Essays on Innovation, Growth, and Inequality

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List of Abbreviations

Abbreviation	Full Definition
SBTC	Skilled Biased Technical Change.
R&D	Research and Development.
CRRA	Constant Relative Risk Aversion
NUTS2	Nomenclature of Territorial Units for Statistics – Level 2 in EUROSTAT Data base.
GDP	Gross Domestic Product.
OECD	Organization for Economic Co-operation and Development.
GMM	Generalized Method of Moments.
TSLS-HT	Two-Stage Least Squares – Heteroskedasticity Method.
PPS	Purchasing Power Standard.
RPI	Retail Price Index.
PCT	Patent Cooperation Treaty.
EUROSTAT	European Union statistical office.
BHPS	British Household Panel Survey.
OBV	Omitted Variables Bias.
IV	Instrumental Variable.
IMF	International Monetary Fund.
IPR	Intellectual Property Rights.

Summary

This thesis studies three essential topics in growth, innovation, and inequality. First, we propose a model to describe the relationship between the productivity of two kinds of workers (highly and low-skilled) and economic growth along the "creative destruction" concept. Our results reveal that the social planner intervention is efficient in allocating economic resources when unskilled labour productivity is very low. However, highly and low-productive skilled labour and highly productive unskilled labour do not involve such intervention due to the efficiency of a decentralized economy to achieve the desired growth. Next, using the Generalized Method of Moments (GMM) and Two-Stage Least squares (TSLS)-Heteroskedasticity methods, we study the impact of innovation on income inequality in the European cross-regional panel data. We find that innovation decreases income inequality in general but increases the gap in the top of the income distribution. Finally, we examine the effect of innovation on wage inequality and different wage shares in the UK regions by using British Household Panel Survey (BHPS) data. We utilize parametric and non-parametric approaches to find where innovation has the highest effect on wage distribution. The results show that innovation increases the general measures of wage inequality, while it does not show any impact on the top and the bottom wage shares.

Paper 1: Innovation and economic growth with heterogeneous labour productivity

Abstract

Innovation and technological progress are the drivers of economic growth. This study argues that heterogeneity in labour productivity is critical in the extent of economic growth and resource allocation. We expand the model used by (Acemoglu et al., 2018) to describe the relationship between the productivity of two kinds of workers (highly and low-skilled) and economic growth along the line of the "creative destruction" concept. In our model, skilled and unskilled workers are employed in the intermediate sector affecting the level of Research & Development (R&D). The results show that the social planner intervention is efficient in allocating economic resources when unskilled labour productivity is very low. In this case, reallocating these resources to improve unskilled labour productivity will enhance economic growth. However, highly and low-productive skilled labour and highly productive unskilled labour do not involve such intervention due to the efficiency of a decentralized economy to achieve the desired growth in this manner. Moreover, we study the best policy for the government to promote growth. Our findings indicate that the optimal policy is subsidizing low-productive firms and providing advisory services to the low- productive unskilled employees to boost economic growth.

*1.1 **Introduction***

The efficient design of the industrial policy plays an important role in generating growth at the country level. Keeping in mind that allocating the economic resources to support firms and enhance labour productivity is one of the main pillars of this policy. However, there is uncertainty about the best policy for allocating these resources and its relationship with innovation and R&D. In this paper, we build a model that shows the functionality of subsidizing firms and employees depending on their productivity. The model produces heterogeneity in the firm and labour productivity levels, predicting dissimilarities in economic growth across countries. Although investment in R&D is crucial for the economy to grow faster, its cost is not necessarily associated with technological progress. For instance, the USA in the eighties experienced a huge yearly investment in R&D that exceeded the "foregone tax revenue" (Hall, 1993). But the question: Is this R&D spending reflecting improvement in technology and productivity of labour, or is it related to other marketing and administrative research? Hence, our model highlights the effect of the different skilled groups of labour on R&D intensity, which leads to efficiency in directing the countries' public funding to obtain high levels of economic growth. The model also coordinates the investment in R&D to economic growth by describing the mechanism of government intervention in the economy to achieve optimal results in enhancing low-skilled labour productivity.

Economic growth is one of the main essential subjects that has drawn the attention of many economists. There is still a debate about the optimal use of resources that impacts its enhancement. This kind of debate is due to the ambiguity about its reasons. Firms' productivity is often the core of this debate regarding how the developed models are suitable to fit the dynamics of firm entry and exit, output, and R&D. Less known, however, is the effect of heterogeneous labour productivity on growth. In this paper, we aim to fill this gap by considering two different kinds of labour (skilled and unskilled) with different types of productivity (high and low) and study their impact on economic growth.

In traditional economic theory, economists have examined capital formation to explain economic growth. In their view, capital could cause labour productivity to rise in a dynamic investment and growth. These models did not present intangible capital, such as human capital and technological progress, as endogenous factors in their analysis. Considering this part in formulating economic growth is essential in two aspects. First, technological progress might be a source of sustained growth and make it possible for capital persistence even if the ratio of capital to primary inputs starts to grow large. Second, considering technological progress as an endogenous variable in these models could help explain the portion of measured growth in the national product that cannot attribute to the accumulation of inputs. Expanding this concept to include Research and Development (R&D) and human capital enriches the ability of these models to explain the factors that account for economic growth.

In order to understand this concept within the framework of this study, it needs to focus on the notion of innovation design and how the allocation of workers (skilled and unskilled labour) affects productivity growth when they are heterogeneous. The model we use is a version of the Schumpeterian theory of firm evolution and growth, developed by (Klette and Kortum, 2004). The main question of this paper is to know how technological changes affect the allocation of economic resources when labour are heterogeneous in their productivity and what is involved in enhancing the economic growth in the case of inefficient use of these resources. Another vital point to consider is related to economic policies (subsidies or taxes) that governments could adopt to achieve this target. Many countries use subsidies or taxes on the labour force or firms to stimulate economic growth through fostering R&D investments, but the impact of such policies is still unknown. We aim to compare the social welfare for high and low-productive employees when there is a centralized and decentralized economy.

We explore these points in a model that fits some of the Schumpeterian Growth Models, which are more convenient for undertaking policy analysis than other models. For example, in the expanding variety models, there are no incentives for the different agents in the economy to support distortionary taxes. In contrast, in the models of Schumpeterian Growth, there is a conflict of interest, and distortionary policies exist through the creative destruction concept. Another advantage of these models is that they "provide us with a guide about the reason of adopting polices that reduce the equilibrium growth rate by some countries"(Acemoglu, 2008).

Our main contribution in this paper is to extend the analysis of (Acemoglu et al., 2018) that builds on the endogenous technological change literature (Romer, 1990), (Aghion and

Howitt, 1990), (Grossman and Helpman, 1991), and especially on (Klette and Kortum, 2004) and (Lentz and Mortensen, 2008). We aim to include the reallocation of heterogeneous skilled and unskilled workers in their model, which changes the optimal distribution of resources that influence economic growth and the movement of the labour force between sectors. Papers like (Piva et al., 2006) show that both skilled and unskilled workers are affected by the improvement in technology, in which considering them in the analysis is very useful in this regard. In our model, heterogeneity emerges from the differences in employees' productivity and not only from the firm's productivity. Even though labour is one of the elements of a firm's productivity, it is not necessarily the case that they are both moving in the same direction. Technology, capital, and other factors could affect the firm's productivity differently than labour productivity. For example, the reason behind the low productivity of the firm could be its lack of technology, and yet it could have a high level of labour productivity. Hence, we study this part by separating the productivity of two kinds of labour (skilled and unskilled labour) which adds to the previous literature in several directions. First, it adds to the study of (Acemoglu et al., 2018) by coping with productivity for various types of workers. This difference leads to finding different results in equilibrium for wages, prices, output, intermediate goods, threshold quality, and social planner optimality solutions. Ultimately, there will be different kinds of allocation of the economic resources between the two models depending on the best scenario for government to intervene in the economy. Second, the methodology used in this paper is also different than the previous papers. Here, we derive the wages in equilibrium according to the productivity of each worker's type in the central equation of intermediate goods (and in the R&D) production function and not to the relative wages as in the previous papers. The specification for each labour productivity type in this model helps classify wages according to each of these types, and we believe that these kinds of adjustments add to the endogenous growth models literature. Third, there is a different allocation of intermediate and final goods production in equilibrium concerning the previous models. This allocation situates the effect of each type of labour's productivity on the firm's value function and several quality levels, as illustrated in the following sections. Accordingly, the value function of the firm has two conflicting controls (high and low type productivity), which direct such value into the targeted policy. The higher the productivity of one of them, the more it will be able to dominate the other and increase the firm’s value. Fourth, we contribute to the study of (Klette and Kortum, 2004) by allowing the model to adjust depending on the various skill productivities, and this kind of adjustment in innovation covers both entrants and incumbents. In this case, the success in innovation facilitates the expansion of product space. However, this is limited to the profitability of production, which depends on the productivity of labour and firms.

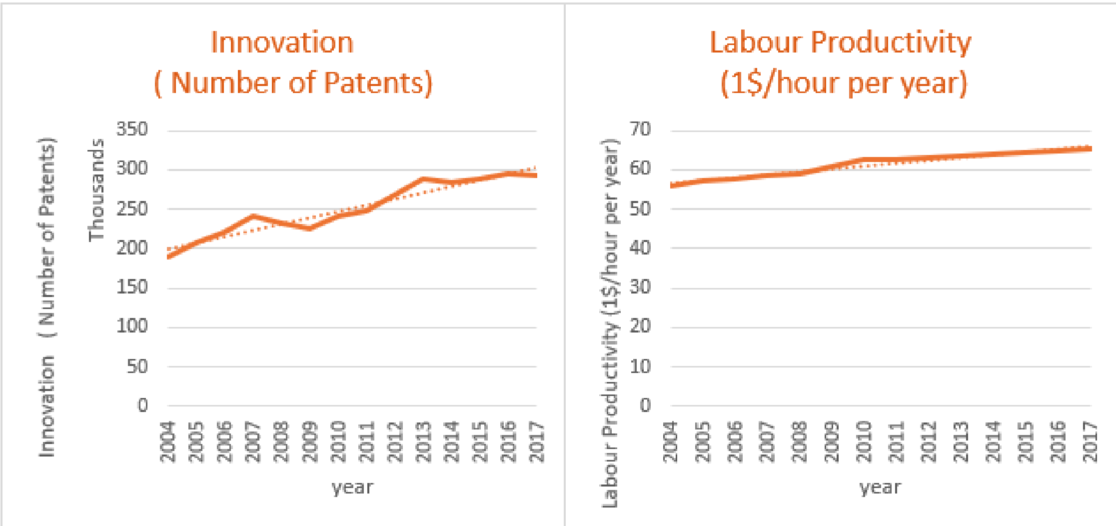
1.2 Motivation

Governments follow different policies to improve innovation and economic growth. One of them is subsidizing firms based on their labour productivity with the expectation that highly productive workers will increase the added value for produced goods and services. This kind of subsidy improves overall productivity, decreases manufacturing costs, and in the long run, increases economic growth. Figures (1-1) and (1-2) show that innovation and labour productivity during the period from 2004 to 2017 in USA and China are moving in the same direction, while figure (1-3) shows that this is not the case in Japan for the same period where labour productivity is increasing over time with the decrease in innovation. As investment in innovation is one of the primary sources of enhancing innovative capacity, why do we find such differences in the effect of these policies on labour productivity and, ultimately, on economic growth?

To answer this question, we need to know which kind of policy the social planner must adopt to use economic resources efficiently.[1]. (Klette and Kortum, 2004) argue that the persistence differences in a firm's productivity are positively correlated with R&D intensity. From this point of view, we extend the analysis besides this concept to include labour productivity as one of the main factors influencing the firm's productivity. Accordingly, we aim to study the heterogeneity in labour productivity (skilled and unskilled) and their effect on the relation between a firm's productivity and innovation intensity[2] (R&D intensity).

In the next section, we start our analysis by overviewing the literature and showing its relationship with this study. Next, we explain the proposed model and the policy analysis in more detail. Finally, we point out the results of the analysis and further research on this topic.

Figure 1-1: Innovation and Labour Productivity in USA from 2004-2017[3]



[1] Note that the increase in innovation effort is considered an indicator of the enhancement in efficiency and growth.
[2] For this study, we focus on investment in innovation; the firm's funding is based on public incentives as the first point.
[3] Source: Labour Productivity is collected from Our World In Data (OWID-2021), and patents are collected from World Bank (2021).

Figure 1-2: Innovation and Labour Productivity in China from 2004-2017[4]

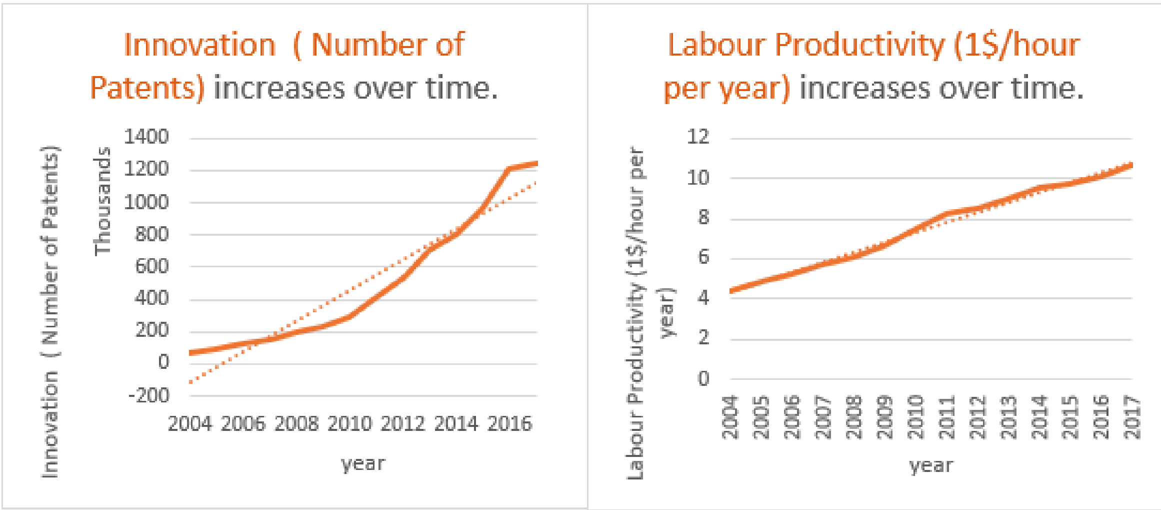
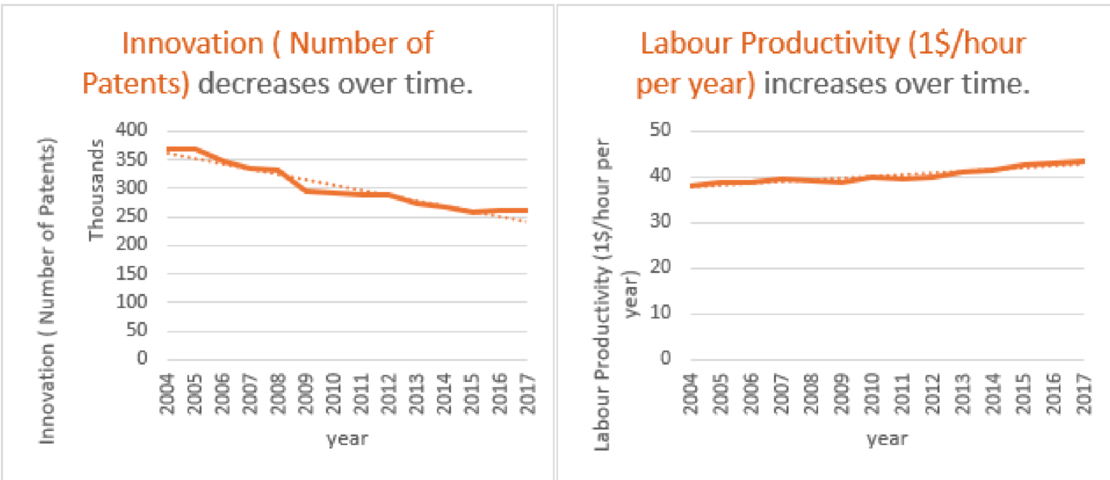


Figure 1-3: Innovation and Labour Productivity in Japan from 2004-2017[5]



1.3 Literature review

This paper is related to two main disciplines of literature. First, studies of dynamic economic growth are the basis of our study, including (Aghion and Howitt, 1990),(Romer, 1990), (Grossman and Helpman, 1991), (Aghion and Howitt, 1994), (Francois and Roberts, 2003), (Klette and Kortum, 2004), (Kerr et al., 2012), (Akcigit and Kerr, 2018) and (Acemoglu

[4] Source: Labour Productivity is collected from Our World In Data (OWID-2021), and patents are collected from World Bank (2021).
[5] Source: Labour Productivity is collected from Our World In Data (OWID-2021), and patents are collected from World Bank (2021).

et al., 2018). An essential aspect of this strand of literature is that when there is development in modern technology, it tends to displace the old one. This substitution could be complete or partial, in which intermediate inputs interact with the old ones. In these papers, they derive economic growth from technological changes, and the stock of human capital determines this growth. Within this frame, successful researchers along the quality dimension tend to eliminate the monopoly power of their antecedents. This process is called "Creative Destruction" and implies creating positive spillovers on other firms, in which they perform less research than is socially optimal. The fundamental difference in this paper is that we add the heterogeneity at the firm and workers level, while these papers do not consider this part. In addition, we classify human capital into two kinds of labour (skilled and unskilled) with different productivity and study the impact of such differences on economic growth. Although (Lentz and Mortensen, 2008) have firm heterogeneity in their model, they do not include the capacity for innovation. On the other hand, (Acemoglu et al., 2018) consider this part, but they do not cover the heterogeneity in the productivity of skilled and unskilled labour in their model.

Next, innovation policy studies are another critical, relevant literature to our paper. For example, (Serrano-Velarde, 2008) studies the effect of R&D subsidies on firms' investment decisions using a quantile regression method. He finds that this effect varies according to the amount of R&D investment in the firm. In addition, (Goolsbee, 1998) shows that US government spending on R&D raises wages, and the majority of that spending goes to higher wages, which makes it difficult for the government to increase inventive activity. More specifically (Bloom et al., 2002) test the effect of financial incentives on R&D investment and find that tax incentives increase the intensity of R&D effectively. More recently, (Burstein and Atkeson, 2015) study the effect of policy-induced changes in the firm's investment in innovation on aggregate productivity growth. Furthermore, (Akcigit et al., 2016) study the optimal policy design for R&D with externalities. The fundamental difference between these papers and our study is that they do not consider the classification of human capital as skilled and unskilled when analyzing the effect of industrial policy on the intermediate and R&D sectors, while this study does. Accordingly, this has two implications. The first is the movement of workers across different levels of the production process (within intermediates and between final goods and intermediates) as a result of different incentive schemes between them. The second is allocating economic resources so that within different types of workers, there has to be a distinct industrial policy to fulfill the efficient use of these resources. Our contribution in this strand of literature is to study the effect of several types of policies (taxes or subsidies) on economic growth based on examining the best allocation of resources. We propose a diversion in the policy towards training and qualifying unskilled employees to be efficient in acquiring the knowledge required to achieve specific tasks, especially tasks that need specific knowledge. Recently, some studies have covered these kinds of policies as an outcome of heterogeneity but from different perspectives. They diverge from our study in how heterogeneity is defined and used to stimulate the economy towards growth. For example, (Peters, 2020) studies heterogenous markups across sectional distribution and their effect on economic growth. However, we study the heterogeneity in labour productivity as an equilibrium outcome jointly determined by the firm's productivity. This heterogeneity builds on the idea that labour productivity is part of the innovation process and eventually leads to economic growth depending on the creative destruction and size of innovation in the steady state. There is a different theme in the other paper (Peters, 2020), where "markups emerge as an equilibrium outcome," and the innovation rate must be allocated to be part of the economic growth in the steady state. Moreover, our study focuses on economic growth and labour productivity combined with the firm's productivity at the country level, while (Peters, 2020) draws attention to cross-country differences and the role of frictions that stand against the new product entering the market. The costs associated with these frictions are in two forms: entry and expansion costs. In this part, our model studies the variable cost, which is mainly related to the changes in skilled and unskilled labour wages. It connects Changes in this cost to the productivity of each type of worker. Another part of the literature studies the heterogeneity in Research & Development (R&D) investment (incumbent and new firms) (Atkeson and Burstein, 2019). The policy in this category is achievable when "innovative investment technologies" parameters are well known. The model presented by (Atkeson and Burstein, 2019) has not concentrated on productivity and welfare gains, while our study does. Their point in reallocating economic resources depends on the level of investment in different categories of innovation. On the other hand, our concern is to reallocate these resources depending on the diversity in labour productivity. In this regard, the policy works towards the efficiency in using these resources and enhancing labour performance as an indicator of the progress in economic growth.

The diversity in research devoted to innovation is another strand of literature found by (Akcigit et al., 2021). Their model has two types of research: Basic and applied, and the optimal economic solution is inefficiency in "cross-subsidization on applied research ."In this specification, their model differentiates between public and private research, while in our model, we do not have such a separation between these two types. Even though both models have the same level-up firm's quality function, they are different in the characteristics of inputs that they use to reach the balanced growth path. The diversity in the type of research used (Akcigit et al., 2021) involves two different creative destruction parameters, which is not the case in our model. On the other side, our model has two parameters for each type of labour productivity, which leads to different results regarding the firm's value, the growth in equilibrium, and the optimal reallocation of resources. In other words, our model tries to find an internal solution to reach the optimal allocation of economic resources when heterogeneity exists in labour productivity. In contrast (Akcigit et el., 2021) model scrutinize the external heterogeneity in research investment and its effect on generating spillovers between basic and applied research.

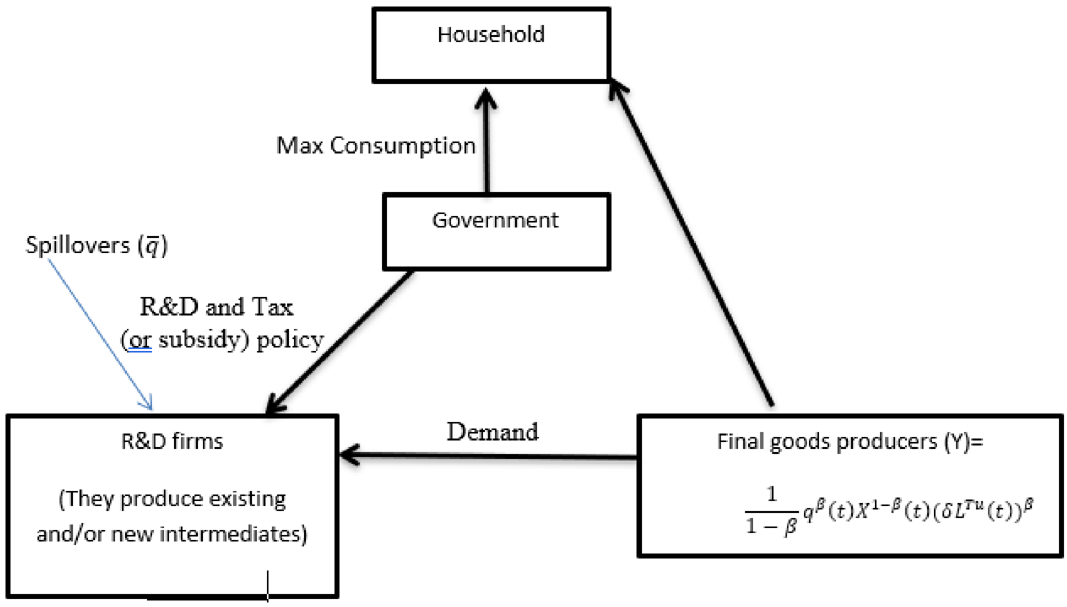
1.4 Sketch of the Model

Before going into the technical details, Figure (1-4) provides a structural framework of the proposed model. We assume that there is one sector in the economy, and the production process goes through three primary levels: producers of final outputs, R&D firms (which produce existed, improved, or new intermediates), and consumers. Final goods producers demand intermediate goods from research firms and use these intermediates as inputs. When they use physical capital, the model assumes the total depreciation of this capital in each period (t).

According to this model, the leading human capital factor in producing final goods is low-skilled labour because, at this level, workers do not need to accomplish sophisticated or highly skilled tasks. However, research firms invest in human capital (skilled and unskilled labour) to produce new intermediate inputs or improve the quality of existing ones. Skilled and unskilled labour differ in their productivity (capacity), and research firms differ in their innovative capacity. This point is the main contribution of this paper. We also assume that there is a free movement of unskilled labour between final output and R&D firms (and vice versa), in which equilibrium wages are identical among them. Also, there is a free movement of skilled and unskilled labour between R&D and intermediate goods production.

The research firm has an exclusive right over the use of its new product or the improved one, and the firm that has a monopoly over the use of the latest technology receives a flow of profits. Because of the lack of efficiency in using the resources in the decentralized economy, the social planner (government) has a crucial role in allocating these resources by adopting a tax-subsidy policy, a form of "industrial policy." For this policy to be effective, it has to induce marginal cost pricing without removing the incentive for innovating a new product.

Figure 1-4: Illustrative Diagram of the Model



1.5 __The Model__

__1.5.1 Households: -__

Considering (Acemoglu et al., 2018) model, we use the following Constant Relative Risk Aversion (CRRA) household preferences: -

$$U = \int_0^{\infty} \exp(-\rho t) \left(\frac{C(t)^{1-\sigma} - 1}{1-\sigma} \right) dt, \qquad (1)$$

Where ρ is the discount rate, σ is the coefficient of CRRA, and $C(t)$ is the aggregate consumption at a time (t). Assume that the economy is closed[6]. The resource constraint of the economy presents the aggregate output which is greater than or equal to the aggregate consumption plus total resources expended on intermediates and R&D. So, we can write the resource constraint of the economy as follows: -

$$Y(t) \geq C(t) + X(t) + Z(t) \qquad (2)$$

[6] This analysis can be extended to include an open economy. This part is not performed in this paper, which we leave for future research.

Where $Y(t)$ is the aggregate spending on output, $X(t)$ is the aggregate spending on intermediate goods (existing intermediates), and $Z(t)$ is the aggregate investment in R&D (new intermediates). All of them are at the time (t).

The labour market-clearing condition is: -

$$L^T + L^{T(R\&D)} = L^D = L^S \qquad (3)$$

Where $L^T(t)$ is the aggregate labour demand in final and intermediate goods production (existing intermediates), $L^{T(R\&D)}$ is the aggregate labour demand in intermediate goods production (new intermediates), $L^D(t)$ is the total demand of labour, and $L^S(t)$ is the total supply of labour. For each (L^T, and $L^{T(R\&D)}$), there are two types of workers: Skilled (represented by L^{Ts}), and unskilled (represented by L^{Tu})[7]. Moreover, wages for each type are identical between (final goods, intermediates, and R&D firms) because of the free labour movement between these levels in the same industry. So, the representative households maximize their utility according to the following budget constraint.[8]:-

$$\dot{A}(t) + C_i(t) \leq r(t)A(t) + S(t) + W^s(t)L^{Ts}(t) + W^u(t)L^{Tu}(t)$$

(4)

Where $A(t)$ is the households' total physical assets (tangible assets), $\dot{A}(t) = \frac{\partial A(t)}{\partial t}$, $r(t)$ is the interest rate, $S(t)$ is the households' total savings (cash and deposits), L^{Ts} is the total number of skilled labour, L^{Tu} is the total number of unskilled labour, $W^s$is the wage of skilled labour, W^u is the wage of unskilled labour. Then, within this specification, there is one control variable (C) , and one state variable (A). Accordingly, the Hamiltonian has the following expression: -

[7] On the practical side, skilled labour or "Highly skilled labour" is measured by workers who have tertiary education level and above, while unskilled labour or "low-Skilled labour" is measured by workers who have less than primary and lower secondary education or do not have any qualifications (Source: EUROSTAT-LFS).
[8] No-Ponzi condition.

$$H(C,A,\lambda) = \frac{C(t)^{1-\sigma} - 1}{1-\sigma} e^{-\rho t} + \lambda \left\{ rA + S + W^s l^{Ts} + W^u l^{Tu} - C - \dot{A} \right\}$$

(the derivation of this function is shown in *proof A*), and Euler Equation can be written as follows: -

$$\rightarrow \frac{C^*}{C} = \frac{r-\rho}{\sigma} \qquad (5)$$

Equation (5) presents the economic growth in this economy when there is no government intervention. In the following analysis, we explain the optimal value functions for the other variables.

1.5.2 Final goods

Assume that we have the following production function for final goods: -

$$Y(t) = \frac{1}{1-\beta} q^{\beta}(t)\, X^{1-\beta}(t)(\delta L^{TU}(t))^{\beta} \qquad (6)$$

Where $0 < \beta < 1$, $X(t)$ is the quantity of intermediate goods, δ is the productivity of unskilled labour, and $q(t)$ is the quality of the product. Also, assume a competitive market in the final goods; its price is normalized to one in every period (t) without loss of generality. The term $1-\beta$ is included for simplicity. The main factors of production are labour and intermediate goods, while we normalize physical capital to one for simplicity. This normalization would not affect the analysis as the target is to study the heterogeneity in labour in a specific sector and its impact on economic growth. There is innovation in developing intermediate goods, which leads to quality improvement. The firm which succeeds in innovation has the monopolistic power to produce a new intermediate or develop an existing one until an invention replaces the previous one.

1.5.3 R&D firm (Existing intermediates)

Following (Akcigit and Kerr, 2018) and (Acemoglu et al., 2018), we assume linear technology production function for intermediate goods. The central assumption is that this intermediate is produced by a product line developed specifically to produce it. Assume that θ represents the productivity of skilled labour for R&D and intermediate goods, and δ represents the productivity of unskilled labour to produce final, R&D, and intermediate goods. The skilled labour productivity type has one of two values: high θ^H and low θ^L. We describe the probability of the high type of skilled labour productivity of prominence as $[prob(\theta^H) \in (0,1)]$, and the probability of the low type of skilled labour occurrence equals $(1 - prob(\theta^H))$. Similarly, the type of unskilled labour productivity has one of two values: high δ^H and low δ^L. We describe the probability of the high type of unskilled labour of prominence as $[prob(\delta^H) \in (0,1)]$, and the probability of the low type of unskilled labour occurrence equals $(1 - prob(\delta^H))$. Moreover, the probability of each of the types mentioned above is determined exogenously.

Regarding the previous specification, we define the technological production function that produces intermediate goods as follows: -

$$X = \bar{q}[\theta\alpha L^T + \delta(1-\alpha)L^T] \tag{7}$$

Where α is the percentage of skilled labour to total L^T, $1-\alpha$ is the percentage of unskilled labour to total L^T. θ is the productivity of skilled labour (L^{Ts})for the intermediate product, δ is the productivity of unskilled labour (L^{Tu}) for the intermediate product (also for the final goods), $\bar{q}$ is the average total quality in that sector in the economy, and $L^T = L^{Ts} + L^{Tu}$.The marginal cost for this product can be defined as follows (*see proof B*):-

$$mc = \frac{\partial TC^I}{\partial X} = \frac{\alpha w^s + (1-\alpha) w^u}{[\alpha\theta + (1-\alpha)\delta]\bar{q}} \qquad (8)$$

Where $\alpha w^s + (1-\alpha) w^u$ equals the sum of skilled and unskilled wages, which are presented later by equations (17) and (18), noting that physical capital is normalized to one in this model, as the target is to study the effect of human capital on economic growth. According to our specifications, there are two main indications for this model. First, intermediate goods have exact marginal costs. Second, the marginal product of unskilled labour in the final good level grows at the same rate as the intermediate goods level, which generates the same unskilled labour allocation across these levels in the steady state.

Equation (8) implies that all allocations depend on skilled and unskilled labour productivity and wages. Higher wages cause higher marginal cost, while higher labour productivity leads to lower marginal cost. Average total productivity $\bar{q}$ is also affected by labour productivity.

1.6 <u>Stationary equilibrium prices, profits, and wages</u>

Producers of final goods intend to maximize the following profit (π_T) function: -

$$\pi_T = \max_{X \geq 0} \left[\frac{1}{1-\beta} q^\beta \, X^{1-\beta} \, (\delta L)^{Tu^\beta} - W L^{Tu} - \, pX \right] \qquad (9)$$

Where p is the price of the intermediate good, L^{Tu} is assumed to be unskilled labour and satisfies the distribution of unskilled labour as specified in the intermediate level. Differentiate (9) with regards to X; then we have the following: -

$$\frac{\partial \pi}{\partial X} = \delta^\beta q^\beta X^{-\beta} L^{Tu^\beta} - p = 0 \qquad (10)$$

So, the inverse demand for intermediate goods presents the following equation: -

$$\rightarrow p = \delta^{\beta} q^{\beta} X^{-\beta} {L^{Tu}}^{\beta} \qquad (11)$$

For the producer of the intermediate goods (monopolist), the profit function(π^{I}) is as follows:-

$$\pi^{I} = \max_{X \geq 0} \{(p - mc)\, X\} \qquad (12)$$

Substituting the inverse demand for intermediate goods in (12) and substituting the marginal cost of producing an intermediate product from (8) in (12) leads to the following: -

$$\pi = \max_{X \geq 0} \left\{ \delta^{\beta} q^{\beta} X^{1-\beta} {L^{Tu}}^{\beta} - \frac{\alpha w^{s} + (1-\alpha) w^{u}}{[\alpha\theta + (1-\alpha)\delta]\bar{q}} X \right\} \qquad (13)$$

X^{*}, p^{*}, and π^{*} in the stationary equilibrium are as follows (derivations in *proof C*): -

$$\rightarrow X^{*} = \delta \left[\frac{(1-\beta)[\alpha\,\theta + (1-\alpha)\delta]\bar{q}}{\alpha w^{s} + (1-\alpha) w^{u}} \right]^{\frac{1}{\beta}} L^{Tu} q \qquad (14)$$

And

$$p^{*} = \frac{\beta^{\beta}}{(1-\beta)^{1+\beta}} \qquad (15)$$

$$\pi^{*} = \delta\, \breve{\pi}\, q \qquad (16)$$

Where $\breve{\pi} = \left(\beta^{1-\beta}\right) L^{Tu}$.

To find the optimal wages (unskilled) in this economy, we can use the profit function in (9) and maximize it regarding L^{Tu}. Using the same methodology in the intermediate sector for both (skilled and unskilled labour) leads to the following optimal wages for the two types: -

$$w^{u*} = \delta \left(\frac{\beta}{1-\beta}\right)^{\beta} \bar{q} \qquad (17)$$

and

$$w^{s*} = \theta \left(\frac{\beta}{1-\beta}\right)^{\beta} \bar{q} \qquad (18)$$

(Derivations in *proof D*). Substitute (17) and (18) in (14) leads to: -

$$X^* = \frac{\delta\,(1-\beta)^{1+\beta}}{\beta^{\beta}} L^{Tu} q \qquad (19)$$

X^* in (19) represents the equilibrium aggregate quantity of intermediate goods used to produce final products. This analysis shows that profits and intermediate goods quantities depend on the quality of the intermediate products. One of the critical elements of this result is that we can use this concept to explain the role of labour productivity (skilled and unskilled) in determining this quality. The following sections explain this case in more detail.

*1.7 **R&D firm (New intermediates)***

In this model, we assume technology is developed by an existing market firm or a new entrant. The outcome of this process is realized stochastically. When the development in the intermediate product is caused to happen, the quality of that product over time is improved by size φ as follows: -

$$q(t + \Delta t) = q + \varphi \bar{q} \qquad (20)$$

Where $\varphi > 0$ is a multiplicative term and randomly realized. The vintage of the old technology becomes publicly available, which gives the innovating firm a technological lead for the new intermediate good over other competitors. Workers are different in their skills and productivity, which influence the innovation process. Within this frame, we have two types of workers (skilled and unskilled). Each has different productivity to produce intermediate goods, in which the firm productivity is the outcome of the change in their productivity. It is important to note that developing a new intermediary at each period (t) requires a minimum level of productivity for each type of worker, and each of them has the same productivity among levels.

Assume that $\hat{A}$ represents the type of the firm productivity for intermediate goods; its type has one of two values: high $\hat{A}^{H}$ and low $\hat{A}^{L}$. We describe the probability of the high type of prominence as $[prob(\hat{A}^{H}) \in (0,1)]$, and the probability of low type occurrence equals $(1 - prob(\hat{A}^{H}))$, and it is determined exogenously. The low type is an absorbing state, and we assume that each firm transitions from high to low type to be exogenous, with a rate denoted by h.

We define R&D technology for any new intermediate product (Z) as: -

$$Z = \hat{A}^{\gamma}\, n^{\gamma} {l^{T(R\&D)}}^{1-\gamma} \quad (21)$$

Utilizing equation (21), the cost function for R&D can be explained as (*see Proof E*): -

$$\rightarrow \mathrm{CR} = [w^{s}\hat{\alpha} + w^{u}(1-\hat{\alpha})]\; n\; \mathrm{J}(\mathrm{z}, \hat{A}) \qquad (22)$$

Where $\mathrm{J}(\mathrm{z}, \hat{A}) = z^{\frac{1}{1-\gamma}} \hat{A}^{-\frac{\gamma}{1-\gamma}}$, $\hat{\alpha}$ is the percentage of skilled labour to total R&D workforce ($l^{T(R\&D)}$), while $1 - \hat{\alpha}$ is the percentage of unskilled labour to total R&D workforce $l^{T(R\&D)}$. (n) represents the number of product lines used to produce intermediate goods. Because new R&D technology is skilled labour intensive, intuitively $\hat{\alpha} > \frac{1}{2}$.

Assuming free movement of the labour force from one level to another, then wages (for each workers-skilled and unskilled) in R&D firms equals wages in equilibrium in intermediate and final production (and vice versa) as described by equations (17) and (18). Within the specification of this model, we classify wages in these levels into two portions (skilled and unskilled). This classification concludes that the equilibrium wages equal the sum of wages for both skilled and unskilled workers.

From (22), there are two points to consider. First, research and development depend on the employees' productivity, reducing marginal costs. When both kinds of workers have high productivity, there will be more reduction in marginal cost because of the higher intensity of skilled workers in R&D. Next, two kinds of human resources (skilled and unskilled) with different productivities specifies heterogeneous wages among them. The cost of innovation depends not only on the innovation intensity, number of product lines, worker types, and wages but also on skilled and unskilled labour wages. Hence, the heterogeneity of labour productivity has an essential role in the way that resources are allocated. To demonstrate this, we need to figure out the changes in equilibrium when there is a flow in research and development. Section (1.8) illustrates this in more detail.

Proposition 1. *Consider the static equilibrium characterized above.* w^{s*} and w^{u*} are sufficient for allocating the economic resources in the entire sector, and the equilibrium wage for each kind of labour depends on the productivity of each type.

Proof. Follows directly from *proof C*.

Proposition 1 reveals that the productivity of each kind of labour has a different impact on wages. More specifically, the factors that affect the equilibrium wages for skilled and unskilled labour are the same except for the difference in productivity. With any change in this productivity, the equilibrium wage for each type shifts to a new point.

By substituting for skilled and unskilled wages in equilibrium, we reach the following formula for the cost of R&D: -

$$\mathrm{CR} = \left[\hat{\alpha}\theta\left(\frac{\beta}{1-\beta}\right)^{\beta}\bar{q} \; + \delta\left(\frac{\beta}{1-\beta}\right)^{\beta}\bar{q}(1-\hat{\alpha})\right] n\,\mathrm{J}(\mathrm{z},\hat{\mathrm{A}})$$

$$\mathrm{CR} = [\hat{\alpha}\,\theta \; + (1-\hat{\alpha})\,\delta\,]\left(\frac{\beta}{1-\beta}\right)^{\beta}\bar{q}\,n\,\mathrm{J}(\mathrm{z},\hat{\mathrm{A}})$$

1.8 Value functions

The value function of the firm that produces intermediate goods has one of the following two formulations: -

1.8.1 Value function for the new entrant

The value function for a new entrant who successfully produces or develops a new product and does not have any previous production depends only on the expected value of return and flow rate of innovation minus the cost of R&D. Accordingly, the Belman's value function for the new entrant becomes as follows: -

$$\mathrm{r}\,V^e(q) =$$

$$\max_{z^e}\left\{n\, z^e\, EV^e\big(q', \hat{\mathrm{A}}^e, \theta^e, \delta^e\big) - \big[[w^s\hat{\alpha} + w^u(1-\hat{\alpha})]\big]\, n\, \mathrm{J}\big(\mathrm{z}^e, \hat{\mathrm{A}}^e\big) + \frac{\partial V^e(q)}{\partial q}\frac{\partial q}{\partial t}\right\} \quad (23)$$

Where r is the interest rate, and EV^e is the expected value of return from the product, which is a function of the improvement in the quality of that product (size of innovation), firm type, and labour productivity. Deriving (23) with regards to z^e leads to (*see proof F*):-

$$z^{e*} = \hat{\mathrm{A}}^e\left[\frac{(1-\gamma)\, EV^e\big(q', \hat{\mathrm{A}}^e, \theta^e, \delta^e\big)}{[w^s\hat{\alpha} + w^u(1-\hat{\alpha})]}\right]^{\frac{1-\gamma}{\gamma}} \quad (24)$$

From (24), the flow rate of innovation depends on the different types of labour productivity alongside their wages. The transition from low (high) to high (low) type in labour productivity increases (decreases) the innovation flow, while the increase (decreases) of wages decreases (increases) this flow. At the same time, firm's productivity has a positive effect on the flow of innovation. Moving from low to high productive firm increases the intensity of innovation because of the enhancement in its performance. However, firms with low productivity minimize the probability of having intensity in developing a new product, which reduces the flow rate of innovation.

1.8.2 Value function for the existing firm

The existing firm's situation is different because it could have the previous production. Here, there are four changes to the stationary equilibrium. First, increase in the R&D cost. Second, changes in the value function are due to the change in quality over time and the effect of innovation capacity. Third, changes that could cause the firm's exit from the market, like losing one or more of its product lines because of creative destruction (denoted by τ) or facing an economic shock (denoted by ζ). Finally, we measure the transition from high productivity to low type by an exogenous rate (h).

