with higher rates of innovation tended to experience greater wage inequality, a finding echoed by Lee (2011) for European regions. Lee and Clarke (2019) further explored this phenomenon in the UK, showing that high-tech employment growth led to wage increases primarily at the top of the distribution, with limited spillovers to low-skilled workers. Guo (2019), focusing on Chinese city-regions, confirmed a similar pattern: innovation activity positively correlated with income inequality, particularly in metropolitan areas with higher levels of economic development. These findings point to a common empirical observation: innovation tends to generate geographically concentrated benefits that do not automatically diffuse to peripheral regions or to the broader workforce.

However, empirical evidence is far from unanimous in suggesting a deterministic link between innovation and inequality. Several studies have found more nuanced, or even contradictory, results depending on the institutional, policy, and developmental context. For example, Law et al. (2020), using panel data methods across multiple countries, found that innovation had a negative effect on income inequality in high-income economies, suggesting that innovation can be inclusive when supported by adequate institutions. Similarly, Liu and Lawell (2015), analysing Chinese provincial data, concluded that innovation could reduce inequality if it was accompanied by policies promoting skill development and inclusive urbanisation. In a study of developing countries, Asamoah et al. (2021) used a spatial panel approach to show that innovation and entrepreneurship had mixed effects on income

inequality, with positive spillovers in some regions and negative outcomes in others, depending on absorptive capacity and the structure of local economies.

Industry-level analyses also produce varied findings. Shi et al. (2020)employed firm-level data from OECD economies and found that technological innovation increased firm-level wages overall but disproportionately benefited high-skilled workers. This confirms the presence of innovation premia but raises concerns over distributional effects. Aghion et al. (2017) examined the "innovation premium to low-skill jobs" and found that in some contexts, innovation could boost employment and earnings even at the lower end of the wage distribution, particularly in sectors with strong complementarities between skilled and unskilled labour. Meanwhile, Hatipoglu (2012) offered cross-country evidence that the relationship between inequality and innovation might be bidirectional: not only does innovation influence inequality, but high levels of inequality may also constrain innovation by limiting access to education and reducing social mobility.

Firm-level heterogeneity is another important factor identified in empirical research. Bloom et al. (2018) analysed U.S. employer-employee matched data and observed the "disappearing large-firm wage premium", attributing this partly to differences in innovation intensity across firms. They showed that while leading innovators offered high pay to top-tier workers, the wage advantage for middle and lower-tier employees had eroded over time. A similar dynamic was observed in Latin America: Gómez (2021) used data from Argentine manufacturing firms and showed that innovation increased the wages of managers and technicians but had no significant impact on production workers, thus exacerbating wage inequality within firms.

In developing economies, findings remain mixed. Gonçalves et al. (2008) found that in Brazil and Argentina, the adoption of new technologies led to higher productivity and firm-level profitability but did not translate into more equitable wage structures. Cirera and Martins-Neto (2023) , analysing Brazilian micro-level data, found that innovative firms paid higher wages on average, yet these gains were concentrated in specific occupations and did not reduce overall inequality. In contrast, Ludmer (2019) presented a critical view from the Argentine textile industry, arguing that apparent innovations were often superficial and did not meaningfully improve labour conditions or wage equity. These cases highlight that the nature and depth of innovation, whether radical or incremental, matter greatly in determining its distributional consequences.

Other empirical work has explored how globalisation and international trade interact with innovation to shape wage inequality. Onaran and Stockhammer (2008), analysing Central and Eastern European manufacturing sectors, found that foreign direct investment (FDI) combined with technological upgrading widened wage gaps between skilled and unskilled workers. Akerman et al. (2013) documented similar findings, whereby trade-linked innovation led to higher wage inequality in exporting firms relative to non-exporters. Meanwhile, Pereira and Galego (2019) highlighted diverging patterns of wage inequality across European countries, attributing some of this divergence to national differences in the speed of technological adoption and the protection of workers in innovation-intensive sectors. In Asia, Choi and Jeong (2005) found evidence of a skill premium following rapid technological change in Korea, while Pi and Zhang (2018) confirmed SBTC dynamics in multiple developing economies. Yet, Esquivel and Rodríguez-López (2003) presented a more complex picture for Mexico, where trade and technology influenced inequality before and after NAFTA, with outcomes dependent upon industry characteristics.

Firm-level studies have increasingly attempted to capture micro-dynamics linking innovation to wage inequality. Masso and Vahter (2024), analysing Estonian firms, found that innovation contributed to gender wage gaps, particularly widening disparities in high-technology sectors. Magda et al. (2021) observed that firms in Central and Eastern Europe with higher innovation output displayed greater internal wage inequality, supporting the notion that innovation premiums are unevenly distributed. These findings echo the theoretical perspectives of Lazonick and Mazzucato (2013), who argue that innovation systems disproportionately reward capital owners and strategic employees while socialising risks across the broader workforce. Sbardella et al. (2017) adopted a complex-systems approach to European regions and found that higher technological capabilities were associated with simultaneously higher average wages and greater wage inequality, suggesting that innovation can act as a dual force of prosperity and polarisation.

Recent empirical advances have considered the role of institutions, labour market regimes and intellectual property protection. Chu et al. (2016) examined cross-country data and argued that stronger unionisation could limit the inequality-enhancing effects of innovation, while Zhang et al. (2018) demonstrated that intellectual property regime design has a significant impact on wage inequality by influencing the monopoly rents generated by innovation. Osorio and Pinto (2020) further exhibited that R&D incentives can lead to rising

inequality unless offset by strong redistribution mechanisms. Antonelli and Scellato (2019) looked at directed technological change and found that innovation often favours the skill sets of already advantaged workers, reinforcing pre-existing income disparities. These findings are complemented by Fragkandreas (2022), whose causal analysis suggests that innovation systems co-evolve with inequality in a way that can be self-reinforcing over time.