In addition, there are two types of firms and labour, both demonstrated by high or low type (firm/labour). Each of these types presents its productivity when it is high or low, and they are not necessarily moving in the same direction when they shift from one level to another. The increase (decrease) in labour productivity does not always enhance (reduce) the firm's productivity because other factors affect this productivity (e.g., technology, capital, etc.). We present the flow rate of innovation intensity for this part by (z^H, z^L), which generates two value functions,$\mathrm{V}^H, \mathrm{V}^L$. Notice that z^H is related to the high type firm, while z^L is related to the low type. The reason is that the firm's value differs according to the change in its type or its employees' productivity from (high) to (low). Depending on that, we describe the Belman's value function for the existing firm that produces a product with high type productivity as follows: -

$$\mathrm{r}\, V^H(q) =$$

$$\max_{z^H \geq 0}\Big\{\breve{\pi}\, q + \frac{\partial V^H(q)}{\partial q}\frac{\partial q}{\partial t} - [w^s\hat{\alpha} + w^u(1-\hat{\alpha})]\, n\, \mathrm{J}\big(\mathrm{z}^H, \hat{\mathrm{A}}^H\big) + n\, z^H E V^H\big(q', \hat{\mathrm{A}}^H, \theta^H, \delta^H\big) -$$

$$(\tau + \zeta)\, V^H(q) - h(V^H(q) - V^L(q))\Big\} \quad (25)$$

This equation leads to a flow of innovation for the high type firm/labour equals (*see* proof *G*):-

$$z^{*H} = \hat{A}^H \left[\frac{(1-\gamma)\, EV^H\left(q', \hat{A}^H, \theta^H, \delta^H\right)}{[w^s \hat{\alpha} + w^u(1-\hat{\alpha})]}\right]^{\frac{1-\gamma}{\gamma}} \quad (26)$$

However, the Belman's value function for the low-type firm/labour becomes as follows: -

$$\mathrm{r}\, V^L(q) =$$

$$\max_{z^L \geq 0}\left\{\breve{\pi}\, q + \frac{\partial V^L(q)}{\partial q}\frac{\partial q}{\partial t} - [w^s \hat{\alpha} + w^u(1-\hat{\alpha})]\, n\, \mathrm{J}\left(\mathrm{z}^L, \hat{A}^L\right) + n\, z^L EV^L\left(q', \hat{A}^L, \theta^L, \delta^L\right) - (\tau + \zeta)\, V^L(q)\right\} \quad (27)$$

And the innovation flow rate for the low type is: -

$$z^{*L} = \hat{A}^L \left[\frac{(1-\gamma)\, EV^L\left(q', \hat{A}^L, \theta^L, \delta^L\right)}{[w^s \hat{\alpha} + w^u(1-\hat{\alpha})]}\right]^{\frac{1-\gamma}{\gamma}} \quad (28)$$

From (24), (26), and (28), we can generalize the optimal rate of flow of innovation for the firm/labour as follows: -

$$z^{*type} = \hat{A}^{type} \left[\frac{(1-\gamma)\, EV^{type}\left(q', \hat{A}^{type}, \theta^{type}, \delta^{type}\right)}{[w^s \hat{\alpha} + w^u(1-\hat{\alpha})]}\right]^{\frac{1-\gamma}{\gamma}} \quad (29)$$

Equation (29) shows consistency in the results between the new and existing firms' flow of innovation. Both are influenced positively by the labour and firm productivity for each type. Moreover, the quality of product has an important role in increasing this flow. It is positively affecting the change in innovation intensity. According to this parameter, there is a threshold quality level for each type of firm/labour, in which it can proceed in producing the good only if the quality exceeds that level. This progressivity in quality means that $[q^{type} > {q_{min}}^{type}, type \in \{high, low\}]$. Otherwise, the value of production equals zero. The function of the threshold quality of production ${q_{min}}^{Low}$ for (low type) firm/labour can be explained as (*see Proof H*): -

$${q_{min}}^L = \frac{\bar{\bar{\mathrm{M}}}^L}{\breve{\pi}} \quad (30)$$

where $\overline{\overline{\mathrm{M}}}^{L} = \max_{z^{L}\geq 0}\left\{\left[[w^{s}\hat{\alpha} + w^{u}(1-\hat{\alpha})]\right] n\, \mathrm{J}\left(\mathrm{z}^{L}, \hat{\mathrm{A}}^{L}\right) + n\, z^{L} EV^{L}\left(q', \hat{\mathrm{A}}^{L}, \theta^{L}, \delta^{L}\right)\right\}$, and $\breve{\pi} = \beta^{1-\beta} L^{Tu}$.

On the other hand, the threshold quality of production ${q_{min}}^{High}$ for (High type) firm/labour (see *proof H*): -

$$ {q_{min}}^{H} = \frac{\overline{\overline{\mathrm{M}}}^{H}}{\breve{\pi}} \qquad (31) $$

Where $\overline{\overline{\mathrm{M}}}^{H} = \max_{z^{H}\geq 0}\left\{ [w^{s}\hat{\alpha} + w^{u}(1-\hat{\alpha})]\, n\, \mathrm{J}\left(\mathrm{z}^{H}, \hat{\mathrm{A}}^{H}\right) + n\, z^{H} EV^{H}\left(q', \hat{\mathrm{A}}^{H}, \theta^{H}, \delta^{H}\right) \right\}$, and $\breve{\pi} = \beta^{1-\beta} L^{Tu}$.

The minimum quality for each type is affected by the distribution of labour productivity type. The higher (lower) the productivity of the worker's type, the higher (lower) the threshold quality. However, the increase (decrease) in the wages for skilled and unskilled workers increases (decreases) this level. In addition, firm's productivity has a significant impact on the minimum quality level for each type of firm (high and low). The increase (decrease) in the productivity of the firm, increases (decreases) the threshold quality for each type..

1.9 ***<u>Productivity distribution</u>***

The equilibrium growth rate in this model equals (*see Proof I*): -

$$ G = \tau\varphi \qquad (32) $$

This expression has the same concept in the quality ladder models, in which the growth rate depends on the frequency ($creative\ destruction\ rate\ \tau$) and size of innovation($multiplicative\ term\ \varphi$). (Peters, 2020) has a very close form but from a different perspective, where he assumes heterogeneity between the firm's markups. In this regard, there is isolation between the creative destruction concept, the rate of innovation in existing products, and the rate of expansion.

1.10 Balanced Growth Path Equilibrium

Definition: The Balanced growth path equilibrium according to this model includes the following variables for every (t), q, and $\bar{q}$: -

$\{X^{*}, p^{*}, \pi^{*}, W^{s*}, W^{u*}, \mathrm{z}^{*e}, \mathrm{z}^{*H}, \mathrm{z}^{*l}, q_{min}{}^{H}, q_{min}{}^{l}, V^{e}(q), V^{l}(q)\ , V^{H}(q), \mathrm{G}^{*}, Y^{*}, Z^{*}, r^{*}\}$

Such that (i) intermediate goods production X^{*} satisfies (14), (ii) final good price p^{*} satisfies (15), (iii) final good producer's profits π^{*} satisfy (16), (iv)skilled labour wage W^{s*} satisfies (18), (v) unskilled labour wage W^{u*} satisfies (17), (vi) flow rate of innovation for the new entrant z^{*e} equals to (24), (vii) flow rate of innovation for high type firm z^{*H} equals to (26), (viii) flow rate of innovation for low type firm z^{*l} equals to (28), (ix) threshold quality of production for low type (firm/labour) $q_{min}{}^{l}$ equals to (30), (x) threshold quality of production for high type (firm/labour) $q_{min}{}^{H}$ equals to (31), (xi) value function for the new entrant $V^{e}(q)$ equals to (23), (xii) value function for high type firm/labour $V^{H}(q)$ and low type firm/labour $V^{L}(q)$ equal to (25) and (27), (xiii) steady state growth rate G^{*}satisfies (32), (xiv) aggregate output Y^{*} satisfies (33), (xv) aggregate R&D expenditures Z^{*} satisfy (34), and (xvi) the interest rate r^{*}satisfies the Euler Equation (5).

1.11 Pareto optimality and resources allocation

To study this part, we can evaluate the Pareto optimality of the decentralized equilibria by comparing the optimal solution to this economy with the optimal solution to the social planner problem.

The social planner attempts to maximize the following representative households' utility:-

$$U = \int_{0}^{\infty} \exp(-\rho t) \left(\frac{C(t)^{1-\sigma} - 1}{1-\sigma} \right) dt$$

The specification of the economy's possibilities frontier consists of the static and dynamic cases, where

$$Y(t) = \frac{1}{1-\beta}\left[q^{\beta}(t)\, X^{1-\beta}(t)\right](\delta L^{Tu}(t))^{\beta} = C(t) + X(t) + Z(t) \qquad (33)$$

In equilibrium and from (19) we have,

$$X^{*} = \delta\, \frac{(1-\beta)^{1+\beta}}{\beta^{\beta}}\, L^{Tu}\bar{q}$$

By substituting X^{*} from (19) in (6) then $Y^{*} = \frac{1}{\beta^{\beta(1-\beta)}(1-\beta)^{\beta^2}}\delta L^{Tu}\bar{q}$. This means that $Y^{*} - X^{*} = \frac{1}{\beta^{\beta(1-\beta)}(1-\beta)^{\beta^2}}\delta L^{Tu}\bar{q} - \frac{(1-\beta)^{1+\beta}}{\beta^{\beta}}\delta L^{Tu}\bar{q}$. So

$$Y^{*} - X^{*} = \left[\frac{\beta^{\beta} - \beta^{\beta(1-\beta)}(1-\beta)^{\beta^2}(1-\beta)^{1+\beta}}{\beta^{\beta(1-\beta)}(1-\beta)^{\beta^2}\beta^{\beta}}\right]\delta L^{Tu}\bar{q}$$

$$Y^{*} - X^{*} = \frac{\beta^{\beta}}{\beta^{\beta}}\left[\frac{1 - \beta^{-\beta^2}(1-\beta)^{\beta^2}(1-\beta)^{1+\beta}}{\beta^{\beta(1-\beta)}(1-\beta)^{\beta^2}}\right]\delta L^{Tu}\bar{q}$$

$$Y^{*} - X^{*} = \left[1 - \frac{(1-\beta)^{\beta^2}(1-\beta)^{1+\beta}}{\beta^{\beta^2}}\right]\frac{\delta L^{Tu}\bar{q}}{\beta^{\beta(1-\beta)}(1-\beta)^{\beta^2}}$$

$$Y^{*} - X^{*} = \left[1 - \frac{(1-\beta)^{1+\beta+\beta^2}}{\beta^{\beta^2}}\right]\frac{\delta L^{Tu}\bar{q}}{\beta^{\beta(1-\beta)}(1-\beta)^{\beta^2}}$$

In this case,

$$Z^{*} = Y^{*} - X^{*} - C = \left[1 - \frac{(1-\beta)^{1+\beta+\beta^2}}{\beta^{\beta^2}}\right]\frac{\delta L^{Tu}\bar{q}}{\beta^{\beta(1-\beta)}(1-\beta)^{\beta^2}} - C \qquad (34)$$

In order to find an expression for $\bar{q}^{*} = \frac{\Delta Q}{\Delta t}$ in an interval of time Δt, there is $z(t)\Delta t$ flow of one innovation, and its productivity increase by φ as in (20). For more than one innovation within the same time interval, we use the measure $o(\Delta t)$ as a second-order in Δt. Using this reasoning leads to the following equation,

$$\bar{q}(t + \Delta t) = \varphi Q(t) z(t)\Delta t + (1 - z(t)\Delta t)\bar{q}(t) + o(\Delta t)$$

By subtracting $\bar{q}(t)$ from both sides and dividing by Δt, and taking the limit as $\Delta t \to 0$, then

$$\bar{q}^*(t) = (\varphi - 1)z(t)\bar{q}(t) \qquad (35)$$

On the aggregate level, multiplying the cost of innovation CR by the aggregate investment in R&D (Z) equals the outcome of multiplying the flow rate of innovation by the average total quality. $In\ equation\ form, we\ have\ \ z(t)\bar{q}(t) = \mathrm{CR}\big(\mathrm{z}, \mathrm{n}, \hat{\mathrm{A}}\big)Z(t)$. So,

$$\bar{q}^*(t) = (\varphi - 1)\mathrm{CR}\,Z(t) \qquad (36)$$

Now, substitute (22) and (34) in (36), then

$$\bar{q}^*(t) = (\varphi - 1)[w^s\hat{\alpha} + w^u(1-\hat{\alpha})]n\mathrm{J}\big(\mathrm{z}, \hat{\mathrm{A}}\big)\left[\left[1 - \frac{(1-\beta)^{1+\beta+\beta^2}}{\beta^{\beta^2}}\right]\frac{\delta L^{Tu}\bar{q}}{\beta^{\beta(1-\beta)}(1-\beta)^{\beta^2}} - C\right]$$

The social planners’ Hamiltonian is described as: -

$$H(C, Q, \mu) = \frac{C(t)^{1-\sigma} - 1}{1-\sigma}e^{-\rho t} + \mu.\left\{(\varphi - 1)[w^s\hat{\alpha} + w^u(1-\hat{\alpha})]n\mathrm{J}\big(\mathrm{z}, \hat{\mathrm{A}}\big)\left[\left[1 - \frac{(1-\beta)^{1+\beta+\beta^2}}{\beta^{\beta^2}}\right]\frac{\delta L^{Tu}\bar{q}}{\beta^{\beta(1-\beta)}(1-\beta)^{\beta^2}} - C\right]\right\}$$

The control variable is C, and the state variable is quality $(\bar{q})$. By derivation (*see proof J*), the growth rate for the social planner can be explained by the following equation: -

$$Growth \rightarrow \frac{C^*}{C} = \frac{1}{\sigma}\left[(\varphi - 1)[w^s\hat{\alpha} + w^u(1-\hat{\alpha})]nJ(\mathrm{z}, \hat{\mathrm{A}})\ \left[\left[1 - \frac{(1-\beta)^{1+\beta+\beta^2}}{\beta^{\beta^2}}\right]\frac{\delta L^{Tu}}{\beta^{\beta(1-\beta)}(1-\beta)^{\beta^2}}\right] - \rho\right] \quad (37)$$

Comparing the Pareto optimal growth rate with the equilibrium growth rate, we find that the growth rate in the decentralized economy could be greater or less than the growth rate in the decentralized economy. It depends on the size of innovation (multiplicative term φ), cost of innovation (which is a function of skilled and unskilled wages), the productivity of skilled and unskilled labour, and total quality. In particular, if the size of innovation or labour productivity is enormous, the growth rate in the decentralized economy is more efficient than the social planner allocation. On the other hand, if the size of innovation or unskilled labour productivity is shallow, as shown in δ for the centralized economy equation, then Pareto's optimal allocation is higher than the equilibrium growth. A low rate of unskilled labour productivity leads to less efficient unskilled workers in the final and R&D sectors. As a result, in this case, the social planner is more efficient than the decentralized economy in reallocating low-productive unskilled labour to the final and R&D production.

Proposition 2. In the above-described model, the decentralized equilibrium is not always Pareto suboptimal. The Pareto optimal allocation involves a growth rate in the case of social planner intervention, which is greater or less than the equilibrium growth rate in the decentralized economy. In the case of skilled labour (highly and low-productive), large size of innovation or highly productive unskilled labour, a decentralized economy is more efficient than the social planner equilibrium. On the other hand, if unskilled labour productivity is meagre (or small innovation), the social planner option is more efficient in allocating human resources (skilled and unskilled labour) than the decentralized economy.

Proposition 2 indicates that the equilibrium in the decentralized economy is growing more or less than the optimum allocation. The reason for that is due to a lack of clarity on the ability of the social planner to use economic resources more intensively after innovation. Furthermore, the innovation valuation differs from the social planner's perspective on one side and the decentralized economy on another side. In a specific case, highly productive skilled and unskilled labour and low-productive skilled labour involve less government intervention than very low productive unskilled labour.

*1.12 **<u>Policy analysis</u>***

To explain this part, assume that government imposes a tax (denoted by T) on the firm's R&D spending.

According to this model, the specific solution for each type (firm/labour) is as follows: -

$$V^{type}(q) = \left(1 - e^{\bar{\bar{I}}t}\right)\frac{\bar{\bar{\pi}} {q_{min}}^{type} + \bar{\bar{\mathrm{M}}}^{type}(z(T))}{\bar{\bar{I}}} \quad (38)$$

As taxes discourage investment in R&D, then the increase in taxes on R&D spending reduces the balanced growth path of the firm's innovation intensity. The decrease in innovation intensity reduces $\bar{\bar{\mathrm{M}}}^{type}$, reducing the firm's discounted value function.

At the aggregate level, we know that the creative destruction rate equals: -

$$\tau(T) = z^l(\mathrm{T})\boldsymbol{\Omega} + z^H(\mathrm{T})\boldsymbol{\Omega} + \mathrm{z}^e(T)$$

And the long-run economic growth rate equals: -

$$G = \tau(T)\varphi$$

Hence, the increase in taxes on R&D decreases (z), and the economic growth rate decreases as well. This analysis shows that the opposite applies when we have a subsidy policy, which means that subsidizing the R&D expenses is an effective policy to enhance economic growth. Notice that this impact is more effective with the increase in the value of the employees' type, which indicates that subsidizing firms with higher employee productivity has more efficient allocation than subsidizing other types of firms.

Going further in the analysis, suppose that the social planner selects a policy to enhance workers' productivity by providing advisory support[9] to the firms to train their workers. The impact of such policy can be explained by this model as follows: -

Suppose that each firm has a financial advisory (denoted by s) to enhance the capacity of its workers. The policy impacts innovation intensity, the value of the firm, creative destruction, and economic growth rate. First, as a result of effective consulting and training services provided to the workers, their innovation capacity will be enhanced. We noticed from (24) and (29) that the increase in the employee's productivity type increases the innovation intensity $(z(s))$, which is influenced by the employee's productivity. When labour productivity is high, the firm's capacity will be high and will increase the innovation intensity. Second, we have the following value function of producing the intermediate good for each type: -

$$VN^{type}(q) = \left(1 - e^{\bar{\bar{I}}t}\right)\frac{\bar{\bar{\pi}}{q_{min}}^{type} + \bar{\bar{M}}^{type}(z(s))}{\bar{\bar{I}}}$$

The increase in (z) due to the increase in (s)will increase the firm's value. Finally, at the aggregate level, we have: -

$$\tau(s) = z^{l}(\mathrm{s})\boldsymbol{\Omega} + z^{H}(\mathrm{s})\boldsymbol{\Omega} + \mathrm{z}^{e}(s)$$

And,

$$G = \tau(s)\varphi$$

[9] This kind of support is indirect funding (subsidy), and it comes through signing contracts with specialized consulting and training firms to provide such services.

This equation indicates that increased (s) increase creative destruction and economic growth rates.

This analysis shows that financial support for advisory and training services to the employees is an essential factor in stimulating the economy and enhancing the economic growth rate. This result has two implications. First, the persistence of the high productivity of the employees through training has a positive impact on economic growth. Second, these kinds of services positively influence employees' productivity from low to high, which empowers innovation flow and improves growth.

1.13 Discussion and Extensions

The model developed in this paper predicts essential government intervention when the productivity of the firm or labour is low. However, the high level of productivity does not require such intervention. In this context, stimulating innovation is achieved through reallocating resources to satisfy the low-skilled labour needs in developing their knowledge. This kind of reallocation involves subsidizing low-productive firms and conducting specialized training programs for low-skilled labour. We expect that our model is capturing the real world to be relevant to policy in two aspects. First, we predict in this model that economic growth is different across countries which arise from the heterogeneity in firms' productivity. We assume two types of firm productivity (high and low) which are determined exogenously. Since a firm's productivity has a positive effect on innovation intensity, the firm's value of the high-type firm is higher than that of the low-type firm. At the aggregate level, subsidies to low-productive firms will eventually enhance economic growth. Subsidies to highly productive firms do not lead to the same target because they are already in the position of optimal utilization of knowledge spillovers as described in the model. The implication of this model is found in the work of (Sissoko, 2011). This study finds that R&D subsidies to different firms in

38 European countries between 1985 and 2004 created more economic gains for low-productive firms than for highly productive firms. This fact is explained in our model by the significant decrease in marginal cost in the intermediate sector (R&D) when the firm is moving from the low to high type.

Second, this model has set the heterogeneity in labour productivity to capture the role of labour force in stimulating the economy. It is shown in the model that training subsidies for low-skilled workers is the best policy to achieve high levels of innovation intensity and economic growth. In this framework, specialized training improves the quality of the product which reflects high level of innovation intensity and economic growth. The outcome of this model solves the difference in the "types of workers", and it is very useful in computing the "returns to training" as suggested by (Ballot et al., 2006). In the public policy, this model fills the gap in literature by providing a paradigm of the "returns to training", especially for low-skilled employees. It helps in redirecting the policy from taxes on firms towards specialized training for low-skilled labour.

1.14 Conclusions

This paper's outcome indicated that labour productivity heterogeneity impacts resource allocation and economic growth. Adding the productivity of skilled and unskilled labour to the previous literature models altered the distribution of wages between both highly skilled and low-skilled workers in equilibrium. This effect also appeared in the difference between the centralized and decentralized economy in allocating resources. In the case of social planner intervention in the economy, the appropriate utilization of these resources will be very effective when labour productivity (specifically unskilled labour) is very low. Reallocating human resources in such a situation can enhance the optimal use of these economic resources and eventually enhance economic growth.

In order to figure out the optimal resource allocation policy, this paper explained the equilibrium values of the economic indicators before and after the innovation flow. This way of analysis complies with the one mentioned in (Bilbao-Osorio and Rodríguez-Pose, 2004), in which they indicated that the relationship between R&D investment, technological potential, innovation, and growth has to show the path policymakers should follow to ensure economic growth in any given region.

Given these points and a more detailed analysis of industrial policy, this paper revealed that indirect funding through subsidizing advisory services enhances workers' productivity. As noted, the model explained the effect of such policy on R&D investment and growth.

Another essential outcome to consider is that the threshold productivity for high-type firms is higher than that for low-type firms due to the higher R&D value for high-type firms. Equally important is the value of the firm. Since the increase in innovation intensity increases the firm's value, the value of the high-type firm is higher than that of the low-type firm. This result was observed by (Acemoglu et al., 2018) but with a difference in the distribution of wages between high-skilled and low-skilled workers. To our knowledge, this point is not analyzed in the previous literature.

The model developed in this paper can be implemented on quantitative data. Simulated Method of Moments (SMM) is widely used in literature for that purpose and has many advantages, which (McFadden, 1989) explained these advantages in more detail. In order to estimate the model parameters and moments using this method, calibration, and bootstrap techniques are required. One of the limitations of this model is the difficulty of obtaining data related to skilled and unskilled labour productivity.

Another direction for further research is to compare the results of different datasets and analyze the results of policy simulations. The estimation, in this case, can be carried out using the Generalized Method of Moments (GMM) and country fixed effect, in which Ordinary Least

Squares (OLS) are used as a benchmark model. One of the main functions that could be used is the linearized version of the innovation flow presented in this model, which is a function in human capital (skilled and unskilled labour) devoted to R&D.

Proof A

We have the following Hamiltonian expression: -

$$H(C, A, \lambda) = \frac{C(t)^{1-\sigma} - 1}{1-\sigma} e^{-\rho t} + \lambda \{rA + S + W^s l^{Ts} + W^u l^{Tu} - C\}$$

C is the control variable, and A is the state variable.

- Derive $H(C, A, \lambda)$with regards to C leads to the following: -

$$\frac{\partial H}{\partial C} = C(t)^{-\sigma} e^{-\rho t} - \lambda = 0$$

$$\rightarrow \lambda = C(t)^{-\sigma} e^{-\rho t}$$

- Derive λ with regards to time (t), then we have: -

$$\rightarrow \lambda^* = -\rho C(t)^{-\sigma} e^{-\rho t} - \sigma C(t)^{-\sigma-1} \frac{\partial C}{\partial t} e^{-\rho t}$$

Where $\lambda^* = \frac{\partial \lambda}{\partial t}, and\ C^* = \frac{\partial C}{\partial t}.\ So$

$$\rightarrow \lambda^* = -C(t)^{-\sigma} e^{-\rho t} [\rho + \sigma C(t)^{-1} C^*]$$

- Derive $H(C, A, \lambda)$ with regards to the state variable(A) and equate it with $-\lambda^*$ then we have: -

$$\frac{\partial H}{\partial A} = -\lambda^* = \lambda\, r$$

- Substitute for λ and λ^*, then we have: -

$$-\lambda^* = \lambda\, r$$

$$\rightarrow C(t)^{-\sigma} e^{-\rho t} [\rho + \sigma C(t)^{-1} C^*] = C(t)^{-\sigma} e^{-\rho t}\, r$$

$$\rightarrow \rho + \sigma C(t)^{-1} C^* = r$$

$$\rightarrow \sigma C(t)^{-1}C^{*} = r - \rho$$

$then,$

$$\rightarrow \frac{C^{*}}{C} = \frac{r-\rho}{\sigma}$$

Proof B

The technology production function is: -

$$X = \bar{q}[\theta\alpha\, L^{T} + \delta\,(1-\alpha)\, L^{T}]$$

Rearranging equation (7), then we have: -

$$L^{T} \;= \frac{1}{\bar{q}}\left[\frac{X}{\alpha\,\theta+(1-\alpha)\delta}\right]$$

We can write the total cost of the intermediate product as follows: -

$$TC^{I} = w^{s}\alpha\, L^{T} + \; w^{u}\,(1-\alpha)\, L^{T}$$

Substitute for L^{T} then: -

$$TC^{I} = w^{s}\alpha\; \frac{1}{\bar{q}}\left[\frac{X}{\alpha\,\theta+(1-\alpha)\delta}\right] + \; w^{u}(1-\alpha)\; \frac{1}{\bar{q}}\left[\frac{X}{\alpha\,\theta+(1-\alpha)\delta}\right]$$

Derive TC^{I} with regards to X, then the marginal cost becomes as follows: -

$$mc = \frac{TC^{I}}{\partial X} = \; \frac{\alpha\, w^{s} + (1-\alpha)\, w^{u}}{[\;\alpha\,\theta + (1-\alpha)\delta]\bar{q}}$$

Proof C

Derive (13) according to X then we have: -

$$\frac{\partial \pi_{j}}{\partial X} = (1-\beta)\delta^{\beta}q^{\beta}\; X^{-\beta}\; L^{Tu^{\beta}} - \frac{\alpha\, w^{s} + (1-\alpha)\, w^{u}}{[\alpha\,\theta + (1-\alpha)\,\delta]\bar{q}} = 0$$

$$X^{-\beta} = \frac{\alpha\, w^s + (1-\alpha)\, w^u}{\delta^\beta[\alpha\,\theta + (1-\alpha)\,\delta]\bar{q}{L^{Tu}}^\beta(1-\beta)\, q^\beta}$$

$$\rightarrow \frac{1}{X^\beta} = \frac{\alpha\, w^s + (1-\alpha)\, w^u}{\delta^\beta[\alpha\,\theta + (1-\alpha)\delta]\bar{q}{L^{Tu}}^\beta(1-\beta)q^\beta}$$

$$\rightarrow [\alpha\theta + (1-\alpha)\delta]\bar{q}{L^{Tu}}^\beta(1-\beta)q^\beta = X^\beta[\alpha\, w^s + (1-\alpha)w^u]$$

$$\rightarrow X^\beta = \frac{\delta^\beta(1-\beta)[\alpha\theta + (1-\alpha)\delta]\bar{q}{L^{Tu}}^\beta q^\beta}{\alpha\, w^s + (1-\alpha)w^u}$$

$$\rightarrow X^* = \left[\frac{\delta^\beta(1-\beta)[\alpha\theta+(1-\alpha)\delta]\bar{q}{L^{Tu}}^\beta q^\beta}{\alpha\, w^s+(1-\alpha)w^u}\right]^{\frac{1}{\beta}} = \delta\left[\frac{(1-\beta)[\alpha\,\theta+(1-\alpha)\delta]\bar{q}}{\alpha w^s+(1-\alpha)w^u}\right]^{\frac{1}{\beta}} L^{Tu}q$$

And by substituting X^* in the inverse demand, we get: -

$$p^* = \frac{\alpha w^s + (1-\alpha)w^u}{(1-\beta)\bar{q}[\alpha\,\theta + (1-\alpha)\delta]}$$

<u>Proof D</u>

<u>Stationary equilibrium wages</u>

To find the optimal wages in this economy, we can use the profit function of the producers of the final goods, presented in (9), and maximize it with regards to L. Accordingly,

$$w^{u*} = \delta^\beta \frac{\beta}{1-\beta}\, q^\beta\ \ {X^*}^{1-\beta}\ {L^{Tu}}^{\beta-1}$$

Substitute forX^*, then we have: -

$$w^{u*} = \frac{\beta}{1-\beta}\; q^{\beta}\; \delta \left[\frac{(1-\beta)[\,\alpha\theta + (1-\alpha)\delta]\bar{q}\; L^{\beta} q^{\beta}}{\alpha\, w^{s} + (1-\alpha)w^{u}}\right]^{\frac{1-\beta}{\beta}} {L^{Tu}}^{\beta-1}$$

$$\rightarrow w^{u*}[\alpha\, w^{s} + (1-\alpha)w^{u}]^{\frac{1-\beta}{\beta}} = \delta(\alpha\theta + (1-\alpha)\delta)^{\frac{1-\beta}{\beta}}\, \beta(1-\beta)^{\frac{1-2\beta}{\beta}}\, q\, \bar{q}^{\frac{1-\beta}{\beta}}$$

From the perspective of the intermediate goods, we can find the equilibrium wages for skilled and unskilled labour using the profit function of the intermediate goods firms, as follows: -

$$\pi^{I} = p\; \bar{q}\; [\theta L^{Ts} + \delta L^{Tu}] - \; w^{s} L^{Ts} - w^{u} L^{Tu}$$

$Derive\;\; \pi^{I}\; with\, regards\, to\; L^{Ts}\; and\; L^{Tu};\; then\, we\, have\, the\, following: -$

$$\frac{\partial \pi^{I}}{\partial L^{Ts}} = \theta p\; \bar{q} - w^{s} = 0$$

$$\frac{\partial \pi^{I}}{\partial L^{Tu}} = \delta\; p\; \bar{q} - w^{u} = 0$$

So $w^{s*} = \; \theta\, p^*\, \bar{q}, and \;\; w^{u*} = \delta\, p^*\, \bar{q}$. Substitute for the value of p^* and $(\alpha w^{s*} + (1-\alpha)w^{u*})$ in equilibrium then $w^{s*} = \theta\, \frac{\alpha w^{s} + (1-\alpha)w^{u}}{(1-\beta)[\alpha\, \theta + (1-\alpha)\delta]}$, and $w^{u*} = \delta\, \frac{\alpha w^{s} + (1-\alpha)w^{u}}{(1-\beta)[\alpha\, \theta + (1-\alpha)\delta]}$. This means that $\alpha w^{s} + (1-\alpha)w^{u} = \frac{1}{\delta} {w^{u}}^{*} (1-\beta)[\alpha\, \theta + (1-\alpha)\delta]$. Substitute this in the equilibrium wages described by$(w^{u*}[\alpha w^{s} + (1-\alpha)w^{u}]^{\frac{1-\beta}{\beta}} = (\alpha\, \theta + (1-\alpha)\delta)^{\frac{1-\beta}{\beta}}\, \beta(1-\beta)^{\frac{1-2\beta}{\beta}}\, q\, \bar{q}^{\frac{1-\beta}{\beta}})$, then

$$\rightarrow {w^{u*}}^{\frac{1}{\beta}} \left[\frac{1}{\delta}(1-\beta)[\alpha\, \theta + (1-\alpha)\delta]\right]^{\frac{1-\beta}{\beta}} = \delta(\alpha\, \theta + (1-\alpha)\delta)^{\frac{1-\beta}{\beta}}\, \beta(1-\beta)^{\frac{1-2\beta}{\beta}}\, q\, \bar{q}^{\frac{1-\beta}{\beta}}$$

$$\rightarrow w^{u*\frac{1}{\beta}} = \delta^{\frac{1}{\beta}} \ \frac{\beta}{1-\beta} \ q \ \bar{q}^{\frac{1-\beta}{\beta}}$$

$$\rightarrow w^{u*} = \delta \ \left(\frac{\beta}{1-\beta}\right)^{\beta} \ \bar{q}$$

Now for w^{s*} we have $w^{s*} = \theta \frac{\alpha w^{s}+(1-\alpha)w^{u}}{(1-\beta)[\alpha \ \theta+(1-\alpha)\delta]}$. Substituting for $\alpha w^{s} + (1-\alpha)w^{u}$ then $w^{s*} = \frac{\theta}{\delta}\frac{w^{u*}(1-\beta)[\alpha \ \theta+(1-\alpha)\delta]}{(1-\beta)[\alpha \ \theta+(1-\alpha)\delta]} = \frac{\theta \ w^{u*}}{\delta}$, and substituting for w^{u*} then: -

$$w^{s*} = \theta \frac{\delta \ \left(\frac{\beta}{1-\beta}\right)^{\beta} \bar{q}}{\delta} = \theta \left(\frac{\beta}{1-\beta}\right)^{\beta} \bar{q}$$

Substitute w^{s*} and w^{u*} in $p, X, and\ mc$, then in equilibrium, we have: -

$$p^{*} = \frac{\alpha w^{s} + (1-\alpha)w^{u}}{(1-\beta)\bar{q}[\alpha\theta + (1-\alpha)\delta]}$$

$$p^{*} = \frac{\left(\frac{\beta}{1-\beta}\right)^{\beta}(1-\beta)\bar{q}[\alpha\theta+(1-\alpha)\delta]}{(1-\beta)\bar{q}[\alpha\theta+(1-\alpha)\delta]} = \frac{\beta^{\beta}}{(1-\beta)^{1+\beta}} \quad ,$$

$$X^{*} = \delta \frac{(1-\beta)^{1+\beta}}{\beta^{\beta}} L^{Tu} q \quad ,$$

and

$$mc = \frac{\alpha w^{s} + (1-\alpha)w^{u}}{[\alpha \ \theta + (1-\alpha)\delta]\bar{q}} = \frac{\alpha \ \theta \left(\frac{\beta}{1-\beta}\right)^{\beta} \bar{q} + (1-\alpha)\delta \ \left(\frac{\beta}{1-\beta}\right)^{\beta} \bar{q}}{[\alpha\theta + (1-\alpha)\delta]\bar{q}} = \left(\frac{\beta}{1-\beta}\right)^{\beta}$$

Accordingly, the substitution for the profit of the intermediate producer leads to the following profit equilibrium for the final product producer-

$$\pi = \max_{X \geq 0}\{(p - mc)X\}$$

$$\pi^* = (p^* - mc^*)X^*$$

$$\rightarrow \pi^* = \left(\frac{\beta^\beta}{(1-\beta)^{1+\beta}} \quad - \left(\frac{\beta}{1-\beta}\right)^\beta\right)\frac{\delta(1-\beta)^{1+\beta}}{\beta^\beta}L^{Tu}q$$

$$\rightarrow \ \pi^* = \left(\frac{\beta^\beta - (1-\beta)\beta^\beta}{(1-\beta)^{1+\beta}} \quad \right)\delta\,\frac{(1-\beta)^{1+\beta}}{\beta^\beta}L^{Tu}q$$

$$\rightarrow \pi^* = \delta\left(\frac{1-(1-\beta)}{\beta^\beta} \quad \right)L^{Tu}q$$

$$\rightarrow \pi^* = \delta\left(\frac{\beta}{\beta^\beta} \quad \right)L^{Tu}q$$

$$\rightarrow \pi^* = \delta\left(\beta^{1-\beta}\right)L^{Tu}q$$

$$\rightarrow \pi^* = \delta\ \breve{\pi}\ q$$

Where $\breve{\pi} = \beta^{1-\beta}L^{Tu}$.

Proof E

Define the firm's R&D technology (Z) as follows: -

$$Z = \ \hat{A}^\gamma\ n^\gamma l^{T(R\&D)^{1-\gamma}}$$

Rearrange (21) and re-write it in terms of $l^{T(R\&D)}$, then we have: -

$$l^{T(R\&D)^{1-\gamma}} = \frac{Z}{\hat{A}^\gamma\ n^\gamma}$$

$$\rightarrow l^{T(R\&D)} = \left(\frac{Z}{\hat{A}^\gamma\ n^\gamma}\right)^{\frac{1}{1-\gamma}}$$

$$\rightarrow l^{T(R\&D)} = \frac{Z^{\frac{1}{1-\gamma}}}{\hat{A}^{\frac{\gamma}{1-\gamma}} n^{\frac{\gamma}{1-\gamma}}}$$

As the innovation intensity of the firm (flow rate of innovation) is $z = \frac{Z}{n}$, then: -

The R&D cost function can be defined as: -

$$\mathrm{CR}(\mathrm{Z}, \mathrm{n}, \hat{\mathrm{A}}) = w^s\, \hat{\alpha}\, l^{T(R\&D)} + w^u(1-\hat{\alpha}) l^{T(R\&D)} = [w^s\hat{\alpha} + w^u(1-\hat{\alpha})] l^{T(R\&D)}$$

Substitute for $l^{T(R\&D)}$, then: -

$$\mathrm{CR} = [w^s\hat{\alpha} + w^u(1-\hat{\alpha})] Z^{\frac{1}{1-\gamma}} \hat{\mathrm{A}}^{-\frac{\gamma}{1-\gamma}}\, n^{-\frac{\gamma}{1-\gamma}}$$

$$\rightarrow \mathrm{CR} = [w^s\hat{\alpha} + w^u(1-\hat{\alpha})] n^{\frac{1}{1-\gamma}} z^{\frac{1}{1-\gamma}} \hat{\mathrm{A}}^{-\frac{\gamma}{1-\gamma}}\, n^{-\frac{\gamma}{1-\gamma}}$$

$$\rightarrow \mathrm{CR} = [w^s\hat{\alpha} + w^u(1-\hat{\alpha})]\, n\, z^{\frac{1}{1-\gamma}} \hat{\mathrm{A}}^{-\frac{\gamma}{1-\gamma}}$$

$$\rightarrow \mathrm{CR} = [w^s\hat{\alpha} + w^u(1-\hat{\alpha})]\, n\, \mathrm{J}(\mathrm{z}, \hat{\mathrm{A}})$$

Where $\mathrm{J}(\mathrm{z}, \hat{\mathrm{A}}) = z^{\frac{1}{1-\gamma}} \hat{\mathrm{A}}^{-\frac{\gamma}{1-\gamma}}$.

<u>Proof F</u>

Derive (23) concerning z^e , and rearrange we get the following: -

$$\rightarrow \frac{1}{1-\gamma} [w^s\hat{\alpha} + w^u(1-\hat{\alpha})] n \frac{\partial \mathrm{J}(\mathrm{z}^e, \hat{\mathrm{A}}^e)}{\partial \mathrm{z}^e} = n\ \ EV^e(q', \hat{\mathrm{A}}^e, \theta^e,\ \delta^e)$$

$$\rightarrow \frac{1}{1-\gamma} [w^s\hat{\alpha} + w^u(1-\hat{\alpha})]\, n\, z^{e^{\frac{\gamma}{1-\gamma}}} \hat{\mathrm{A}}^{e^{-\frac{\gamma}{1-\gamma}}} = \mathrm{n}\, EV^e(q', \hat{\mathrm{A}}^e, \theta^e,\ \delta^e)$$

Where $\mathrm{J}(\mathrm{z}^e, \hat{\mathrm{A}}) = z^{e\frac{1}{1-\gamma}} \hat{\mathrm{A}}^{-\frac{\gamma}{1-\gamma}}$, and z^e is the flow rate of innovation for the new entrant. Then, the previous equation leads to:

$$\rightarrow z^{e\frac{\gamma}{1-\gamma}} = \hat{\mathrm{A}}^{e\frac{\gamma}{1-\gamma}} \frac{(1-\gamma) EV^e(q', \hat{\mathrm{A}}^e, \theta^e, \delta^e)}{[w^s \hat{\alpha} + w^u(1-\hat{\alpha})]}$$

$$z^{*e} = \hat{\mathrm{A}}^e \left[\frac{(1-\gamma)\, EV^e(q', \hat{\mathrm{A}}^e, \theta^e, \delta^e)}{w^s \hat{\alpha} + w^u(1-\hat{\alpha})}\right]^{\frac{1-\gamma}{\gamma}}$$

Proof G

Derive (25) co$ncerning$ z^H we get the following: -

$$\frac{1}{1-\gamma} [w^s \hat{\alpha} + w^u(1-\hat{\alpha})] n \frac{\partial \mathrm{J}(\mathrm{z}^H, \hat{\mathrm{A}}^H)}{\partial \mathrm{z}^H} = n\, EV^H(q', \hat{\mathrm{A}}^H, \theta^H, \delta^H)$$

$$\rightarrow \frac{1}{1-\gamma} [w^s \hat{\alpha} + w^u(1-\hat{\alpha})]\ z^{H\frac{\gamma}{1-\gamma}} \hat{\mathrm{A}}^{H^{-\frac{\gamma}{1-\gamma}}} = EV^H(q', \hat{\mathrm{A}}^H, \theta^H, \delta^H)$$

Where $\mathrm{J}(\mathrm{z}^H, \hat{\mathrm{A}}) = z^{H\frac{1}{1-\gamma}} \hat{\mathrm{A}}^{-\frac{\gamma}{1-\gamma}}$, and z^H are the flow rate of innovation for high type firm. Then, the previous equation leads to:

$$z^{*H} = \hat{\mathrm{A}}^H \left[\frac{(1-\gamma)\, EV^H(q', \hat{\mathrm{A}}^H, \theta^H, \delta^H)}{w^s \hat{\alpha} + w^u(1-\hat{\alpha})}\right]^{\frac{1-\gamma}{\gamma}}$$

Derive (27) co$ncerning$ z^L we get the following: -

$$\rightarrow \frac{1}{1-\gamma} [w^s \hat{\alpha} + w^u(1-\hat{\alpha})] n\, z^{\frac{\gamma}{1-\gamma}} \hat{\mathrm{A}}^{L^{-\frac{\gamma}{1-\gamma}}} = \mathrm{n}\, EV^L(q', \hat{\mathrm{A}}^L, \theta^L, \delta^L)$$

Where $\mathrm{J}(\mathrm{z}^{L}, \hat{\mathrm{A}}) = z^{L\frac{1}{1-\gamma}} \hat{\mathrm{A}}^{-\frac{\gamma}{1-\gamma}}$, and z^{L} is the flow rate of innovation for low type firm. Then, the previous equation leads to:

$$z^{*L} = \hat{\mathrm{A}}^{L} \left[\frac{(1-\gamma)\, EV^{L}(q', \hat{\mathrm{A}}^{L},\, \theta^{L}, \delta^{L}\,)}{w^{s}\hat{\alpha}\; + w^{u}(1-\;\hat{\alpha})} \right]^{\frac{1-\gamma}{\gamma}}$$

Proof H

To ***find $q_{min}{}^{L}$:***

Rearrange (27) as follows: -

$$(\mathrm{r} + \tau + \zeta)\, V^{L}(q) - \frac{\partial V^{L}(q)}{\partial q}\frac{\partial q}{\partial t}$$

$$= \breve{\pi}\, q - \max_{z^{L} \geq 0} \left\{ [w^{s}\hat{\alpha} + w^{u}(1-\hat{\alpha})]\, n\, \mathrm{J}(\mathrm{z}^{L}, \hat{\mathrm{A}}^{L}) + \; n\, z^{L} EV^{L}(q', \hat{\mathrm{A}}^{L},\, \theta^{L}, \delta^{L}) \right\}$$

Define: -

$$\bar{\bar{I}} = \tau + \zeta + \mathrm{r}\,,$$

$and\;\; \bar{\bar{\mathrm{M}}}^{L} = \max_{z^{L} \geq 0} \left\{ [w^{s}\hat{\alpha} + w^{u}(1-\hat{\alpha})]\, n\, \mathrm{J}(\mathrm{z}^{l}, \hat{\mathrm{A}}^{L}) + \; n\, z^{L} EV^{L}(q', \hat{\mathrm{A}}^{L},\, \theta^{L}, \delta^{L}\,) \right\}$, then we have the following: -

$$\rightarrow \bar{\bar{I}}\, V^{L}(q) - \frac{\partial V^{L}(q)}{\partial t} = \breve{\pi}\, q - \bar{\bar{\mathrm{M}}}^{L}$$

Since this equation presents a First-order difference equation, then we can integrate it using complementary function and particular integral as follows: -

$$\rightarrow Complementary\ function{:}-looking\ for\ a\ solution\ where{:}-$$

$$\bar{\bar{I}}V^L(q) - \frac{\partial V^L(q)}{\partial t} = 0$$

$$\rightarrow Guess\ that\ we\ have\ a\ solution\ of\ the\ form\ V^L(q) = Ae^{mt}$$

$$\frac{\partial V^L(q)}{\partial t} = mAe^{mt}$$

$$\rightarrow \bar{\bar{I}}\ Ae^{mt} - mAe^{mt} = 0$$

$$\rightarrow m = \bar{\bar{I}}$$

$$\rightarrow V^L(q)^c = Ae^{\bar{\bar{I}}t}$$

$$\rightarrow particular\ integral \rightarrow Guess\ V^L(q) = k\ where\ k\ is\ constant$$

$$\frac{\partial V^L(q)}{\partial t} = 0$$

$$\bar{\bar{I}}\ k - 0 = \breve{\pi}\ q - \bar{\bar{\mathrm{M}}}^L$$

Using the method of undetermined coefficients, then we have: -

$$k = \frac{\breve{\pi}\ q - \bar{\bar{\mathrm{M}}}^L}{\bar{\bar{I}}}$$

$$\rightarrow VN^L(q)^p = \frac{\breve{\pi}\, q - \bar{\bar{\bar{\mathrm{M}}}}^L}{\bar{\bar{I}}}$$

Then the general solution for $VN^L(q)$ becomes as follows: -

$$V^L(q) = V^L(q)^c + V^L(q)^p$$

$$General\ solution \rightarrow V^L(q) = Ae^{\bar{\bar{I}}t} + \frac{\breve{\pi}\, q - \bar{\bar{\bar{\mathrm{M}}}}^L}{\bar{\bar{I}}}$$

$$at\ t = 0\ \rightarrow V^L(q) = V_0^L$$

$$so\ at\ t = 0\ \rightarrow\ A + \frac{\breve{\pi}\, q - \bar{\bar{\bar{\mathrm{M}}}}^L}{\bar{\bar{I}}} = V_0^L$$

$$A = V_0^L - \left[\frac{\breve{\pi}\, q - \bar{\bar{\bar{\mathrm{M}}}}^L}{\bar{\bar{I}}}\right]$$

$$Specific\ solution \rightarrow VN^L(q) = \left[VN_0^L - \left[\frac{\breve{\pi}\, q - \bar{\bar{\bar{\mathrm{M}}}}^L}{\bar{\bar{I}}}\right]\right] e^{\bar{\bar{I}}t} + \frac{\breve{\pi}\, q - \bar{\bar{\bar{\mathrm{M}}}}^L}{\bar{\bar{I}}}$$

With the boundary condition $V^L(q_{min}) = 0$, then we have: -

$$Specific\ solution \rightarrow V^L(q) = \left(1 - e^{\bar{\bar{I}}t}\right) \frac{\breve{\pi}\, {q_{min}}^L - \bar{\bar{\bar{\mathrm{M}}}}^L}{\bar{\bar{I}}}$$

Which means that: -

$$q_{min}{}^{L} = \frac{\bar{\bar{\mathrm{M}}}^{L}}{\breve{\pi}} = \frac{1}{\breve{\pi}}\left[\max_{z^{L}\geq 0}\left\{[w^{s}\hat{\alpha} \ + w^{u}(1- \ \hat{\alpha})]\, n\, \mathrm{J}\left(\mathrm{z}^{L},\hat{\mathrm{A}}^{L}\right) + n\, z^{L}EV^{L}\left(q',\hat{\mathrm{A}}^{L},\ \theta^{L},\delta^{L}\ \right)\right\}\right]$$

<u>To find $q_{min}{}^{H}$:-</u>

Rearrange (25) as follows: -

$$(\mathrm{r}+\tau+\zeta)\ V^{H}(q) + h(V^{H}(q) - V^{L}(q)) - \frac{\partial V^{H}(q)}{\partial q}\frac{\partial q}{\partial t} \ = \breve{\pi}\ q$$

$$-\max_{z^{H}\geq 0}\left\{\ [w^{s}\hat{\alpha} \ + w^{u}(1- \ \hat{\alpha}]\, n\, \mathrm{J}\left(\mathrm{z}^{H},\hat{\mathrm{A}}^{H}\right) + n\, z^{H}EV^{H}\left(q',\hat{\mathrm{A}}^{H},\ \theta^{H},\delta^{H}\right)\ \right\}$$

Define: -

$$\bar{\bar{I}} = \tau+\zeta+\mathrm{r}$$

$$and$$

$\bar{\bar{\mathrm{M}}}^{H} = \max_{z^{H}\geq 0}\left\{\ [w^{s}\hat{\alpha} \ + w^{u}(1- \ \hat{\alpha})]\, n\, \mathrm{J}\left(\mathrm{z}^{H},\hat{\mathrm{A}}^{H}\right) + n\, z^{H}EV^{H}\left(q',\hat{\mathrm{A}}^{H},\ \theta^{H},\delta^{H}\ \right)\right\}$, then we have the following: -

$$\bar{\bar{I}}\, V^{H}(q) + h\left(V^{H}(q) - \ V^{L}(q_{min})\right) - \ \frac{\partial V^{H}(q)}{\partial t} = \breve{\pi}\ q - \bar{\bar{\mathrm{M}}}^{H}$$

Rearrange and substitute for $V^{L}(q_{min})$, then we have: -

$$\rightarrow -\frac{\partial V^{H}(q)}{\partial t} + \left(\bar{\bar{I}}+h\right)V^{H}(q) \ = \left[\breve{\pi}\ q - \bar{\bar{\mathrm{M}}}^{H}\right] + h\left(1 - e^{\bar{\bar{I}}t}\right)\frac{\breve{\pi}\ q - \bar{\bar{\mathrm{M}}}^{H}}{\bar{\bar{I}}}$$

$$\rightarrow -\frac{\partial V^{H}(q)}{\partial t} + \left(\bar{\bar{I}}+h\right)V^{H}(q) \ = \left[1+\frac{h}{\bar{\bar{I}}}\right]\left(\breve{\pi}\ q - \bar{\bar{\mathrm{M}}}^{H}\right) - \frac{\breve{\pi}\ q - \bar{\bar{\mathrm{M}}}^{H}}{\bar{\bar{I}}}\, h\, e^{\bar{\bar{I}}t}$$

Since this equation presents a First-order difference equation, then we can integrate it using complementary function and particular integral as follows: -

$$\rightarrow Complementary\ function: -looking\ for\ a\ solution\ where: -$$

$$\left(\bar{\bar{I}} + h\right)V^{H}(q) - \frac{\partial V^{H}(q)}{\partial t} = 0$$

$$\rightarrow Guess\ that\ we\ have\ a\ solution\ of\ the\ form\ V^{H}\left(q_{j}\right) = Ae^{mt}$$

$$\frac{\partial V^{H}(q)}{\partial t} = mAe^{mt}$$

$$\rightarrow \left(\bar{\bar{I}} + h\right) Ae^{mt} - mAe^{mt} = 0$$

$$\rightarrow m\ = \left(\bar{\bar{I}} + h\right)$$

$$\rightarrow V^{H}(q)^{c} = Ae^{\left(\bar{\bar{I}}+h\right)t}$$

$$particular\ integral \rightarrow Guess\ V^{H}(q) = k_{0} + k_{1}e^{\bar{\bar{I}}t}$$

$$\frac{\partial V^{H}(q)}{\partial t} = k_{1}\bar{\bar{I}}e^{\bar{\bar{I}}t}$$

$$\rightarrow \left(\bar{\bar{I}} + h\right)\left[k_{0} + k_{1}e^{\bar{\bar{I}}t}\right] - k_{1}\bar{\bar{I}}e^{\bar{\bar{I}}t}\ = \left[1 + \frac{h}{\bar{\bar{I}}}\right]\left(\breve{\pi}\ q - \bar{\bar{\mathrm{M}}}^{H}\right) - \frac{\breve{\pi}\ q - \bar{\bar{\mathrm{M}}}}{\bar{\bar{I}}} h\ e^{\bar{\bar{I}}t}$$

Using the method of undetermined coefficients, then we have: -

$$\left(\bar{\bar{I}}+h\right)k_0+hk_1e^{\bar{\bar{I}}t} \ =\left[1+\frac{h}{\bar{\bar{I}}}\right]\left(\breve{\pi}\,q-\bar{\bar{\mathrm{M}}}^{H}\right)-\frac{\breve{\pi}\,q-\bar{\bar{\mathrm{M}}}}{\bar{\bar{I}}}h\,e^{\bar{\bar{I}}t}$$

$$\to\left(\bar{\bar{I}}+h\right)k_0 \ =\left[1+\frac{h}{\bar{\bar{I}}}\right]\left(\breve{\pi}\,q-\bar{\bar{\mathrm{M}}}^{H}\right)$$

$$\to k_0 \ =\frac{\left(\breve{\pi}\,q-\bar{\bar{\mathrm{M}}}^{H}\right)}{\bar{\bar{I}}}$$

Now for k_1, we have: -

$$hk_1e^{\bar{\bar{I}}t}=-\frac{\breve{\pi}\,q-\bar{\bar{\mathrm{M}}}^{H}}{\bar{\bar{I}}}he^{\bar{\bar{I}}t}$$

$$\to k_1=-\frac{\breve{\pi}\,q-\bar{\bar{\mathrm{M}}}^{H}}{\bar{\bar{I}}}$$

So,

$$V^H(q)=k_0+k_1e^{\bar{\bar{I}}t}$$

$$\to V^H(q)=\frac{\left(\breve{\pi}\,q-\bar{\bar{\mathrm{M}}}^{H}\right)}{\bar{\bar{I}}}-\frac{\breve{\pi}\,q-\bar{\bar{\mathrm{M}}}^{H}}{\bar{\bar{I}}}e^{\bar{\bar{I}}t}$$

$$\to V^H(q)^P=(1-e^{\bar{\bar{I}}t})\frac{\left(\breve{\pi}\,q-\bar{\bar{\mathrm{M}}}^{H}\right)}{\bar{\bar{I}}}$$

Then the general solution for $V^H(q)$ becomes as follows: -

$$V^H(q) = V^H(q)^c + V^H(q)^p$$

$$General\ solution \rightarrow V^H(q) = Ae^{(\bar{\bar{I}}+h)t} + (1 - e^{\bar{\bar{I}}t})\frac{(\breve{\pi}\ q - \bar{\bar{\mathrm{M}}}^H)}{\bar{\bar{I}}}$$

$$at\ t = 0\ \rightarrow V^H(q) = V_0^H$$

$$so\ at\ t = 0\ \rightarrow\ A = V_0^H$$

With the boundary condition $V^L(q_{min})$, $V^H(q_{min}) = 0$, then we have: -

$$Specific\ solution \rightarrow V^H(q_{min}) = (1 - e^{\bar{\bar{I}}t})\frac{(\breve{\pi}\ {q_{min}}^H - \bar{\bar{\mathrm{M}}}^H)}{\bar{\bar{I}}}$$

Which means that: -

$${q_{min}}^H = \frac{\bar{\bar{\mathrm{M}}}^H}{\breve{\pi}} = \frac{1}{\breve{\pi}}\left[\max_{z^H \geq 0}\left\{\ [w^s\hat{\alpha}\ + w^u(1 -\ \hat{\alpha})]\ n\ \mathrm{J}\left(\mathrm{z}^H, \hat{\mathrm{A}}^H\right) + n\ z^H E V^H\left(q', \hat{\mathrm{A}}^H,\ \theta^H, \delta^H\ \right)\right\}\right]$$

<u>Proof I</u>

Define $\boldsymbol{\Omega}(q,t)$ as the overall productivity distribution for firms and labour, divided into two conditional distributions. These are the firm's productivity distribution $\boldsymbol{\Omega}_F(q,t)$ with high/low type and its percentage from the overall productivity distribution equals to a, and labour productivity distribution $\boldsymbol{\Omega}_L(q,t)$ with high/low type for each labour productivity and its percentage from the overall productivity distribution equals to $(1-a)$. Explain this expression in an equation form leads to: -

$$\boldsymbol{\Omega}(q,t) = a\ \boldsymbol{\Omega}_F(q,t) +\ (\mathbf{1} - \boldsymbol{a})\ \boldsymbol{\Omega}_L(q,t),$$

Also, $q(t+\Delta t)=\int_0^\infty q \; d\Omega(q,t+\Delta t)$, which equals $a\int_0^\infty q \; d\boldsymbol{\Omega}_F(q,t+\Delta t)+(1-a)\int_0^\infty q \; d\Omega_L(q,t+\Delta t) = a\int_0^\infty[\Delta\tau(q+\varphi\bar{q})+(1-\Delta\tau)q] \; \boldsymbol{\Omega}_F(q,t)+(1-a)\int_0^\infty[\Delta\tau\,(q+\varphi\bar{q})+\;(1-\Delta\tau)\,q]\,\boldsymbol{\Omega}_L(q,t)$

Then:

$$\frac{q(t+\Delta t)-q(t)}{\Delta t}$$

$$=a\int_0^\infty \tau[(q+\varphi\bar{q})-q] \; \boldsymbol{\Omega}_F(q,t)+(1-a)\int_0^\infty \tau[\,(q+\varphi\bar{q})-q]\,\boldsymbol{\Omega}_L(q,t)$$

And

$$\frac{q(t+\Delta t)-q(t)}{\Delta q(t)}=a\int_0^\infty \tau[(q+\varphi)-q] \; \boldsymbol{\Omega}_F(q,t)+(1-a)\int_0^\infty \tau[\,(q+\varphi)-q]\,\boldsymbol{\Omega}_L(q,t)$$

Hence, the growth equals to:

$$Growth=\tau\varphi\left[a\int_0^\infty \boldsymbol{\Omega}_F(q,t)+(1-a)\int_0^\infty \boldsymbol{\Omega}_L(q,t)\;\right]=\tau\varphi\int_0^\infty \boldsymbol{\Omega}(q,t)$$

In equilibrium $\int_0^\infty \boldsymbol{\Omega}(q,t)=1$, which leads to the result that $G=\tau\varphi$, where G is the equilibrium growth rate.

Another method to find the growth in equilibrium is by defining $\boldsymbol{\Omega}$ as the overall productivity distribution, the inflow and outflow of productivity for each progress in quality must be equal in stationary equilibrium. Explain this expression in an equation form leads to: -

$$\boldsymbol{\Omega}_t(q)=\boldsymbol{\Omega}_{t+\Delta t}(q)$$

Where Δt is the time interval and $G=\frac{\partial q}{\partial t}\frac{1}{q}$. So,

$$\boldsymbol{\Omega}_t(q)=\;\boldsymbol{\Omega}_t(q(1+G\Delta t)-\tau\Delta t\left[\boldsymbol{\Omega}_t(q)-\boldsymbol{\Omega}_t\left[q-\varphi\int_0^\infty q\,\Omega(q)\;dq\right]\right]$$

$$\rightarrow -\boldsymbol{\Omega}_t(q(1+G\Delta t)+\boldsymbol{\Omega}_t(q)=-\tau\Delta t\left[\boldsymbol{\Omega}_t(q)-\boldsymbol{\Omega}_t\left[q-\varphi\int_0^\infty q\Omega(q)\ dq\right]\right]$$

$$\rightarrow\ \boldsymbol{\Omega}_t(q(1+G\Delta t)-\boldsymbol{\Omega}_t(q)=\tau\Delta t\left[\boldsymbol{\Omega_t(q)}-\boldsymbol{\Omega}_t\left[q-\varphi\int_0^\infty q\Omega(q)\ dq\right]\right] \qquad \text{(iiii)}$$

$$\rightarrow \frac{\boldsymbol{\Omega}_t(q(1+G\Delta t)-\boldsymbol{\Omega}_t(q)}{\Delta t}=\tau\left[\boldsymbol{\Omega}_t(q)-\boldsymbol{\Omega}_t\left[q-\varphi\int_0^\infty q\Omega(q)\ dq\right]\right]$$

$$\lim_{\Delta t\to 0}\frac{\boldsymbol{\Omega}_t(q(1+G\Delta t)-\boldsymbol{\Omega}_t(q)}{\Delta t}=qG\ \Omega(q) \qquad \text{(V)}$$

Substitute for (iiii) from (V), leads to the following distribution: -

$$q\Omega(q)=\frac{\tau\left[\boldsymbol{\Omega}_t(q)-\boldsymbol{\Omega}_t\left[q-\varphi\int_0^\infty q\Omega(q)\ dq\right]\right]}{G}$$

And the expected value is: -

$$E(q)=\int_0^\infty q\Omega(q)\ dq=\frac{\tau}{G}\int_0^\infty\left[\boldsymbol{\Omega}_t(q)-\boldsymbol{\Omega}_t\left[q-\varphi\int_0^\infty q\Omega(q)\ dq\right]\right]d\,q$$

$$=\frac{\tau}{G}\varphi\int_0^\infty q\Omega(q)\ dq$$

In equilibrium $E(q)=G=\int_0^\infty q\Omega(q)\ dq$, and leads to the result that $G=\tau\varphi$ where G is the equilibrium growth rate.

<u>Proof J</u>

The social planners' Hamiltonian is described as: -

$$H(C,Q,\mu) = \frac{C(t)^{1-\sigma}-1}{1-\sigma}e^{-\rho t}$$

$$+\mu.\left\{(\varphi-1)[w^s\hat{\alpha}\right.$$

$$\left.+w^u(1-\hat{\alpha})]n\mathrm{J}(\mathrm{z},\hat{\mathrm{A}})\left[\left[1-\frac{(1-\beta)^{1+\beta+\beta^2}}{\beta^{\beta^2}}\right]\frac{\delta L^{Tu}\bar{q}}{\beta^{\beta(1-\beta)}(1-\beta)^{\beta^2}}-C\quad\right]\right\}$$

The control variable is C, and the state variable is quality ($\bar{q}$).

- Derive $H(C,z,\mu)$ with regards to C leads to the following: -

$$\frac{\partial H}{\partial C} = C(t)^{-\sigma}e^{-\rho t} - \mu = 0$$

$$\rightarrow \mu = C(t)^{-\sigma}e^{-\rho t}$$

Derive μ with regards to time (t), then we have: -

$$\rightarrow \mu^* = -\rho C(t)^{-\sigma}e^{-\rho t} - \sigma C(t)^{-\sigma-1}\frac{\partial C}{\partial t}e^{-\rho t}$$

Where $\mu^* = \frac{\partial \mu}{\partial t}$, and $C^* = \frac{\partial C}{\partial t}$.

So we have the following: -

$$\rightarrow \mu^* = -C(t)^{-\sigma}e^{-\rho t}[\rho + \sigma C(t)^{-1}C^*]$$

- Derive $H(C,z,\mu)$ with regards to $\bar{q}$ and equate it with ($-\mu^*$) leads to the following: -

$$\frac{\partial H}{\partial \bar{q}} = -\mu^* = \mu.\left\{(\varphi - 1)[w^s \hat{\alpha} + w^u(1-\hat{\alpha})]n\mathrm{J}(\mathrm{z},\hat{\mathrm{A}})\left[\left[1 - \frac{(1-\beta)^{1+\beta+\beta^2}}{\beta^{\beta^2}}\right]\frac{\delta L^{Tu}}{\beta^{\beta(1-\beta)}(1-\beta)^{\beta^2}}\right]\right\}$$

- Substitute for μ and μ^*, then we have: -

$$C(t)^{-\sigma}e^{-\rho t}[\rho + \sigma C(t)^{-1}C^*]$$

$$= C(t)^{-\sigma}e^{-\rho t}.\left\{(\varphi - 1)[w^s \hat{\alpha} + w^u(1-\hat{\alpha})]n\mathrm{J}(\mathrm{z},\hat{\mathrm{A}})\left[\left[1 - \frac{(1-\beta)^{1+\beta+\beta^2}}{\beta^{\beta^2}}\right]\frac{\delta L^{Tu}}{\beta^{\beta(1-\beta)}(1-\beta)^{\beta^2}}\right] - \rho\right\}$$

Rearrange and write the equation according to the growth in consumption then: -

$$Growth \rightarrow \frac{C^*}{C} = \frac{1}{\sigma}\left[(\varphi - 1)[w^s \hat{\alpha} + w^u(1-\hat{\alpha})]n\mathrm{J}(\mathrm{z},\hat{\mathrm{A}})\left[\left[1 - \frac{(1-\beta)^{1+\beta+\beta^2}}{\beta^{\beta^2}}\right]\frac{\delta L^{Tu}}{\beta^{\beta(1-\beta)}(1-\beta)^{\beta^2}}\right] - \rho\right]$$

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***Paper 2**: Innovation and Income Inequality in the European Regions*

Abstract

In this paper, we study the impact of innovation on income inequality using European cross-regional panel data. In addition, we analyze other control factors that influence this relationship, including GDP, net migration, unemployment rate, and employment rate of highly skilled and low-skilled labour, alongside other factors. Our results show that innovation decreases the general measure of income inequality, and the gap in the middle of the income distribution, while it increases the gap at the top of the income distribution. Endogeneity problems usually arise in such models due to omitted variable bias, which appears in the reverse effect of income inequality on innovation. We solve this problem by applying two methods. First, we use the Generalized Method of Moments (GMM) which is proposed by (Arellano and Bover, 1995) and (Blundell and Bond, 1998) in which they use additional moment conditions with lagged differences of the dependent variable that are orthogonal to the levels of the disturbance. Second, we implement the Two-Stage Least Squares TSLS (Lewbel, 2012) method by identifying structural parameters of the endogenous covariates, especially since the external instruments for our model are very weak and not easy to find.

2.1 __Introduction__

Income inequality has long been an exciting subject among economists, as many developed countries have witnessed a massive increase in income inequality since the seventies of this century. However, the pattern in other developed countries like Europe was different, in which income inequality in these countries rose slightly. The same applies to the gap between the ninth and first deciles of the income distribution. A significant part of this increase is within educational groups (Aghion et al., 2002).

A wide range of research investigated the reason for the gap between different groups' income at the firm, region, and country levels. Although the literature supports the idea that innovation plays a vital role in changing this gap, the direction and sign of such a relation are not clear yet. To answer this question, we scrutinize the factors that affect income inequality in the European regions. The heterogeneity between these regions helps explain the reasons behind the discrepancies in income for different skill levels. In this study, we use a panel dataset of European regions, which we present in two main dimensions (years and regions). In addition, we use **the Nomenclature of Territorial Units for Statistics** (NUTS) level2 which Eurostat establishes in agreement with each European member. We cover the period from (1993 to 2011) by compromising two different sources. These are European Community Household Panel (ECHP) and European Union Survey on Income and Living Conditions (EU-SILC).

Figure (2-1) [10] illustrates the relationship between the number of patents and income inequality for all the European countries using time series data (from 1980 to 2018). The left side of the figure plots years (x-axis) against the percentile of income inequality on the top 10% (between 90% and 100% of the income distribution) (y-axis) and the number of patents (which presents a second y-axis on the exact figure). To the right side of this figure, we plot years (x-axis) against the Gini Index (which presents a general measure of income inequality (y-axis)

[10] The two graphs present time series data.

and the number of patents (second y-axis). This figure to the right shows a clear pattern between the general measure of income inequality (Gini Index[11]) and the number of patents in EU countries. The figure shows a negative relationship between them since the mid-nineties. On the other hand, in the exact figure to the left, there is a very close positive pattern between top income[12] shares and number of patents. This trend provides at least evidence of the inequality-innovation link and on top of the income distribution. At the regional level, a similar negative pattern goes in figure (2-2)[13], where we find a negative trend between income inequality (measured by the Gini Index) and the number of patents for three European regions (France-Paris Region, Italy- center, and Spain- Community of Madrid).

Consequently, this motivates us to investigate the existence of such a relationship and its direction in European regions. To do this, we follow the estimation method which is used by (Aghion et al., 2018) but on different data sets. We implement this on the European regional data while they carry out their study on the USA state levels. Also, we tackle the endogeneity problem in the model using two methods (GMM and TSLS-Heteroskedasticity), while they construct "The Appropriation Committees of the Senate and of the House of Representatives" as an instrument for innovation. Moreover, we analyze the gap in income as an outcome of complementarity between asymmetry in wealth (negative) and technological change accompanied by improvement in labour productivity (positive gap in wages). Due to the vast reduction in markups caused by market rivalry, the effect of the former is higher than the latter. Hence, we expect positive technological change decreases income inequality, especially in the overall distribution and in the inter decide ratio of the income distribution for different kinds of labour. However, (Aghion et al.,2018) model the effect of innovation on income

[11] Gini Index has been the most popular method of measuring income inequality.

[12] The top income share (top of the income distribution) is measured by the share of income owned by the top 10% and the top 1% of the income distribution. This measure is also used by (Aghion et al., 2018) but on different data sets and using a different methodology. We use these two measures at the top to show the effect of innovation on income inequality in the affluent middle- and upper-income class and not only the upper-income class.

[13] The graphs present three European regions with a time series trend from 1980 to 2018.

inequality (specifically on the top income shares) by focusing mainly on the entrepreneurial income as this part of income primarily benefits from innovation.

Many papers support our findings. For example, many studies indicate that innovation is the key to reducing income inequality[14]. Innovation affects the allocation of resources in different ways, as stated by (Antonelli and Gehringer, 2017) and (Claudia et al., 2018), in which the competition in the market between companies because of innovation and economic growth could increase wage inequalities in the economy. However, the effect of the decrease in income inequality stemming from the reduction in markups overcomes the increase in wage inequality stemming from Skilled Biased Technical Change (SBTC) and will eventually reduce income inequalities Another side of the literature argues that this decrease in income inequality is mainly due to the decrease in wage gaps through knowledge spillover, which is one of the main factors that avail workers with lower skills. The dissemination of knowledge increases their productivity and decreases the gap between their income and the income of highly skilled workers. For example, (Lee M, 2011) argues that the ability of workers to enhance their productivity through learning from highly skilled workers will increase their wages and cause a reduction in income inequality.

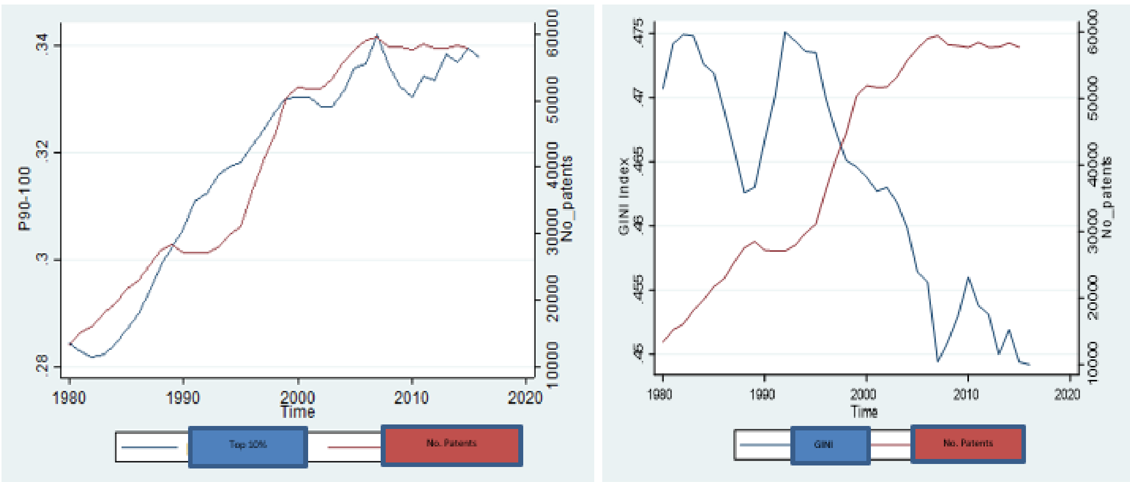
From another perspective, it is not necessarily the case that this link starts from innovation and ends in inequality, but it could be the other way around. A decrease in inequality may increase the aggregate demand for goods and services (Hatipoglu, 2012), which impacts the firms' investment in research and development due to the change in their profits. Depending on this fact, we cover the potential endogeneity problem between innovation and income inequality and try to solve it in this paper.

We direct our contribution to three main dimensions. First, we use dynamic instrumental variables and heteroskedastic methods to study the effect of patents on inequality

[14] The literature defines income as wages and salaries, self-employed income and entrepreneurs' income, capital income (includes realized property incomes), and social transfers (includes compensations and taxes).

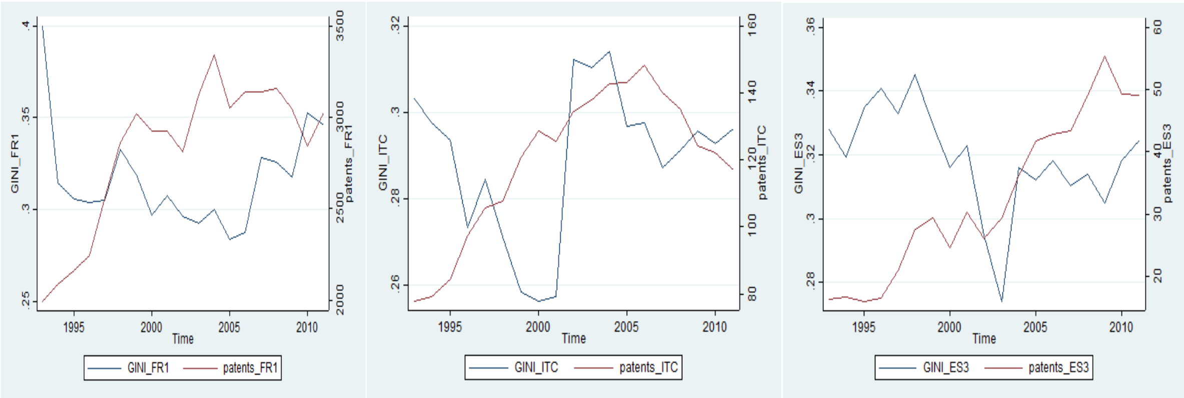
in the European regions, which helps solve the model's endogeneity problem. In contrast, previous studies were mainly concerned with analyzing the effect of the explanatory variables (see (Lee, 2011) and (Lee and Rodríguez-Pose, 2013)) or using different instruments (see (Claudia et al., 2018). Second, this study includes more comprehensive and diverse control variables measures, enhancing the accuracy of the model prediction. Finally, we cover a more expansive range of periods (1993- 2011) using a different dataset source, which forms harmonized information across regions, as the methodologies and procedures to collect the data are similar and coordinated by one source. The study of (Ramos and Royuela, 2014) covers the same period, but it investigates the trend in income inequality and not the reason behind that trend.

Figure 2-1: Number of Patents and different measures of Income Inequality in the EU countries during the period from 1980-2018



Notes: The graph on the left side shows income inequality in the top 10% of the distribution, while the graph on the right side shows the general measure of income inequality (Gini Index)).

Figure 2-2: Gini Index and number of patents in different European regions from 1980-2018



Notes: these graphs show the Gini Index and the number of Patents in three different EU-Regions: France-Paris Region (graph on the left), Italy-Centre (graph in the center), and Spain- Community of Madrid (graph on the right). These regions are classified according to NUTS2-EUROSTAT.

2.2 Literature review

In literature, three main strands analyze the relationship between innovation and income inequality. First, through testing the linkage between economic growth and income inequality. The empirical articles of (Paukert, 1973), (Ahluwalia, 1976), (Papanek and Kyn, 1986), (Alesina and Rodrik, 1994), (Persson and Tabellini, 1994), and (Perotti, 1996) support this argument. In this strand of literature, income inequality increases in the early stage of economic development, later it starts to decrease because of individuals' movements from underdeveloped sectors (for example, less sophisticated sectors like agriculture and sectors that use old technology) to more developed sectors, which in turn increase the share of people working in that sector and increase their average income per capita with a decrease in their income gap. This relationship has been dubbed the "Kuznets inverted-U curve ."This point of view depends on unskilled labour's savings, which becomes very high when the transition is fast and very low when the transition is complete. This fluctuation reflects the increase in income inequality in the first period of transition and its reduction in the later period of development.

However, other authors show that this relationship does not exist within the same notion. For example, (Barro, 2000) argues that the relationship between income inequality and economic growth does not explain the bulk of variations in inequality across countries or over time. His results from a broad panel show a slight overall relationship between income inequality and growth and investment rates.

It is worth mentioning that the reverse effect of income inequality on economic growth could exist because of the endogeneity that arises in these models. For example, (Odedokum and Round, 2004) paper shows evidence of a reduction in economic growth due to high-income inequality and through the decrease in secondary and tertiary education alongside other demographic and political factors. The same negative link between the degree of income dispersion and regional growth in European regions over the period 1993-2002 has been shown in (Ezcurra, 2007) paper, which applies to all the measures used in this study.

On the other hand, some studies show a positive relationship between economic growth and income inequality. (Rodrigues-Pose and Tselios, 2008) indicate a positive relationship between income, educational inequality, and economic growth, while they do not find a causal effect. In addition, (Perugini and Martino, 2008) show evidence of labour market centrality in the regional income inequality levels, with a positive relationship between inequality and growth. The same outcome applies to (Lee, 2011) but with a little link between knowledge-based industries and inequality except in the case of the financial sector. Notwithstanding the evidence, (Ramos and Royuela, 2014) and (Castells-Quintana et al., 2015) do not observe a positive relationship between inequality and growth in the early stage of development.

Our contribution to this strand of literature is by using different data sets and explanatory variables. Some of these papers use data from the country level, while we use data from the regional level. Other papers use regional data but with different sources and methodologies. In addition, these papers use economic growth measured by Gross Domestic Product (GDP) as a variable indicating the economic development without studying other factors that could affect this relationship; instead, our focus is on technological change measured by innovation and controlled by other variables that could affect this relation.

Second, another strand of literature utilizes innovation as an alternative term to economic development, in which they analyze the relationship between innovation and income inequality through endogenous growth models and skill-biased technical change. One of the leading papers in this literature is (Romer, 1990), in which he argues that the development in technological change gives the incentive to increase the output per hour worked and consequently reduce the income gap. Similarly, (Aghion and Howitt, 1992) parameterize the degree of market power and find a positive effect of innovation on the growth rate. This growth is also affected in the case of learning by doing, which creates more distortion with more research than manufacturing. Meanwhile, (Katz and Murphy, 1992) results show a strong relationship between the fluctuations in the growth rate of the supply of college graduates and college wage premiums.

Another argument in this discipline raises the context of skill-biased technical change. This context is mainly explained by (Katz and Murphy, 1992), (Acemoglu, 1998) and (Krusell et al., 2000), whom they propose different models to illustrate the reason behind the fall in the skill premium[15] in the seventies and its increase in the eighties in the USA. The critical factor in their analyses relies on the concept of technological-skill complementarity as in (Katz and Murphy, 1992) and (Krusell et al., 2000) or capital-skill complementarity as in (Acemoglu,

[15] Literature defines skill premium as the percentage of skilled labour wages compared to unskilled labour.

1998). The main finding of their framework is that the elasticity of substitution between equipment (or technology) and the two types of labour (skilled and unskilled) determines the direction of skill premium. They show a decrease in skill premium over time when the elasticity of substitution between these two types of labour and physical capital (or technology) is the same, while the opposite happens when there is variation in these two elasticities towards skilled labour.

The empirical findings of (Caselli, 1999) further interpret the increase in USA wage inequality. This study shows that skills primarily drive technology adoption, and a positive correlation exists between its development within the industry and the average capital-output ratio in that industry. Despite this view, (Lioyd-Ellis H, 1999) develops a different model of endogenous technological change and wage inequality and argues that the changes in skilled labour are not the only reason behind the increase in USA wage inequality. He finds that even when technological change is not skill-biased, wage inequality rises when new technologies grow at a rate higher than the rate of absorption (the rate at which technology-specific skills can be acquired).

For many authors, the implication of technical change for the labour market is their primary concern. For example, (Acemoglu, 2002) shows the evidence of skilled bias acceleration during the past few decades and the concept of profit incentives in adopting technology. He refers to the skill-biased to the acceleration in skilled labour supply, and in his paper in 2007, he proves that under specific assumptions, the marginal product of the factor of production increase proportionally by the increase in the supply of that factor which causes technological change. Using different frameworks (supply-demand-institutions framework) to explain these changes, (Goldin and Katz, 2008) find that the relative skill supplies are the reason behind the differences in highly skilled workers' wage premium, and this also depends on whether this supply is greater or less than the relative demand on that factor. Also, (Hemous and Olsen, 2014) show that the increase in the skill premium in the USA since the 1960s is due to endogenous labour supply, in which the replacement of unskilled labour with machines increases wage inequality. This framework occurs in three phases, starting with stable income inequality, then investment in automation accompanied by an increase in skill premium, and finally, economic stability with less wage growth for low-skilled than high-skilled labour. From the different perspectives of implementing the logical consequence of endogenous growth literature and skill-biased technical change, the recent paper of (Aghion et al., 2018) concludes that the reason behind the increase in the gap between highly skilled (presented by entrepreneurs and CEOs) and low skilled labour is due to the existence of markups and innovation intensities in each sector. They show a positive and significant relationship between measures of innovation and top income inequality (top 1% of the income distribution), while they find a very weak relationship between innovation and broad measures of income inequality. Their findings show that, to a certain degree, there is causality from innovation to top-income shares. This result is supported by (Claudia et al., 2018) and (Benos and Tsiachtsiras, 2018) using instrumental variables. These articles find a significant effect of innovation on increasing the gap in the overall income inequality distribution, whereas this effect is increasing the gap on the top of the income distribution.

Finally, the Kuznets hypothesis finds new support when integrated with the Schumpeterian legacy. According to the Schumpeter framework, technological change is economic growth's ultimate cause. Hence, the faster the rate of technological change and economic growth rate, the lower the income inequality levels should be. The Schumpeterian hypothesis applies to the right side of the Kuznets' inverted U, meaning that it mainly concerns countries and historic times beyond the radical transformation (Antonelli and Gehringer, 2013). In this case, the speed of introducing new technology is likely to determine the relationship between innovation and income inequality. This concept means that innovation decreases income inequality when the economy moves quickly towards new inventions. According to these models, the monopoly power, and the profits of the previous innovations last much less. As a result, the benefits to consumers are becoming faster. On the opposite side, a slow rate of technological change leads to a prolonged transfer of the benefits of technological change that enables innovators to keep large shares of these benefits and increase income inequality. The long period of acquiring new technology eventually leads to a positive link between innovation and income inequality.

Our contribution to the second and third strand of literature is by studying the causal effect of innovation on income inequality and not only the correlation between them. Because of the problem of selecting weak instruments that usually arise in this case, we implement new econometric tools to solve the endogeneity problem in the model. First, we use the tool developed by (Lewbel, 2012), which is very useful when no external instruments are available, especially since finding appropriate instruments is often problematic in this context. Second, we use the Generalized Method of Moments (GMM) which was developed by (Arellano and Bover, 1995) and (Blundell and Bond, 1998). Using these methods to solve the model's endogeneity distinguishes this study from most previous literature that uses different external instruments. For example, (Benos and Tsiachtsiras ,2018) use charges for the use of intellectual property, while (Aghion et al., 2018) use USA Appropriation committees of the Senate and the House of Representatives and Knowledge Spillovers as an instrument for innovation. Despite these treatments' functionality, there is a probability of omitted variables bias which could cause inconsistency in the model estimates.

2.3 <u>Data and Variables</u>

The dataset used in this study is a panel of 81 European regions (including 28 European countries) over 19 years (1993-2011). The number of observations is less than that due to missing data in specific years, and they differ depending on the data availability for the variables and the method (technique) used. We use NUTS2 classification, a hierarchical system for dividing up the economic territory of EU and include basic regions for applying regional policies. We justify all other data to comply with this classification as well. The reason behind adopting such classification is to consider patents at a more aggregate level of regions to avoid any inaccuracy in linking the invention to the area where the inventor lives. This classification also complies with the OECD REGPAT Database presentation. For example, inventors who work in the same place might live in different zones in the same large city, which leads to imperfect information about the number of patents related to that region if we consider more subdivisions like NUTS3.

The dependent variable for the econometric model is income inequality. The data includes two primary sources. The first is the European Community Household Panel (ECHP), and the second is the European Union Survey on Income and Living Conditions (EU-SILC). The ECHP is a panel survey containing homogeneous data on individuals and households interviewed yearly, with eight waves available (from 1993/1994-2001). The Member States involved were Belgium, Denmark, Germany, Ireland, Greece, Spain, France, Italy, Luxembourg, the Netherlands, Austria, Portugal, Sweden, and the United Kingdom. The EU-SILC gives a broader sample of European countries for the period. “This project was launched in 2003 based on a "gentlemen's agreement" in six Member States (Belgium, Denmark, Greece, Ireland, Luxembourg, and Austria) and Norway” (Source: EUROSTAT). From the legal point of view, this project became effective in 2004 for fifteen European countries and now “extends to all the European countries including Switzerland, Iceland, and Norway” (Source: EUROSTAT). It covers the period from (2003-2011). We fill the gap in 2001 and 2002 by taking the weighting average for the last two years before 2001 and after 2002.