The empirical literature at the regional level adds further nuance to this debate. Cortinovis et al. (2024) found significant intra-regional wage inequality in Dutch regions associated with economic diversification and innovation intensity. De Oliveira et al. (2024) confirmed similar patterns in Brazilian regions, where innovation amplified wage disparities across municipalities. In contrast, Asamoah et al. (2021) demonstrated that in certain African contexts, innovation and entrepreneurial activity could reduce inequality due to high employment multipliers in low-productivity sectors. Khan and Pazir (2023), using panel threshold models across dynamic economies, found that only once technological capabilities exceed a certain level does innovation begin to exacerbate inequality, indicating that the innovation–inequality nexus may be nonlinear.

Together, the empirical evidence portrays a complex but consistent picture: innovation is rarely neutral in its impact on wage structures. In many contexts, especially advanced economies and high-technology sectors, it tends to widen wage dispersion by increasing the returns to skilled labour and by concentrating rents in innovation-intensive firms and regions. In developing countries, the picture is more heterogeneous - innovation may exacerbate or reduce inequality depending on the composition of the labour force, institutional arrangements, and linkages with trade and FDI. Findings highlight that the distributional effects of innovation depend critically on complementary factors such as education systems, labour market policies, intellectual property regimes, and regional absorptive capacities. Consequently, while innovation remains a key driver of growth, its inequality implications require careful policy attention to ensure that technological transformation does not come at the expense of social cohesion.

Taken as a whole, the theoretical and empirical literatures suggest that innovation operates as a double-edged sword: while it is an essential driver of economic growth, competitiveness, and structural transformation, it also generates asymmetries in how the gains from technological progress are distributed across workers, firms, sectors, and regions. Theoretical models from Schumpeterian creative destruction to modern frameworks of skill-

biased and directed technological change predict that innovation will tend to favour skilled labour, high-productivity firms and innovation-dense regions, thereby widening wage differentials unless offset by education, labour-market institutions and redistributive policy. Empirical evidence largely supports this view, demonstrating that innovation is often associated with higher wage inequality both between and within firms, and across regions. However, empirical results also reveal that these inequality-enhancing effects are not universal, instead being mediated by country-specific institutional settings, sectoral composition, stages of development, and the depth of human-capital endowments. Together, the literature underscores the need for complementary policies that enable innovation-driven growth to proceed without eroding social cohesion and equity in the distribution of wages.

3. Methodology

This section outlines the methodological approach adopted in this dissertation, which is based on a meta-analytical framework. This chapter begins by outlining the concept and procedural steps of meta-analysis, including its advantages and limitations. It then proceeds with the description of the literature review process and the selection criteria used to determine the final pool of empirical studies included in the meta-regression.

3.1. Metanalysis: concept, objectives and procedures

Meta-analysis is a statistical technique designed to synthesise the quantitative findings of multiple empirical studies that investigate a similar research question(Glass, 1976; Neves et al., 2016; Stanley et al., 2008). First introduced formally by Glass (1976), the method has since gained widespread acceptance in fields such as medicine, psychology, education, and increasingly in economics and social sciences. In the context of this dissertation, meta-analysis serves as tool to integrate heterogeneous findings from the empirical literature on the impact of innovation on wage inequality, allowing for a systematic evaluation of existing research evidence. This method also allows us to understand the trends in the literature and to understand better each individual effects of variables on our effect size variable (Borenstein et al., 2009).

At its core, meta-analysis. this aims to estimate a pooled or overall effect size by combining results from individual studies, each weighted according to its precision, the inverse of its variance (Borenstein et al., 2009). This aggregation enhances statistical power and allows for the exploration of patterns, moderators, and potential biases that would not be discernible through narrative reviews alone (Borenstein et al., 2009). Moreover, it enables a deeper understanding of the consistency and robustness of relationships across different contexts, time periods, and methodological approaches (Stanley et al., 2008).

The meta-analytic procedure follows a rigorous protocol consisting of several key steps (Rosenthal, 1979; Stanley et al., 2008). The first step involves formulating a clear and focused research question, which in this study concerns the direction and magnitude of the effect of innovation on wage inequality. The second step entails a comprehensive literature search, using explicit inclusion and exclusion criteria to identify relevant empirical studies. The third stage is data extraction, in which information such as the effect size, standard error, study

characteristics, and methodological attributes are recorded. These data are then used to compute a weighted average effect size, using either fixed-effects or random-effects models depending on the degree of heterogeneity present among the included studies (Borenstein et al., 2009; DerSimonian & Laird, 1986; Neves et al., 2016). If it is high, such heterogeneity can then be explained by means of a multivariate meta-regression (Neves & Sequeira, 2018).

Publication bias refers to the tendency for studies with statistically significant or theoretically expected results to be more likely published than those with null or insignificant findings (Neves et al., 2016; Rothstein et al., 2006; Song et al., 2012). This phenomenon can seriously distort the results of a meta-analysis by overestimating the true effect size and direction, as the body of available evidence becomes unrepresentative of the research conducted (Rothstein et al., 2006). This phenomenon is particularly significant, as some journals or reviewers may have a tendency to favour studies reporting statistically significant results or novel findings - an issue commonly referred to as the 'file drawer problem' (Rosenthal, 1979).

3.2. Literature Search and Selection Criteria

The accuracy, validity, and generalisability of the meta-analytic estimates depend largely on the quality and comprehensiveness of the underlying evidence base (Higgins et al., 2003) knowing that typically larger data analyses will bring more reliable results. Given the primary aim of this study - to examine the relationship between innovation and wage inequality -, a meticulous review methodology was adopted to ensure the inclusion of all pertinent empirical research in the meta-analysis. A comprehensive search strategy was implemented using several prominent academic databases, namely, Scopus, Web of Science databases. These platforms were specifically chosen due to their extensive and multidisciplinary coverage of economics, social sciences, innovation studies, and labour economics literature. The search involved a carefully constructed set of Boolean search strings, combining keywords related to the core research question: ("innovation" OR "technological change" OR "R&D" OR "patents" OR "technological innovation") AND ("wage inequality" OR "income inequality" OR "earnings dispersion" OR “skill-premia” OR “Wage polarisation”). A total of 357 articles were identified, of which 273 were found on the Web of Science database and 84 on the Scopus database. To further ensure comprehensiveness, citation tracking techniques were utilised, including both backward citation tracking (reviewing

reference lists of identified studies) and forward citation tracking (identifying subsequent studies that cited the initially selected key articles). Additionally, a more extensive layer was added in the second stage by applying the same search in Google Scholar, resulting in substantial growth in the total number of articles related to the research question. Given the substantial volume of studies available, explicit inclusion and exclusion criteria were established to start narrowing the results into the final dataset to be used in the meta-analysis. The articles that were the theoretical studies, articles that did not provided a clear econometric value or a t-value of the effect size, articles that did not used innovation factors and wage factors on their analysis, articles that did not had innovation as their independent variable and finally articles that did not report the necessary standard errors. At the end, only 12 articles remained with a total of 291 observations to be analysed.

Since we had a wide range of indicators, scales and units in the collected estimates, it was necessary to transform the reported effect size into a single value applying the commonly used method in meta-analysis: the calculation of the partial correlation coefficient ($\boldsymbol{r_i}$) and its respective standard deviation ($\boldsymbol{se_i}$) (Ugur, 2014), that are expressed as stated below:

$$\boldsymbol{r_i} = \frac{\boldsymbol{t_i}}{\sqrt{\boldsymbol{t^2}_i + \boldsymbol{df_i}}} \qquad (3.1)$$

$$\boldsymbol{se_i} = \sqrt[2]{\frac{(1 - r_i^2)}{\boldsymbol{df_i}}} \qquad (3.2)$$

where: $\boldsymbol{t_i}$ concerns the t-statistic associated with the coefficient of the effect size and $\boldsymbol{df_i}$ denotes the corresponding degrees of freedom.

After applying this methodology, a total of 61 results with a negative r_i value were obtained, one result was null, and 198 results were positive. The range of values varies between -0,3640 (Greiner et al., 2004) and 0,4794 (Greiner et al., 2004). Additionally, some common patterns were identified across the studies, which are important to highlight. Regarding innovation indicators, the most frequently used measure was patents or patent-related indexes, employed in 41% of the total observations (120 out of 292). This was followed closely by R&D intensity, used as a proxy for innovation in 37.5% of the

observations (109). The studies predominantly focused on developed European countries, reflecting both the availability of consistent innovation data and the relevance of innovation policy in these regions. Furthermore, the most common level of analysis was geographical units such as municipalities, regions, or countries, which accounted for 56% of the total observations. The table below lists the average values of r_i and se_i per study, as well as some of the min characteristics of each study.

Table 1 - Summary of the main characteristics of the studies

Author	Number of estimates	Average effect size R_i	Average standard error (Se_i)	Time frame	Sample countries	Measure of innovation	Unit of analysis
Aghion et al.(2017)	42	-0,0044	0,0013	2004-2015	UK	R&D intensity	Individuals/ Families
Andreassen (2018)	95	0,09156	0,02578	1995-2015; 1998-2003; 1995-1998; 2004-2009; 1999-2003	Norway	Patents application divided by 1000; Patents application per thousand; Patents divided by 1000; Patents per thousand population	Municipalities
Angelini et al.(2009)	11	0,15082	0,09889	1994-2001	France, Italy, Netherlands, Portugal, Spain and UK	Expenditure for innovation-related machinery per worker; Share of firms with product innovations; Share of innovative firms	Industries
Breau et al. (2014)	14	0,12582	0,06273	1996, 2001-2006	Canada	Number of Patents;	Municipalities

						Knowledge intensive Business Services	
Cattani et al.(2024)	8	0,04405	0,07525	2000-2015	12 OCDE countries	Ln of patent density; Ln of R&D expenditures per worker; R&D expenditures per worker	Countries
Choi & Jeong (2005)	8	0,03407	0,01943	1998-2001	South Korea	R&D intensity; Expenditure on the information and communication technology to GDP; Percentage of Scientists and Engineers; Total Factor Productivity	Individuals/ Families
Cirera & Martins-Neto(2023)	12	-0,0001	0,0001	2014-2017	Brazil	Expenditure in R&B by firms	Individuals/ Families
Cirillo et al.(2017)	26	0,01455	0,00975	2010	Italy, France, Germany and Spain	Innovation index; Multi dimension index of innovation;	Companies
Gómez (2021)	20	0,0117	0,0241	2010-2012	Argentina	Spending on innovation per worker	Industries
Greiner et al (2004)	6	0,12638	0,17179	1964-1999; 1974-1998	US; Germany	R&D intensity; R&D investment and Patents	Country

Lee(2011)	40	0,144616	0,10708	1996-2001	EU	Employment in knowledge intensive per total employment; Patents per million population	Region
Van Reenen (2011)	9	-0,031042	0,10271	1980-2004	11 OCDE countries	ICT intensity /investment; R&D Investment	Industries

4. Estimation of mean effect size and publication Bias

Estimating the average effect size is a fundamental step in meta-analysis, which allows having a quantitative synthesis that integrates the results from individual empirical studies into a single, coherent estimate (Gurevitch et al., 2018; Higgins et al., 2003; Rothstein et al., 2006; Stanley et al., 2008). This synthesis provides a comprehensive view of the magnitude and direction of a relationship across multiple independent studies, thereby enhancing statistical power and yielding more precise and reliable conclusions than those obtained from individual studies alone (Borenstein et al., 2009). In this thesis, the mean effect of interest specifically concerns the impact of innovation on wage inequality, a critical economic and social issue with extensive implications for public policy, theoretical development and to deepen understand their economic impact.