We measure income inequality by five leading indicators: the Gini Index, income inequality between 90% and 10% of the income distribution, the income share of the top 10%, the income share of the top 1%, and the bottom 10% income share (variables are defined in the Appendix). We chose these indicators because of their popularity in literature, and we can utilize them to show the change in income within any country, region, or group over time. In addition, Gini Index alone does not provide a clear picture of specific segments of the income distribution. To precisely explain the differences between one income distribution and another, we need different percentiles of that distribution. We use the definition of the Gini Index as the ratio of the cumulative distribution of overall income or wealth over the area of perfect equality of income. Its percentage ranges from 0 to 100%, in which 0 represents complete equality, and 100% represents complete inequality. We follow (Ramos and Royuela, 2014) in computing this index based on the "equivalised" household disposable income concept. "It included income from wages and salaries, self-employment incomes, capital incomes and realized property incomes, cash transfers from the general government less taxes and social security contributions paid by the households" (Ramos and Royuela, 2014). The calculation of this index depends on dividing the total disposable income of the household by the equivalisation factor. "The equivalisation factor is calculated by weighting each household member according to the OECD-modified scale, which was first proposed in 1994. This scale gives a weight of 1.0 to the first person aged 14 or more, a weight of 0.5 to other people aged 14 or more, and a weight of 0.3 to people aged 0-13" (EUROSTAT).

Our primary explanatory variable is innovation. The data for this variable is collected from Organization for Economic Co-operation and Development (OECD) data set and measured by patent applications per million inhabitants filed at the Patents Cooperation Treaty (PCT), which include the inventor(s)'s country (ies) of residence for each region. Other candidate measures for this variable include relevant inputs, total factor productivity, and R&D

expenditures. We choose the number of patents because our interest is to measure the flow of the innovation process rather than the factors that generate this flow. Another reason is the limitations in using these measures. For example, criticism associated with the specific input measure has the possibility that other essential inputs have a significant effect on technical change, and not including them affects the accuracy of the results. R&D expenditures are one of these inputs and could overlap with other factors. In addition, there are problems associated with equilibrium assumptions in the long run when using total factor productivity. In the long run, the economic system encounters structural and organizational changes that may cause difficulty measuring this variable. From a different perspective, past empirical studies use patent-related indicators and apply some measures to account for differences in the quality of individual patents (Aghion et al., 2005), referred to as citation-weighted patent grants. In comparison, we consider patent applications the most suitable measure of technological progress, which measures the flow of newly available knowledge. The increasing evidence of the actual meaning of patent citations suggests relying on the number of patents without attempting to use citations as a proxy for their quality.

We collect the other control variables from European Statistical Office (Eurostat) and (OECD) databases. These variables include net migration, GDP per capita, unemployment rate, low-skilled labour employment rate, high-skilled labour, and taxes. We follow the Eurostat measurement of "net migration," which depends on the crude rate[16] of net migration, including statistical adjustment during the year, and its value is expressed per 1000 inhabitants, "unemployment rate" is measured by unemployment rates by sex and age in each region, "GDP per capita" is measured by Gross Domestic Product (GDP) in constant prices[17], "Employment

[16] According to Eurostat, the crude rate of net migration is equal to the difference between the crude rate of population change and the crude rate of natural change (that is, net migration is considered as the part of population change not attributable to births and deaths).

[17] To remove the effect of inflation, we use GDP in constant prices (the base year 2010) and measured by Purchasing Power Standard (PPS). In this way, we eliminate price differences between countries, regions and over the years. PPS is an "artificial currency unit" (Eurostat) that presents a unit of currency that can buy the same amount of goods and services in any region or

rate of low-skilled labour" represents the employment rate of low-skilled labour to the total number of employees (low-skilled labour is measured by workers who have less than primary and lower secondary education), and "employment rate of highly-skilled labour" is measured by people with tertiary education and above who are employed as a percentage of the total number of employees for each region. Finally, taxes are measured by taxes levied on the average personal income obtained from the formal economy, including wages, salaries, investment, and business profits divided by GDP per capita in constant prices (2010). The full definition of all the variables is explained in the Appendix.

2.4 __Control Variables__

We use a set of control variables to avoid any inappropriateness in estimating the model. We divide them into two main categories: economic and sociodemographic. The economic factors include the employment rate of skilled and unskilled labour, unemployment rate, GDP per capita, and taxes, while the sociodemographic factor includes net migration.

We use the employment rate of skilled labour as defined[18] in (Ramos and Royuela, 2014), (Lee and Rodriguez-Pose, 2013), and (Castells-Quintana et al., 2015). Furthermore, we add the employment rate of unskilled labour[19] to show the combined effect of both (skilled and unskilled labour) on income inequality. These workers include employed people working in all sectors of the economy, not only in particular sectors. Substantial evidence in the literature supports this point and highlights that the role of highly skilled labour and technology is changing the income gap. Income inequality is associated with skill-biased technological

country in the European Union. It is calculated by dividing the aggregates of a country in national currency by its respective purchasing power parities.

[18] The percentage of workers with tertiary education level and above to the total number of employees between 16 and 64 years measures the highly skilled labour employment rate variable (Source: EUROSTAT-LFS).

[19] The percentage of workers who have less than primary and lower secondary education or do not have any qualifications to the total number of employees and are between 16 and 64 years measures the Low-skilled labour employment rate variable (Source: EUROSTAT-LFS).

change through the effect of the returns to skilled and unskilled labour. As higher-skilled workers perform non-routine tasks and have higher productivity than low-skilled workers, they earn higher returns than low-skilled workers. This return gap is mainly related to three main factors: the decline in manufacturing employment, change in technology, and a slowdown in the growth of the college-educated population (Bound and Johnson, 1992). Accordingly, there is a link between skill-biased technological change and employment shares for different skill groups (Liu and Lawell, 2015), which explains innovation's impact on skill premium. In this regard, it is worth noting that our concern in this paper is in the changes in disposable income and not only in wages, and hence we include in the analysis the changes in other elements such as capital gains and social transfers.

Our second control variable is the unemployment rate which is also used by (Castells-Quintana et al., 2015), (Breau, 2017), (Benos and Tsiachtsiras, 2018), and (Aghion et al., 2018). This variable addresses the business cycle fluctuations, which we expect to increase income inequality .

Third, we use GDP per capita in constant prices as a control variable because it impacts income inequality through its effect on economic growth. Many previous papers show empirical evidence of the significant link between GDP per capita and income distribution (e.g. (Castells-Quintana et al., 2015), (Liu and Lawell, 2015), (Antonelli and Gehringer, 2017); and (Benos and Tsiachtsiras, 2018)).

Next, we choose net migration as a control variable because it reflects the net movement of labour, especially highly skilled labour. It is unclear in the literature if the migration-inequality link exists. For example, the study (reed, 2001) shows that immigration has contributed to the changes in income inequality, mainly due to the changes in population structure. In contrast, (Breau, 2017) finds no significant effect of immigration on income inequality. In this study, we examine the possible effect of such a relationship by using a different method and covering more diverse variables. Here, there is a possibility of endogeneity in net migration because of its link with other factors (e.g., immigrant concentrations, remittances, skill composition, competition in labour market among groups) that have an impact on income inequality in the regional level. This point is beyond the scope of this paper and further research is needed in this topic.

Even though migration is the outcome of tax policy (see Aghion et al., 2018), we do not rule out the effect of taxes. It is an essential component of income and gives a clear picture of why the changes in income inequality. Remind that the changes in disposable income measure income inequality in this paper, and tax is one of the elements of this income. We control this factor to find what part of the disposable income is mainly affected by technological change.

Finally, to test the consistency of our results, we add other controls that are employment ratios of different sectors (Agriculture, manufacturing, and financial sector, which we include in the sensitivity analysis) (Castells- Quintana et al., 2015)).

Notice that in this study, we consider population by counting patents for each region per million inhabitants since the relative increase in population in a specific region potentially increases the number of patent applications compared with other low population regions. For this reason, we eliminate that effect by dividing the number of patents by population per million inhabitants for each region. In this case, we give weight to each region according to per inhabitant's contribution to the innovation process and not only to the total number of patents for that region.

2.5 __Descriptive Data Analysis__

Table (2-1) shows summary statistics of the main variables in our panel data set, including their mean, standard deviation, and minimum and maximum values. From 1993 to

2011, income inequality in European regions varied between 0.169 and 0.556, with an average of 0.299. It is relatively not very high in comparison with other developed countries. The Gini Index variation indicates that European regions' heterogeneity is wider than across countries. In the same table, we notice that the average percentages for the unemployment and employment rates for highly skilled and low-skilled workers are %9, 35%, and 44%, respectively. There is a considerable gap between the highest and lowest percentage of employment rates for highly and low-skilled workers. This gap is due to the discrepancies between regions in economic development. It is shown in the difference between the highest and lowest values of GDP per capita. However, the gap between the highest and lowest flow of migrants ranges from -30.6 to 28.2 per 1000 inhabitants. It has an average of 2.88 per 1000 inhabitants.

Going further in the analysis, the box plot in Figure (2-3) shows that Portugal has the highest median Gini Index of intra-regional income inequality, while Slovenia has the lowest. On the other hand, Germany has the highest internal variation in income inequality across European regions. We notice from the figure that the box and the whiskers in the German plot are more expansive than in other countries. (Frick and Goebel, 2008) show an increase in income inequality between the eastern and western parts of Germany since there is an increase in the degree of regional variations within the western part of the country. The average market income for the eastern part of Germany is lower than the western part; this is due to the increase in the unemployment rate and decrease in capital income in the eastern part comparing it with the western part. At the inter decile range of the income distribution, we notice a very close pattern between this segment and the general measure of income inequality (Gini Index), as shown in figures (2-3) and (2-4).

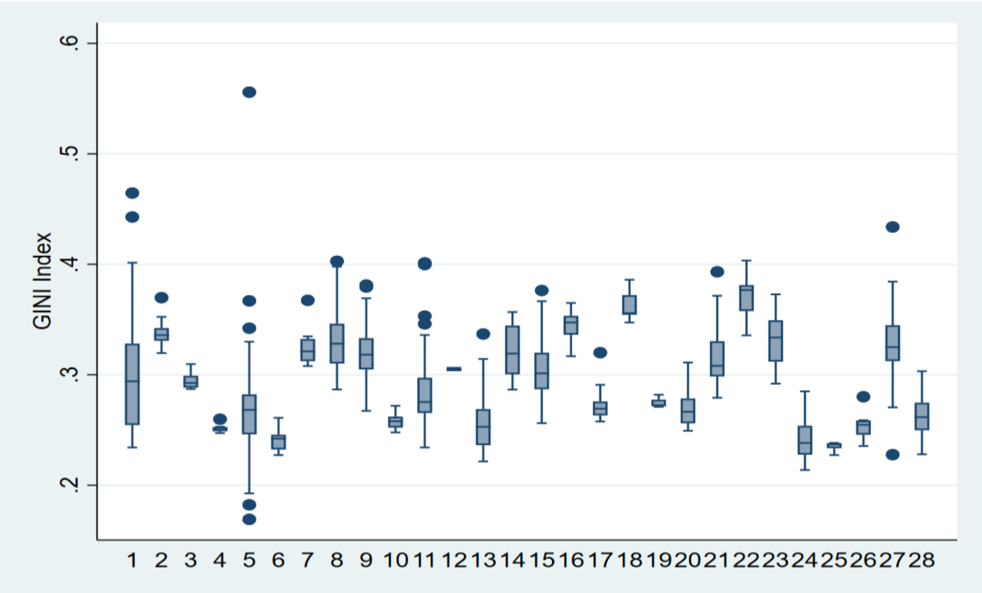
At the regional level, we notice from figures (2-5) and (2-6) that there is a negative correlation between patents and the Gini Index and the same negative trend between patents and the inter decide range of the income distribution. This trend persistence, even when considering the middle 80% of the income distribution, motivates us to study this relation in more detail and use more advanced econometric techniques. On the other hand, figure (2-7) shows a positive correlation between patents and the top 10% income share. The top 10% of income distribution seems to benefit from innovative activities and tells about the gap between average income on one top decile and overall average income distribution, which presents the gap between the upper-middle income class and the average households. In most European regions, the top decile of income distribution encountered a steady period of stability during this study. In addition, the top of the income distribution changes is less than that in the overall income distribution across regions.

The number of patent applications is just as necessary, as shown in figure (2-8). From this figure, we notice that Germany, France, and the UK have the highest percentage of patent applications to the Patent Cooperation Treaty (PCT) designated to European Patents Office (EPO), with around 50% of the total. The following figure (2-9) shows no significant change in this percentage when we include the number of patents granted by the European Patents Office (EPO). Also, we notice the same share pattern for each country between the two figures, which indicates that countries with a high level of patent protection presumably have a high level of patent applications. Depending on this fact, and to avoid duplication in the results, we use one of these two measures, patent applications filed at the PCT, as a measurement of innovation.

Table 2-1: Summary Statistics

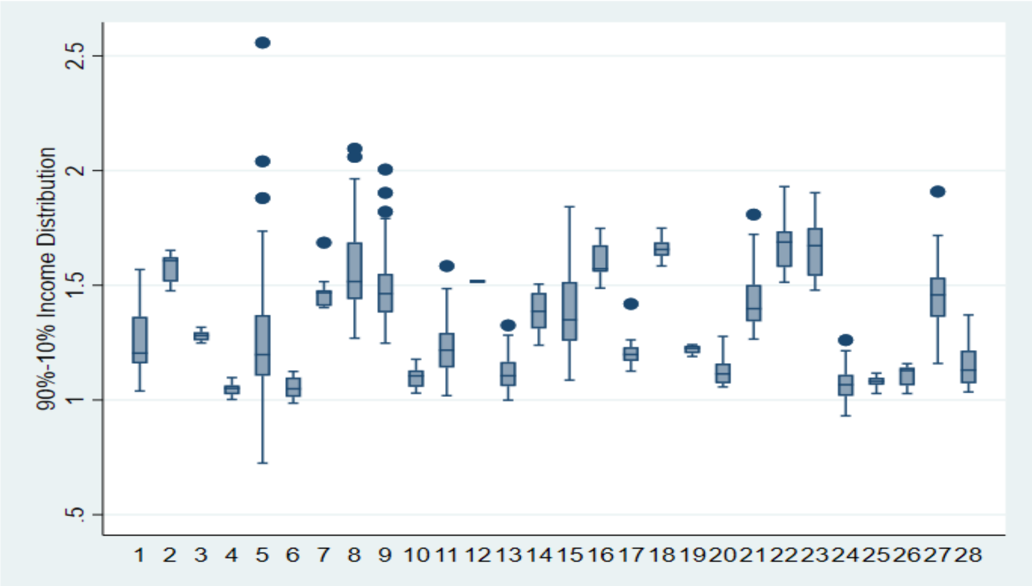
Variables	(1) N	(2) mean	Overall	(3) Std.Dev between	Within	(4) min	(5) max
Gini Index	1,078	0.299	0.0411	*0.0365*	*0.0221*	0.169	0.556
Net Migration	970	2.8756	5.7823	4.5807	3.5617	−30.6	28.2
GDP per capita	864	60,541.09	42,678.02	42772.36	3906.073	10751	224084
Patents per million Inhabitants	1,292	74.97	96.32	101.84	18.66	0	590.1
Unemployment rate	1,032	0.090	0.0460	0.0381	0.0258	0.0180	0.293
Taxes	915	0.1446	0.0287	0.00189	0.009369	0.0337	0.3303
The employment rate (High skilled)	1,015	0.345	0.0918	0.0859	0.0332	0.128	0.625
The employment rate (low skilled)	1,002	0.442	0.140	0.1366	0.0321	0.0677	0.733

Figure 2-3: Box plot graph (Gini Index) on the EU country level[20]



Notes: The X-axis presents European countries, and Y-axis presents Income Inequality which the Gini Index measures.

Figure 2-4: Box plot graph (90-10% of the income distribution) on the EU country level[21]



Notes: The X-axis presents European countries, and Y-axis presents 90%-10% of the income distribution.

[20] Numbers in the graph are presented as follows: - (1. Belgium, 2. Bulgaria, 3. Cyprus, 4. The Czech Republic, 5. Germany, 6. Denmark, 7. Estonia, 8. Greece, 9. Spain, 10. Finland, 11. France, 12. Croatia, 13. Hungary, 14. Ireland, 15. Italy, 16. Lithuania, 17. Luxembourg, 18. Latvia, 19. Malta, 20. Netherlands, 21. Poland, 22. Portugal, 23. Romania, 24. Sweden, 25. Slovenia, 26. Slovakia, 27. UK, 28. Austria).

[21] Numbers in the graph are presented as follows: - (1. Belgium, 2. Bulgaria, 3. Cyprus, 4. The Czech Republic, 5. Germany, 6. Denmark, 7. Estonia, 8. Greece, 9. Spain, 10. Finland, 11. France, 12. Croatia, 13. Hungary, 14. Ireland, 15. Italy, 16. Lithuania, 17. Luxembourg, 18. Latvia, 19. Malta, 20. Netherlands, 21. Poland, 22. Portugal, 23. Romania, 24. Sweden, 25. Slovenia, 26. Slovakia, 27. UK, 28. Austria).

Figure 2-5: panel data scatter plot of log Index index and log number of patents per million inhabitants in the European regions, (1993-2011)

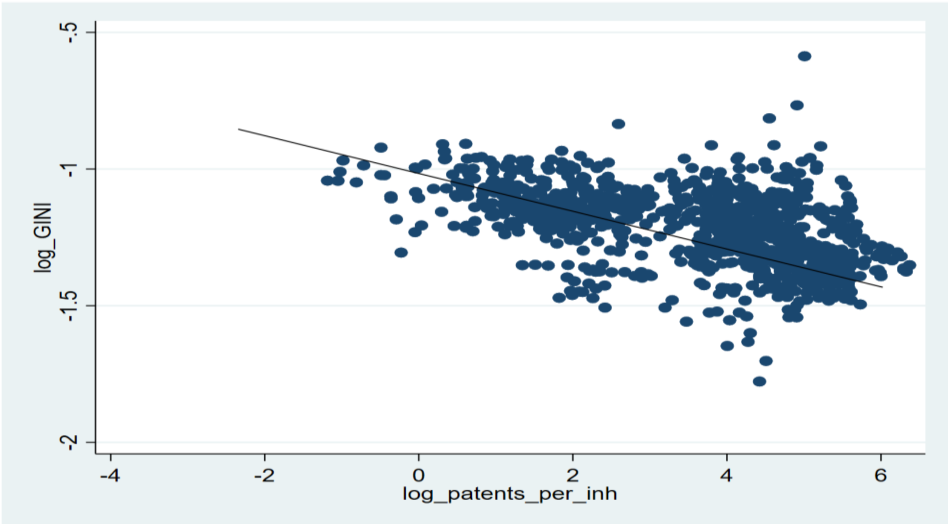


Figure 2-6: panel data scatter plot of log (between 90% and 10%) of income distribution and log number of patents per million inhabitants in the European regions (1993-2011)

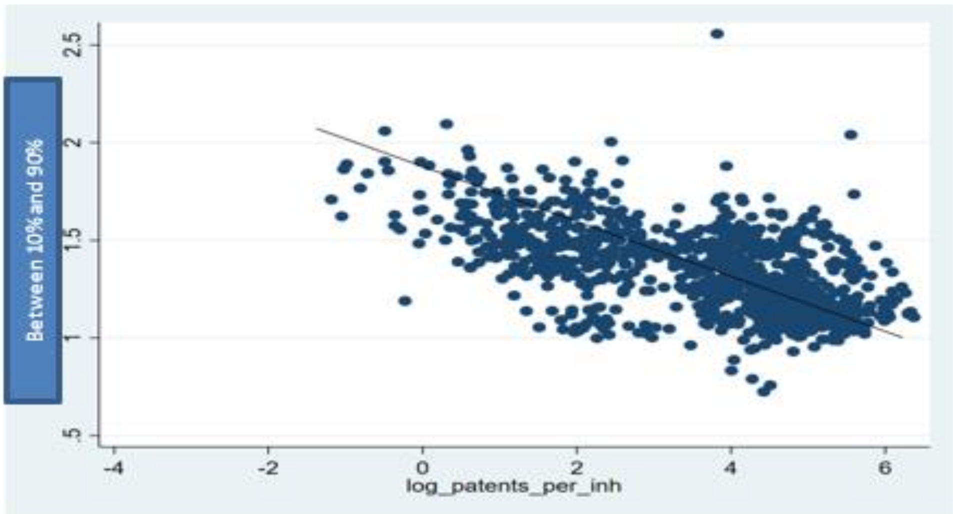


Figure 2-7: panel data scatter plot of log (Top 10%) of income distribution and log number of patents per million inhabitants in the European regions, (1993-2011)

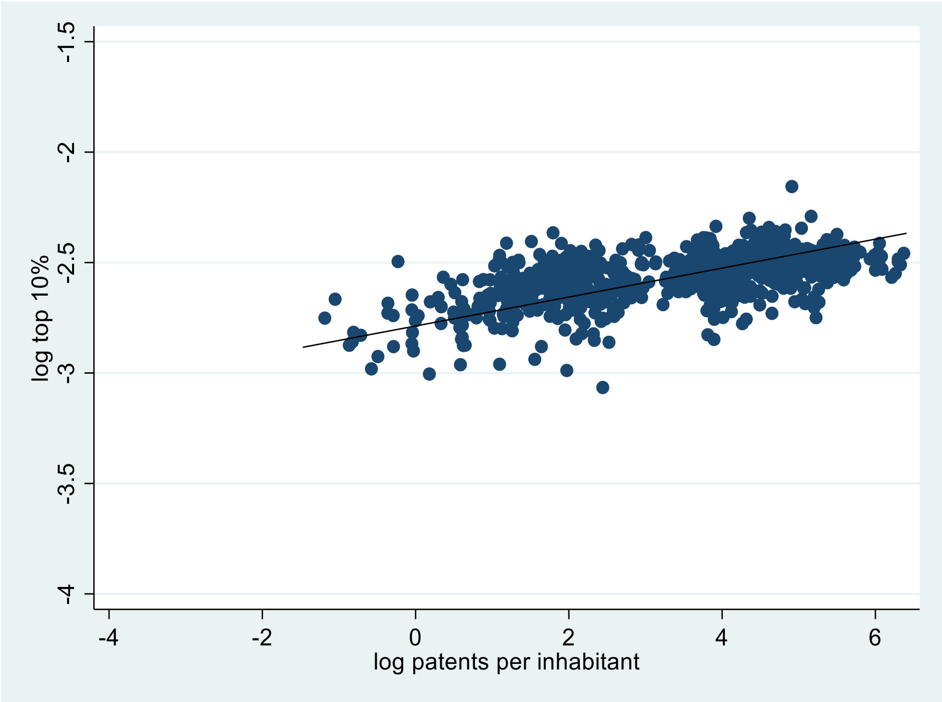


Figure 2-8: Pie Chart: Number of patent applications per million inhabitants to the PCT designated to the EPO

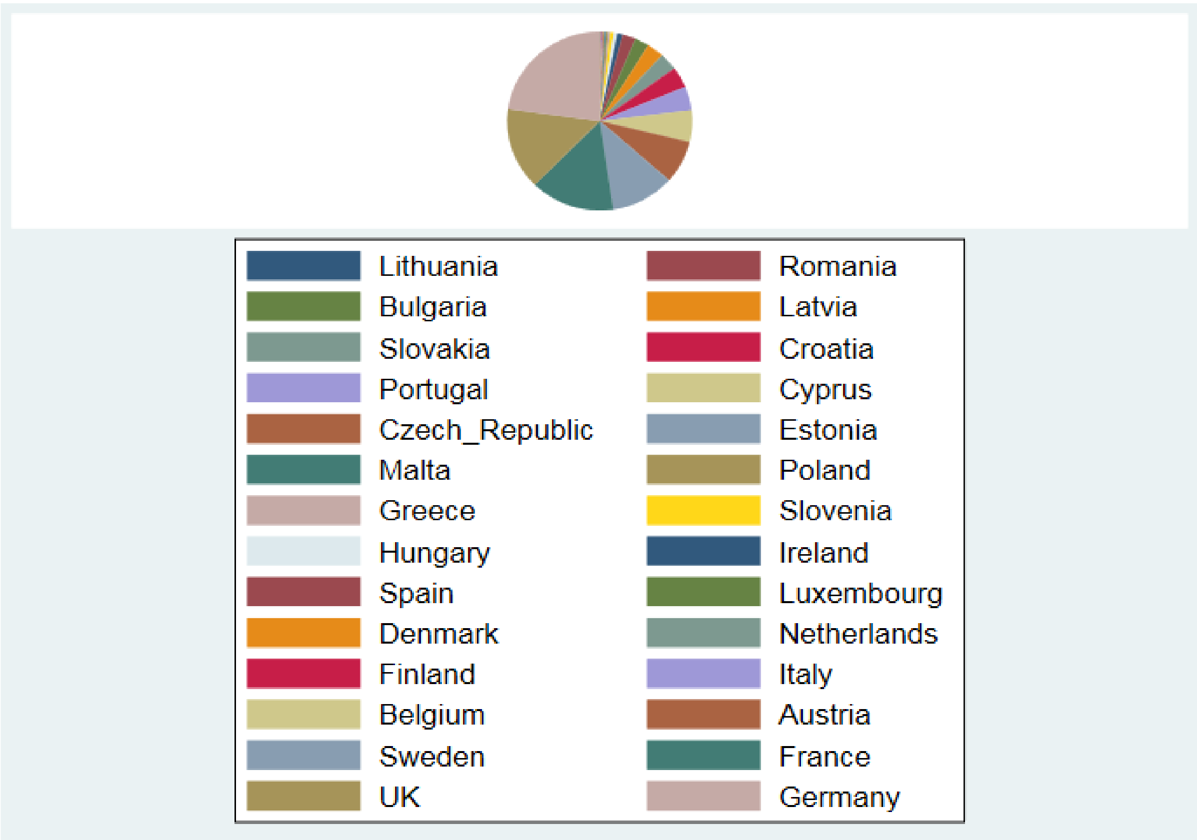
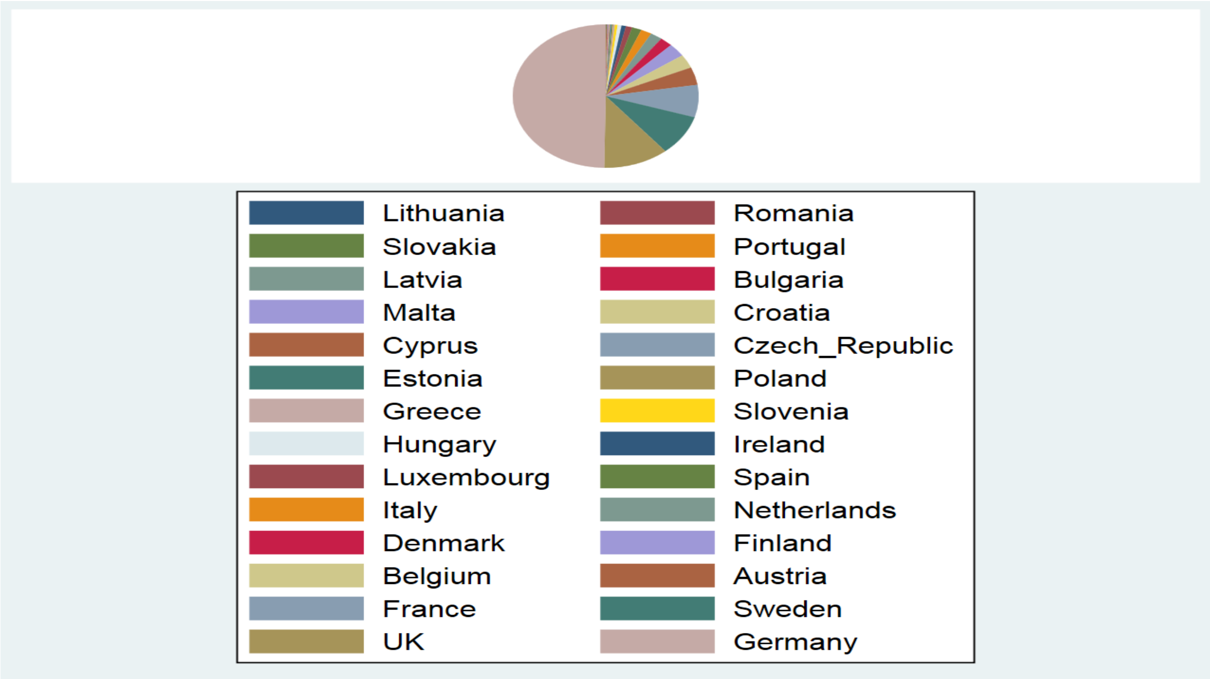


Figure 2-9: Pie chart: Number of patents per million inhabitants granted from EPO



2.6 Econometric Estimation

We follow the same estimation method (Aghion et al., 2018) and use the number of patent applications per million inhabitants filed at the Patent Cooperation Treaty (PCT) by priority year as a measure of innovation. In this manner, we regress (Income inequality) on the total number of patents per million inhabitants and the other control variables.

To achieve this target, first, we estimate the static model which has the following form:

-

$$\log(INEQ_{it}) = A + \beta_i + \beta_t + \beta_1 \log(Innov_{it}) + \beta_k X_{it} + \varepsilon_{it} \quad (1)$$

Where (INEQ) stands for the different measures of income inequality, and we measure it by five leading indicators as has been mentioned before, β_i is a region fixed effect, β_t is a year fixed effect, INNOV is innovation (in the log), (X) is a vector of control variables, A is the intercept, and ε_{it} is the disturbance term, while β_1, β_k represent the model parameters. Within this specification, i represents the region, and t represents the time. β_1 explains the elasticity of income inequality concerning innovation.

Second, we estimate the model by using GMM method in the following dynamic form:-

$$\log(INEQ_{it}) = C + \alpha_0 \log(INEQ_{it-1}) + \alpha_1 \log(Innov_{it}) + \alpha_2 \log(Innov_{it-1}) + \alpha_k X_{it} + \gamma_i + u_{it} \qquad (2)$$

Where $(INEQ_{it-1})$ stands for the different measures of income inequality in the time (t-1), $(Innov_{it-1)}$ is innovation in the time (t-1), C is the intercept, , $\alpha_0, \alpha_1, \alpha_2, \alpha_k$ represent the model parameters, γ_i *is the unobserved region time invariant error term*, and u_{it} is the disturbance term.

2.7 __Endogeneity Problem and Instrumental Variables__

The endogeneity problem may arise in this study due to two main factors. First is the reverse effect of income inequality on innovation, which (Aghion et al., 2018) argue could happen through the barriers formed by incumbents against new entrants when top incomes increase. Accordingly, this leads to a downward bias on the model estimates and eliminates the relationship between income inequality and innovation.

Second, Omitted Variables Bias (OVB) could arise when the relationship between regressions estimates has different sets of control variables unobserved in the data. The method used in this study allows controlling for unobserved regional characteristics and separating any bias that could arise from the correlation of these characteristics with the explanatory variable. As stated by (Panizza U, 2002), this kind of bias is one of the main obstacles to using panel data analysis, and the following section explains this in more detail. Also, there is a high probability of omitted variable bias when estimating the top income share-innovation link. This bias is where estimates' signs and statistical power are inconsistent when using such statistical models.

Two previous papers use the Instrumental Variable (IV) method to solve this problem. However, they are different in specifying this instrument. First, (Benos and Tsiachtsiras, 2018) handle this problem by using "charges for the use of intellectual property, receipt" from the International Monetary Fund (IMF) as an IV. They argue that the highest money is allocated to countries with high-quality patents. To show the positive impact of Intellectual Property Rights (IPR) on innovation, they focus on the receipts from IMF, not payments to innovative countries. Second, (Aghion et al., 2018) use "U. S Appropriation committees of the Senate and of the House of Representatives" and "Knowledge Spillovers (measured by citations) ."They argue that the committee's structure is exogenous, and legislators nominated to this committee usually push the grants in the state they represent. Hence, they encourage innovation through this kind of discretionary funding which is not required to be allocated to particular programs by law. In addition, knowledge spillover reduces the cost of innovation and enhances the innovation process through the efficient use of past innovation intensities.

We contribute using a different approach based on two methods in this concept. First is the method introduced by (Lewbel, 2012) and developed by (Baum CF, and Schaffer ME, 2012) to implement its STATA software. This method is implemented by “identifying structural parameters in the regression model with endogenous covariates when external instruments are not found” (Lewbel, 2012). In identifying the structural parameters, the correlation between the covariates and the product of heteroscedastic errors is restricted, which relies on higher moments. Generated instruments in this approach are constructed from “auxiliary equations' residuals from the first-stage regression of each endogenous covariate on all exogenous covariates multiplied by each of the included exogenous variables in mean-centered form. As these auxiliary regression residuals have zero covariance with each covariate used to construct them, the means of the generated instruments will be zero by construction" (Lewbel, 2012). Nevertheless, the elements of the exogenous variables with the centered covariates will not be zero if there is heteroskedasticity in the error process. To apply this method, we test the "Scale-related Heteroskedasticity" (Bresch-Pagan type test) and find that it rejects the null hypothesis of homoscedasticity and assumes heteroscedasticity.

Second, we use the dynamic panel data method presented by (Arellano M and Bover O, 1995) and (Blundell R Bond S, 1998), in which they use additional moment conditions with lagged differences of the dependent variable that are orthogonal to levels of the disturbances. This method depends on combining regression in levels with regression in first differences in a system of equations. To achieve these additional moments, they assume that the panel-level effect is unrelated to the first observable difference of the dependent variable. In this context, they solve the potential endogeneity problem by instrumenting explanatory variables in the transformed difference equation with lagged values of the dependent variable. In addition, they instrument the explanatory variables in the level equations with lags of the first differences of the dependent variable. To implement this method, we test the exogeneity of the control variables (X_{it}) which must satisfy $\Delta\varepsilon_{it}$, $E(X_{is}\varepsilon_{it}) = 0$ for all s and t, where $s > t$. In this regard, we use Wu-Hausman test, and find that these variables are orthogonal to the error terms. Moreover, we test if disturbances are heteroscedastic, or not, by using Breusch-Pagan / Cook-Weisberg and White/Koenker tests for heteroskedasticity. These tests are under the null hypothesis that the disturbance is homoscedastic. The results of both tests reveal P-values equal=0 for all the regression models used in this paper, which indicates the presence of heteroskedasticity in the residuals. This also shows that in this context using GMM is more efficient than using IV method. Finally, we use the Arellano-Bond test to check if there is serial correlation in the first differenced errors. According to this test, P-values for the first differenced errors give strong evidence against the null hypothesis of zero autocorrelation at order 1. What matters in this test is the existence of serial correlation in the first-differenced errors at an order higher than one. According to our results, P-values for the different dependent variables (Gini Index, the inter-decide range of the income distribution, and the top of the income distribution) are 0.9369, 0.2824, and 0.4224, respectively. This result shows no significant autocorrelation in the first-differenced errors at order 2.

We believe that using two methods instead of one is very useful in two aspects. First, it helps in tackling the endogeneity in the model. Second, it makes comparing the results and examining their accuracy possible.

2.8 Estimation Results

Initially, we estimate the coefficients of the baseline model by using a panel regression with pooled OLS, random effects (RE), fixed effects (FE). Next, we implement the two other methods: GMM, and TSLS-Heteroskedasticity. The results in tables (2-2) and (2-3) reveal consistency between all these methods, where we use the overall measure of income inequality (Gini Index) and the middle 80% income inequality as dependent variables. For example, in the baseline model, the first three columns in these tables show a robust decrease in Gini Index at a (1%) significance level with the improvement in innovation. It suggests that an increase in the number of patents per million inhabitants by one unit decreases the Gini Index on average by 3% (between -4.87% and -2.9%, where we use pooled OLS, fixed effect, and random effects) assuming that the other control variables are constant. In other words, the elasticity of income inequality with respect to innovation is 3% on average. The magnitude of this elasticity is very close in the three methods. These results support the outcomes in (Greenwood and Jovanovic, 1990), (Antonelli and Gehringer, 2017), and (Claudia et al., 2018). The same tables show that the increase (decrease) in GDP per capita has a significant effect in decreasing (increasing) Gini Index (significant at 10% level), and it explains on average 4.3% of the changes in income inequality (in OLS, FE, and RE). The same result applies to taxes on primary income[22] which explains around 0.04% of the changes in income inequality using the three previous methods. The magnitude of the tax coefficient is very low because income inequality has other components (wages and profits) that vary significantly in the income distribution. We discuss this kind of interaction between these elements in sections (2.9) and (2.10). However, we find a significant positive effect of highly skilled and low-skilled labour on the Gini Index (significant at 1% level), and the same significant sign effect applies to the coefficient on the unemployment rate. Similarly, the effect of innovation and other control variables on the inter decide range of income inequality (which are shown in table (2-3)) have identical results to their effect on the Gini Index (in terms of the signs and the significance levels). It indicates that excluding the top 10% income share and the bottom 10% income share does not change the results, and there is consistency in these outcomes. On the other hand, net migration does not affect income inequality (in both measures: Gini Index and middle 80% income inequality) and has a low magnitude.

[22] The definition of this category of taxes is defined in the Appendix.

Table 2-2: Innovation and income inequality (Gini Index) in the EU regions using different methods

Dependent Variables → Independent Variables ↓	(1) POLS Gini	(2) FE Gini	(3) RE Gini	(4) GMM Gini	(5) HT Gini
Lag (1)	-	-	-	0.4100*** (0.04)	-
Patents	-0.0487*** (0.004)	-0.0292*** (0.01)	-0.0399** (0 .01)	-0.0350*** (0.005)	-0.0501*** (0.004)
Net Migration	0.0001 (0.001)	-0.0025 (0.003)	-0.0023 (0.002)	-0.0006 (0.0007)	0.0001 (0.0008)
Unemployment	0.5247** (0.12)	0.3386*** (0.13)	0.3071*** (0.11)	0.3775*** (0.10)	0.5199*** (0.12)
GDP per Capita	-0.1030** (0.05)	-0.0053* (0.003)	-0.0200* (0.01)	-0.0381*** (0.01)	-0.1004*** (0.05)
Taxes	-0.0008** (0.0003)	-0.0001* (0.00006)	-0.0003* (0.0002)	-0.0010** (0.0004)	-0.0010*** (0.0003)
Highly skilled labour	0.2678*** (0.06)	0.0553* (0.03)	0.1081* (0.06)	0.4898*** (0.08)	0.2852*** (0.06)
Low-skilled labour	0.2636*** (0.03)	0.5161*** (0.11)	0.4282*** (0.07)	0.3539*** (0.05)	0.2631*** (0.03)
Constant	-1.3159*** (0.03)	-1.3925*** (0.10)	-1.3334*** (0.06)	-0.9663*** (0.06)	-1.3100*** (0.03)
No. Observations	**621**	**621**	**621**	**589**	**621**

*Note: Variables' descriptions are given in the Appendix. Gini Index, patents, and GDP per capita are taken in logs. We use pooled OLS in column (1), Fixed Effects in column (2), Random Effects in column (3), GMM in column (4), and Heteroskedasticity Method in column (5). Gini Index is lagged by one year in the GMM method. Clustered standard errors are presented in parenthesis. ***p<0.01, **p<0.05. *p<0.1 present levels of significance.*

In the same tables, in columns (4) and (5), we use GMM and Heteroskedasticity methods to tackle the model's endogeneity problem. The results show that innovation decreases Gini Index, and the same effect exists on the middle 80% income inequality. In these two methods, the values of the coefficients on patents, where we use the Gini Index as a dependent variable, are -3.5% and -5%, respectively, while the values of the coefficients on patents, where we use 80% middle income inequality as dependent variable, are -3% and -8.2%, respectively. These results satisfy (Antonelli and Gehringer, 2017) from the point of view that the effect of innovation in reducing (increasing) profits stemming from the wealth overcomes the increase (decrease) in the changes in wage gaps stemming from work. We cover this part in more detail in section (2-10).

Table 2-3: Innovation and 90%-10% of the income distribution in the EU regions using different methods

Dependent Variables → **Independent Variables ▼**	**(1) POLS 90%-10%**	**(2) FE 90%-10%**	**(3) RE 90%-10%**	**(4) GMM 90%-10%**	**(5) HT 90%-10%**
Lag (1)	-	-	-	0.4103***	-
				(0.04)	
Patents	-0.0796***	-0.0288**	-0.0470***	-0.0295***	-0.0820***
	(0 .01)	(0.01)	(0.01)	(0.006)	(0.01)
Net Migration	0.0014	-0.0003	-0.0003	0.0001	0.0012
	(0.001)	(0.003)	(0.001)	(0.0008)	(0.002)
Unemployment	1.3928***	1.6491***	1.5240***	0.9719***	1.4127***
	(0.15)	(0.16)	(0.14)	(0.12)	(0.15)
GDP per Capita	-0.0153*	-0.0073***	-0.1891***	-0.1425***	-0.0099*
	(0.01)	(0.002)	(0.05)	(0.04)	(0.006)
Taxes	-0.0004*	-0.0010*	-0.0002*	-0.0001*	-0.0006*
	(0.0002)	(0.0006)	(0.0001)	(0.0001)	(0.0003)
Highly skilled labour	0.2779***	0.5796***	0.3926***	0.0096*	0.3166***
	(0.08)	(0.15)	(0.13)	(0.01)	(0.08)
Low-skilled labour	0.5144***	1.0554 ***	0.8327***	0.4424***	0.5069***
	(0.04)	(0.14)	(0.10)	(0.06)	(0.04)
Constant	1.1559***	1.0427***	1.1423***	0.6175***	1.1460***
	(0.04)	(0.11)	(0.07)	(0.07)	(0.04)
No. Observations	**619**	**619**	**619**	**587**	**619**

*Note: Variables' descriptions are given in the Appendix. 90%-10% income inequality, patents, and GDP per capita are taken in logs. We use pooled OLS in column (1), Fixed Effects in column (2), Random Effects in column (3), GMM in column (4), and Heteroskedasticity Method in column (5). Gini Index is lagged by one year in the GMM method. Clustered standard errors are presented in parenthesis. ***p<0.01, **p<0.05. *p<0.1 present levels of significance.*

In addition, the results indicate that the unemployment and the employment rate of skilled and unskilled labour have a significant positive effect on Gini Index (all are significant at a 1% level). The same applies to the effect of these variables on the middle 80% income inequality, which complies with our previous results, where we used pooled OLS, fixed effects, and random effects. The magnitudes of highly and low-skilled labour coefficients are relatively high. Their positive signs reveal that the increase (decrease) in the supply of highly and low-skilled labour increases (decreases) the gap between different income groups. However, GDP per capita negatively affects Gini Index. The increase (decrease) in GDP per capita decreases (increases) the middle 80% income inequality. It explains on average 6.9% of the changes in

Gini Index, and around 7.6% of the changes in the middle 80% income inequality. This result indicates that the increase (decrease) in GDP per capita by one unit decreases (increases) income inequality by 7%, and decreases (increases) the gap in the middle 80% of the income distribution by 7.6%(assuming that the other independent variables are constant). Even though taxes have a very low magnitude, they negatively affect these two income inequality measures, and their coefficient values are -0.01% in GMM (-0.01% in Heteroskedasticity) and -0.001 in GMM (-0.006% in Heteroskedasticity), respectively. This result indicates that taxes mitigate income inequality and have "a significant redistributive impact" (Joumard, 2012). This kind of taxes absorb a very high portion of disposable income, primarily from higher tax brackets, and eventually transferred to low-income groups through social transfers (e.g., education, retirement savings, health, etc.). Accordingly, the significant negative sign of the coefficient on patents reveals two dominant effects. First, the negative effect of capital gains (creative destruction effect) that overcomes the effect of technical change in wages will be illustrated later in this paper. Second, we show in the negative sign in the taxes coefficient the negative effect of this covariate on decreasing the gap in disposable income. It is also explained by (Mercader-Parts and Levy, 2004) that tax-benefits systems in European regions reduce market income[23] inequality.