Two primary methodological approaches exist for estimating this mean effect: the fixed-effects model and the random-effects model. Each approach makes distinct assumptions regarding the nature of variability among studies, influencing both the estimation procedures and the interpretation of results (Veroniki & McKenzie, 2024). The fixed-effects model presumes the existence of a single, true effect size common across all studies, suggesting that any observed differences in study outcomes arise solely due to random sampling error. This model is suitable when studies are highly homogeneous, employing comparable methods, populations, and measurement strategies (Borenstein et al., 2009). The advantage of this model lies in its simplicity and interpretability; however, its assumption of homogeneity is often restrictive, particularly when studies differ markedly in characteristics such as research context, sample composition, or econometric methodologies (Borenstein et al., 2009). In this approach the mean size effect is calculated by the weighted average of the effects $\boldsymbol{r_i}$,with weights correspond to the inverse of the respective variance $\frac{\mathbf{1}}{\boldsymbol{se_i^2}}$.

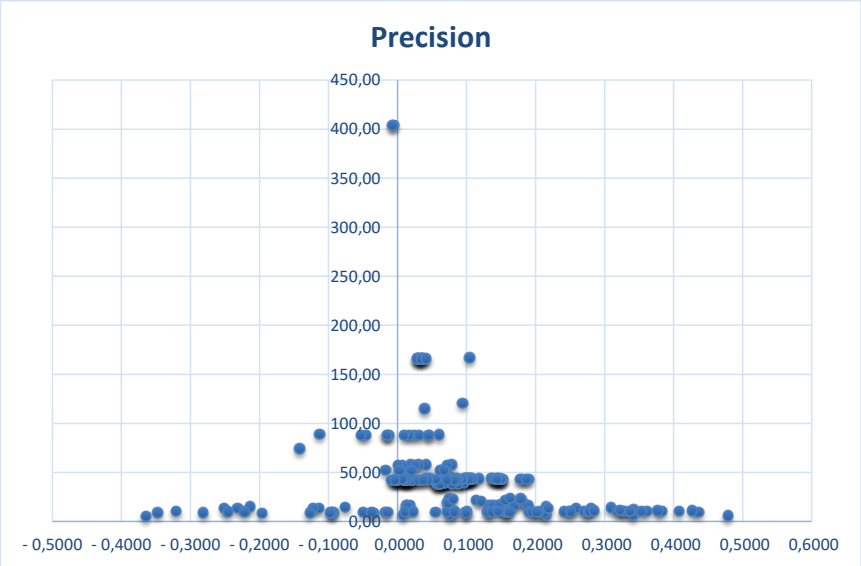
In contrast, the random-effects model acknowledges inherent heterogeneity among studies, assuming that each study estimates an effect drawn from an underlying distribution of true effects. Variability thus arises both from sampling error within individual studies and genuine differences in the true effects across diverse study contexts, methods, population and measurements (DerSimonian & Laird, 1986). This model typically provides more realistic and generalisable estimates, especially in contexts characterised by methodological diversity and contextual variation, as is often the case in economic research examining

complex phenomena such as innovation and wage inequality. Consequently, the random-effects model is commonly preferred in practice for its robustness and capacity to incorporate heterogeneity explicitly into the meta-analytic framework (Viechtbauer, 2016). This model assumes the existence of both within-study variance and between-study variance. The random effects estimator also corresponds to a weighted average of the effect sizes, with weights given by $\mathbf{1}/(\boldsymbol{se_i^2} + \boldsymbol{\theta^2})$, where $\boldsymbol{se_i^2}$ represents the variation of sampling errors and $\boldsymbol{\theta^2}$ represents the variation between studies.

The application of these models to the sample considered in this meta-analysis reveals a divergent average effect of innovation on wage inequality. However, the magnitude and direction of the effect vary depending on the estimation method employed. When the fixed effects model is applied, the average effect is virtually zero, with a coefficient of -0.0001. In contrast, the random effects model produces a positive average effect of 0.0605. This divergence highlights the sensitivity of the results to underlying model assumptions, particularly regarding the homogeneity of effects across studies. The fixed effects model assumes that all studies share a common true effect size, whereas the random effects model allows for heterogeneity, capturing both within and between study variance (Borenstein et al., 2009).

In order to address the potential problem of publication bias, we employ one of the most widely used graphical methods - the funnel plot. This tool plots individual study effect sizes against their precision (that is, the inverse of the standard errors). In the absence of publication bias, the plot should resemble a symmetrical inverted funnel. Asymmetry in the funnel plot may indicate that smaller studies with non-significant results are missing from the published literature (Egger et al., 1997) – that is, the existence of publication bias. The figure 1 below, presents funnel plot constructed to examine the presence of publication bias in the meta-analysis of the relationship between innovation and wage inequality based on Egger (1997) methodology.

Figure 1 *- Funnel Plot for the analysis of the impact of innovation on wage inequality (test of publication Bias)*



The funnel plot suggests the existence of a symmetry around the average mean value (0,067), which tend to indicate the absence of *Publication Bias*. However, despite its usefulness, this method carries a degree of ambiguity and subjectivity that is intrinsic to visual inspections. To address this limitation, a complementary approach was adopted to assess the presence of publication bias. Specifically, to complement the visual inspection, formal statistical tests can be employed. Egger's regression test (Egger et al., 1997) regresses the effect size on its standard error, testing for the asymmetry of the funnel plot. This method is formally expressed as follows:

$$r_i = \propto_0 + \propto_1 Se_i + \mu_i \qquad (4.1)$$

In the presence of publication bias, higher standard errors tend to report larger effect sizes. This means that $\propto_1$ differs significantly from zero and there should exist a high correction between r_i and Se_i. On the other hand, if the results vary randomly around the

mean effect $\propto_0$ independently of $\boldsymbol{Se_i}$, this suggest no substantial evidence of publication bias (Egger et al., 1997; Stanley, 2005). Thus, a test to $\propto_1$=0 is a test to the existence of publication bias, while a test to $\propto_0$=0 is a test to the existence of a true effect size beyond publication bias. Nevertheless, it is essential to acknowledge two key methodological challenges when estimating the previous equation: (i) the presence of heteroscedasticity in the error term μ_i, which arises due to variation in standard errors across individual estimates; and (ii) intra-study autocorrelation among estimates, which may occur because estimates from the same study share the same samples and specifications (Stanley, 2005). The presence of heteroscedasticity is defined as the situation where the variance of residuals is not constant across observations (White, 1980). In meta-analyses, heteroscedasticity often arises due to variability in study designs, differing sample sizes, methodological heterogeneity, or measurement errors across studies (Stanley et al., 2008). Although heteroscedasticity does not result in biased coefficient estimates, it adversely affects the accuracy of standard errors, potentially compromising statistical inference and leading researchers toward misleading conclusions regarding the significance of analysed effects (White, 1980). To address this issue, a common procedure involves dividing both sides of the equation by the standard error, resulting in the transformed expression:

$$\boldsymbol{t_i = \alpha_0 precision_i + \alpha_1 + v_i} \quad (4.2)$$

where $\boldsymbol{t_i}$ denotes the t-statistic associated with each partial correlation coefficient $\boldsymbol{r_i}$ in the primary studies, and $\boldsymbol{precision_i}$ represents the inverse of the standard error $\boldsymbol{1/Se_i}$. In this specification, the coefficients are reversed - the Funnel Asymmetry Test (FAT) evaluates the significance of the intercept α_1 to detect publication bias, while the Precision Effect Test (PET) examines the slope α_0, which indicates whether a genuine underlying effect remains after accounting for bias (Stanley, 2005).

Regarding the second issue, autocorrelation among multiple estimates drawn from the same study, one proposed solution in the literature involves restricting the meta-analysis to a single effect size per study (Lipsey & Sjoholm, 2005). The standard meta-analysis approach techniques assume that all observations are independent, and if this assumption is violated it

may conduct to type I error and the result may mislead conclusion(Borenstein et al., 2009). The application of a clustered robust standard error (grouped by study) may adjust the model and lead to a more thorough result. While seemingly straightforward, this approach introduces two major limitations: first, the selection of a single representative estimate inherently involves a degree of subjectivity, potentially introducing selection bias (Borenstein et al., 2009); second, it substantially reduces the sample size, which can significantly undermine statistical power and the representativeness of the results. Given these drawbacks, more robust alternatives have emerged and gained traction in the meta-analytic literature. Three widely accepted approaches are: (i) the application of Ordinary Least Squares (OLS) regression with clustered standard errors, treating each study(article) as a cluster; (ii) OLS with bootstrapped standard errors; and (iii) the use of hierarchical (multilevel) models, in which estimates are grouped based on shared study-level characteristics. In contrast to the first two approaches, hierarchical models allow researchers to disentangle within-study and between-study variation (Neves & Sequeira, 2018; Ugur et al., 2016; Van den Noortgate et al., 2013). A hierarchical model can be specified as follows:

$$\boldsymbol{Y_{i,j} = (\beta_0 + \gamma_{0,j}) + (\beta_1 + \gamma_{i,j})X_{i,j} + \varepsilon_{i,j}} \quad (4.3)$$

where *i* indexes' observations and *j* refer to clusters (e.g., studies or articles); β_0 and β_1 are the fixed intercept and slope, respectively, while $\gamma_{0,j}$ and $\gamma_{1,j}$ represent the random intercept and slope components across groups.

While the three methods account for intra-study correlation, it is important to note that they can yield differing coefficient estimates and significance levels. This divergence reflects their fundamental conceptual differences: OLS assumes fixed coefficients across studies, whereas hierarchical models permit variation in coefficients between studies (Neves & Sequeira, 2018). Additionally, OLS performs optimally only under balanced data conditions. By contrast, hierarchical models use maximum likelihood estimation techniques, such as restricted maximum likelihood, which are better suited to datasets with unequal numbers of observations per group. As a result, hierarchical models provide asymptotically efficient estimates even with unbalanced data structures (Hox, 2003). To ensure analytical robustness, the selected variables were incorporated into three distinct regression specifications: (i) an

Ordinary Least Squares (OLS) regression with clustered robust standard errors, (ii) an OLS bootstrap regression, and (iii) a multivariate mixed-effects model.

Table 2 – Publication bias test

Coefficient	OLS cluster robust	OLS bootstrap	Mixed effects
Precision	-0,0003071* (0,00014)	-0,0003071 (0,0143801)	-0,000199 (0,000179)
Constant	1,539262 (0,226788)	1,539262* (0,9437067)	1,090678* (0,5643416)
Total observations	291	291	291
Total studies	12	12	12

*Notes: standard errors in parenthesis; significance levels: *** p-value < 0.01, ** p-value < 0.05, * p-value < 0.1*

An analysis of the scatter plot and the three estimation methods reveals that there is no evidence of publication bias. In fact, the table above shows that the constant is not statistically different from zero, which denotes the absence of publication bias. Moreover, *Precision* is not statistically significant in any of the three estimates, suggesting that the overall effect of innovation on wage inequality. However, it should be noted that an overall zero effect does not necessarily imply that innovation has no impact on wage inequality. In fact, the impact may be positive in some specific circumstances and negative in others and both types of impact may offset each other. We explore this in more detail in the next section.

5. Multivariate meta regression

In this chapter we estimate a multivariate meta-regression with the aim of explaining the heterogeneity of the effect sizes reported in the primary studies.