We extend our analysis using GMM and Heteroskedasticity methods to test the link between innovation and the top 10%- and top 1%-income shares. We find a significant effect of innovation on increasing these measures, illustrated in the table (2-4). For example, the values of the coefficients on patents, where we use the top 10% income share as a dependent variable, are 0.06% in GMM and 3% in Heteroskedasticity, and both are significant at a 1 %

[23] Market income is defined as a household's total pre-tax income obtained from their activities in the formal economy, "including wages and salaries and self-employment income (net of employer insurance contributions and other benefits, but gross of employee contributions to such schemes), property income(interest, rents, dividends) as well as occupational pensions from employers, regular interhousehold cash transfers and other sources of income which are not redistributive government transfers" (Mercader-Parts and Levy, 2004).

level. Similarly, the values of the coefficients on patents, where we use the top 1% income share as a dependent variable, are 0.04% in GMM and 2.9% in Heteroskedasticity, and both are significant at a 1%. This result means that in the dynamic model, the increase (decrease) in the number of patents per million inhabitants by one unit increases (decreases) the top 10% income shares by 0.06%, while it increases (decreases) the top 1% income shares by 0.04% (assuming that the other control variables are constant). The magnitudes of these measures' coefficients are lower than the magnitude of the general measures of income inequality (Gini Index and the middle 80% of the income distribution). We explain this drop in magnitude by the lower variations in the top 10% and top 1% of the income distribution in comparison with the other parts of the distribution. The other control variables, except highly skilled labour, are negatively significant at a 1%. The increase (decrease) in the supply of the latter increases (decreases) the gap in the top 10%- and top 1%-income shares.

Nevertheless, the question is, why do we find such an increase in the top income shares as a reaction to innovation? The answer to this question is illustrated by (Aghion et al., 2018) and (Josifidies and Supic, 2020). There is capital concentration in the top income shares, that is, "innovation benefits are shared between firm owners, top managers (and CEOs) and inventors" (Aghion et al., 2018); this is increasing the gap in the top 10% and the gap in the top 1% income shares through increasing their compensation (markups) relative to the other income shares. However, taxes do not influence the top income shares since progressive taxation significantly changes the 80% middle income inequality "at the expense of the top income share" (Josifidies and Supic, 2020).

We notice that the magnitude and the significant level of the coefficients in GMM and Heteroskedasticity methods are very close to those in the baseline model estimates. Coefficients on net migration are inconsistent, with a contrast in their estimates, and they have a comparatively tiny magnitude. These findings are often seen as an outcome of technological advancement and its effect on profits from capital that capture a high proportion of the changes in income inequality, which leads to the low magnitude and little information for estimating the effect of net migration on income inequality (Claudia et al., 2018).

Table 2-4: Innovation and top 10%- 1% income shares in the EU regions using GMM & TSLS(HT)

Dependent Variables → **Independent Variables ▼**	**(1)** **GMM** **Top 10%**	**(2)** **H.T.** **Top 10%**	**(3)** **GMM** **Top 1%**	**(4)** **H.T.** **Top 1%**
Lag (1)	0.3444*** (0.04)	-	0.3243*** (0.04)	-
Patents	0.0056*** (0.002)	0.0319*** (0.003)	0.0038*** (0.001)	0.0289*** (0.003)
Net Migration	-0.0017*** (0.0006)	-0.0013*** (0.0004)	-0.0010*** (0.0003)	-0.0009*** (0.0003)
Unemployment	-0.8256*** (0.10)	-0.8229*** (0.08)	-0.6823*** (0.10)	-0.4839*** (0.09)
GDP per Capita	-0.1614*** (0.03)	-0.0955*** (0.03)	-0.1411*** (0.02)	-0.1011*** (0.03)
Taxes	-0.0002 (0.0004)	-0.0001 (0.0004)	-0.0003 (0.0006)	-0.0006 (0.0006)
Highly skilled labour	0.2460*** (0.09)	0.0032* (0.002)	0.1230*** (0.04)	0.0422* (0.03)
Low-skilled labour	-0.2179*** (0.05)	-0.2550*** (0.02)	-0.1411*** (0.04)	-0.2336*** (0.03)
Constant	-1.6151*** (0.11)	-2.4852*** (0.02)	-1.4443*** (0.08)	-1.6882*** (0.06)
No. Observations	**587**	**619**	**587**	**619**

*Note: Variables' descriptions are given in the Appendix. The top 10% income share, top 1% income share, and GDP per capita are taken in logs. We use GMM in columns (1) and (3) and Heteroskedasticity Method in columns (2) and (4)). Top income shares are lagged by one year in the GMM method. Clustered standard errors are presented in parenthesis. ***p<0.01, **p<0.05. *p<0.1 present levels of significance.*

2.9 Tax & Benefits System

In this section, we study the tax and benefits system in European regions to figure out if the increase (decrease) in taxes truly reflects an increase (decrease) in the welfare system in these regions, which eventually leads to a decrease (increase) in the gap in incomes. Especially in the case that we measure the dependent variable in this study by inequality in disposable income, in which tax is one of the elements in this measure. Accordingly, changes in technology would not only cause variation in income inequality resulting from rents or wages, but it would be the case that income inequality is sensitive to the changes in tax and benefits system at the regional or yearly levels.

To do this, we utilize the model used by (Mercader-Prats and Levy, 2004) and apply this to our panel data analysis instead of the cross-sectional analysis in their paper. There are two main effects on income inequality (measured by the Gini Disposable Income Index). First, we express the regional market income's effect each year concerning the average market income of the European regions. Second, we express the effect of the average market income of the European regions concerning the average market income for all regions and years. We present these two effects in the following equation:

$$Gini_{it}^{j} = B + \delta_i + \delta_t + \delta_1 \ln\left(\frac{MI_{it}^{j}}{MI^{j}}\right) + \delta_2 \ln\left(\frac{MI^{j}}{MI}\right) + \varepsilon_{it}$$

Where (Gini) stands for disposable income inequality, δ_i is a region fixed effect, δ_t is a year fixed effect, MI_{it}^{j} is regional market income in each year, MI^{j} is the average market income of the European regions, MI is the average market income for all regions and years in the European regions, and ε_{it} is the disturbance term. $At\ the\ same\ time, \delta 1\ and\ \delta_2$ represent the model parameters, and B is the intercept. Within this specification, i represents the region, and t represents the time (year). In this equation, we use fixed effects, as explained by (Mercader-Prats and Levy,2004), to obtain variations in regions' specifications under control (e.g., market inequality, economic performance, etc.). As illustrated in table (2-5), our results show that Gini Index for Disposable Income negatively depends on the relative market income at the regional and yearly levels. Their magnitudes indicate that the increase (decrease) in regional market income each year relative to the average regional market income explains (a 3%) decrease (increase) in disposable income inequality. In comparison, the increase (decrease) in average regional market income relative to yearly average market income explains (a 7%) decrease (increase) in disposable income inequality. We also use random effects and find the same negative significant relationship between relative market income at the regional and yearly levels and disposable income inequality, which are significant at the 10% level.

Table 2-5: Tax-Benefits Effect on Gini Index in the EU regions

Dependent Variable → **Independent Variables** ↓	Fixed Effects Gini	Random Effects Gini
$\frac{MI_{it}^{j}}{MI^{j}}$	-0.0347*** (0.01)	-0.0170* (0.01)
$\frac{MI^{j}}{MI}$	-0.0693*** (0.02)	-0.0646*** (0.02)
Constant	0.2905*** (0.001)	0.2915*** (0.004)
No. Observations	672	672

*Note: $\frac{MI_{it}^{j}}{MI^{j}}$ and $\frac{MI^{j}}{MI}$ are in log. Clustered standard errors are presented in parenthesis. ***p<0.01, **p<0.05. *p<0.1 present levels of significance.*

This result shows that regions with high relative market income before tax are more efficient in redistributing income components after tax than regions with less relative market income. In addition, regions with high relative market income over time tend to take up the tax system's benefits in reducing income inequality after tax. These results indicate that the tax-benefits system in the European regions, alongside wages and rents, has an impact on changing income inequality in these regions. Depending on these results, we must take in consideration that the negative sign of the coefficient on patents has two explanations. First, the results show that the negative effect of patents on capital profits dominates the effect of patents on wage inequality. Second, by controlling for the effect of taxes on income inequality, innovation is still decreasing income inequality and not spurious with the changes in taxes. Our findings also show that the European regions are efficient in redistribution the outcome of taxes. This filed needs further research which does not fall within the scope of this study.

2.10 Rental (profits) effect on Income Inequality

Another point to consider in our analysis is not only the role of taxes in changing the gap in income inequality but also the effect of wages (earnings from employment) and rent (profits for businesses) on this measure, as our primary dependent variable is measured by inequality in disposable income. According to the SBTC literature[24] We expect that innovation increases income inequality due to the bias in demand for skilled workers as an outcome of technological change. However, the Schumpeterian literature [25] predicts a negative link between these two variables because of "the role of entrepreneurship in the introduction of radical innovations," as stated by (Antonelli and Gehringer, 2017). From their point of view, this is an essential element of disposable income in determining the changes in income inequality. This kind of variation in the direction of the technological change effect on disposable income inequality leads us to study this part in more detail. For this reason, we replace highly skilled and low-skilled ratios used in the "Econometric Estimation" section with two other variables that reflect the labour share and population ratio with tertiary education attainment at the regional level. Each of these two variables is expected to increase income inequality due to their participation in directing income towards highly skilled groups as an outcome of the skill-bias hypothesis that is raised by the SBTC theory[26]. However, we interpret the rent effect by adding an interaction term between the two factors (labour share and population ratio with tertiary education). Since a certain level of labour share usually determines capital share, our interaction term explains the effect of skill intensity on income inequality in line with the share of capital in each region. Accordingly, at a specific level of

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[24] For more details, see ((Helpman, 1997), (Aghion and Howitt, 1997), (Vanhoudt, 2000), (Grossman, 2001), (Acemoglu, 2002), (Acemoglu, 2003), (Burstein and Vogel, 2010), (Costinot and Vogel, 2010), (Okazawa, 2013), and (Aghion et al., 2014)).

[25] For more details see ((Schumpeter, 1934), (Schumpeter, 1942), (Bruton et al., 2013), (Aparicio et al., 2016), and (Antonelli and Gehringer, 2017).

[26] It is presumed by (Antonelli and Gehringer, 2017) that "the direction of technological change works together with the intensity of skills in an economy."

labour/capital share, there is a change in the skill intensity that leads to reduced (increased) income inequality through an increase (decrease) in labour productivity and profits for entrepreneurs (newcomers), as specified in the Schumpeterian literature.

Labour share is measured by dividing compensation per employee by GDP per capita, while the population ratio with tertiary education is measured by people who have tertiary education divided by population. The source of data about these two variables has been collected from Eurostat Regional Statistics.

Table 2-6: Labour share and skilled labour effects on income inequality in the EU regions

Dependent Variable → **Independent Variables** ↓	Gini	90%-10%
Lag (1)	0.5196*** (0.04)	0.4744*** (0.04)
Patents	-0.0288*** (0.01)	-0.0362*** (0.01)
Net Migration	0.0001 (0.001)	0.021 (0.02)
Unemployment	0.2296** (0.08)	0.8440*** (0.13)
GDP per Capita	-0.0468** (0.02)	-0.1003** (0.05)
Taxes	-0.0001* (0.00006)	-0.0004* (0.00024)
Labour Share	0.0409*** (0.007)	0.1517*** (0.05)
Population Ratio with Tertiary Education	0.5676** (0.20)	0.5081*** (0.16)
Interaction Term (Labour Share*Population Highly Skilled Ratio)	-0.0482** (0.02)	-0.5189*** (0.02)
Constant	-0.6756*** (0.07)	0.6058*** (0.07)
No. Observations	524	522

*Note: Variables' descriptions are given in the Appendix. Gini Index, 90%-10% income inequality, patents, and GDP per capita are taken in logs. Gini Index and 90%-10% income inequality are lagged by one year in the GMM method. We use dynamic panel data GMM presented by (Arellano and Bover, 1995), (Blundell and Bond, 1998). Clustered standard errors are presented in parenthesis. ***p<0.01, **p<0.05. *p<0.1 present levels of significance.*

We apply the GMM method to test the accuracy of the previous hypotheses. We find a significant negative effect of innovation on the Gini Index and the middle 80% income inequality, as illustrated in table (2-6). According to the other control variables, we find a significant effect of the increase (decrease) in unemployment on increasing (decreasing) income inequality and a significant decreasing (increasing) effect of the increase (decrease) in GDP per capita and taxes on these measures. In addition, the new control variables that we use in this estimate show evidence of the significant positive effects of the labour share and population ratio with tertiary education on the Gini Index and middle 80% income inequality, which support the SBTC hypotheses. However, the significant negative effect of the interaction term between these two factors, shown in the same table, complies with the Schumpeterian theory. In conclusion, we can say that the overall effect of the improvement in the technological change on decreasing income inequality revealed in this paper combines two effects. First the effect of technological change on the wage gap due to the change in demand for skilled labour, which we have illustrated in different sections of this study. Second, the role of new technology in changing the structure of profits leads to decreasing the gap in disposable income because of the changes in productivity, the creation of new firms, and the new structure of profits. Our results show that the second effect overcomes the first one, ultimately leading to a significant effect of the improvement in the technological change on decreasing disposable income inequality.

Another approach to consider is by using the exact measure of inequality for wage and rent, where we do not need to use the previous variables as a tool to distinguish between the effect of technological change on these two measures. This option is applicable in figuring out the effect of innovation on wage inequality, while it is not affordable to study the effect of innovation on rent inequality due to the lack of information about profits for households or individuals. To find wage inequality, we use individual monthly earnings adjusted by the Retail

Price Index (RPI) to fix the changes in prices, which are collected from Eurostat Regional Statistics. In addition, we exclude tax as individual earnings are measured by primary income before taxes and any social transfers. Due to the similarity in findings between GMM and Heteroskedasticity, it is adequate to use GMM in testing the accuracy of the SBTC hypothesis. The results of the effect of innovation and other control variables on wage inequality (measured by the Gini Index and middle 80% wage inequality) are summarized in table (2-7). Once again, the results show that innovation increases wage inequality at a 1% level, which supports our previous findings on labour and the population with tertiary education ratios.

Table 2-7: Innovation and wage inequality (Gini Index and Middle 80% wage inequality) in the EU regions

Dependent Variable → **Independent Variables** ↓	Gini	90%-10%
Lag (1)	0.7820*** (0.02)	0.4788*** (0.03)
Patents	0.0265*** (0.004)	0.0611*** (0.007)
Net Migration	0.0007** (0.0003)	0.0002* (0.0001)
Unemployment	0.1211** (0.05)	0.6525*** (0.11)
GDP per Capita	-0.0292 (0.03)	-0.0587 (0.06)
HSK	0.0843* (0.05)	0.2164* (0.12)
LSK	0.1306 *** (0.03)	0.4082*** (0.06)
Constant	-0.1862 *** (0.07)	0.6902*** (0.14)
No. Observations	783	579

*Note: Variables' descriptions are given in the Appendix. Gini Index, 90%-10% income inequality, patents, and GDP per capita are taken in logs. Gini Index and 90%-10% income inequality are lagged by one year in the GMM method. We use dynamic panel data GMM presented by (Arellano and Bover, 1995), (Blundell and Bond, 1998). Clustered standard errors are presented in parenthesis. ***p<0.01, **p<0.05. *p<0.1 present levels of significance.*

2.11 __Innovation at the Sectoral Level__

In this section, we study innovation in five primary sectors in the European regions: High Technology (Advanced), Information and Communication Technology (ICT), Pharmaceuticals, Semiconductors, and Biotechnology. As in sections (2-8) and (2-10), we measure innovation in these industries by the number of patent applications per million inhabitants' filed at the PCT. Using the same measure for innovation compares the results and keeps the analysis consistent.

The results in table (2-8) show that patents in High Technology, ICT, Pharmaceuticals, and Biotechnology significantly adversely affect the general measure of income inequality (Gini Index). However, there is no significant effect of patents in Semiconductors on the Gini Index. We notice that the ICT sector has the highest impact on income inequality (in absolute values) (16.6 %, significant at 1%), while the Biotechnological sector has the lowest effect on this measure (in absolute values) (0.09 %, significant at 5%). Hence, the increase in the number of patents by one unit creates a 16.51% difference in the income inequality between these two sectors. Equally important is the effect of taxes on the general measure of income inequality (Gini Index), and it is significantly negative in these four sectors. However, the highest of these in its coefficient magnitude on taxes is patents in Biotechnology (0.02% in absolute values), while the lowest is patents in Pharmaceuticals (0.001% in absolute values). It is noticed from table (2-8) that the increase in coefficient magnitude on taxes from the ICT sector (highest in its effect on income inequality) to the Biotechnology sector (lowest in its effect on income inequality) is countered by a shift from higher to lower coefficient magnitude in the number of patents between these two sectors. The same thing applies to Pharmaceuticals and Biotechnology sectors. Nevertheless, there is no specific pattern in the movement from the highest to the lowest effect of patents and taxes, and vice versa, on income inequality. For example, the efficient movement from Pharmaceuticals (lower innovative sector in reducing income inequality than ICT or High Technology) to High Technology or ICT (higher innovative sectors impact on income inequality than Pharmaceuticals), is associated with a higher effect of taxes on the Gini Index in the ICT or High Technology sectors than the pharmaceutical sector.

Hence, there is a lack of clarity about the progressivity of the tax system between innovative sectors in the European regions to eliminate the gaps in income distribution. However, the highest effect of innovation in the ICT sector on the Gini Index is apparent, mainly due to the reduction in its cost of investment in comparison with the other sectors. The reduction in investment cost causes acceleration in creative destruction and increases market rivalry, squeezing any extra profits (Antonelli, and Gehringer, 2017). This cost reduction is described by (Guellec and Paunov, 2017) in three categories: entry cost, disseminating digital innovation, and scaling cost without mass (less intensity in labour and capital). These results are also supported by (Brynjolfsson et al., 2007), that creative destruction in "IT Intensive Industries" in the USA following the nineties was an essential element in increasing "the risk that firms face in markets."

It is evident from the other control variables that they have the same results revealed in section (2-9) in terms of their signs and significance levels. For example, the unemployment rate, highly skilled labour, and low-skilled labour significantly increasing the Gini Index in all five sectors. On the other hand, GDP per capita and taxes have a significant adverse effect on Gini Index (significant at 10%) in High Technology, ICT, Pharmaceuticals, and Biotechnology, and there is no effect of net migration on the Gini Index in all the five sectors (including Semiconductors). On the contrary, the technology in the Semiconductors involves the negligible effect of innovation and taxes on the Gini Index. In this industry, there is uncertainty in "asset price, entering the product market, and understanding the production process" (Meyer, 2004), which makes it hard to predict the effect of innovation and taxation on the general measure of income inequality in this industry.

Table 2-8: Innovation and income inequality in the sectoral levels in the EU regions using GMM

Dependent Variables → **Independent Variables ↓**	**Gini**	**Gini**	**Gini**	**Gini**	**Gini**
Lag (1)	0.4834*** (0.04)	0.5121*** (0.04)	0.4633*** (0.04)	0.5237*** (0.04)	0.4048*** (0.04)
Patents_High_Tech	-0.0149*** (0.004)	-	-	-	-
Patents_ICT	-	-0.0166*** (0.004)	-	-	-
Patents_pharm	-	-	-0.0116** (0.005)	-	-
Patents_semi_cond	-	-	-	-0.0055 (0.004)	-
Patents_biotech	-	-	-	-	-0.0092** (0.004)
Net Migration	-0.0013 (0.0008)	-0.0008 (0.0008)	-0.0001 (0.0008)	-0.0017 (0.0013)	-0.0008 (0.0008)
Unemployment	0.2865*** (0.10)	0.3271*** (0.10)	0.4261*** (0.12)	0.2690** (0.11)	0.2560** (0.11)
GDP per Capita	-0.0613*** (0.02)	-0.0414* (0.02)	-0.0596* (0.03)	-0.0206* (0.01)	-0.1260*** (0.04)
Taxes	-0.0006** (0.0003)	-0.0005* (0.0003)	-0.0001* (0.0001)	0.0001 (0.0005)	-0.0021*** (0.0005)
Highly skilled labour	0.4108*** (0.09)	0.3508*** (0.08)	0.4959*** (0.08)	0.3851*** (0.08)	0.5456*** (0.09)
Low-skilled labour	0.3016*** (0.06)	0.3043*** (0.06)	0.2966*** (0.10)	0.1109* (0.06)	0.2671*** (0.06)
Constant	-1.1107*** (0.11)	-1.0750*** (0.10)	-1.1634*** (0.10)	-0.8838*** (0.10)	-1.1639*** (0.10)
No. Observations	**578**	**584**	**466**	**466**	**562**

*Note: Variables' descriptions are given in the Appendix. Gini Index, patents in different sectors, and GDP per capita are taken in logs. Gini Index is lagged by one year in the GMM method. We use dynamic panel data GMM, which is presented by (Arellano and Bover, 1995), (Blundell and Bond, 1998). Clustered standard errors are presented in parenthesis. ***p<0.01, **p<0.05. *p<0.1 present levels of significance.*

From the other side, we test the effect of innovation on the top 10% and top 1% income shares in the five mentioned sectors. The results are illustrated in tables (2-9) and (2-10), in which we find the same effect of innovation on these two measures regarding their signs, significance levels, and order of their magnitude in comparison with the results in section (2-8). Furthermore, there is a significant effect of innovation on increasing the gap in the top income shares in all sectors; this is because market rents are mainly stemming from “investors and top managers and less to the average workers” (Guellec and Paunov, 2017) hence increasing (decreasing) top income shares with technology expansion (contraction). There is a lower significance level for the coefficients on patents compared with their counterparts in table (2-8) since the fluctuations in patents on the top income shares are less than the fluctuations in patents on the overall income distribution. It is also noticed from tables (2-9) and (2-10) that patents in Pharmaceuticals have the highest impact on the top income shares (≈ 1% in the top10% income share, ≈ 0.03% in the top1% income share, and both are significant at 10% level), while patents in High Technology and ICT have the lowest impact on these measures (≈ 0.02% in top 1% income share, ≈ 0.01% in top 1% income share, and both are significant at 10% level). The difference in the patents magnitude between pharmaceuticals and ICT is 0.98% on the top 10% income shares and 0.02% on the top 1% income shares). Accordingly, ICT does not show a very high magnitude in its effect on top income shares compared to the other industries. As mentioned before, the short duration of monopolistic power explains this for innovators in this industry. Ultimately causes a slight increase in their markups because of the reduction in barriers to entering this market. In addition, the capital that is required in the ICT industry is much lower than in other industries (e.g., Pharmaceuticals and Semiconductors), which need fewer "special facilities to develop innovations" (Guellec and Paunov, 2017). While in more traditional industries like Pharmaceuticals, the cost to enter the market is very high, which hinders the entry of new competitors and increases the magnitude of technology on the top income shares.

Further, there is a significant effect of the increase (decrease) in the supply of highly skilled labour on increasing (decreasing) the gap in the top income shares (significant at 1% level), while taxes do not impact these measures. The increase in highly skilled labour by one per cent increases the top 10% and 1% income shares by around 80% and 1.08 in most sectors, respectively (assuming that the other independent variables are constant). On the contrary, the increase (decrease) in net migration, unemployment rate, GDP per capita, and low-skilled labour decrease (increase) the gap in the top income shares (significant at 1% level) in all sectors. This outcome shows consistency in the results between the effect of patents in different innovative industries and overall number of patents on different measures of income inequality.

Table 2-9: Innovation and top 10% income share in the sectoral levels in the EU regions using GMM

Dependent Variables → **Independent Variables ↓**	**Top 10%**	**Top 10%**	**Top 10%**	**Top 10%**	**Top 10%**
Lag (1)	0.3403***	0.3563***	0.3343***	0.2641***	0.2919***
Patents_High_Tech	0.0021*	-	-	-	-
Patents_ICT	-	0.0022*	-	-	-
Patents_pharm	-	-	0.0069*	-	-
Patents_semi_cond	-	-	-	0.0064*	-
Patents_biotech	-	-	-	-	0.0023*
Net Migration	-0.0010*	-0.0016*	-0.0023*	-0.0016*	-0.0015*
Unemployment	-0.7686***	-0.8745***	-0.9211***	-1.1521***	-0.8189***
GDP per Capita	-0.1818***	-0.1672***	-0.1784***	-0.1771***	-0.2295***
Taxes	-0.0005	-0.0001	-0.0004	0.0001	-0.0010
Highly skilled labour	0.3325***	0.3389***	0.3544***	0.4600***	0.3774***
Low-skilled labour	-0.1907***	-0.2475***	-0.1601**	-0.4240***	-0.1200***
Constant	-1.6284***	-1.5573***	-1.7574***	-1.6746***	-1.7461***

No. Observations	576	582	464	465	560

*Note: Variables' descriptions are given in the Appendix. The top 10% income share, patents in different sectors, and GDP per capita are taken in logs. The top 10% income share is lagged by one year in the GMM method. We use dynamic panel data GMM, which is presented by (Arellano and Bover, 1995), (Blundell and Bond, 1998). Clustered standard errors are presented in parenthesis. ***p<0.01, **p<0.05. *p<0.1 present levels of significance.*

Table 2-10: Innovation and top 1% income share in the sectoral levels in the EU regions using GMM

Dependent Variables → **Independent Variables ↓**	**Top 1%**	**Top 1%**	**Top 1%**	**Top 1%**	**Top 1%**
Lag (1)	0.3203***	0.3563***	0.3343***	0.2641***	0.2919***
Patents_High_Tech	0.0011*	-	-	-	-
Patents_ICT	-	0.0012*	-	-	-
Patents_pharm	-	-	0.0033*	-	-
Patents_semi_cond	-	-	-	0.0023*	-
Patents_biotech	-	-	-	-	0.0021*
Net Migration	-0.0008*	-0.0003*	-0.0001*	-0.0010*	-0.0002*
Unemployment	-0.2796***	-0.4666***	-0.8331***	-1.2221***	-0.7918***
GDP per Capita	-0.1424***	-0.1341***	-0.1429***	-0.1681***	-0.3027***
Taxes	-0.0001	-0.0001	-0.0002	0.0001	-0.0001
Highly skilled labour	0.4243***	0.39694***	0.3634***	0.4710***	0.3872***
Low-skilled labour	-0.1610***	-0.2362***	-0.1466**	-0.3933***	-0.1118***
Constant	-1.9366***	-1.6423***	-1.7644***	-1.7784***	-1.4432***
No. Observations	**576**	**582**	**464**	**465**	**560**

*Note: Variables' descriptions are given in the Appendix. The top 1% income share, patents in different sectors, and GDP per capita are taken in logs. The top 1% income share is lagged by one year in the GMM method. We use dynamic panel data GMM, which is presented by (Arellano and Bover, 1995), (Blundell and Bond, 1998). Clustered standard errors are presented in parenthesis. ***p<0.01, **p<0.05. *p<0.1 present levels of significance.*

2.12 __Discussion__

So far, we have shown empirically that technological change negatively affects broad measures of income inequality at the aggregate and sectoral levels using different econometric techniques. This result complies with (Claudia et al., 2018), specifically that their empirical results present the diverse effect of innovation on overall income distribution. In contrast to this result, (Benos N and Tsiachtsiras G, 2018) find weak evidence of causality effect between innovation and income inequality while they find a significant effect of innovation on the top income inequality, and this effect is weak when they include defensive patents. On the other hand, (Aghion et al., 2018) show that innovation increases the gap in the top income shares.

We justify our results in four main points. First, following the creative destruction concept as stated by (Aghion and Howitt, 1992), (Aghion and Howitt, 1998), (Jones and Kim, 2014), and (Aghion et al., 2018), the existence of new technology destroys a large part of the old capital. Consequently, incumbent firms are forced to exit the market because of their losses, which leads to wealth redistribution and income inequality reduction.

Second, another strand of literature (for example (Aparicio et al., 2016) supports the argument that the developments in information and communication technology decrease income inequality through its success in creating new firms. Henceforth, incumbents are engaged in progressive innovation, which leads to the movement of the labour force to a higher income level. It complies with our results in section (2-11), especially that high-technology and ICT sectors, which are the main aspects of establishing new businesses, have the highest effect on income inequality compared to other sectors.

Third, the competition that arises because of technological change and the entry of new innovating firms reduce barriers to entering the market. Accordingly, it reduces extra profits and eliminates the monopolistic power of the existing firms. The reduction in these profits, in turn, reduces the income of the owners of these firms, so income inequality decreases. This argument is addressed by (Anatonelli and Gehringer, 2013), who show that this mechanism is one of the interpretations of the effect of technological change on income distribution. In that case, innovation is initiated by entrepreneurs who present the middle class, and those newcomers generate profits from scratch, which decrease the general levels of income inequality.

Finally, a high proportion of skilled workers in the labour market needs more effort to enhance their productivity. Hence, with this increase in productivity, the relative supply of skilled workers increases income inequality in the short run (Acemoglu, 1998).

Our results reveal that the top 10% of the income distribution is also in line with the theory of skill-biased technical change. In this segment, the movement at the high-end of the distribution can occur. It asserts the vulnerability of unskilled labour to the technological change resulting from new technology (Acemoglu and Autor, 2011). In this case, technological development pushes the demand toward highly skilled labour; hence the endogenous allocation between skill groups does not necessarily raise the income for all workers. Consequently, there will be a high probability of an increase in the gap between high and low-skilled labour. Due to the differences in inter-sector income, technological specialization increases income inequality on the top of the distribution and causes different levels of jobs across sectors (Permana et al., 2018).

2.13 Employment in Different Sectors

From the policy perspective, it is beneficial to decompose employment in economic sectors to determine the possibility of progression in specific areas. For this reason, we add other control variables, including the employment rate in three main sectors (Agriculture, Manufacturing, and Services). These are the main sectors in the economy that deploy a high percentage of the labour force and empirically have been analyzed in literature for their impact on income inequality. We must note, however, that by adding these variables, we lose some data for specific years as they are unavailable, but this will not affect the validity of our results. The data source for these variables is Eurostat, and we explain their definition in the Appendix.

Tables (2-11) and (2-12) summarize the estimated results of using GMM and TSLS-Heteroskedasticity methods, respectively, by adding employment in (Agriculture, Manufacturing, and Services) sectors to the baseline model. Again, we find a substantial effect of innovation in decreasing the general measure of income inequality (Gini Index) (significant at 1% level) . However, innovation increases the gap in the top 10%- and 1%-income shares (significant at 1%), which comply with our previous findings. In addition, the unemployment rate, highly skilled labour, and low-skilled labour have a significant positive effect on Gini Index and the middle 80% income inequality, while GDP per capita and taxes negatively affect these measures. On the top income shares (10% and 1%), there is also consistency in the results, where the increase (decrease) in net migration, unemployment rate, GDP per capita, and low-skilled labour decrease (increase) the gap in these measures, while the increase (decrease) in highly skilled labour has a significant effect on increasing (decreasing) the gap in the top income shares.

Recently, there have been different findings in the literature about the relationship between Employment in Agriculture and income inequality. For example, (Mishra et al., 2009) and (Sutherland, 2019) pointed out that employment in the agricultural sector increases the gaps in income . This link "involves diminishing returns with agriculture," and it has a profound effect in countries with less intensity in technology, specifically developing countries. Despite this, (Ding et al., 2011) find that this effect is relatively small because of the "high-cost technologies" that lead to the reduced outcome for low-income farmers. However, other papers (e.g., Tang, 2022) do not find any relationship between employment in agriculture and income inequality, referring to the lack of technology in agriculture in developing countries. Our results show that agriculture employment does not affect all measures of income inequality (Gini Index, middle 80% income inequality, top 10% income share, and 1% income share). We justify this result because it relates to developed countries, where agriculture is very technical in European regions, compared with other developing countries analyzed in the previous literature. However, manufacturing employment negatively affects Gini Index and the middle 80% income inequality in the European regions, while it does not impact the top income shares (top 10% and top 1%). This adverse effect is due to the increase of employment concentration in manufacturing in specific regions, enhancing productivity per capita and efficiency, which "facilitates smoothing income gaps between wealthiest households and others" (Guo et al., 2022) in the whole income distribution, while in the top income shares this effect disappears because of the high concentration of wealthy households in this segment. This result indicates that any policy must consider the potential increase in inequality when there is a decline in the manufacturing sector, mainly in developed countries like the European regions.

In addition, from the GMM and the TSLS- Heteroskedasticity methods, this study finds that the services sector provided a positive coefficient on the general measure of income inequality (Gini Index) and the middle 80% income inequality at a 1% significant level, which complies with (Raeskyesa, 2020). As stated by (Namini and Hudson, 2018) that when employment in the services sector increases (decreases), the gaps in income between urban and rural areas increases (decrease) because of the high contribution of this sector to economic growth. However, employment in this sector does not significantly affect the top income shares. We explain this by the high concentration of income in the hands of wealthy people, located at the top of the income distribution, with no significant gaps in this segment.

Table 2-11: Innovation and different measures of income inequality by adding employment in different sectors in the EU regions using GMM

Dependent Variables → **Independent Variables ▼**	**(1)** **Gini**	**(2)** **90%-10%**	**(3)** **Top 10%**	**(4)** **Top 1%**
Lag (1)	0.3319***	0.3942***	0.3477***	0.3477***
	(0.03)	(0.04)	(0.02)	(0.02)
Patents	-0.0258***	-0.0286***	0.0012***	0.0320***
	(0.001)	(0.004)	(0.001)	(0.01)
Net Migration	0.0009	0.0002	-0.0015***	-0.0011***
	(0.0009)	(0.0003)	(0.0003)	(0.0003)
Unemployment	0.2002*	0.7541***	-1.0488***	-1.1890***
	(0.10)	(0.11)	(0.10)	(0.10)
GDP per Capita	-0.0492**	-0.1067***	-0.1685***	-0.0231***
	(0.02)	(0.02)	(0.02)	(0.01)
Taxes	-0.0003*	-0.0001*	0.0001	0.0001
	(0.0002)	(0.0001)	(0.0003)	(0.0003)
Highly skilled labour	0.3381***	0.1045*	0.1487**	0.1326**
	(0.09)	(0.06)	(0.07)	(0.07)
Low-skilled labour	0.3976***	0.4860***	-0.1799***	-0.1290***
	(0.07)	(0.05)	(0.04)	(0.04)
Employment Ratio	0.2705	-0.8652	-0.6076	-0.4900
(Agriculture)	(0.75)	(0.84)	(0.51)	(0.49)
Employment Ratio	-1.2873***	-0.8244***	-0.7082	-0.8080
(Manufacturing)	(0.26)	(0.16)	(0.69)	(0.71)
Employment Ratio	1.4671**	0.2252**	1.0170	1.1010
(Services)	(0.65)	(0.10)	(2.40)	(2.34)
Constant	-0.9158***	0.7774***	-1.4858***	-1.6001***
	(0.09)	(0.09)	(0.06)	(0.08)
No. Observations	**580**	**578**	**578**	**578**

*Note: Variables' descriptions are given in the Appendix. Gini Index, 90%-10% income inequality, Top 10% income share, top 1% income share and GDP per capita are taken in logs. Different measures of income inequality are lagged by one year. Clustered standard errors are presented in parenthesis. ***p<0.01, **p<0.05. *p<0.1 present levels of significance.*

Table 2-12: Innovation and different measures of income inequality by adding employment in different sectors in the EU regions using TSLS (Heteroskedasticity) Method

Dependent Variables → **Independent Variables ↓**	**(1)** **Gini**	**(2)** **90%-10%**	**(3)** **Top 10%**	**(4)** **Top 1%**
Patents	-0.0610*** (0.004)	-0.0851*** (0.01)	0.0245*** (0.003)	0.0433*** (0.002)
Net Migration	0.0004 (0.004)	0.0013 (0.001)	-0.0018*** (0.0001)	-0.0010*** (0.0001)
Unemployment	0.1657* (0.09)	1.0845*** (0.16)	-0.9229*** (0.10)	-1.1020*** (0.10)
GDP per Capita	-0.1035** (0.04)	-0.0130* (0.01)	-0.0964*** (0.03)	-0.0649*** (0.02)
Taxes	-0.0004* (0.0003)	-0.0001* (0.0001)	0.0001 (0.0003)	0.0001 (0.0003)
Highly skilled labour	0.1582** (0.07)	0.0889* (0.05)	0.0675* (0.05)	0.1825* (0.04)
Low-skilled labour	0.2842*** (0.03)	0.5455*** (0.04)	-0.2570*** (0.02)	-0.2340*** (0.01)
Employment Ratio (Agriculture)	-0.4769 (0.42)	-0.4468 (0.40)	-0.0440 (0.17)	-0.0389 (0.18)
Employment Ratio (Manufacturing)	-1.3027*** (0.18)	-1.4467*** (0.23)	0.1380 (0.13)	0.1946 (0.41)
Employment Ratio (Services)	2.7429*** (0.40)	2.7424*** (0.52)	-0.0337 (0.29)	-0.0222 (0.11)
Constant	-1.1096*** (0.04)	1.3523*** (0.05)	-2.4616*** (0.03)	-2.5610*** (0.06)
No. Observations	**612**	**610**	**610**	**610**

*Note: Variables' descriptions are given in the Appendix. Gini Index, 90%-10% income inequality, top 10% income share, top 1% income share and GDP per capita are taken in logs. Clustered standard errors are presented in parenthesis. ***p<0.01, **p<0.05. *p<0.1 present levels of significance.*

2.13 <u>Sensitivity Analysis</u>

Three main concerns usually arise when estimating the models used in this study. Our first concern is that many observations are missed for different regions in each period, especially between 1993 and 2002. Also, selecting the sample is one of the main issues that could affect the accuracy of the estimated coefficients. To deal with these effects, we only include regions that have observations for each period[27] and remove outliers. Precisely, we control these differences in regions by "re-estimating the baseline model" for regions that have observations in the same period, from 2003-2011, for 81 regions in Europe. We summarize these results in table (2-13), which reveals that the coefficients on innovation, where Gini Index and middle 80% income inequality are the dependent variables, remain negative and significant at the 1% level. Once again, innovation increases the gap in the top income share (significant at the 1% level). In addition to this effect, other control variables show robustness in the previous results. For example, the unemployment rate, highly and low-skilled labour always positively affect Gini Index and the middle 80% income inequality, while GDP per capita and taxes negatively affect these measures. However, net migration does not impact Gini Index and the middle 80% income inequality. Again, regarding the top income share, the increase in the supply of highly skilled labour increases the gap in this measure. In addition, the increase (decrease) in net migration, unemployment rate, GDP per capita, and low-skilled labour decrease (increase) the gap between the 100% and 90% of the income distribution .

In contrast, taxes do not significantly affect the top income share, which indicates that removing any period from the baseline model estimation does not change the results. Although the values of the coefficients vary, the coefficients signs and significant levels remain the same.

The second paramount concern is measuring innovation, which could change the results. We use the log of the R&D expenditures as a percentage of Gross Domestic Product (GDP) instead of the number of patents per million inhabitants and estimate the model again. The source of this data is the Eurostat database, and it includes R&D expenditures in four primary sectors, which are: Business enterprise sector, government sector, higher education sector, and private non-profit sector. Once more, we have the same negative signs for the innovation

[27] This methodology is used by (Forbes, 2000) to control for the effect of including different countries that have missed observations. Note that we also exclude years with missed observations.

coefficients on Gini Index and middle 80% income inequality and positive signs for the innovation coefficient on top income share, shown in table (2-14).