A critical early step involved the creation of a comprehensive set of dummy variables designed to capture heterogeneity in study design, estimation approach, sample, period, and measurement methods. These binary variables were developed to control for potential sources of variation across studies and therefore will be included as moderator variables in the multivariate meta-regression analysis.

***Table 3* – Dummy variables created for the meta-analysis**

Variable	Dummies	Description
Journal	D_journal	1 if the study is published in a scientific journal, 0 otherwise
Country	D_Europe	1 if the country under analysis is European or if most countries are European, 0 otherwise
Time Frame	D_TimeFrame_05	1 if the years of the sample are equal or posterior to 2005, 0 otherwise[1]
Unit of Analysis	D_unit_Country	1 if the unit of analysis is the country as whole, 0 otherwise
Unit of Analysis	D_unit_Municipalities	1 if the unit of analysis is the municipalities/regions of a country, 0 otherwise

[1] *The year 2005 was selected as a key cut-off point (D_TimeFrame_05), as it marked the mass adoption of the Google search engine as the dominant gateway to information retrieval. Moreover, it was during this period that key social media platforms such as YouTube and Facebook were launched, initiating a new wave of digital connectivity that dramatically changed the landscape of communication, information dissemination, and knowledge sharing (Kaplan & Haenlein, 2010).*

Unit of Analysis	D_unit_Industries	1 if the unit of analysis is the industries or companies, 0 otherwise
Unit of Analysis	D_unit_individuals	1 if the unit of analysis is individuals, 0 otherwise
Estimation Model	D_est_ols	1 if the estimation method is OLS, 0 otherwise
Estimation Model	D_est_fixed	1 if the estimation model is Fixed Effects, 0 otherwise
Data structure	D_data_cross	1 if the data structure used is cross-section, 0 otherwise
Innovation Measurement	D_innov_patents	1 if innovation is measured by patents or any other indicator containing patents, 0 otherwise
Innovation Measurement	D_innov_rdintesity	1 if innovation is measured by R&D intensity or any other indicator containing R&D intensity, 0 otherwise
Wage inequality measurement	D_wage_gini	1 if wage inequality is measured by the Gini Index, 0 otherwise
Wage inequality measurement	D_wage_skillpremium	1 if the wage inequality is measured by the skill premium, 0 otherwise
Others	D_others_restr_patents	1 if the sample excludes the regions with more patents, 0 otherwise
Others	D_others_innov_lag	1 if the innovation variable is lagged for at least 1 period, 0 otherwise

In addition to the dummies, the square root of the number of citations of each article (*Sqr_citations*) was used as a moderator variable in the multivariate meta-regression in order to capture a possible association between the reported effect sizes and the quality of the article.

Prior to estimating the meta-regression, the correlation matrix with all moderator variables was analysed (Table 5 – annex). The purpose was to identify potential multicollinearity issues that could distort coefficient estimates and statistical inference. In order to eliminate such issues, only variables with a correlation below 50% were included in the meta-regression. They are *D_journalS, D_europeS, D_unit_IndustriesS, D_est_fixedS, D_innov_PatentsS, D_wage_skillpremiumS, D_others_restr_patentsS, D_others_innov_LagS, and SQR_Citations*.

The table below presents the results of the estimation of the multivariate meta-regression using the three techniques mentioned in the previous section.

Table 4- Meta-regression estimates of the innovation's impact on wage inequality

Variable	OLS clustered robust standard errors	OLS bootstrap	Multivariate mixed-effects model
Precision	0,0000062 (0,0000598)	0,0000062 (0,0219223)	0,0000062 (0,0000588)
D_journal	0,0544102 *** (0,0108194)	0,0544102 (0,0621683)	0,0544102 *** (0,0106312)
D_Europe	-0,0012007 (0,010357)	-0,0012007 (0,0634856)	-0,0012007 (0,0106312)
D_unit_industries	-0,0584492 *** (0,109514)	-0,0584492 (0,0527239)	-0,0584492 *** (0,107609)
D_est_Fixed	-0,0880577 *** (0,0073001)	-0,0880577 *** (0,0185925)	-0,0880577 *** (0,0071731)

D_innov_patents	0,0075129 (0,128718)	0,0075129 (0,0262874)	0,0075129 (0,012648)
D_wage_skillpremium	-0,0651598 *** (0,132413)	-0,0651598 (0,052926)	-0,0651598 *** (0,013011)
D_others_restr_patents	0,0213039 ** (0,0084858)	0,0213039 *** (0,0033458)	0,0213039 *** (0,0083382)
D_others_innov_lag	-0,0203173 ** (0,0084863)	-0,0203173 *** (0,0026606)	-0,0203173 ** (0,0083387)
SQR_Citations	-0,0011144 (0,0008545)	-0,0011144 (0,0087025)	-0,0011144 (0,0008396)
Constant	3,376407 *** (0,4822096)	3,376407 (3.151707)	3,376407 *** (0,4738226)
Total Observations	291	291	291
Total studies	12	12	12

*Notes: standard errors in parenthesis; significance levels: *** p-value < 0.01, ** p-value < 0.05, * p-value < 0.1*