Table 2-13: Sensitivity analysis - Sample selection

Dependent Variables → **Independent Variables** ↓	**GMM Gini**	**GMM 90%-10%**	**GMM Top 10%**	**HT Gini**	**HT 90%-10%**	**HT Top 10%**
Lag (1)	0.2816*** (0.004)	0.4104*** (0.01)	0.3533*** (0.01)	-	-	-
Patents	-0.0292*** (0.001)	-0.0135*** (0.002)	0.0130*** (0.001)	-0.0313*** (0.01)	-0.0585*** (0.01)	0.0272*** (0.01)
Net Migration	0.0014 (0.001)	0.00001 (0.0002)	-0.0002* (0.0001)	-0.0005 (0.0004)	0.0002 (0.0002)	-0.001* (0.001)
Unemployment	0.5246*** (0.02)	0.9844*** (0.01)	-0.8638*** (0.01)	1.0038*** (0.19)	2.5215*** (0.23)	-1.5178*** (0.13)
GDP per Capita	-0.0154** (0.01)	-0.1681*** (0.01)	-0.0760*** (0.003)	-0.4341** (0.14)	-0.4202*** (0.02)	-0.0140*** (0.04)
Taxes	-0.0008** (0.0004)	-0.0001* (0.0001)	-0.0001 (0.0003)	-0.0007** (0.0002)	-0.0004* (0.0002)	-0.0001 (0.0003)
Highly skilled labour	0.2814*** (0.02)	0.1946*** (0.04)	0.1481*** (0.01)	0.3952*** (0.10)	0.5133*** (0.13)	0.1181* (0.07)
Low-skilled labour	0.3001*** (0.01)	0.3458*** (0.01)	-0.3225*** (0.01)	0.2107*** (0.06)	0.4744*** (0.07)	-0.2637*** (0.04)
Constant	-1.0656*** (0.01)	0.6675*** (0.01)	-1.4295*** (0.01)	-1.4573*** (0.05)	0.8898*** (0.06)	-2.3471*** (0.03)
No. Observations	**419**	**419**	**419**	**488**	**488**	**488**

*Note: Variables' descriptions are given in the Appendix. Gini Index, 90%-10% income inequality, top 10% income share, patents, and GDP per capita are taken in logs. GMM method is used in columns 1, 2, and 3, while Heteroskedasticity method is used in columns 4, 5, and 6. All the different measures of income inequality are lagged by one year in the GMM method. Clustered standard errors are presented in parenthesis. ***p<0.01, **p<0.05. *p<0.1 present levels of significance.*

Table 2-14: Sensitivity analysis - Dependent variable definition (Research and Development (R&D))

Dependent Variables → **Independent Variables** ↓	**GMM Gini**	**GMM 90%-10%**	**GMM Top 10%**	**HT Gini**	**HT 90%-10%**	**H.T. Top 10%**
Lag (1)	0.4225*** (0.02)	0.5103*** (0.01)	0.3683*** (0.03)	-	-	-
R&D	-0.0307** (0.01)	-0.0576*** (0.005)	0.0081* (0.005)	-0.1630*** (0.02)	-0.2532*** (0.03)	0.0903*** (0.01)
Net Migration	-0.0022 (0.003)	-0.0021 (0.002)	-0.0008* (0.0005)	-0.0035 (0.003)	-0.0043 (0.004)	-0.0008* (0.0005)
Unemployment	0.3358*** (0.03)	0.6983*** (0.06)	-0.6780*** (0.04)	1.0458*** (0.17)	2.4742*** (0.24)	-1.4284*** (0.11)
GDP per Capita	-0.1052*** (0.02)	-0.2153*** (0.01)	-0.1978*** (0.01)	-0.1300* (0.07)	-0.0991* (0.05)	-0.0308* (0.02)
Taxes	-0.0003*** (0.0001)	-0.0002* (0.0001)	-0.0001 (0.0003)	-0.0004*** (0.0001)	-0.0001* (0.0001)	-0.0001 (0.0001)
Highly skilled labour	0.6692*** (0.05)	0.1364*** (0.05)	0.3806*** (0.03)	0.4620*** (0.13)	0.6411*** (0.18)	0.1791*** (0.06)
Low-skilled labour	0.2696*** (0.05)	0.4824*** (0.03)	-0.2954*** (0.03)	0.5808*** (0.07)	0.9878*** (0.10)	-0.4070*** (0.05)
Constant	-1.1036*** (0.04)	0.4630*** (0.03)	-1.5781*** (0.07)	-1.7320*** (0.06)	0.4763*** (0.10)	-2.2082*** (0.05)
No. Observations	**465**	**465**	**465**	**493**	**493**	**493**

*Note: Variables' descriptions are given in the Appendix. Gini Index, 90%-10% income inequality, top 10% income share, R&D, and GDP per capita are taken in logs. GMM method is used in columns 1, 2, and 3, while Heteroskedasticity method is used in columns 4, 5, and 6. All the different measures of income inequality are lagged by one year in the GMM method. Clustered standard errors are presented in parenthesis. ***p<0.01, **p<0.05. *p<0.1 present levels of significance.*

Our last concern is the consistency in the results when we have different specifications in the model. Here, we use pooled OLS and Fixed Effects, and our focus is mainly on the "Fixed Effects for the panel estimation" as the case (Forbes, 2000) because of the truncation in the sample that is usually associated with the GMM technique, which sometimes leads to unstandardized parameters. We utilize these two techniques to estimate the baseline panel model by using the selected sample from 2003-2011 in the European regions and by using a different definition for innovation: the percentage of R&D expenditures to GDP per capita. We use this selected sample to compare the results between this measure and the previous one, which is the number of patents per million inhabitants. Here, we exclude observations in the years where data about patents is unavailable, which we illustrate in tables (2-15) and (2-16). Once again, we find the same effect of patents (and R&D expenditures) on decreasing Gini Index and the middle 80% income inequality. However, patents (and R&D expenditures) increase the gap in the top income share at the 1% level. There is also consistency in the results for the other control variables. Specifically, the unemployment rate and highly skilled and low-skilled labour have a significant positive impact on Gini Index and the middle 80% income inequality, while GDP per capita and taxes negatively affect these measures.

Further, the increase (decrease) in net migration, unemployment rate, GDP per capita, and low-skilled labour decrease (increase) the gap in the top income share, while the increase (decrease) in the supply of highly skilled labour increase (decrease) this gap. However, net migration does not impact Gini Index and the middle 80% income inequality; the same applies to the link between taxes and top income share. These results suggest consistency in the coefficients' signs, which show that even with these differences in the model specifications, the direction of the relationship between innovation and income inequality does not change.

In general, it is noticed from the previous outcomes that the relationship between innovation and the different measures of income inequality is not driven by sample selection (or missed data), variable definitions, or model specifications.

Table 2-15: Sensitivity analysis - Model specifications with patents

	Pooled OLS			Fixed Effects		
Dependent Variables → Independent Variables ↓	Gini	90%-10%	Top 10%	Gini	90%-10%	Top 10%
Patents	-0.0486*** (0.005)	-0.0849*** (0.01)	0.0363*** (0.003)	-0.0412*** (0.01)	-0.0425*** (0.01)	0.0277*** (0.03)
Net migration	-0.0002 (0.0001)	0.0009 (0.008)	-0.0011* (0.001)	-0.0020 (0.002)	-0.0031 (0.003)	-0.0030*** (0.001)
Unemployment	0.7564*** (0.13)	1.7334*** (0.16)	-0.9776*** (0.8)	0.4065*** (0.11)	1.3548*** (0.18)	-1.0493*** (0.09)
GDP per capita	-0.0693*** (0.02)	-0.0250** (0.01)	-0.0942** (0.04)	-0.0141** (0.04)	-0.1663*** (0.05)	-0.1216*** (0.03)
Taxes	-0.0006** (0.0003)	-0.0003* (0.0002)	-0.0001 (0.0003)	-0.0002** (0.0001)	-0.0003** (0.0001)	-0.0001 (0.0001)
Highly skilled labour	0.3622*** (0.07)	0.4634*** (0.09)	0.1012** (0.05)	0.1609*** (0.01)	0.3780** (0.17)	0.0707* (0.04)
Low-skilled labour	0.2204*** (0.04)	0.4889*** (0.04)	-0.2685*** (0.03)	0.3065*** (0.08)	0.5141*** (0.21)	-0.2849*** (0.05)
Constant	-1.3624*** (0.03)	1.0793*** (0.04)	-2.4417*** (0.02)	-1.3116*** (0.06)	1.2803*** (0.14)	-2.4614*** (0.04)
No. Observations	488	488	488	488	488	488

*Note: Variables' descriptions are given in the Appendix. Gini Index, 90%-10% income inequality, top 10% income share, patents, and GDP per capita are taken in logs. We use pooled OLS and Fixed effects for the selected sample. Clustered standard errors are presented in parenthesis. ***p<0.01, **p<0.05. *p<0.1 present levels of significance.*

Table 2-16: Sensitivity analysis - Model specifications with R&D

	Pooled OLS			Fixed Effects		
Dependent Variables → Independent Variables ↓	Gini	90%-10%	Top 10%	Gini	90%-10%	Top 10%
R&D	-0.0862*** (0.01)	-0.1252*** (0.01)	0.0390*** (0.001)	-0.1224*** (0.03)	-0.0691*** (0.02)	0.0532*** (0.03)
Net migration	-0.0001 (0.0001)	0.0011 (0.001)	-0.0019* (0.001)	-0.0027 (0.003)	-0.0007 (0.007)	-0.0020** (0.001)
Unemployment	0.7446*** (0.12)	2.1363*** (0.16)	-1.1917*** (0.09)	0.3736*** (0.13)	1.4530*** (0.18)	-1.0794*** (0.14)
GDP per capita	-0.0423*** (0.01)	-0.0957** (0.05)	-0.1380** (0.04)	-0.0884** (0.04)	-0.3176*** (0.07)	-0.2292*** (0.05)
Taxes	-0.0004** (0.0002)	-0.0003* (0.0002)	-0.0002 (0.0003)	-0.0002** (0.0001)	-0.0004** (0.0002)	-0.0001 (0.0001)
Highly skilled labour	0.2662*** (0.07)	0.1657*** (0.05)	0.1005** (0.05)	0.1215*** (0.03)	0.5922*** (0.17)	0.7137* (0.14)
Low-skilled labour	0.2156*** (0.04)	0.4558*** (0.05)	-0.2402*** (0.03)	0.3662*** (0.14)	0.5622*** (0.20)	-0.1960*** (0.06)
Constant	-1.5019*** (0.03)	0.8839*** (0.04)	-2.3858*** (0.02)	-1.4260*** (0.09)	1.1976*** (0.13)	-2.6234*** (0.10)
No. Observations	493	493	493	493	493	493

*Note: Variables' descriptions are given in the Appendix. Gini Index, 90%-10% income inequality, top 10% income share, R&D, and GDP per capita are taken in logs. We use pooled OLS and Fixed effects for the original sample with the different dependent variable (R&D). Clustered standard errors are presented in parenthesis. ***p<0.01, **p<0.05. *p<0.1 present levels of significance.*

2.14 Extensions

There are issues that could arise in measuring innovation in this paper. One of these issues is using citation-weighted patents. Not all patents have valuable economic outcomes that capture the effect of technological change on income inequality. Moreover, it is not easy to show the heterogeneity in technology when the number of patents is counted. Knowledge spillover is another issue that gives attention to the role of citing the patents in disseminating technology to others. However, the complications concerning knowledge spillover in the European regions lead us to eliminate the use of this measure. For instance, the results of (Maurseth and Verspagen, 2002) indicate that there is a substantially low level of knowledge spillover between EU regions. The source of this divergence is due to the larger citation of patents within EU countries than between the EU regions. Another drawback of measuring citation patents is explained by (Jafe and Rassenfose, 2017) in four major effects. First, the "Office Effect" reflects the difference between offices in practicing citation and the potential bias in citing "local documents". Second, the time effect comes into the site because of the increase in the number of cited patents day by day. Hence, there is a possibility of citing any patent after the year of application that is documented in the study. In this case, it is very difficult to measure accurately the real value of patents and compare them between years. Even though the number of cited patents can be adjusted by counting them over a certain amount of time, valuing these patents across time periods is incommensurable. Third, heterogeneity in the examiners' experience affects the quantity of cited patents in a certain period. In addition, the tendencies to cite patents are different from one sector to another. Finally, there are variances in the strategy of citing "prior art". It is shown in the literature that investment in R&D, the cost of patenting, the importance of the invention, and the return on investment in R&D influence the applicants' choices to disclose the evidence that their inventions are known.

Distinguishing between the effort and the success of the investment in R&D is crucial in our measurement of innovation. Following the interpretation of (Trajtenberg, 1990), the magnitude of R&D effort indicates a general improvement in the number of patents, while "citation-weighted patents" indicates the success of innovation. In this paper, we test the "creative Destruction" and "SBTC" hypotheses which require examining innovative firms' efforts in utilizing human capital resources and their effect on the demand for different skilled groups of workers. It means that our evaluation is more focused on the labour area than on the economic growth area as an output. Ultimately the appropriateness of counting patents in this field overcomes the impediment associated with citing patents.

Another point to consider is the role of particular periods of data in generating the results. After the global financial crisis of 2008, changes might occur in income distribution. These changes may be viewed as an outcome of the economic downturn and negative GDP growth. As our study covers the global financial crisis period, we examine its impact on income inequality by using a dummy variable which equals 1 for the years 2008, 2009, 2010, and 2011, and zeroes otherwise. Our purpose is to show the short-run consequences of this crisis (2008-2011), especially since it takes time for such changes in income to occur. We add this variable to the other independent variables in the dynamic model (GMM) explained in section (2.6) and run the test again. Our findings show that the magnitude and the significant level of innovation (represented by patents) do not change. We also do not spot any changes in the significant levels of the other control variables. As a dummy variable financial crisis does not have any impact on the different measures of income inequality. However, there is a slight increase in the magnitude of the unemployment rate coefficient by around 1.6%, but it is still significant at the 1% level. There are also very small changes in the magnitudes of highly and low-skilled labour coefficients, which equal 1% and 0.01%, respectively. Hence, our findings apply equally well when the global financial crisis period is eliminated from the dataset. On the top income shares (10% and 1%), there is still positive sign of patents coefficient and the magnitudes do not change significantly. Other control variables have the same significant levels and magnitude.

2.15 Conclusions

The creative destruction literature's primary concern is finding the reason behind the link between innovation and income inequality. It attributes that to the shortened duration of the "accumulation of monopolistic rents" (Antonolli and Gehringer, 2017) for new innovators, which leads to reduce (increase) in their profits (rents) with the increase (decrease) in technology. However, in Skill-Biased Technological change (SBTC) literature, this income gap (income from work (wage)) is mainly attributed to the bias in labour skills and the ability of highly skilled groups to use new technology that gives them the advantage of receiving higher income (wage). Despite the general agreement in the literature about this relationship between innovation and income inequality, the net balance between these effects (rents effect and wage effects) has not been studied yet. Moreover, there has been a long-standing debate about the direction and source of these effects. For that purpose, we studied the effect of innovation on income inequality for a panel of European regions from 1993-2011. It came through using the Gini index, middle 80% income inequality, top 10% income share, top 1% income share and bottom 10% income share as measures of income inequality and number of patent applications per million inhabitants filed at the PCT as a measure of innovation alongside other control variables that affect such relation. In addition, by using pooled OLS, Random Effects, and Fixed Effects, we found evidence of a robust effect of innovation in decreasing the general measures of income inequality and middle 80% income inequality. However, innovation increases the gap in the top income shares.

Previous articles about this concept were limited by weaknesses in the instrument variables that they have used or focusing only on the innovation-inequality link at the country level. Together with studying the relationship between income inequality and innovation, we tested the effect of patents on income inequality using dynamic GMM and Two-Stage Least Squares TSLS (Lewbel, 2012) methods to generate valid instruments. Our findings show that there is an effect of innovation on income inequality, consistent with pooled OLS, Random Effects, and Fixed Effects results. However, innovation increases the gap between the higher income groups, which is presented in this study by the top 10%-and 1%-income shares. Furthermore, we tested the validity of our used techniques and found that they are at least relevant and not biased towards specific measures, and they can explain a high portion of the variations in income inequality.

Going further in our analysis, we studied the link between innovation and income inequality at the sectoral level. We found that patents in the high-tech and ICT sectors have the highest significant effect on income inequality. This result reinforces the argument that sectors with a short duration of monopolistic power are more sensitive to the changes in economic development than other sectors. Moreover, we examined this link on employment in different sectors and found that manufacturing is the most powerful sector in absorbing gaps in income inequality than other sectors (mainly the services sector).

Finally, we used sampling selection, variable definitions, and model specifications to check the sensitivity of our results to these variations. We found that our results replicate the same evidence of the previous findings, which confirms that our estimation is not sensitive to these changes. These findings are highly robust when model specifications are considered.

2.16 Policy implications

Our results show that encouraging innovation is one of the important factors that reduce income inequality. We recommend achieving this target by subsidizing new inventions to avoid monopoly in the market and eliminate entry barriers for new entrants. The outcome of this policy is reducing the production cost, which gives the privilege for new entrants to compete in the price.

Another point is that our results indicate that innovation not necessarily cause bad consequences on income inequality. In this situation, there is no need for corrective actions by policymakers. Considering the high-end income distribution when setting up the policy is imperative. We suggest keeping a balance between fostering innovation to incentivize the economy and targeting a low level of income concentration in the hands of a small percentage of the population. It is also important to note in this paper that high economic growth and low unemployment rates narrow the gap between the different groups in the income distribution. However, developing technological change is widening the gap in wages in the European regions. It means that a higher regional economic growth may occur at the expense of unequal wage distribution. This indicates that the policy is recommended to be cohesive to succeed in dealing with income and wage inequality. This policy is not easy to achieve, and it is crucial to think carefully before directing the resources towards any of the economic activities.According to the other results in this study, we recommend other policies that help reduce income inequality, mainly presented in investment in education, enhancing productivity, and managing specialized training for the targeted sectors, primarily since technological change is usually related to skilled labour. Following this policy, low levels of human capital are reallocated to obtain higher income shares. Consequently, there will be an efficient allocation of human resources in a way that finds new channels to eliminate the gap in income for different skill groups.

Appendix

Variables Definition

Variable	Definition
Income	A household's disposable income is calculated according to EUROSTAT Database "by adding together the personal income received by all household members plus income received at the household level". Missing income information is imputed. Disposable household income includes: - all income from work (employee wages and self-employment earnings) - private income from investment and property - transfers between households - all social transfers received in cash including old-age pensions.
Market Income	Household's total pre-tax income obtained from their activities in the formal economy, "including wages and salaries and self-employment income (net of employer insurance contributions and other benefits, but gross of employee contributions to such schemes), property income(interest, rents, dividends) as well as occupational pensions from employers, regular interhousehold cash transfers and other sources of income which are not redistributive government transfers" (Mercader-Parts and Levy, 2004).
Gini Index	One of the broad measures of income inequality,
Top1%	Top 1% income share (income distribution). It represents the income share that is owned by the top 1% of the income distribution.
Top10%	Top 10% income share (income distribution). It represents the income share that is owned by the top 10% of the income distribution.
Bottom 10%	Bottom 10% income share which represents the income share that is owned by the bottom 10% of the income distribution.
90%-10%	Income inequality restricted to the middle 80% of the income distribution (between 90% and 10% of the income distribution).
Patents	Number of patent applications per million inhabitants filed at the PCT.[28]
Patents_ICT	Number of patents per million inhabitants in the ICT sector.
Patents_High_Tech	Number of patents per million inhabitants in sectors that use high technology.
Patents_pharm	Number of patents per million inhabitants in the pharmaceutical sector.
Patents_semi_cond	Number of patents per million inhabitants in the semiconductors.
Patents_biotech	Number of patents per million inhabitants in the biotechnology sector.
R&D	Research and Development (R&D) expenditures as a percentage of Gross Domestic Product (GDP) in four primary sectors, which are mainly:

[28] Patents are counted according to the year in which they were filed at the Patent Cooperation Treaty (PCT) and are broken down according to the International Patent Classification (IPC). "They are also broken down according to the inventor's place of residence, using fractional counting if multiple inventors or IPC classes are provided to avoid double counting" (Source: Eurostat).

	Business enterprise sector, government sector, higher education sector, and private non-profit sector (source: Eurostat Database).
GDP per capita	Gross Domestic Product per capita in constant prices (2010).
Net migration	Difference between the number of immigrants and number of emigrants per thousand.
Unemployment	Unemployment rate.
Highly skilled labour	Percentage of workers who have tertiary education level and above to the total number of employees, and they are between 16 and 64 years (Source: EUROSTAT-LFS).
Low-skilled Labour	Percentage of workers who have less than primary and lower secondary education or do not have any qualification to the total number of employees, and they are between 16 and 64 years (Source: EUROSTAT-LFS).
Taxes	Taxes on average personal income obtained from the formal economy, including wages, salaries, investment, and business profits divided by GDP per capita in constant prices (2010).
Employment	persons on working age who are engaged in the activity (goods or services) for pay (source: EU-LFC).
Employment Ratio (Agriculture)	Percentage of employees in the agricultural sector (which includes activities in agriculture, hunting, forestry, and fishing) to the total number of employees.
Employment Ratio (Manufacturing)	Percentage of employees in the manufacturing sector to the total number of employees.
Employment Ratio (Services)	Percentage of the number of employees in the services sector to the total number of employees.

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Paper 3: ***Innovation, Immigration, and Wage Inequality in the UK Regions***

Abstract

This paper examines the effect of innovation on wage inequality and different wage shares in the UK regions by using British Household Panel Survey (BHPS) data. We use parametric and non-parametric approaches to find where innovation has the highest effect on wage distribution. To achieve this target, we use individual characteristics alongside relatively highly skilled to low-skilled immigrants to test the role of the flow of labour immigrants to the UK regions in this equation. The results show that innovation increases the general measures of wage inequality. Taking the Skill-Biased Technical Change (SBTC) concept, these results can be justified by the bias in demand for highly skilled labour relative to low-skilled labour because of technological change. However, innovation does not show any impact on the top and the bottom wage shares. It is founded that these shares have different characteristics and little changes in wages across them. In addition, we show that there is a perfect substitution between immigrants and natives for highly and low-skilled labour. From the labour supply perspective, wage inequality changes mainly reflect the gap between natives' highly skilled labour and immigrants' low-skilled labour.

3.1 Introduction

There is an ambiguity surrounding the nexus between wage inequality and innovation in many countries from two perspectives. First, the lack of clear definition and measurement of income[29] and wage in literature makes it very difficult to have accurate results. The unclarity that is surrounding this measure leads sometimes to a confusing outcome. To solve this ambivalence, we focus in this paper on wage inequality and follow accurate definition for it in studying the link between innovation and inequality. The term wage measures an individual's monthly earnings from work. This kind of earnings excludes any source of income that comes from wealth or other social transfers (e.g., compensation, unemployment, redundancy, Etc.). Consequently, in this study we consider only the changes in primary income from work, which leads to examining the effect of innovation on the wages of highly skilled labour relative to low-skilled labour. Here, the new tasks created because of such development complement low-skilled labour.

Second, there has been a change in the pattern of wage structure in the UK during the last two decades. This increase has led many economists to give more attention to this part (Machin, 1996). The increase in wage differentials in the UK is becoming more compelling with the changes in technology and the movement of immigrants from other countries to the UK. For example, the yearly and regional levels of wage inequality (measured by the Gini Index) and innovation (measured by the number of patent applications per million inhabitants filed at the PCT) in the UK during the period from 1991 to 2017[30], which are shown in figure (3-1), are positively correlated, and the same trend exists between Gini Index and net migration. Surprisingly, the share increase of immigrants in 1991 and 2006 in the UK regions are highly correlated with the increase in low-skilled labour, as shown in figures (3-2) and (3-3). On the

[29] It is usually measured by disposable income. The main components of disposable income are primary income(wage), income from self-employment, income from investment (capital income), private income, and social transfers. This term is used by Eurostat and OECD databases.

[30] Note: the figure shows yearly and regional values; each year appears frequently.

same regional level, the data for highly and low-skilled immigrants in 2006 (measured by the level of education) confirms this pattern, where low-skilled labour share in Greater London (which has the highest share of immigrants across UK regions) is almost twice as the share of Wales (which has the lowest share of immigrants across UK regions) (see table (A1.2) in the Appendix).

The fact that there would be a connection between technological change and wage inequality in the UK regions from one side and a link between highly and low-skilled immigrants and wage inequality from another side lead us to study these two factors in more detail. To do so, we analyze the characteristics of the UK labour market, the substitution elasticity between highly and low-skilled labour for both immigrants and natives, and their role in changing the wage gap in the UK regions. Even though technological change could explain the profound changes in the link between innovation and wage inequality, there are still other factors that are unexplained in literature and have an impact on wage inequality, which immigration-especially highly and low-skilled immigrants at the regional level- has an essential role in this part. Throughout this paper, we try to explain these elements. In one part, we aim to examine the effect of technological change and other related factors on wage inequality in the UK regions. In another, we investigate the role of highly and low-skilled immigrants in wage inequality in these regions.

Figure 3-1: Innovation, wage inequality, and net migration in UK regions during the period (1991-2017)

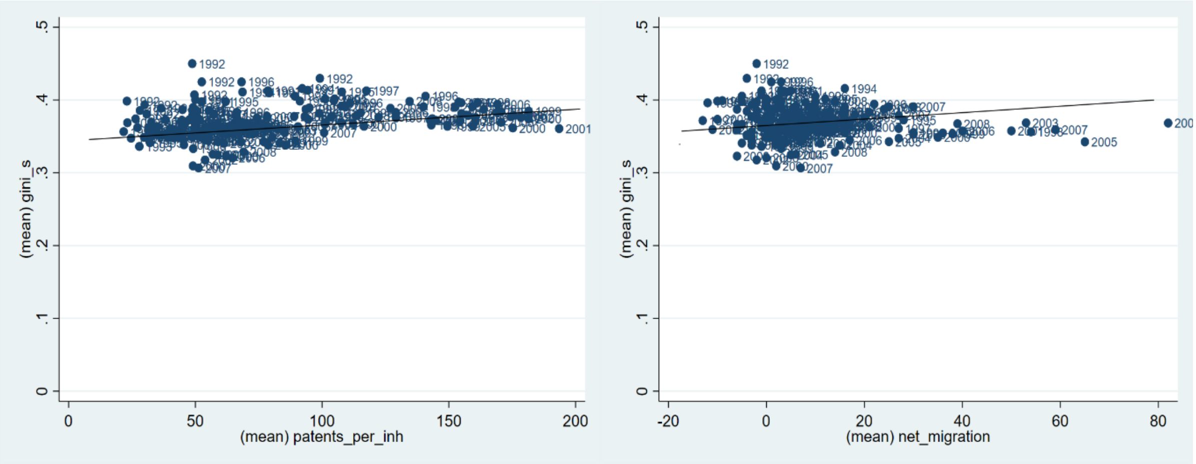
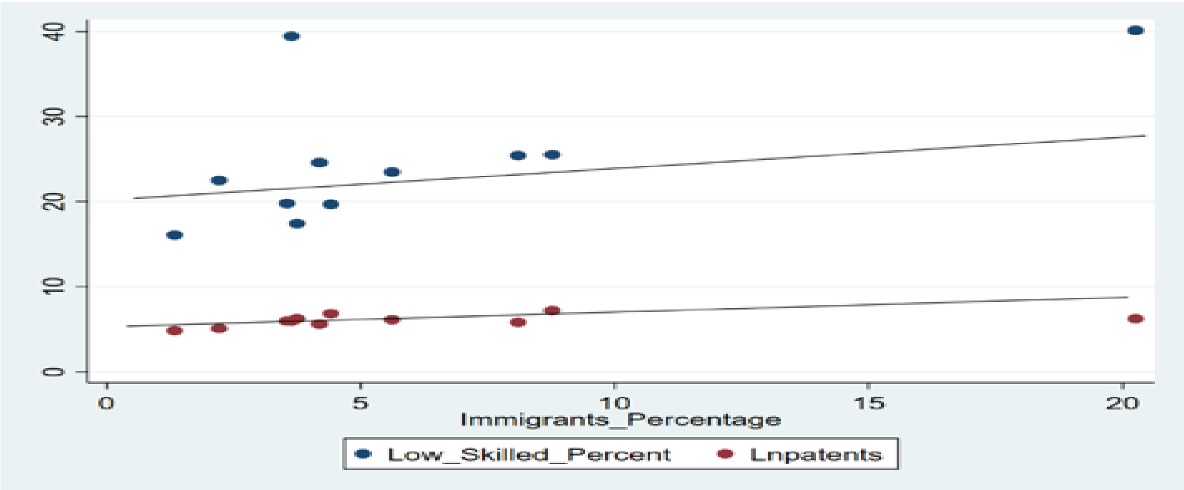


Figure (1-a) Wage inequality and innovation

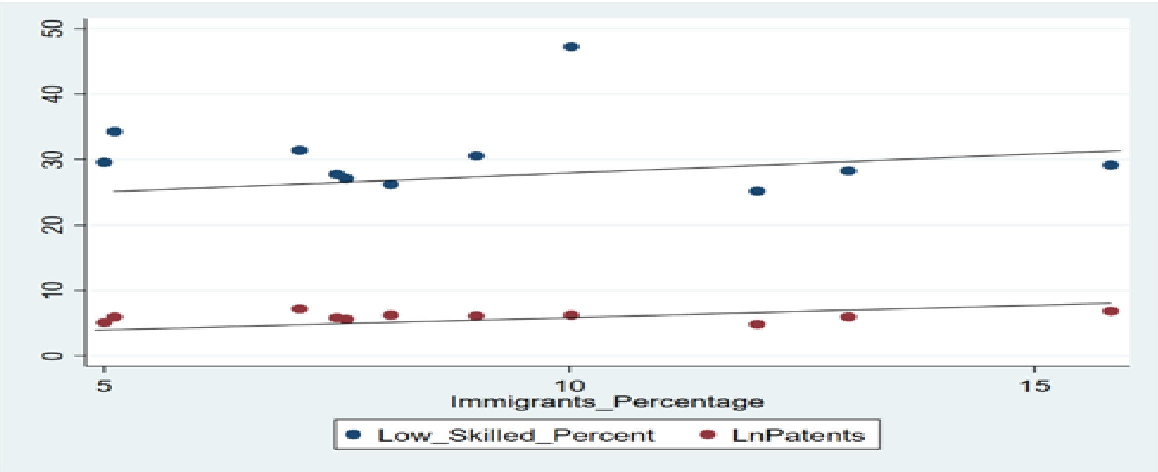
Figure(1-b) Wage inequality and net migration

Figure 3-2: Immigrants and low-skilled labour shares in the UK in 1991



Notes: the blue dots in the vertical axes present the percentage of low-skilled immigrants of the total number of immigrants to the UK regions, while the red dots in the vertical axes present the natural logarithm of patents

Figure 3-3: Immigrants and low-skilled labour shares in the UK in 2006



Notes: the blue dots in the vertical axes present the percentage of low-skilled immigrants of the total number of immigrants to the UK regions, while the red dots in the vertical axes present the natural logarithm of patents

To achieve this target, we test the impact of innovation measured by the number of patent applications per million inhabitants filed at the Patent Cooperation Treaty (PCT) alongside other control variables on wage inequality which is measured by (the Gini Index, Atkinson Index, and Theil Index) and other wage shares. We analyze the existence of these effects utilizing two methodologies. First, we use Kernel density to estimate where in the wage distribution the following factors exist: the impact of innovation, the relative ratio of low-skilled immigrants to highly skilled immigrants, and the individual characteristics of the wage distribution. Second, we use the Generalized Method of Moments (GMM) and Two-Stage Least Square (TSLS)-Heteroskedasticity Methods to test if these factors significantly affect wage inequality. We unite the second one by testing the possibility of substitution between immigrants and natives (highly and low-skilled labour).

This paper has two contributions to the literature. First, it scrutinizes the link between innovation and wage inequality differently. Previous articles are mainly concerned with how innovation affects wage inequality in the economy and the trend of this relation (for example, Angelini et al., 2009, Breau et al., 2014, Etc.). On the other hand, we examine this link by studying the movement of highly and low-skilled immigrants to the UK regions and their impact on such links. This part is essential because of its implications for employment and wages in the local markets. We must recognize that host countries need to adjust their policies to respond to the inauspicious impact of immigrant workers on wages. Even though innovation is significantly influential in this part, it does not necessarily result in a stable gap between wages for highly and low-skilled workers. Our second contribution is the alteration from earlier studies that utilized different methods. We contribute to these studies by using parametric and non-parametric methods to study the effect of (innovation, the relative ratio of low-skilled immigrants to highly skilled immigrants, and immigrants' substitutability) on wage inequality. Our methodology allows us to represent the overall changes in wage inequality through two different methods. First, we use GMM and Heteroskedasticity methods to test the effect of innovation on wage inequality. Then, we estimate the elasticity of substitution between immigrant and native labour by using the residual-regional model for their wages and relative supply (measured by the yearly number of hours). Second, we use Kernel density estimation, which shows where each factor significantly affects the wage distribution. To the best of our knowledge, this is the first study that covers these two methods in one paper.

3.2 Literature Review

It has been seen in literature that technological change disproportionally impacts wages (lee and Clarke, 2019). It is also shown that highly and middle-skilled workers benefit from the positive change in technology, while the average wages fall for low-skilled workers. In this situation, the gap between highly and low-skilled labour is expected to increase when new technology exists. There are different justifications for the way innovation is being viewed to affect wage inequality. One of these is the Skill-Biased Technical Change (SBTC) concept, which is utilized to explain the relative change in the skill premium[31] during the last three decades in many developed countries (e.g. (Katz and Murphy, 1992), (Autor et al., 2003), (Acemoglu and Autor, 2011), Etc). Another piece of evidence in the literature shows the effect of immigrants on different parts of the wage distribution. For example, the study by (Dustmann et al., 2008) finds that there is a negative effect of immigration on the low end of the wage distribution and a positive effect on the top end of that distribution. This finding indicates that the gap between the top and the low end of the wage distribution increases with the increase in the number of immigrants, which confirms that the increase (decrease) in immigrants increases (decreases) wage inequality.

Others like (Brewer and Wren-Lewis, 2016), focus on decomposing inequality by income source and household characteristics (e.g., age, education, and employment status). The main advantage of such an approach is that it helps understand the inequality change by each income element. Another way to do that is by decomposing wage between (composition effects) and within (residuals) groups[32] as per (Lemieux, 2006) and later (Rienzo, 2014) by adding the immigration dimension. We follow the latter one as it helps determine the effect of immigration on the wage of native-born workers. Our methodology is different in that technological change is analyzed by testing its direct effect on wage inequality, not only through decomposition. For that purpose, we use residuals to test the effect of immigrant workers on natives and find the elasticity of substitution between them. (Card, 2009) analyzed this part but from a different perspective. He found the elasticity of substitution to explain the variation in the relative share of skilled groups using different samples and periods.

In addition, the previous empirical studies have different results about the link between innovation and wage inequality. These discrepancies in results are mainly due to the different control variables used in these papers. In particular (Breau et al., 2014) find that innovation

[31] Skill premium is defined as the ratio of the wage of skilled to unskilled workers.
[32] Groups in this context are defined according to education, experience, and age.

increases earnings inequality across 85 cities in Canada. Despite that, the study of (Lee and Rodríguez-Pose, 2013) show limited evidence of this link in the United States cities, comparing them with the European regions. Moreover, the study (Lee, 2011) confirms this pattern in the European regions, but it does not consider the effect of immigrants on this link. Our contribution in this part is by testing the effect of the arrival of a low-skilled immigrants relative to highly skilled immigrants (as groups) on this relation and how the UK labour market responds to this change. This low-skilled flow leads to assessing the impact of those immigrants on the wage structure for natives as per the studies (Card, 2001), (Ottaviano and Peri, 2001) and (Borjas, 2003). The findings of these articles show that one of the main reasons behind the change in the wage structure is immigrants, who are concentrated in the lowest education groups. We use a different methodology in classifying the skill groups than the one used by these papers. This classification depends on two levels: low and high, where the low level represents unskilled labour with elementary knowledge to achieve the job, and the high level represents highly skilled workers with advanced knowledge and education to achieve the required tasks. This classification makes it easier to compare the results and maintain consistency in studying these groups' effects.

3.3 Data Sources and Definitions

We build this analysis on two primary data sources, British Household Panel Survey (BHPS) and Eurostat database. “BHPS was started in 1991 and initially constructed through face-to-face interviews with 5,000 households in the UK, and later in 1999 and 2001, it expanded to include additional 1,500 households in Scotland and Wales, in addition to 2,000 households in Northern Ireland” (source: BHPS). The main advantage of using this data is that it includes many representative household members and individuals from the whole community. On the other hand, Eurostat provides a wide range of general and regional statistics on the European Union, EU member states, and sub-states. The methodology for dealing with this data is harmonized among all the European members. We exclude 1991 and 1997 in addition to Northern Ireland when applying GMM and TSLS-Heteroskedasticity methods due to missing data for a couple of variables in these years and region.

We conduct the empirical analysis in this paper on regional Panel data within the UK from 1991 to 2008. We attempt to choose carefully appropriate measures for each variable in this study. First, our primary dependent variable is wage inequality. To measure this part, we use (Gini Index, Atkinson, Mean Log Deviation, and Theil Index)[33] and a different percentiles of wage distribution (top 1%, top 10%, bottom 10%, 90%-10% wage inequality, and 75%-25% wage inequality). However, to respond to the skewness in the wage distribution, we use the natural logarithm for all these values. As we focus in this paper on wages, we exclude any source of income that does not come from work. Therefore, we select the usual gross pay per month (wage from employment after deductions) in the current job to be used as an indicator of the individual's wage. The reason behind that is the limitations associated with the other measures. For instance, total annual or monthly income incorporates other sources of income (e.g., revenue from sales, payments from pensions plans, income from dividends, or other sources) and not only the income received from work. Including such measures could lead to inaccurate results. On the other side, when using the non-parametric approach, we extend the period for the data to include UK regions from 1991-2017. The data for this part of the analysis is available for all our concerned variables.

Second, the leading independent variable used in this paper is the innovation which we measure by the number of patent applications per million inhabitants filed at the PCT for each region and year. If one application has more than one inventor, it is divided fractionally

[33] The methods used in computing these measures can be found in the Appendix.

among them and subsequently among their region of residence, thus avoiding double counting. The data relating to this variable are drawn from Organization for Economic Co-operation and Development (OECD) data set, which is recognized internationally and provides a unified mechanism to classify patents in all its covered countries. Patents are considered in the literature as one of the most potent measures of innovation because they are an outcome of innovation and are helpful for comparison on the regional level (Lee, 2011).

In addition, we use other variables which are related to individual characteristics (e.g., education, age, experience, sex, Etc.) and macroeconomic indicators that include GDP, Unemployment rate, highly and low-skilled labour (immigrants and natives), private sector participation, female participation, and net migration as controls[34]. We use the first set to estimate the wage structure as it is measured on the individual level, while we utilize the second to estimate the model parameters for innovation and wage inequality. It is worth mentioning that endogeneity could arise in the case of net migration. In the regional level, net migration is correlated with the labour supply, and eventually will cause a change in wage inequality.

This study adjusts for inflation by using the Retail Price Index (RPI) (Base year: 2010), which is published by Office for National Statistics (ONS). The same applies to Gross Domestic Product (GDP) which we adjust in constant prices (2010) because it is also affected by price changes. Regarding age, we classify workers into five groups: less than 25 years old, between 25 and 34 years old, between 35 and 43 years old, between 44 and 54 years old, and over 54 years of age.

To show the role of human capital variables in explaining the changes in wage inequality, we compact the workers' classification in the different education groups into three

[34] The full definition for all the variables used in this study is available in table A1.1 in the Appendix.

primary levels: Highly skilled, middle-skilled, and low-skilled workers[35]. Wage residuals are estimated using OLS "Mincer Equation" (Mincer, 1997). We divide the dataset into (33) region-education cells (three education group levels with eleven regions in the UK). The observed variables for both natives and immigrants include education, experience, age, and interaction term between age and education. In the empirical side, we only use highly and low-skilled labour. We follow this classification because of the polarization pattern of labour demand, which is modified by the version of the skilled-biased technological change.

3.4 Distributional Analysis

In this section, we analyze the effects of innovation (technological change) and low-skilled labour immigrants relative to highly skilled labour immigrants on changes in the UK distribution of wages using a non-parametric approach. To figure out where these factors utilize a substantial impact on the density of wages, we apply the Kernel Density method to explain the changes in wage inequality in the UK regions from 1991 to 2017. First, in figures (3-4) and (3-5), the Kernel Density estimates of men's and women's average monthly log wages from 1991 to 2017 show that the lower tail of the Kernel Density of wages is compressed for both men and women. This shrinkage in the lower part of the distribution indicates an imbalance between the upper and lower part of the wage distribution. Hence, this reflects a gap between high and low wages. To study the reason behind this gap, we focus on three main factors, which are (Individual Characteristics, Innovation, and Low-Skilled Labour Immigrants relative to highly skilled immigrants) by using the Kernel Density Counterfactual effect. We clarify the Counterfactual effect as stated by (DiNardo et al., 1996) "the density that would have prevailed if one of the three mentioned factors (Individual Characteristics, Innovation, and Low-skilled

[35] Highly skilled workers have a high or first degree, middle-skilled workers have a school degree (GCSE, commercial qualifications, or other equivalent qualifications), and low-skilled workers do not have any qualifications.

labour Immigrants) had remained at their 2005 level and employees had been paid according to the wage structure observed in 2011" (DiNardo et al., 1996). The difference between the actual and the counterpart functions shows the changes that occur in wage distribution between the two years. We compare the changes in wages between 2005 and 2011 because labour market in the UK regions have witnessed critical changes before and after these years. For example, the years after 2004 witnessed faster growth in net immigration in most of the UK regions, where highly and low-skilled labour groups were affected in terms of their supply in these regions.

On the other hand, 2011 represents the year when the wages in the UK started to bounce back after the economic downturn, which started in 2008. Moreover, this year's (2011) unemployment peaked at 8.5% and started to fall for many years afterward, and employment has increased by around 2.5 million people since then (Haldane, 2017). These facts show that in 2005 and 2011, the labour market witnessed significant changes in the flow of immigrants and a crucial shift in the unemployment rate. For that reason, comparing the changes in wages between these two years explains the effect of different factors on the fluctuations in wages.

For estimating the Kernel Density, we follow the method that is used by (DiNardo, 1996), which has the following form:

$$\hat{f}_h = \sum_{i=1}^{n} \frac{\theta_i}{h} K(\frac{w-W_i}{h}),$$

Where $\hat{f}_h$ is the Kernel Density estimate, f is a univariate density, w is the wage at any given point, W_i is a random sample of wages, h is the bandwidth calculated using (Sheather and Jones, 1991) selector, $\theta_i(\sum_i \theta_i = 1)$ is the sample weights, and $K(.)$ is the Kernel Density. To study the counterfactual effect (presented by reweighting function) of (Individual Characteristics, Innovation, and Low-Skilled Immigrants relative to highly skilled immigrants) on wages, we estimate the Kernel Density in 2011 as these factors had remained at their 2005. In this case, the counterfactual Kernel Density function has the following expression:

$$\hat{f}_h = \sum_{i=1}^{n} \frac{\theta_i}{h} \hat{\psi}_z (z_i) K(\frac{w-W_i}{h}),$$

Where $\hat{\psi}_z (z)$ is the estimated reweighting function for the three factors (Individual Characteristics, Innovation, and Low-skilled Labour Immigrants relative to highly skilled immigrants) presented by (z), eventually, the effect of these factors on wages is calculated by the difference between the actual and the counterfactual (main characteristics in 2011 remain at their 2005 levels, after adjustment) Kernel Density for each factor.

Starting with the role of innovation (I) on the changes in wages (w), we estimate the joint Kernel Density function (wage and innovation) conditional on time as follows: -

$$f_t(w) = \int dF(w, I, G|t_{w,I,G}),$$

Where (G) represents other influential characteristics (e.g., education, experience, age, region, occupation, marital status, and sex). The counterfactual form of this function can be written as the integral of the density of wages conditional on innovation (I) and the other characteristics (G) at a time (t) over the distribution of innovation (I) conditional on (G) and over the distribution of (G) conditional on time(t), as follows: -

$$f_t(w; t_w = 2011, t_{I|G} = 2005,\ t_G = 2011) =$$

This function illustrates the counterfactual density of wages in 2011 if innovation had remained at its 2005 level, while the other individual characteristics are at their level in 2011. We can rewrite the previous function as follows: -

$$\int\int f(\mathrm{w}|\mathrm{I}, \mathrm{G}\ t_w = 2011)\ dF(I|G, t_{I|G} = 2005) dF(G|t_G = 2011),$$

We can rewrite this function as follows: -

$$\mathrm{f}_t\big(w; t_w = 2011, t_{I|G} = 2005,\ t_G = 2011\big) =$$

$$\int\int \mathrm{f}(\mathrm{w}|\mathrm{I}, \mathrm{G}\ t_w = 2011) \frac{dF(I|G,t_{I|G}=2005)}{dF(I|G,t_{I|G}=2011)}\ dF(I|G, t_{I|G} = 2011) dF(G|t_G = 2011),$$

$$= \int\int \mathrm{f}(\mathrm{w}|\mathrm{I}, \mathrm{G}\ t_w = 2011)\ \psi_{I|G}\ dF(I|G, t_{I|G} = 2011) dF(G|t_G = 2011),$$

Where the reweighting function has the form $\psi_{I|G} = \frac{dF(I|G,t_{I|G}=2005)}{dF(I|G,t_{I|G}=2011)} = I.\frac{\Pr\,(I=1|G,t_{I|G}=2005)}{\Pr\,(I=1|G,\, t_{I|G}=2011)} + (1-I).\frac{\Pr\,(I=0|G,t_{I|G}=2005)}{\Pr\,(I=0|G,\, t_{I|G}=2011)}$, noting that innovation (I)[36] takes the value 0 or 1. There are two probabilities of the occurrence of innovation conditional on the other characteristics in the counterfactual effect. First, is the probability that innovation is obtained in that region and year if its value is greater than the median. Second is the probability of ineffective innovation at the regional and yearly levels if its value is less than the median. Summing up each probability multiplied by the existence of innovation (=1) and its absence (=0) gives $\psi_{I|G}$. To find the above conditional probability function we estimate the following probit model: -

$$\Pr\big(I = 1\big|G, t_{I|G} = t\big) = \Pr\big(\varepsilon > -\beta`_t\, V(G)\big) = 1 - \ \varphi(-\beta`_t V(G))$$

Where $\varphi(.)$ is the cumulative normal distribution, and V(G) is a vector of covariates that is a function of (G). We keep the other individual characteristics unchanged between the two periods. Hence, we show the impact of the changes in innovation on the wage gap by the counterfactual effect of innovation conditional on the other characteristics, as shown in $\psi_{I|G}$.

The result of estimating the effect of innovation on the changes in wages is illustrated in figure (3-6). It shows that changes in innovation conditional on the individual characteristics

[36] * Innovation (I) in the microdata (BHPS) is defined as an individual perception to see her(him)self as someone who is original, comes up with new ideas". It is a dummy variable with a scale (from 1-7) that holds the value of (1) if the answer is over the scale median and (0) if it is less than this median.

significantly expand the middle part of Kernel Distribution after adjustment. The high and low ends (≈10%) of wage distribution do not change significantly after adjustment, indicating a gap in wage distribution between these two groups in the middle 80%. In this segment, the groups of highly and low-skilled labour are in the upper and lower part of the 80% middle-wage inequality. The distribution in this segment is flatter after adjustment, which reveals an increase in the gap between highly and low-skilled labour wages. This finding complies with the SBTC concept, where the demand is biased towards highly skilled workers due to improvement in innovation. On the individual level, we view innovation as the ability of the worker to achieve a high level of improvement in her(his) organization. Innovation in this context is how workers develop new ideas and reflect on this improvement.

Secondly, we use the same method to illustrate the impact of low-skilled immigrants relative to highly skilled immigrants on wage changes. Low-skilled[37] immigrants are identified by giving value (1) if the immigrants are low-skilled and (0) for others (Highly and middle-skilled immigrants). Their conditional density is based on innovative regions (IR), which is scaled up according to the number of patents[38] in 2005. We aim to study the effect of low-skilled immigrants relative to highly skilled immigrants on the wage gap when we keep the rank of the UK regions from the lowest to the highest depending on the number of patent applications to the PCT in each region. Keeping consistency in classifying innovative regions from the lowest to the highest between the two periods helps determine the immigrant labour variations in those regions.

In this case, the joint Counterfactual Kernel Density function has the following form: -

$$\mathfrak{f}_t\left(w; t_w = 2011, t_{LS|IR} = 2005,\ t_{IR} = 2011\right) =$$

[37] Low-skilled labour are workers who do not have any qualifications.
[38] That scale starts from the lowest to highest innovative regions (measured by the number of patent applications per million inhabitants filed at the Patent Cooperation Treaty (PCT)) in 2005.

This function indicates the counterfactual density of wages in 2011 when low-skilled labour immigrants had remained at their level in 2005, while innovative regions are at their level in 2011. Hence, we can rewrite the previous function as follows: -

$$\int\int \mathrm{f}(\mathrm{w}|\mathrm{LS},\mathrm{IR}\ \ t_w = 2011)\frac{dF(LS|IR,t_{LS|IR}=2005)}{dF(LS|IR,t_{LS|IR}=2011)}\ dF(LS|IR,t_{LS|IR} = 2011)dF(IR|t_{IR} = 2011),$$

$$= \int\int \mathrm{f}(\mathrm{w}|\mathrm{LS},\mathrm{IR}\ \ t_w = 2011)\ \psi_{LS|IR}\ dF(LS|IR,t_{LS|IR} = 2011)dF(IR|t_{IR} = 2011),$$

Where the reweighting function has the form $\psi_{LS|IR} = \frac{dF(LS|IR,t_{LS|IR}=2005)}{dF(LS|IR,t_{LS|IR}=2011)}$

$$= LS.\frac{\Pr\ (LS=1|IR,t_{LS|IR}=2005)}{\Pr\ (LS=1|IR,t_{LS|IR}=2011)} + (1-LS).\frac{\Pr\ (LS=0|IR,t_{LS|IR}=2005)}{\Pr\ (LS=0|IR,t_{LS|IR}=2011)},$$

Where LS is low-skilled immigrants relative to highly skilled immigrants, and IR is innovative regions. The outcome of implementing this distribution is shown in Figure (3-7), which shows that the distribution shifted to the right after adjustment and suggests that there is a downgrade in low-skilled labour wages attributed to the movement of low-skilled immigrants relative to highly skilled immigrants in most innovative regions between 2005 and 2011. The shift in labour supply toward low-skilled labour increases the pressure on the lower tail of wage distribution, increasing the wage gap between highly and low-skilled labour groups. The effect of native workers and cross-skilled groups is not apparent in this analysis, which we study in more detail in the next section.

Finally, we study the effect of the other characteristics on the changes in wages by applying Bayes' rule to estimate the reweighting function. In this case, the reweighting function of these characteristics has the form ($\psi_G = \frac{\Pr\ (\mathrm{t}_G=2005|\mathrm{G})}{\Pr\ (t_G=2011|G)}\ .\frac{\Pr\ (\mathrm{t}_G=2011)}{\Pr\ (t_G=2005)}$) in the following equation: -

$$\mathrm{f}_t\left(w; t_w = 2011, t_{I|G} = 2005,\ t_G = 2005\right) =$$

$$\int\int \mathrm{f}(\mathrm{w}|\mathrm{I}, \mathrm{G}\ t_w = 2011)\ dF(I|G, t_{I|G} = 2005) dF(G|t_G = 2005),$$

$$= \int\int \mathrm{f}(\mathrm{w}|\mathrm{I}, \mathrm{G}\ t_w = 2011)\ \frac{dF(I|G, t_{I|G}=2005)}{dF(I|G, t_{I|G}=2011)}\ dF(I|G, t_{I|G} = 2011)\psi_G dF(G|t_G = 2011),$$

In this context, we study the distribution of wages in 2011 as if these characteristics had remained at their 2005 levels. In this case, we calculate the unconditional probability (Pr($t_G = t$) for each year (2005 and 2011) by the weighted number of observations in that year divided by the weighted number of observations in both years.

Moreover, we estimate Pr $(t_G = t|G)$ for each year (2005 and 2011) using the following probit model: -

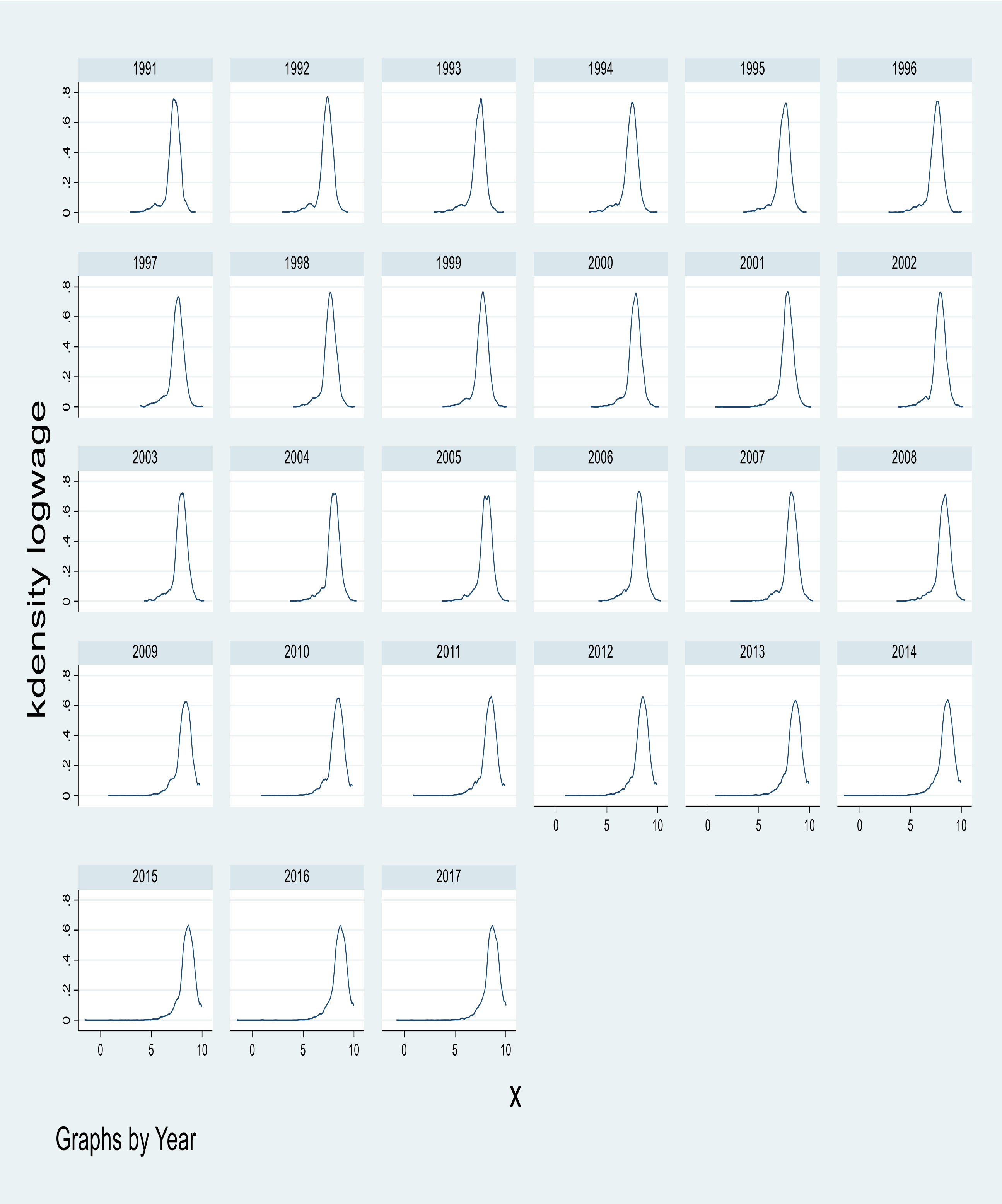
$$\Pr(t_G = t|G) = \Pr\left(\varepsilon > -\beta`_t\, V(G)\right) = 1 - \ \varphi(-\beta`_t V(G))$$

Where $\varphi(.)$ is the cumulative normal distribution, and V(G) is a vector of covariates that is a function of (G). We use the time dummy variable (1 if the year 2011 and 0 if the year 2005) conditional on the individual characteristics to find Pr $(t_G = 2005|G)$ and Pr $(t_G = 2011|G)$.

The distribution result for individual characteristics is shown in figure (3-8), which reveals that these characteristics do not significantly impact the change in wages between these two years. As noted from the same figure, both distributions (before and after adjustment) are almost identical, which leads to the conclusion that these characteristics (experience, age, region, occupation, marital status, and sex) do not influence the changes in wages.

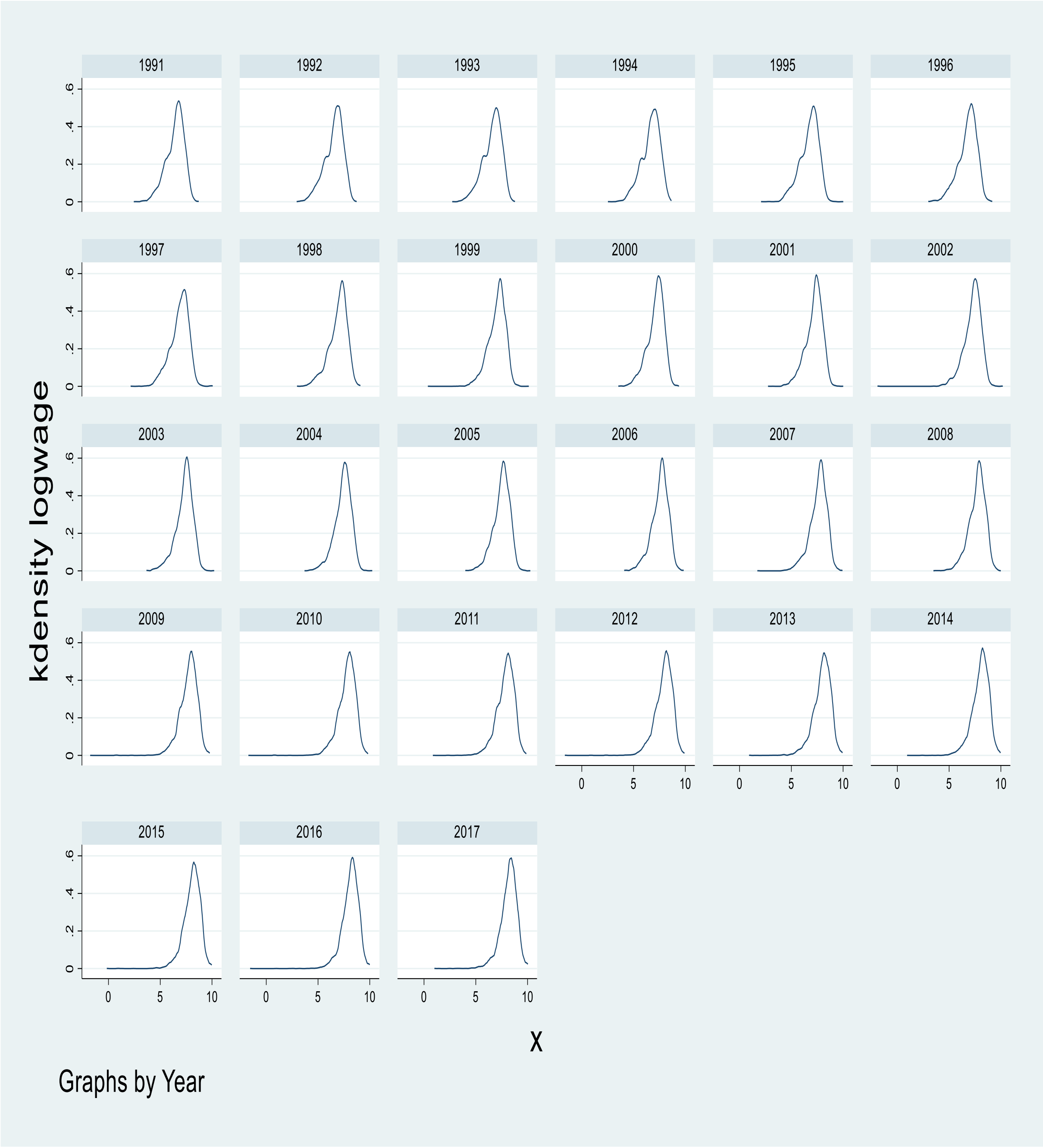
Overall, the previous results show that technological change and the attractiveness of the UK regions to low-skilled immigrants relative to highly skilled immigrants have a significant contribution in determining the changes in wages, which is moving towards the highly skilled labour and away from the low-skilled labour. This outcome explains the skewness in the Kernel density to the right as shown in figures (3-4) and (3-5). However, the individual characteristics do not reveal changes in the wage distribution before and after adjustment.

Figure 3-4: Kernel Density estimates of men's average monthly log wages 1991-2017 (£2010)[39]



[39] Wages are adjusted based on the Retail Price Index (RPI) in 2010.

Figure 3-5: Kernel Density estimates of women's average monthly log wages 1991-2017 (£2010)[40]



[40] Wages are adjusted based on the Retail Price Index (RPI) in 2010.

Figure 3-6: Kernel Density for Innovation

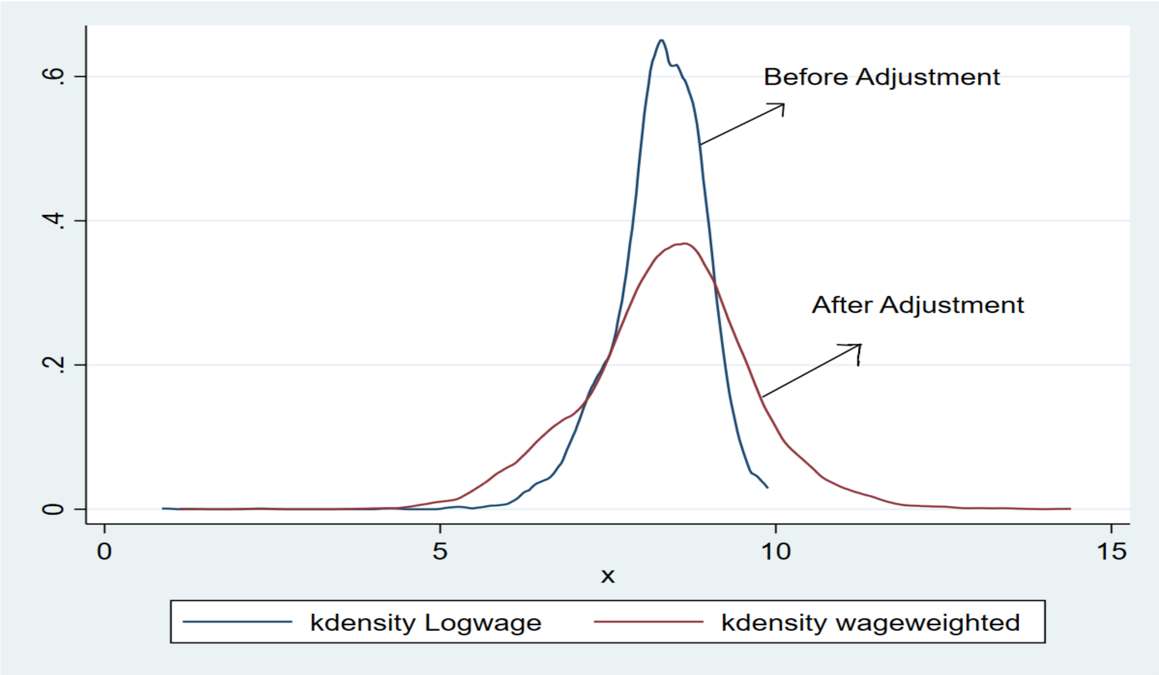


Figure 3-7: Kernel Density for low-skilled Immigrants relative to highly skilled immigrants

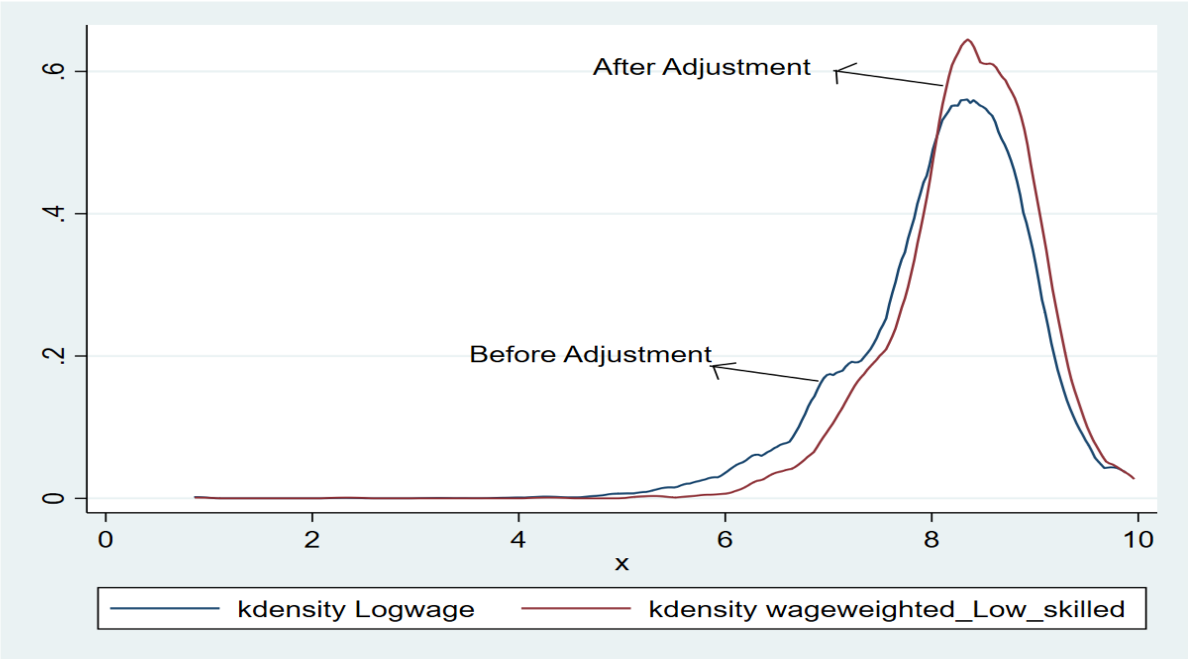
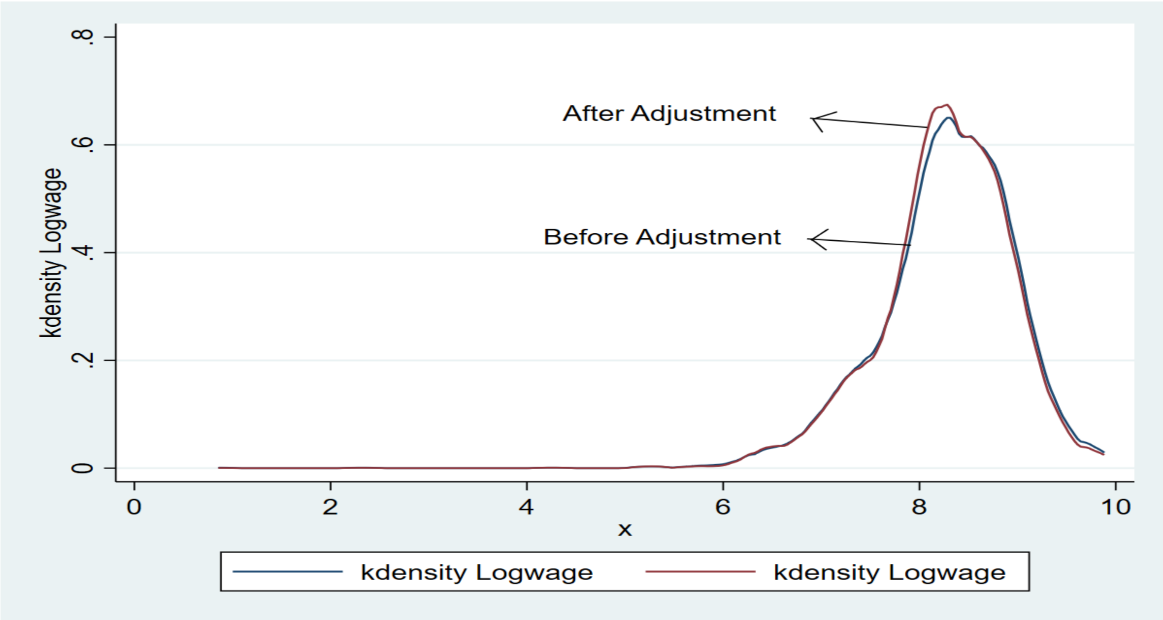


Figure 3-8: Kernel Density for individual characteristics



3.5 __Models and Methodology__

Another way to test the effect of innovation and different skilled immigrants on wage inequality is by using econometric estimation, which relies on estimating three equations. First, the static effect of technological change on wage inequality using other control variables. In this part, we are testing the following model: -

$$\log(WageIneq_{it}) = A + \beta_i + \beta_t + \beta_1 \log(Innov_{it}) + \beta_k X_{it} + \varepsilon_{it} \quad (1)$$

Where $WageIneq_{it}$ is the different measures of wage inequality for region i in year t, $Innov_{it}$ represents innovation measured by patent applications per million inhabitants filed at the Patent Cooperation Treaty (PCT), X_{it} is a vector of control variables which include: net migration, highly skilled immigrants, low-skilled immigrants, unemployment rate, GDP per capita, age, female participation, and private sector participation, Etc. A, β_1, β_k denote the model parameters, where A is the intercept. While the other parameters β_i, β_t display year and region effects, and ε_{it} is the disturbance term.

Second, we estimate the model using the following dynamic form: -

$$\log(WageIneq_{it_{it}}) = C + \alpha_0 \log(WageIneq_{it}(l)) + \alpha_1 \log(Innov_{it}) + \alpha_2 \log(Innov_{it}(l)) + \alpha_k X_{it} + \gamma_i + u_{it} \qquad (2)$$

Where $(WageIneq_{it}(l))$ stands for the time lag of different measures of wage inequality, $(Innov_{it}(L))$ is the time lag of innovation, C is the intercept, $, \alpha_0, \alpha_1, \alpha_2, \alpha_k$ represent the model parameters, γ_i *is the unobserved region time invariant error term*, and u_{it} is the disturbance term.

To test this model, we study the effect of innovation on wage inequality in the UK regions using GMM. The pattern of such estimation is usually considered an essential issue with omitted variable bias and measurement error. We use GMM and Heteroscedasticity Test restrictions to address the problem of endogeneity. Each variable in level in the estimated model is instrumented with lagged -differenced terms. It is tough to find a proper instrument for patents, especially when these instruments (e.g., R & D expenditures, funding reallocation, Etc.) have confounding effects on wage inequality and patents simultaneously, which causes inefficiency in the results. Instead, we use GMM and Heteroskedasticity methods to tackle this problem. In this study, it is more efficient to apply GMM than OLS because, in this situation, there is heteroskedasticity in the disturbance (as shown by the Breusch-Pegan test, which rejects the null hypothesis that there is no heteroskedasticity). The assumptions of GMM estimation and Heteroskedasticity are both well satisfied.

Third , to study the role of the elasticity of substitution between immigrants and natives on the link between innovation and wage inequality, we follow the methodology used by (Card, 2009). The elasticity of substitution between immigrants and natives for each educational group is estimated as follows: -

$$(r_{mit} - r_{nit}) = a + bX_{it} + c\log\left(\frac{S_{mit}}{S_{nit}}\right) + +e_{it} \qquad (3)$$

For region i in year t, $(r_{mit} - r_{nit})$ is the mean residual wage between immigrants (represented by m) and natives (represented by n) for the same educational group, $\frac{S_{mit}}{S_{nit}}$ is the percentage of total yearly hours of work for immigrants to natives for the same educational group, X_{it} is a vector of control variables which include: log(patents), unemployment rate, GDP per capita, experience, female participation, and private sector participation, a, b, c denote the model parameters, where a is constant, and e_{it} is the disturbance term. The parameter c is supposed to be negative, which is the inverse of elasticity of substitution between immigrants and natives (σ) for the same educational group, which means that it equals (-$\frac{1}{\sigma}$).

3.6 Regression Results

3.6.1 Innovation and Wage Inequality

Table (3-1) shows the estimates of the effect of innovation on different measures of wage inequality (Gini Index, Atkinson, Mean Log Deviation, and Theil Index)[41] using GMM with lagged value for one year. In this dynamic form, all the lagged wage inequality measures are positively significant at 10%. Level. The coefficients of innovation for all these measures are positive and significant (at least at the 10% level). This sign indicates that developing technological change (represented by innovation) increases wage inequality, which supports the SBTC. The magnitude of these coefficients ranges between (4% and 10%). It indicates that a 1-point positive increase in the number of patents per million inhabitants increases wage

[41] The computations of these measures are illustrated in Appendix A2.

inequality by around 4% to 10%. It is shown in the same table that wage inequality is affected by the inflow of immigrants, while natives do not have any significant effect on this relation. However, there is a difference between the effect of highly skilled immigrants and low-skilled immigrants on wage inequality. The results show that highly skilled immigrants have an adverse effect on wage inequality with coefficients ranging between 80% and 1.4 (significant at least at 5%), while low-skilled immigrants increase wage inequality and explain on average 1.3 of the changes in the above-mentioned inequality measures (significant at least at 5%). On average, the magnitude of low-skilled immigrants (in absolute values) is higher than highly skilled immigrants, which explains the shift in the low-skilled relative to highly skilled immigrants' distribution that is illustrated in the previous section. Similarly, net migration increases the broad measures of wage inequality which satisfies (Hibbs and Hong, 2015) findings, but they use immigrants' shares in the USA instead of net migration. They find that immigrants' shares increase Gini Index (wage inequality) that explain 24% of the changes in the general measure of wage inequality. The magnitude of net migration in our study is less than that (on average 0.001) due to the inclusion of the net flow of immigrants and emigrants. In our study, around 99% of the regional net migration values are positive, which means that the inflow of immigrants is more prominent than emigrants' outflow in these regions. As a result, immigrants in the UK regions explain a higher volume of changes in wage inequality than emigrants from these regions.

Table 3-1: Innovation and different measures of wage inequality in the UK regions

Dependent Variables → **Independent Variables ▼**	**(1)** **Gini**	**(2)** **Atkinson Index**	**(3)** **Mean Log Deviation**	**(4)** **Theil Index**
Lag (1)	0.1061* (0.06)	0.1886*** (0.06)	0.1782*** (0.05)	0.1187*** (0.04)
patents	0.0377*** (0.01)	0.0935*** (0.02)	0.0998*** (0.03)	0.0989*** (0.03)
Net Migration	0 .0005* (0.0003)	0.0012** (0.0001)	0.0007* (0.001)	0.0020** (0.001)
Unemployment	1.0801*** (0.30)	2.3601*** (0.61)	1.8699*** (0.64)	2.8626*** (0.74)
GDP per capita	0 .0132 (0.02)	0.0106 (0.04)	-0.0202 (0.04)	0.0297 (0.05)
HSKN	-0.1591 (0.12)	-0.3909 (0.25)	-0.4714 (0.36)	-0.2457 (0.30)
LSKN	0.0036 (0.17)	-0.0139 (0.34)	-0.0799 (0.37)	0.1399 (0.42)
HSKI	-0.8373*** (0.31)	-1.3809** (0.64)	-1.4062** (0.67)	-1.0526* (0.59)
LSKI	0.9404*** (0.27)	1.5673*** (0.55)	1.6927*** (0.57)	1.3836** (0.67)
Age	0.0063 (0.11)	0.0035 (0.22)	0.0779 (0.23)	0.0709 (0.27)
Female participation	-0.0394 (0.19)	-0.1297 (0.39)	0.0332 (0.42)	-0.4172 (0.49)
Private sector participation	1.5209 (6.51)	-2.2453 (13.487)	-2.9268 (14.05)	-3.9783 (16.44)
constant	-1.2151*** (0.24)	-2.4687*** (0.49)	-1.348*** (0.52)	-2.1918*** (0.59)
No. Observations	176	176	176	176

Note: Variables' descriptions are given in Appendix (A1.1). Different measures of wage Inequality (Gini Index, Atkinson Index, Mean Log Deviation, and Theil Index), patents, AND GDP per capita are taken in logs, and different measures of wage inequality are lagged by one year. *GMM method is used. Clustered standard errors are presented in parenthesis. ***p<0.01, **p<0.05, *p<0.1 present levels of significance.*

The unemployment rate is another factor that increases wage inequality, with coefficients ranging between 1.08 and 2.87 (significant at 1%). This high magnitude and significant level show that the excess supply of labour increases the gaps in wages. As low-skilled workers (mainly located in the lower tail of the wage distribution) are the most affected group by the changes in labour demand, the changes in labour supply most likely shift the wages for this group more than any other group. Consequently, the wage gap moves in the same direction as the unemployment rate changes. On the other hand, there is no effect for the other control variables (GDP, age, female participation, and private sector participation) on wage inequality.

To evaluate the accuracy of our results about the immigrant and native workers, we use the interaction term[42] for each of these variables with the number of patent applications per million inhabitants filed at the PCT. This interaction term helps study the role of each of these control variables in changing the wage gap in the presence of technology. Using the same other independent variables that are used in table (3-1) and applying lagged value for one year, we find the same results as shown in column (1) in the table (3-2). The magnitude of low-skilled immigrants (in absolute values) is still more extensive than that of highly skilled immigrants, and both are significant at 1%. Meanwhile, patents have a very close magnitude to the one used in table (3-1) and are significant at a 1% level. This result complies with (Xu et al., 2016), which shows that in the American states (from 1996 to 2008), low-skilled immigrants have a powerful effect in increasing income inequality. However, they find that "highly skilled immigrants do depress income inequality for certain segments of the income distribution in the top and at the median income or below" (Xu et al., 2016). Here, they measure income inequality by disposable family income, while we use individual earnings. The similarity between (Xu et al., 2016) and our study appears from the common factor (wages) included in measuring the dependent variable.

We also use in table (3-2) (columns 1-4) different lagged years for patents to study the changes in independent variables over time. We operate various lags from 1 to 4 years. It is noticed from this table that the significant level of the first and second years' lagged patents

[42] To find the interaction term, we multiply each of the following control variables: (Highly skilled Immigrants, low-skilled Immigrants, highly skilled natives, and low-skilled natives) by the number of patent applications per million inhabitants filed at the Patent Cooperation Treaty (PCT).

coefficients continue to exist for up to 4 years. Also, there is an increase in the first lag magnitude and a diminishing magnitude for the second lag.

The effect of patents and unemployment on increasing Gini Index remains significant even when we increase the lags beyond four years. However, the effect of highly and low-skilled immigrants disappears after the first year, and the same applies to the other control variables. It seems that highly and low-skilled immigrants' effect on wage inequality is in the short run (supply side), while the effect of innovation (demand side) and unemployment on wage inequality continues to exist in the long run. This result complies with the SBTC point of view that the technological changes are complementary to skills in their effect on wage inequality (Breau, 2014). It means that as there is improvement in technology, the demand is always biased toward skilled groups, compensating for the changes in labour supply.

Another thing to consider is the effect of innovation and other control variables on different measures of wage shares (top 1%, top 10%, bottom 10%) , 90%-10% wage inequality, and 75%-25% wage inequality, as shown in table (3-3). The top 1%, top 10%, and bottom 10% wage shares are not statistically affected by changes in innovation. The reason behind that is the slight changes in these wage shares in response to innovation, which reflects a negligible effect on this factor. On the contrary, we find that innovation increases the gap in the middle 80% and 50% of the wage distribution (90%-10% and 75-25%). Highly skilled immigrants do not have any impact on the wage shares of the (top 1% and top10%) and the (bottom 10%), while they decrease the gap in the middle 80% and 50% of the wage distribution (90%-10% and 75%-25%). The increase in the supply of the low-skilled immigrants increases the gap in the top 10%, the middle 80%, and the middle 50% of the wage distribution while it decreases the bottom 10% wage share. In addition, the increase in the supply of the highly and low-skilled natives decreases the gap in the middle 80% of the wage distribution, while it does not impact the other wage shares. Another essential control variable is the unemployment rate, which has a significant negative effect on the top 1% and the top 10% wage shares, but a significant positive influence on the bottom 10% wage share. However, the increase in the unemployment rate widens the gap in the middle 80%, and the middle 50% of the wage distribution. These results indicate that the effect of innovation and most of the other influential controls are mainly concentrated in the middle 80% and 50% of the wage distribution, while in the other shares in the top 10% and bottom 10% these effects are ceased to exist.

Even though there is no relation between GDP per capita and broad measures of wage inequality, the results show that the growth in GDP per capita reduces the gap in the top1%, the top 10%, and the middle 80% wage inequality. In contrast, it increases the gap in the bottom 10% wage share but does not affect the middle 50% wage inequality. GDP is an essential factor in reducing inequality because it affects the economic welfare by “reducing corruption, provision of infrastructure, enhancement of the rule of law, government effectiveness, impartial regulation of business, political stability, and democracy” (Zagroski et al., 2014). In our results, the effect of GDP on wage inequality appears to have high influence on the middle 80% wage inequality. The absence of this influence on the overall distribution and the middle 50% indicates that most of the changes in wages as a response to GDP are particularly concentrated in the 10%-25% and 75%-100% of the wage distribution. The effect of GDP on increasing the gap in the bottom 10% wage share reveals that economic growth does not mitigate the gap between the lowest levels of wages, where low-skilled workers are in this segment.

Table 3-2: Innovation and wage inequality in the UK regions at different lags

Dependent Variables → **Independent Variables** ↓	(1) **Gini Year (1) Lag**	(2) **Gini Year (2) Lag**	(3) **Gini Year (3) Lag**	(4) **Gini Year (4) Lag**
Lag (1)	0.1091*	0.1567***	0.2099***	0.2757***
	(0.06)	(0.06)	(0.07)	(0.08)
Lag (2)	-	0.2367***	0.2037***	0.1572**
		(0.05)	(0.06)	(0.08)
Lag (3)	-	-	-0.0353	-0.0701
			(0.06)	(0.07)
Lag (4)	-	-	-	0.1272
				(0.07)
Patents	0.0469***	0.0398**	0.0405**	0.04***
	(0.02)	(0.02)	(0.02)	(0.02)
Net Migration	0.0006*	0.0004	0.0005	0.0003
	(0.0003)	(0.0003)	(0.0003)	(0.003)
Unemployment	1.0286***	0.9742***	1.1180***	0.9946***
	(0.30)	(0.30)	(0.32)	(0.37)
GDP per Capita	0.0023	0.0060	0.0108	0.0259
	(0.02)	(0.02)	(0.02)	(0.02)
Highly skilled/low-skilled labour				
INTER HSKI	-0.2343***	-0.3725	-0.3818	-0.2790
	(0.07)	(0.27)	(0.27)	(0.28)
INTER LSKI	0.2458***	0.0089	-0.0930	0.1538
	(0.07)	(0.61)	(0.61)	(0.65)
INTER HSKN	-0.0332	-0.0268	-0.0332	-0.0464
	(0.03)	(0.03)	(0.03)	(0.03)
INTER LSKN	-0.0199	-0.0544	-0.0450	-0.0571
	(0.04)	(0.04)	(0.04)	(0.04)
Age	0.0022	-0.0143	-0.0065	-0.0219
	(0.11)	(0.11)	(0.11)	(0.13)
Female Participation	-0.0653	-0.1045	-0.1363	-0.0406
	(0.19)	(0.20)	(0.20)	(0.22)
Private Sector Participation	2.7130	5.7438	6.2235	7.6144
	(6.63)	(6.55)	(6.49)	(6.72)
Constant	-1.1176***	-0.8000***	-0.8631***	-0.8936***
	(0.23)	(0.24)	(0.25)	(0.27)
No. Observations	**176**	**165**	**154**	**143**

Note: Variables' descriptions are given in Appendix (A1.1). Gini Index, patents, AND GDP per capita are taken in logs, and Gini Index is lagged by four years. *We use in this test the interaction term between patents and different skilled groups. GMM method is used. Clustered standard errors are presented in parenthesis. ***p<0.01, **p<0.05, *p<0.1 present levels of significance.*

Table 3-3: Innovation and different measures of wage shares in the UK regions

Dependent Variables → **Independent Variables ▼**	**Top1%**	**Top10%**	**Bottom10 %**	**90%-10%**	**75%-25%**
Lag (1)	0.0185	-0.0731	0.0753	0.0990*	0.1415**
	(0.06)	(0.06)	(0.05)	(0.05)	(0.05)
Patents	-0.0215	-0.0029	0.0390	0.2173***	0.0495
	(0.10)	(0.02)	(0.05)	(0.04)	(0.03)
Net Migration	0.0022	0.0011***	-0.0014*	-0.0006	0.0007
	(0.002)	(0.0004)	(0.0009)	(0.007)	(0.007)
Unemployment	-3.3881**	-0.6233*	1.4389*	1.9576**	1.6651**
	(1.54)	(0.33)	(0.80)	(0.91)	(0.66)
GDP per Capita	-0.2571**	-0.0486**	0.1676***	-0.1023*	-0.0179
	(0.11)	(0.02)	(0.05)	(0.06)	(0.05)
Highly skilled/low-skilled labour					
INTER HSKI	0.4554	-0.1145	0.0361	-0.7791***	-0.5274***
	(0.43)	(0.10)	(0.23)	(0.24)	(0.17)
INTER LSKI	-0.0935	0.2364***	-0.3988**	0.4961**	0.7209***
	(0.37)	(0.10)	(0.20)	(0.21)	(0.15)
INTER HSKN	0.2840*	0.0356	0.0088	-0.3473***	-0.0255
	(0.16)	(0.03)	(0.08)	(0.09)	(0.06)
INTER LSKN	0.2079	0.0758	-0.1139	-0.2035*	0.0471
	(0.21)	(0.05)	(0.12)	(0.12)	(0.09)
Age	-0.0324	0.0032	0.3163	-0.0953	0.2908
	(0.60)	(0.13)	(0.31)	(0.32)	(0.25)
Female Participation	-1.3863	-0.2173	1.1670**	0.1120	0.3444
	(1.05)	(0.23)	(0.55)	(0.58)	(0.43)
Private Sector Participation	-7.3700	-3.5183	10.2624	7.3641	9.9234
	(34.83)	(7.97)	(19.26)	(19.70)	(14.25)
Constant	0.1931	-0.9121***	-6.6176***	2.2910***	0.3055
	(1.13)	(0.27)	(0.66)	(0.70)	(0.49)
No. Observations	**176**	**176**	**176**	**176**	**176**

Note: Variables' descriptions are given in Appendix (A1.1). Different measures of wage shares, patents, AND GDP per capita are taken in logs, and different measures of wage shares are lagged by one year. *We use in this test the interaction term between patents and different skilled groups. GMM method is used. Clustered standard errors are presented in parenthesis. ***p<0.01, **p<0.05, *p<0.1 present levels of significance.*

Equally important is the positive effect of net migration on the top 10% wage share, while it does not impact the top 1% wage share, the middle 80% wage inequality, or the middle 50% wage inequality. There is no sign for any impact of net migration on the middle 80%- and

50% wage inequality, which means that the response of wage inequality to this factor is essentially concentrated in the high and low ends of the wage distribution (top 10% and bottom 10% wage shares). This finding satisfies (Card, 2009), where immigrants are clustered at these two parts of the education distribution. The positive effect of net migration on the top 10% wage share (high end of the wage distribution) but the negative effect on the bottom 10% wage share (low end of the wage distribution) is illustrated by the fact that many skilled immigrants are downgraded when they arrive in the UK regions. As a result, this places them at different locations in the wage distribution (Dutsmann et al., 2013)[43] than where they are genuinely in, it suppresses the wages at the bottom of the distribution and comes up with their growth at the top. This mismatch between immigrants' skills and occupations when they start their work in different regions in the country leads to a higher relative density of immigrants in the bottom part of the distribution and a lower relative density of immigrants at the top of that distribution. Eventually, the excessive demand on the top would increase the wages, while the shortage of demand on the bottom would decrease them. The top 1% wage share includes a very small margin of changes in wages as a response to net migrants, which does not reveal any significant link between these two variables.