The results presented in the Table 4 reveal that three variables (*D_others_innov_lag, D_others_restr_patents*, and *D_est_fixed*) are consistently statistically significant across all specifications. This consistent significance suggests that these variables may play a structurally important role in shaping the relationship between innovation and wage inequality. Analysing each one of these variables, we can access that *D_others_restr_patentsS* captures whether a study imposes geographic restrictions, by excluding the provinces or municipalities with a high number of patents per capita. The positive and statistically significant coefficient associated with this variable indicates that when such high-innovation regions are removed from the sample, the observed effect of innovation on wage inequality tends to increase. This finding may suggest that in less innovation-intensive areas, the introduction of innovation exerts a more disruptive influence on local labour markets, possibly due to lower absorptive capacity or weaker skill-matching mechanisms, leading to

greater wage divergence. In contrast, highly innovative regions may already possess more inclusive innovation ecosystems or better institutional frameworks that cushion the inequality-enhancing effects of technological change (Lee, 2011; Lee & Rodríguez-Pose, 2016). On the other hand, *D_others_innov_lag*, which denotes the presence of a time lag in the innovation variable, consistently shows a negative and significant relationship with wage inequality. This suggests that when innovation is modelled with a temporal delay, its impact on wage inequality appears to diminish or even reverse. One plausible interpretation is that the redistributive effects of innovation may take time to materialise: initially, innovation may concentrate rewards among skilled workers, but over time, as new technologies diffuse and spillovers reach broader segments of the labour market, the wage gap may narrow. This delayed effect is in line with endogenous growth theories where learning, adjustment, (Acemoglu, 2008; Acemoglu & Restrepo, 2020). Additionally, *D_est_fixed*, indicating the use of fixed-effects models, is also significant across all three regressions. This may reflect either a methodological artefact, suggesting that studies using fixed effects tend to yield systematically different (and more negative) estimates or could hint at publication bias if journals or authors disproportionately favour models that control for unobserved heterogeneity. Given the popularity of fixed-effects estimators in panel data studies, particularly in applied labour economics, this result warrants caution in interpreting findings from such models without appropriate robustness checks.

In addition to these three consistently significant variables, three others, *D_journal, D_unit_Industries*, and *D_wage_skillpremium*, are statistically significant in two out of the three regression models, suggesting a potentially strong, though slightly more model-sensitive, influence on the relationship between innovation and inequality. The *D_journal* variable indicates that studies published in academic journals are more likely to report a positive effect of innovation on wage inequality. This may reflect a tendency for peer-reviewed literature to emphasise significant or novel findings, raising again the possibility of publication bias. It may also be that higher-quality studies, more likely to be published in journals, are better able to detect complex innovation-inequality dynamics. Regarding the *D_unit_Industries*, the results suggest a negative relationship between innovation and wage inequality when the unit of analysis is the industry or company level. This may point to the equalising role of innovation within sectors, where productivity gains or technological upgrading benefit a broader segment of workers, possibly through wage compression mechanisms or workforce upskilling (Bloom et al., 2018). It implies that, within innovative industries, the returns to

innovation may be more evenly distributed than when aggregated at regional or national levels. Lastly, *D_wage_skillpremium*, which identifies studies that use the skill premium as their inequality measure, also shows a negative relationship. This suggests that studies using more targeted or innovation-specific measures of wage dispersion tend to find a narrowing of the wage gap. One interpretation is that when innovation is captured not as a broad macro trend but in terms of its direct impact on firm-level wage structures, the effect appears more inclusive. It may also indicate that innovation-led wage premiums are less distorted when adjusted for worker skills.

Additionally, the results clearly indicate that the variables *D_Europe*, *D_innov_patents*, and *SQR_Citation* are not statistically significant in explaining the effect of innovation on wage inequality. This lack of statistical relevance suggests that, within the scope of this meta-analysis, neither the geographical focus on European countries (*D_Europe*), nor the use of patent-based innovation measures (*D_innov_patents*), nor the squared number of citations (*SQR_Citation*) contribute meaningfully to variations in the reported effect sizes. These findings may imply that the influence of innovation on wage inequality is not driven by regional context alone, nor by this specific proxy for innovation.

6. Conclusion

This dissertation investigated the relationship between innovation and wage inequality through a systematic review and meta-analysis of the empirical literature. Innovation is widely recognised as a key driver of growth, productivity and competitiveness in modern economies, yet its distributive consequences are contested. While theories such as skill-biased technological change and Schumpeterian creative destruction anticipate widening wage gaps (Acemoglu, 2003; Aghion & Howitt, 1992b), empirical findings have often been mixed and fragmented. By quantitatively synthesising a large body of studies, this dissertation provides clearer evidence of how innovation shapes the distribution of wages across workers, firms, and regions.

The meta-analytical results offer several important insights. They show that, on average, innovation has a positive yet statistically insignificant effect on wage inequality. This finding partially supports a substantial strand of literature showing that new technologies tend to benefit skilled workers, high-technology firms, and urban regions (Breau et al., 2014; Cirillo et al., 2017; Lee, 2011). The positive and statistically significant coefficient on the *D_others_restr_patents* dummy suggests that in less innovation-intensive areas, technological change exerts a stronger disruptive impact on wage structures. This may reflect lower absorptive capacity and weaker skill-matching mechanisms in such regions, which amplify wage divergence. By contrast, in highly innovative regions, more inclusive innovation ecosystems and stronger institutional frameworks may mitigate the inequality-enhancing effects of innovation, cushioning workers from the disruptive pressures of technological change. (Andreassen, 2018; Breau et al., 2014; Lee, 2011; Miao et al., 2020). The negative and significant coefficient for *D_others_innov_lag* indicates that when innovation is modelled with a temporal lag, its estimated impact on wage inequality diminishes. This points to the existence of delayed redistribution effects: while innovation may initially widen wage gaps, diffusion and spillovers over time can attenuate these disparities (Andreassen, 2018). Taken together, these results suggest that the distributive consequences of innovation cannot be reduced to a single direction of effect. Rather, they depend on the methodological lens, the regional innovation context, and the time horizon considered. In regions with strong innovation ecosystems, inequality effects appear less severe, while in lagging regions the same processes can be more polarising. Over time, however, the inequality-enhancing effects of

innovation may weaken, supporting the view that innovation has both short-run disruptive and longer-run equalising components.

In addition to the consistently significant variables, the analysis of *D_unit_Industries* and *D_wage_skillpremium* also provides relevant insights. The negative and statistically significant coefficient of *D_unit_Industries* suggests that, when the unit of analysis is at the industry or firm level, innovation is associated with a reduction in wage inequality. This finding points towards the possibility that productivity gains and technological upgrading within firms or sectors may be more evenly shared among workers, thereby compressing wage differentials. Similarly, the negative and significant effect of *D_wage_skillpremium* indicates that studies using the skill premium as a measure of inequality tend to report a narrowing of wage disparities. This outcome suggests that innovation, when measured in relation to its direct impact on returns to skills, may promote more inclusive wage dynamics, contrasting with broader aggregate measures of inequality. Together, these results highlight that the level of analysis and the chosen inequality indicator crucially shape the observed distributive consequences of innovation.

Like any study, this dissertation faces some limitations. The significant role of methodological choices highlights that results across studies are not fully comparable, and fixed-effects estimators appear to drive systematic differences. In addition, the significance of regional exclusions suggests that heterogeneity in spatial coverage can distort findings, while the role of time lags underlines the importance of longitudinal data, which is still limited in many contexts. Data availability also remains a challenge, particularly in developing economies, where longitudinal or firm-level datasets are scarce. Future research should therefore pay close attention to these factors. Greater methodological consistency, more careful consideration of regional contexts, and the explicit modelling of time lags in the relationship between innovation and inequality would all contribute to more robust and comparable evidence. Extending meta-analyses to new waves of innovation, including artificial intelligence and green technologies, would also be valuable in assessing whether the same temporal and spatial dynamics hold in different technological domains.

In conclusion, the meta-regression shows that innovation's effect on wage inequality is conditional, not deterministic. By identifying the specific conditions under which innovation is more inequality-enhancing or inequality-reducing, this dissertation adds further insights

and underscores the importance of methodological rigour and contextual sensitivity in understanding the complex link between technological progress and income distribution.

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Annexes

Table 5 - Correlation Matrix between variables

Variables	D_journal	D_Europe	D_TimeFrame_05	D_Unit_Municipalities
D_journal	1,00000			
D_Europe	-0,19490	1,00000		
D_TimeFrame_05	-0,59290	0,10220	1,00000	
D_Unit_Municipalities	-0,49310	0,12410	0,13200	1,00000
D_unit_Industries	0,25700	-0,14060	0,05390	-0,40690
D_unit_Individuals	-0,14400	-0,16060	0,24150	-0,39090
D_est_olsS	-0,21340	0,34270	0,23170	0,52250
D_est_fixedS	0,26250	-0,10630	-0,23320	-0,36780
D_data_cross	0,18680	-0,18730	0,16300	-0,37080
D_innov_patents	-0,32170	0,31960	0,12460	0,70400
D_innov_rdintesity	0,08320	-0,25840	0,32220	-0,65660
D_wage_gini	-0,50690	0,26480	0,14190	0,86050
D_wage_skillpremium	0,14360	-0,08900	-0,00540	-0,52720
D_others_restr_patents	-0,25770	0,13910	0,12140	0,37120
D_others_innov_lag	-0,25100	0,13550	0,19960	0,36160

Comentado [PN1]: Atenção que nesta tabela devem estar apenas as variáveis que constam na Tabela 3 + SQR Citations. Todas as outras têm de ser retiradas.
Para além disso, os nomes dessas variáveis devem ser iguais aos da Tabela 3.

Comentado [J[2R1]: resolvido

Table 6- Correlation Matrix between variables (continue)

Variables	D_unit_Industries	D_unit_Individuals	D_est_olsS	D_est_fixed
D_journal				
D_Europe				
D_TimeFrame_05				
D_Unit_Municipalities				
D_unit_Industries	1,00000			
D_unit_Individuals	-0,28180	1,00000		
D_est_olsS	0,05330	-0,43380	1,00000	
D_est_fixedS	-0,45370	0,55290	-0,80660	1,00000
D_data_cross	0,91130	-0,25680	-0,02470	-0,41340
D_innov_patents	-0,33220	-0,47740	0,58010	-0,39020
D_innov_rdintesity	0,48730	0,52770	-0,21680	0,08510
D_wage_gini	-0,42220	-0,40560	0,54010	-0,37950
D_wage_skillpremium	-0,03090	0,74160	-0,33920	0,33280
D_others_restr_patents	-0,15100	-0,14510	0,28960	-0,23360
D_others_innov_lag	-0,14710	-0,14140	0,28210	-0,22760

Table 7- Correlation Matrix between variables (continue)

Variables	D_data_crossS	D_innov_patent	D_innov_rdintesity	D_wage_gini
D_journal				
D_Europe				
D_TimeFrame_05				
D_Unit_Municipalities				
D_unit_Industries				
D_unit_Individuals				
D_est_olsS				
D_est_fixedS				
D_data_cross	1,00000			
D_innov_patents	-0,27900	1,00000		
D_innov_rdintesity	0,42500	-0,62080	1,00000	
D_wage_gini	-0,38480	0,72160	-0,68120	1,00000
D_wage_skillpremium	-0,14370	-0,54100	0,56690	-0,54700
D_others_restr_patents	-0,13760	0,30400	-0,24370	0,35770
D_others_innov_lag	-0,13410	0,29610	-0,23740	0,34850

Table 8- Correlation Matrix between variables (continue)

Variables	D_wage_skillpremium	D_others_restr_patents	D_others_innov_lag
D_journal			
D_Europe			
D_TimeFrame_05			
D_Unit_Municipalities			
D_unit_Industries			
D_unit_Individuals			
D_est_olsS			
D_est_fixedS			
D_data_cross			
D_innov_patents			
D_innov_rdintesity			
D_wage_gini			
D_wage_skillpremium	1,00000		
D_others_restr_patents	-0,19570	1,00000	
D_others_innov_lag	-0,19060	-0,07580	1,00000