Other control variables, namely age, female participation, and private sector participation, do not significantly affect the different measures of wage shares in the UK regions. We illustrate this by the fact that within-group wage structure accounts for most of the changes in overall wage inequality. It means that these age groups obtain the same skills when they reach a particular level of experience at work and hence do not make any gap between their wages. However, female participation makes a difference in the bottom 10% wage share, and it is aligned with the experience that this group obtains when they reach a particular level of experience at their work, which enhances their competitive advantage in the market. Hence,

[43] The data used in this study is based on the British Labour Force Survey, Q1 1992-Q4 2005.

the bottom 10% wage share moves in the same direction as female participation. For other wage shares and the broad measures of wage inequality, the results show that males and females in the UK labour market are very close in their wage structure. Similarly, there is no difference between the public and private sectors in the UK job market.

3.6.2 Between groups wage inequality

In the previous analysis, we control for the changes in labour supply within immigrants and natives, but it is vital to know these groups' roles in changing wage inequality between them. In other words, where the high (low) wage inequality in highly innovative (less) regions in the UK comes from when we control for these groups (between highly and low-skilled Immigrants and natives). Hence, in this section, we study the impact of innovation on wage inequality when we add highly skilled and low-skilled workers between immigrants and natives. To achieve this, we use the dynamic model (GMM) to test the same data in the previous section and add two other new ratios: highly skilled natives to low-skilled immigrants' ratio (HSN/LSI) and low-skilled natives to highly skilled immigrants' ratio LSN/HIS, to the other control variables that are used in equation (1). The results are shown in table (3-4), which consists of four columns, each one representing one extra year time lag of the wage inequality, and this varies from 1 (represented in the first column) to 4 years (represented in the fourth column).

It is evident from the table (3-4) that innovation still increases wage inequality (Gini Index). In addition, the ratio of highly skilled natives to low-skilled immigrants shows a positive significant coefficient, while the ratio of low-skilled natives to highly skilled immigrants does not impact wage inequality. This result indicates that the main reason behind the change in wage inequality as a response to technology is the wage gap between highly skilled natives and low-skilled immigrants. Furthermore, this effect continues to exist and is enormously significant even when we increase the lags beyond four years, and the same applies to the coefficient on innovation. In this case, the technological shift is biased towards highly skilled natives against low-skilled immigrants and not directed to highly skilled immigrants against low-skilled natives. On the other hand, the other control variables that are used in table (3-4) (from columns 1 to 4) confirm the same signs and significant levels when these variables are used in table (3-2). Furthermore, the coefficient on the unemployment rate is positively significant in the four years lags, which is also in line with the table (3-2) results.

Table 3-4: Innovation and wage inequality in the UK at different lags (Within and between groups)

Dependent Variables → / **Independent Variables** ↓	(1) **Gini Year (1) Lag**	(2) **Gini Year (2) Lag**	(3) **Gini Year (3) Lag**	(4) **Gini Year (4) Lag**
Lag (1)	0.1182**	0.1572***	0.2078***	0.2782***
	(0.06)	(0.06)	(0.07)	(0.07)
Lag (2)	-	0.2417***	0.2134***	0.1725**
		(0.05)	(0.06)	(0.08)
Lag (3)	-	-	-0.0495	-0.0808
			(0.06)	(0.07)
Lag (4)	-	-	-	0.0963
				(0.07)
Patents	0.0463***	0.0396**	0.0423***	0.0371**
	(0.02)	(0.02)	(0.02)	(0.02)
Net Migration	0 .0006*	0.0004	0.0004	0.0003
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Unemployment	1.0833***	1.0555***	1.2066***	1.0964***
	(0.30)	(0.30)	(0.32)	(0.37)
GDP per Capita	0.0097	0.0126	0.0182	0.0365
	(0.02)	(0.02)	(0.02)	(0.02)
Highly skilled/low-skilled labour				
INTER HSKI	-0.2112**	-0.3403	-0.3383	-0.3045
	(0.09)	(0.30)	(0.29)	(0.30)
INTER LSKI	0.2159***	-0.4052	-0.5781	0.0281
	(0.07)	(0.80)	(0.80)	(0.88)
INTER HSKN	-0.0387	-0.0307	-0.0395	-0.0532
	(0.03)	(0.03)	(0.03)	(0.04)
INTER LSKN	-0.0410	-0.0765	-0.0713	-0.0839
	(0.04)	(0.05)	(0.05)	(0.06)
HSN/LSI	0.0058***	0.0480***	0.0541***	0.0169***
	(0.001)	(0.005)	(0.005)	(0.006)
LSN/HIS	-0.0077	0.0456	0.0517	0.0143

Dependent Variables → / Independent Variables ↓	(1) **Gini Year (1) Lag**	(2) **Gini Year (2) Lag**	(3) **Gini Year (3) Lag**	(4) **Gini Year (4) Lag**
	(0.01)	(0.05)	(0.05)	(0.06)
Age	-0.0108	-0.0121	-0.0228	-0.0568
	(0.11)	(0.109)	(0.11)	(0.13)
Female Participation	-0.0471	-0.0708	-0.1184	-0.0482
	(0.19)	(0.196)	(0.21)	(0.22)
Private Sector	2.9163	6.3887	7.4478	8.7136
Participation	(6.62)	(6.59)	(6.54)	(6.74)
Constant	-1.1641***	-0.8636***	-0.9318***	-0.9944***
	(0.24)	(0.24)	(0.26)	(0.28)
No. Observations	**176**	**165**	**154**	**143**

Note: Variables' descriptions are given in Appendix (A1.1). Gini Index, patents, AND GDP per capita are taken in logs, and Index Index is lagged by four years. *We use in this test the interaction term between patents and different skilled groups. In addition, we use highly skilled native labour to low-skilled immigrant labour and low-skilled native labour to highly skilled immigrant labour ratios. GMM method is used. Clustered standard errors are presented in parenthesis. ***p<0.01, **p<0.05, *p<0.1 present levels of significance.*

From the previous results, we find that by controlling for the labour supply in the UK regions, the essential effect on wage inequality comes from the gap between highly skilled natives and low-skilled immigrants. It seems that native highly skilled workers do not compete with native low-skilled workers in the UK regional labour market. Especially the case that our findings reveal that native highly and low-skilled labour do not affect wage inequality in the short and long run. The primary source of the changes in wage inequality is highly and low-skilled immigrants, as we have shown in the previous section. In the next section, we test if there is a substitution between immigrants and natives for the same skill groups.

3.6.3 The elasticity of Substitution Between Immigrants and Natives

Using equation (3), the results in table (3-5) show that the change in labour supply coefficient between immigrants and natives is significantly negative for both highly and low-skilled labour. This coefficient equals 0.07 for highly skilled labour and 0.03 for low-skilled labour. It means that the elasticity of substitution between highly skilled immigrants and natives equals (1/0.07= 14.29). In addition, the elasticity of substitution between low-skilled immigrants and natives equals (1/0.03= 33.33). Hence, highly and low-skilled immigrants and natives are perfectly substitutable. Moreover, the elasticity of substitution between low-skilled immigrants and natives is higher than the elasticity of substitution between highly skilled immigrants and natives. It indicates that native low-skilled labour has a very high response to the inflow of low-skilled immigrants compared to the response of native highly skilled labour to the inflow of highly skilled immigrants. Consequently, this result explains the higher coefficient magnitude of low-skilled than highly skilled immigrants.

Table 3-5: Estimated Model for the Elasticity of Substitution between Immigrants and Natives in the UK regions

	Highly skilled	**Low-skilled**
	(1)	(2)
Dependent Variables →	Difference in Wage Residuals	Difference in Wage Residuals
▼ **Independent Variables**		
Total hours (Immigrants/Natives)	- 0.07*** (0.0001)	- 0.03*** (0.00002)
Other control variables		
Patents	Yes	Yes
Unemployment	Yes	Yes
GDP per capita	Yes	Yes
Experience	Yes	Yes
Female share	Yes	Yes
Private sector share	Yes	Yes
No. Observations	**176**	**176**

Note: Variables' descriptions are given in Appendix (A1.1). Patents, total hours (Immigrants/Natives), AND GDP per capita are taken in logs. The *OLS method is used to estimate the parameters of this model. We estimate this model by using two levels of education (High and Low), each of which is estimated separately. The dependent variable is the difference in wage residuals between immigrants and natives, and the independent variable is the percentage of yearly total hours of immigrants to natives. In contrast, the other regional level control variables are (the number of patents, unemployment rate, GDP per capita, experience, female share, and private sector share). Clustered standard errors are presented in parenthesis. ***p<0.01, **p<0.05, *p<0.1 present levels of significance.*

From these results, we conclude that highly and low-skilled immigrants impact native wage inequality. However, the wage gap is not concentrated among the natives themselves. Also, the effect of low-skilled immigrants is higher than that of highly skilled immigrants on wage inequality, which complies with the previous results. Even though this effect is in the short run, as illustrated in the previous section, these adjustments in the labour market to the inflow of immigrants to the UK regions are crucial in predicting the gaps in wages.

3.7 Comparison between the GMM and Heteroskedasticity methods

To tackle the problem of endogeneity in the model, specifically the endogeneity in patents, we use the GMM method, as explained in the previous section. This method helps avoid any possible omitted variable bias and measurement errors in estimating the model. Another method that is beneficial to use where the instrument is unavailable, as in this study, is the Heteroskedasticity Method (Two-Stage Least Squares TSLS), proposed by (Lewbel, 2012). This method has the same heteroskedasticity covariance restriction which GMM identifies. However, the main advantage of the Heteroskedasticity method is that "it obtains identification even when all the elements of the instruments are regressors" (Lewbel, 2012).

We apply the Heteroskedasticity method to the same UK data used in the previous section and compare the results between this method and the GMM method. It is shown in table (3-6) that the results are similar between the two methods. There are tiny differences in the magnitude of some of the coefficients. However, this variation in magnitude does not change the signs and the significant levels of these coefficients. For example, when Gini Index is used as a dependent variable, the patent coefficient's magnitude level equals 4% in GMM, while it equals 8% in the Heteroskedasticity method with a 1% significant level in both methods. In the same way, the coefficients of net migration and low-skilled immigrants are at almost the same level in the two methods, in which the differences in these coefficients do not exceed 2%.

Table 3-6: Innovation and different measures of wage shares in the UK regions using TSLS (Heteroskedasticity) method

Dependent Variables → **Independent Variables ↓**	**Gini**	**Top10%**	**Top 1%**	**Bottom 10%**
Patents	0.0901***	0.0203	0.0006	-0.1001
	(0.01)	(0.02)	(0.04)	(0.12)
Net Migration	0.0009**	0.0010***	0.0022	-0.0039***
	(0.0004)	(0.0004)	(0.002)	(0.0009)
Unemployment	0.5593*	-0.9793***	-3.0660**	0.4631***
	(0.34)	(0.34)	(1.35)	(0.08)
GDP per Capita	-0.0288	-0.0820***	-0.1392*	0.2555***
	(0.02)	(0.02)	(0.08)	(0.05)
INTER HSKI	-0.3845*	0.1170	0.4457	0.3332
	(0.23)	(0.12)	(0.47)	(0.27)
INTER LSKI	0.3618*	0.2369*	1.0239	-0.0536*
	(0.19)	(0.13)	(0.69)	(0.03)
INTER HSKN	-0.0450	2.4657	13.494**	7.1382
	(0.03)	(2.69)	(6.80)	(13.88)
INTER LSKN	0.0387	1.7815	-17.6086	-1.6560
	(0.04)	(3.87)	(15.50)	(8.86)
Age	0.0003	0.2429	-0.0116	-0.0414
	(0.13)	(0.22)	(0.49)	(0.28)
Female Participation	0.2636	0.2298	-0.6646	0.1611*
	(0.25)	(0.24)	(0.97)	(0.09)
Private Sector	18.091	3.4960	0.6921	-11.0038
Participation	(17.33)	(6.90)	(27.66)	(15.81)
Constant	-1.2689***	-0.9129***	-1.3458	-6.2751***
	(0.29)	(0.29)	(1.15)	(0.66)
No. Observations	**176**	**176**	**176**	**176**

Note: Variables' descriptions are given in Appendix (A1.1). Different measures of wage shares, patents, AND GDP per capita are taken in logs. The heteroskedasticity *method is used. Clustered standard errors are presented in parenthesis. ***p<0.01, **p<0.05, *p<0.1 present levels of significance.*

Moreover, the unemployment rate and highly skilled immigrants have the same significant influence in their coefficients between the two methods, and the same applies to the other measures (top 1%, top 10%, and bottom 10%). Similarly, between groups analysis[44]

[44] Between-groups analysis is when we add two other control variables (between groups) to equation (1) which are: Highly skilled natives to low-skilled immigrants ratio and the low-skilled natives to highly skilled immigrants ratio.

which is shown in table (3-7), confirms that there is consistency in terms of the signs and significant levels of the coefficients on variables.

In conclusion, the two methods used in this section show stable results. Both methods solve the endogeneity in the model and confirm the effect of innovation on wage inequality in the UK regions. Also, the results reveal that innovation influences the middle 80% and the middle 50% wage inequality, as shown in table (3-3). On the other hand, these methods do not show any effect of innovation on the top 1%, the top 10%, and the bottom 10% wage shares.

Table 3-7: Within and between labour groups' effects on wage inequality (Gini Index) in the UK regions using GMM and TSLS (Heteroskedasticity) methods

	GMM		**Heteroskedasticity Test**	
Dependent Variables →	(1) Gini Within groups	(2) Gini Within & Between groups	(3) Gini Within Groups	(4) Gini Within& Between Groups
Independent Variables ▼				
Lag (1)	0.1091* (0.06)	0.1182** (0.06)	-	-
Patents	0.0469*** (0.02)	0.0463*** (0.02)	0.0901*** (0.01)	0.0936*** (0.01)
Net Migration	0.0006* (0.003)	0 .0006* (0.0003)	0.0009** (0.0004)	0.0009** (0.0004)
Unemployment	1.0286*** (0.30)	1.0833*** (0.30)	0.5593* (0.34)	0.7026** (0.3578)
GDP per capita	0.0023 (0.02)	0.0097 (0.02)	-0.0288 (0.02)	-0.0241 (0.02)
INTER HSKI	-0.2343*** (0.07)	-0.2112** (0.09)	-0.3845* (0.23)	-0.3126* (0.04)
INTER LSKI	0.2458*** (0.07)	0.2159*** (0.07)	0.3618* (0.19)	0.8719* (0.47)
INTER HSKN	-0.0332 (0.03)	-0.0387 (0.03)	-0.0450 (0.03)	-0.0443 (0.03)
INTER LSKN	-0.0199 (0.04)	-0.0410 (0.04)	0.0387 (0.04)	0.0026 (0.04)
HSN/LSI	-	0.0058*** (0.001)	-	0.0556*** (0.02)
LSN/HIS	-	-0.0077 (0.01)	-	0.0512 (0.08)

Age	0.0022 (0.11)	-0.0108 (0.11)	0.0003 (0.13)	0.0459 (0.13)
Female participation	-0.0653 (0.19)	-0.0471 (0.19)	0.2636 (0.25)	0.3224 (0.25)
Private sector participation	2.7130 (6.63)	2.9163 (6.62)	18.091 (17.33)	16.1653 (17.31)
Constant	-1.1176*** (0.23)	-1.1641*** (0.24)	-1.2689*** (0.29)	-1.3668*** (0.29)
No. Observations	**176**	**176**	**176**	**176**

Note: Variables' descriptions are given in Appendix (A1.1). Gini Index, patents, AND GDP per capita are taken in logs, and using GMM (Gini Index) is lagged by one year. *GMM and Heteroskedasticity methods are used. Clustered standard errors are presented in parenthesis. ***p<0.01, **p<0.05, *p<0.1 present levels of significance.*

3.8 Robustness check (European Regions)

In this section, we perform a robustness check to test the magnitude and significant level of excluding the UK, Germany, and Sweden from the European dataset. Remarkably, these two countries have similar labour market characteristics to the UK. We use the same econometric model mentioned in the previous section and run the regression utilizing the GMM method. Wage inequality for the European regions is computed using the Eurostat database. Age, female participation, and private sector participation are excluded from this model as it is shown that they have a negligible effect on the broad measures of wage inequality. Furthermore, we use two variables for highly and low-skilled labour instead of four, in which each of these two variables includes immigrant workers and native workers. To this end, we aim to test the consistency in the results in the nexus between innovation and wage inequality for the European regions and compare the results when we exclude countries with similar labour market structures as the UK (e.g., Germany and Sweden).

Table (3-8), column (1) shows that the coefficient of patents for European regions has a vital significant positive sign. In the same table, column (2) indicates that this relationship exists and is not spurious when the UK, Germany, and Sweden are excluded from the data. These results are confirmed by obtaining the same significant coefficients for the other control covariates. The same table shows that the patents' coefficient has a higher magnitude (1 to 2 percentage increase) when the UK, Sweden, and Germany are excluded from the data than the coefficient of patents for all the European regions.

Table 3-8: Robustness Check- Wage Adjustments in the European Regions

Dependent Variables → **Independent Variables** ↓	(1) **Europe**	(2) **Exclude UK, Germany, Sweden**
	Gini	**Gini**
Lag (1)	0.7820***	0.7222***
	(0.02)	(0.02)
Patents	0.0265***	0.0416***
	(0.004)	(0.004)
Net Migration	0.0007**	0.0003**
	(0.0003)	(0.0002)
Unemployment	0.1211**	0.1072**
	(0.05)	(0.05)
GDP per Capita	-0.0292	-0.0295
	(0.03)	(0.03)
HSK	0.0843*	0.0092*
	(0.05)	(0.005)
LSK	0.1306 ***	0.0631*
	(0.03)	(0.04)
Constant	-0.1862 ***	-0.2609 ***
	(0.07)	(0.07)
No. Observations	**783**	**566**

Note: Variables' descriptions are given in Appendix (A1.1). Gini Index, patents, AND GDP per capita are taken in logs, and Gini Index is lagged by one year. *GMM Method is used. Clustered standard errors are presented in parenthesis. ***p<0.01, **p<0.05, *p<0.1 present levels of significance.*

Consequently, there is a less effect of technological change on increasing wage inequality for countries with similar labour market structures to the UK. Since less-flexible markets and low levels of migration in other European regions would be the main reason behind the increase in this magnitude. The low percentage of immigrants to these regions is mainly countered by little substitution of highly and low-skilled labour compared with the UK, Germany, and Sweden. It is also found in literature that “the institutional nature of the markets for unskilled labour” (Yabuuchi and Chaudhuri, 2007) has a very important effect on wage inequality.

Another explanation is related to the role of the welfare system and unionization. In primitive welfare structures and low union density - as is the case in other European countries – there is rigidity in the changes in wages in the lower tail of the wage distribution in these countries' regions. It means that those offering low-skilled services have lower flexibility than highly skilled workers to command higher wages, which increases the magnitude of patents' effect on the gap in wages relative to other regulated countries. In Sweden and Germany, particularly in the UK, this does not exist, as high welfare rates, unionization, and more effective labour market regulations allow regions in these countries to be more efficient in controlling such an increase (or decrease) in the gap in wages.

On the supply side, the response of wage inequality to the changes in labour supply (for both highly and low-skilled labour) is higher when we include all the European regions rather than when we exclude the UK, Germany, and Sweden. As shown in the previous paragraph, this magnified labour supply effect is countered by a more-flexible response from the demand side to innovation changes. Adding the UK, Germany, and Sweden regions to the other European regions leads to higher absorption of the excess wage gaps. In other words, the accumulated effect of increasing labour supply by adding these regions is absorbed by the flexibility of the UK, Germany, and Sweden labour markets to reduce the detrimental impact of technology on wage inequality.

*3.9 **Discussion***

Our results showed that innovation increases wage inequality in the UK regions. It appears that wage inequality strongly responds to the technical change effect on wage gaps between highly skilled and low-skilled workers. This finding is also shown in the work of (Autor et al., 2006), in which they find evidence that the change in wage structure is mainly due to the demand shift on job tasks as an outcome of technology. In addition, by testing the model used in this study, we demonstrated that highly and low-skilled immigrants and natives are perfectly substitutable. This result suggests that low-skilled immigrants relative to highly skilled immigrants affect the wage inequality of natives. It is also shown that the increase in the supply of the low-skilled immigrants increase wage inequality. However, the increase in the supply of the highly skilled immigrants decreases this gap. We explain this result by the effect of technological change on increasing the wage skill premium as it primarily benefits highly skilled labour. This wage gap in the UK labour market is reinforced in the short run by the gap between highly and low-skilled immigrants. Given the above outcome, it complies with the model of (Aghion and Howitt, 1998) which reveals that the increase in the demand for highly skilled labour with the new technology will eventually increase wage inequality.

Changes in wage inequality in this context because of new technology differ from their creative destruction effect on income inequality explained in the previous paper (paper 2). In this paper, we find a significant effect of innovation on increasing wage inequality, while in the previous one, we found a significant effect of innovation on reducing income inequality. Both results comply with literature, in which the introduction of new technology, as stated by (Breau et al., 2014), increases the demand for highly skilled labour relative to low-skilled labour and eventually has asymmetry-expanding effects on wages. The definition of income in the creative destruction literature covers a broader scope of elements. To be specific, income includes earnings from work (wage) and earnings from wealth (rent from capital), in addition to other social benefits and transfers. The reduction in income of the newcomers (entrepreneurs) from rent (profit) – because of the creative destruction[45] - would cause a decrease in income asymmetries between income holders due to the short duration of monopolistic power of the newcomers. "The appreciation of this effect on rent should mitigate, if not overcome, the SBTC

[45] The creative destruction concept goes through four stages: destruction that eliminates a large segment of capital, entry of new firms, reduction in markups, and increase in savings (see (Antonelli and Gehringer, 2017).

effect on wages" (see (Antonelli and Gehringer, 2017). As a result, income inequality is moving in the opposite direction with the changes in technology.

Another point to consider is the implications of our findings for innovation policies. Enhancing the education system is considered as an effective tool to tackle the wage gaps among the other policies. Specifically, our results show that achieving this on the regional level is preferable to increasing public expenditure on enrolment in higher education. Equally important is that we recommend reallocating resources towards training on innovation and mainly on-the-job training programs, which significantly impact the performance of low-skilled and middle-skilled workers. Accordingly, these groups will be rewarded by the increase in wages as they become more able to master the new technology. Also, we have shown that highly skilled immigrants are less detrimental to wage inequality than low-skilled immigrants, so migration policy is recommended to be selective towards highly skilled workers.

Given that our interest in this paper is on wage as a source of income, the policy may be functional when promoting productivity at both the firm and the individual levels. To enhance productivity, human capital has to be highly qualified, and institutions need to act toward reducing the gap in wages. However, maintaining a low level of the wealth gap and strengthening the social benefits are also important for social welfare. Hence, the overall policy has to be harmonized in targeting equal opportunities in the economy. For instance, huge investment in R&D involves an increase in the demand for highly skilled labour relative to low-skilled labour. The increase in the wage gap between different skilled workers groups because of this investment eliminates the potential progression of social equality. Here, the government may reallocate its resources to be more focused on qualifying low-skilled labour and enhancing their productivity. The overall outcome of such policy does not harm social income equality and at the same time bolster economic growth by improving the productivity of the firms and the labour. Such inclusion of innovation helps overcome this kind of barriers to the overall policy.

3.10 ***Conclusions***

In this paper, we have shown evidence of the effect of innovation on wage inequality in the UK regions. We tested this effect using parametric and non-parametric approaches, focusing on the low-skilled relative to highly skilled immigrant labour's role in this relation. The results revealed that there is an impact of innovation on increasing the overall measures of wage inequality (Gini Index, Atkinson Index, mean log index, Theil Index), and this complies with (Acemoglu and Autor, 2011), (Autor, 2003), and (Breau, 2014)). It is explained by the fact that technology substitutes for low-skilled labour and reduces their share in employment and wages. Highly skilled jobs, as a complement, will increase wages and employment shares. The decline in the middle of the distribution leads to the polarization of the labour market into highly skilled and low-skilled employment, which implies that the increase (decrease) in innovation increases (decreases) wage inequality.

In addition, the increase in the supply of highly skilled immigrants reduces wage inequality , while the increase in the supply of the low-skilled immigrants increases the gaps in wages. However, it is shown in this study that native labour (highly and low-skilled) does not have any impact on broad measures of wage inequality. These results are confirmed using interaction terms for highly and low-skilled immigrants and native labour with innovation. It is also demonstrated that innovation and immigrant labour have the same outcomes on the middle 80% wage inequality. On the top 1%, top 10%, bottom 10%, and middle 50%, there is no sign that there is an impact of innovation on these segments. These shares seem to have different characteristics and little changes in wages across them.

To check the robustness of the previous results, we examined the validity of our estimates by excluding countries with similar labour market characteristics to the UK, like Germany and Sweden. Despite the low number of these excluded observations, we found that innovation increases wage inequality on the yearly and regional levels, with more substantial evidence of such a relationship in other European regions. More-flexible labour markets, a welfare system, and higher levels of migration seem to be the root of this association between the UK, Germany, and Sweden than the other European countries.

Finally, to examine whether the changes in wage inequality are concentrated among natives, we found the elasticity of substitution between immigrants and natives for the highly and low-skilled groups. Our results indicated that immigrants are a perfect substitute for natives for these groups, which means that immigrants influence natives' wage inequality in the UK regions. Consequently, the technological change in these regions boosts both innovation and immigration, and in the short run, the gap between highly and low-skilled labour is widened with the inflow of those immigrants.

We recommend applying the methodology used in this study to cover the role of labour unions and international trade on the kink between innovation and income/wage inequality. These two topics are beyond the scope of this research because our main target is to test the effect of innovation on inequality with the existence of different skilled labour groups (natives and immigrants). We leave these two subjects to further research.

Appendices

A1. Tables and Figures

Table (A1.1) Variables Definition

Variable	Definition
Wage	The individual wage is measured by Gross pay per month per individual adjusted using the Retail Price Index (RPI).
Gini Index	One of the broad measures of wage inequality (computation is illustrated in A2).
Atkinson Index	One of the broad measures of wage inequality (computation is illustrated in A2).
Mean Log Deviation	One of the broad measures of wage inequality (computation is illustrated in A2). It is computed by using the Generalized Entropy Index when $\propto$= 0, which is the parameter that regulates the weight between wages at different parts of the wage distribution.
Theil Index	One of the broad measures of wage inequality (computation is illustrated in A2). It is computed by using the Generalized Entropy Index when $\propto$ = 1.
Top1%	Top 1% wage share (wage distribution). It represents the wage share that is owned by the top 1% of the income distribution.
Top10%	Top 10% wage share (wage distribution). It represents the wage share that is owned by the top 10% of the wage distribution.
Bottom10%	Bottom 10% wage share (wage distribution). It represents the wage share that is owned by the bottom 10% of the wage distribution.
90%-10%	Wage inequality restricted to the middle 80% of the income distribution (between 90% and 10% of the income distribution).
75%-25%	Wage inequality restricted to the middle 50% of the income distribution (between 75% and 25% of the income distribution).
Patents	The number of patent applications per million inhabitants filed at the PCT[46].
Innovation (BHPS)	An individual's perception of her(him)self as someone who is original and comes up with new ideas (Dummy). It is used as one of the elements in estimating the Kernel Density function.
GDP per capita	Gross Domestic Product per capita in constant prices (2010).
Net migration	Difference between the number of immigrants and number of emigrants per thousand.
Unemployment	Unemployment rate.

[46] Patents are counted according to the year in which they were filed at the Patent Cooperation Treaty (PCT) and are broken down according to the International Patent Classification (IPC). “They are also broken down according to the inventor's place of residence, using fractional counting if multiple inventors or IPC classes are provided to avoid double counting” (source: EUROSTAT).

Variable	Definition
Total Number of Labour	The total number of labour (which includes highly, middle, and low-skilled labour).
HSKI	The number of highly skilled immigrants / Total Number of Labour.
LSKI	The number of low-skilled immigrants / Total Number of Labour.
HSKN	The number of highly skilled natives / Total Number of Labour.
LSKN	The number of low-skilled natives / Total Number of Labour
INTER HSKI	Interaction between patents and highly skilled immigrants Percentage, which equals (patents) *(Highly skilled immigrants Percentage).
INTER LSKI	Interaction between patents and Low-skilled immigrants Percentage, which equals (patents) *(Low-skilled immigrants Percentage).
INTER HSKN	Interaction between (patents) and (Highly skilled natives Percentage), which equals (patents) *(Highly skilled natives Percentage).
INTER LSKN	Interaction between (patents) and (Low-skilled natives Percentage), which equals (patents) *(Low-skilled natives Percentage).
HSK	The total number of highly skilled labour (Immigrants and Natives)/Total Number of Labour.
LSK	The total number of low-skilled labour (Immigrants and Natives)/Total Number of Labour.
HSN/LSI	Highly skilled natives to low-skilled immigrants ratio.
LSN/HIS	Low-skilled natives to highly skilled immigrants ratio.
Age	Five age groups for workers which include: less than 25 years old, between 25 and 34 years old, between 35 and 43 years old, between 44 and 54 years old, and over 54 years old.
Female Participation	The number of female workers/total number of workers.
Private Sector Participation	The number of workers in the private sector/total number of workers in all sectors.

Table (A.1.2) Immigrants, education, and average monthly wages in the UK regions

Number	Region	Working Age Share of UK population (percent)	Immigrants (percent)	Low education level (percent)	High education level (percent)	Average monthly wages (GBP Currency)
1	North East	4.09	5	30	7	3,161.261
2	North West	11.39	9	31	6	3,232.994
3	Yorkshire and the Humber	8.56	7.6	27	10	3,151.448
4	East Midlands	7.59	13	28	7	3,130.37
5	West Midlands	8.91	7.5	27	8	3,084.416
6	East of England	9.67	15.82	29	6	3,677.224
7	Greater London	12.82	17.77	47	4	4,642.638
8	South East	14.64	7.1	31	5	3,527.221
9	South West	8.78	8.08	26	9	3,083.931
10	Wales	4.75	4.02	25	6	2,835.596
11	Scotland	8.8	5.11	34	4	3,212.489

Notes: based on the Eurostat database and BHPS of 2006.

Table (A1.3) Actual Wage Residuals on the regional and yearly levels for low-skilled labour in the UK (1991-2008)

Regi on / Year	1	2	3	4	5	6	7	8	9	10	11	Total years
1991	0.013495	0.025057	0.021237	0.015755	0.01821	0.020288	0.012721	0.029358	0.015707	0.009093	0.015347	0.196268
1992	0.011685	0.025675	0.015849	0.013891	0.014342	0.014878	0.01182	0.027639	0.019226	0.010255	0.012743	0.178001
1993	0.011919	0.023414	0.013148	0.018539	0.012977	0.016693	0.012682	0.019059	0.015939	0.008377	0.011111	0.163858
1994	0.005761	0.021014	0.011119	0.014201	0.010787	0.01606	0.011713	0.019756	0.015651	0.004494	0.010542	0.141098
1995	0.006869	0.019514	0.010489	0.012725	0.012942	0.015713	0.009672	0.016865	0.016573	0.003382	0.011277	0.13602
1996	0.005735	0.018412	0.009913	0.016371	0.01152	0.0155	0.010681	0.020719	0.016406	0.0042	0.01178	0.141235
1997	0.005281	0.019004	0.009001	0.012829	0.014728	0.015448	0.01086	0.019917	0.016384	0.006082	0.008548	0.138083
1998	0.003984	0.017889	0.010881	0.019724	0.013154	0.013884	0.007656	0.01426	0.014587	0.006805	0.008515	0.13134
1999	0.002722	0.010419	0.008043	0.007544	0.007485	0.007563	0.003772	0.006655	0.009932	0.02217	0.021858	0.108162
2000	0.002297	0.008083	0.005755	0.007689	0.007517	0.005357	0.003585	0.007542	0.006864	0.021555	0.016166	0.09241
2001	0.001201	0.006563	0.003828	0.005118	0.005155	0.00368	0.003384	0.006333	0.003938	0.015424	0.012051	0.066673
2002	0.000684	0.00749	0.003912	0.003329	0.004252	0.002821	0.002619	0.005792	0.003398	0.018164	0.008537	0.060997
2003	0.001742	0.006839	0.003595	0.006198	0.003332	0.001801	0.004101	0.004882	0.003888	0.015698	0.008747	0.060823
2004	0.000439	0.005837	0.002914	0.003537	0.004111	0.003608	0.001936	0.006735	0.003633	0.016063	0.010904	0.059717
2005	0.000858	0.004109	0.003829	0.002605	0.003281	0.002942	0.001984	0.002743	0.003031	0.010423	0.007806	0.043611
2006	0.000873	0.002955	0.002589	0.002812	0.00377	0.003487	0.00112	0.002305	0.002229	0.009533	0.009123	0.040795
2007	0.00082	0.003582	0.003807	0.002901	0.002671	0.002443	0.001875	0.001901	0.002848	0.008855	0.007965	0.039667
2008	0.000587	0.004238	0.002709	0.003392	0.002943	0.001092	0.001896	0.002093	0.001864	0.007739	0.007881	0.036434
Total Regions	0.076952	0.230092	0.142618	0.169159	0.153176	0.163259	0.114075	0.214553	0.172097	0.198311	0.200899	

Source: British Household Panel Survey (BHPS).

Table (A1.4) Actual Wage Residuals on the regional and yearly levels for middle-skilled labour in the UK (1991-2008)

Regi on / Year	1	2	3	4	5	6	7	8	9	10	11	Total years
1991	0.012677	0.03794	0.025139	0.02013	0.019962	0.033651	0.025473	0.060536	0.033355	0.011686	0.029732	0.31028
1992	0.011564	0.04092	0.019748	0.023166	0.023459	0.024948	0.035822	0.053646	0.040534	0.012473	0.029605	0.315885
1993	0.011784	0.042684	0.024669	0.019418	0.023416	0.030411	0.036567	0.054108	0.044385	0.009445	0.035551	0.332438
1994	0.010436	0.044272	0.02608	0.021023	0.027848	0.031748	0.029921	0.059732	0.036265	0.013091	0.023637	0.324053
1995	0.014557	0.036974	0.024067	0.023766	0.02691	0.034898	0.028682	0.052186	0.036461	0.009458	0.019941	0.307901
1996	0.013648	0.029179	0.022253	0.024816	0.026061	0.027658	0.031171	0.053697	0.034907	0.009289	0.022389	0.295068
1997	0.010146	0.036428	0.02242	0.023932	0.025479	0.026319	0.026527	0.045693	0.031205	0.010233	0.0226	0.280982
1998	0.008346	0.028583	0.021044	0.026735	0.026984	0.026775	0.024068	0.040327	0.026818	0.010704	0.013907	0.254292
1999	0.006636	0.020576	0.01452	0.015942	0.015809	0.02181	0.014519	0.026555	0.018441	0.044707	0.048479	0.247992
2000	0.004739	0.0188	0.012826	0.011715	0.015631	0.018199	0.01264	0.026482	0.016217	0.035686	0.043163	0.216098
2001	0.005233	0.013876	0.012752	0.009445	0.014058	0.013319	0.009634	0.023138	0.014899	0.034226	0.036574	0.187155
2002	0.003521	0.016252	0.02218	0.010585	0.009942	0.01615	0.009999	0.023571	0.017005	0.036838	0.038091	0.204134
2003	0.003269	0.012181	0.013646	0.013061	0.01121	0.015485	0.011096	0.019206	0.014223	0.034212	0.035699	0.183288
2004	0.004747	0.013247	0.013974	0.010203	0.008699	0.014823	0.009603	0.016024	0.014006	0.035443	0.032148	0.172916
2005	0.002673	0.013324	0.011187	0.008721	0.010852	0.0143	0.008937	0.020271	0.012699	0.032821	0.036075	0.171859
2006	0.00372	0.014907	0.010175	0.012795	0.010296	0.019425	0.007024	0.020161	0.013224	0.031504	0.037695	0.180925
2007	0.003116	0.012897	0.009898	0.011209	0.01358	0.015087	0.009096	0.017903	0.011967	0.036279	0.039213	0.180247
2008	0.003982	0.015828	0.00758	0.011697	0.012803	0.014694	0.008024	0.021748	0.011171	0.034381	0.031071	0.172979
Total Regions	0.134793	0.448868	0.314158	0.298361	0.323	0.399699	0.338804	0.634983	0.427779	0.442476	0.57557	

Source: British Household Panel Survey (BHPS).

Table (A1.5) Actual Wage Residuals on the regional and yearly levels for highly skilled labour in the UK (1991-2008)

Regi on / Year	1	2	3	4	5	6	7	8	9	10	11	Total Years
1991	0.001884	0.014171	0.007655	0.013645	0.011021	0.008582	0.010325	0.020425	0.011537	0.005136	0.009851	0.114233
1992	0.003237	0.01587	0.012571	0.010623	0.014332	0.017598	0.015162	0.02246	0.013604	0.006673	0.014513	0.146644
1993	0.005828	0.015127	0.015341	0.011196	0.01925	0.013051	0.01865	0.027965	0.010989	0.005909	0.015886	0.159193
1994	0.007043	0.015951	0.014365	0.008847	0.017931	0.014856	0.018902	0.027155	0.017835	0.008612	0.015916	0.167413
1995	0.005023	0.017138	0.018153	0.011659	0.023228	0.017562	0.020516	0.024784	0.02347	0.010161	0.016791	0.188486
1996	0.007525	0.019006	0.0199	0.009336	0.023091	0.015015	0.021082	0.025571	0.022837	0.009256	0.013193	0.185812
1997	0.006484	0.017121	0.020019	0.008788	0.019044	0.015785	0.020032	0.031777	0.022973	0.009168	0.015757	0.186948
1998	0.007383	0.022555	0.017845	0.009946	0.016556	0.01879	0.022466	0.037422	0.015987	0.009414	0.017015	0.195379
1999	0.005225	0.015653	0.012885	0.007959	0.01391	0.011783	0.014833	0.027283	0.011565	0.022861	0.038	0.181956
2000	0.005236	0.01501	0.010773	0.010161	0.014282	0.013011	0.014966	0.026959	0.013374	0.024802	0.043293	0.191868
2001	0.006259	0.01327	0.008894	0.008478	0.014993	0.01084	0.014191	0.026383	0.013032	0.024696	0.043941	0.184977
2002	0.006005	0.014932	0.009308	0.007611	0.014192	0.015675	0.023008	0.026015	0.014113	0.02543	0.042529	0.198817
2003	0.006757	0.017462	0.013119	0.007616	0.014433	0.016796	0.01401	0.027177	0.015593	0.027499	0.04098	0.201441
2004	0.004674	0.01798	0.012061	0.009237	0.011785	0.015557	0.013348	0.02899	0.015186	0.031963	0.040626	0.201406
2005	0.004985	0.020812	0.012531	0.012059	0.015002	0.01609	0.010315	0.030646	0.019154	0.028996	0.046033	0.216623
2006	0.006823	0.0231	0.013772	0.01373	0.017918	0.019712	0.011857	0.032582	0.014352	0.034278	0.051274	0.239399
2007	0.005174	0.025785	0.014501	0.010276	0.018038	0.017001	0.010815	0.043363	0.015983	0.038454	0.050651	0.25004
2008	0.00403	0.019102	0.013536	0.011158	0.01848	0.01984	0.012023	0.034871	0.015966	0.039545	0.050516	0.239067
Total Regions	0.099577	0.320045	0.247228	0.182326	0.297484	0.277544	0.286501	0.521827	0.287551	0.362852	0.566764	

Source: British Household Panel Survey (BHPS).

Table (A1.6) Descriptive Summary

Variable	Mean	Standard Deviation
Dependent Variables (Innovation)		
Gini Index	0.3669	0.0339
Atkinson	0.1178	0.0169
Mean Log Deviation	0.2791	0.0448
Theil Index	0.2322	0.0348
Dependent Variable (Wage Shares)		
90%-10% wage inequality	8.0091	1.7565
75%-25% wage inequality	2.6072	0.3514
Top 10% Wage Share	0.2497	0.0134
Top 1% Wage Share	0.0447	0.0086
Bottom 10%	0.0147	0.0023
Independent Variables		
Patents per Million Inhabitants	78.6781	41.9739
Net Migration	8.1061	13.5232
Unemployment Rate	0.0666	0.0230
GDP Per Capita in Constant Prices-PPS	29173.26	15142.98
Other Independent Variables (Individual Characteristics)		
Age Groups (Percentage from the total Sample Group)		
Age group < 25	0.1782	0.0216
25 =< Age group < 34	0.2318	0.0382
34 =< Age group < 44	0.2591	0.0294
44 =< Age group< 54	0.2077	0.0224
Age group => 54	0.1233	0.0295
Female Participation	0.5187	0.0211
Private Sector	0.0012	0.0007

Table (A1.6) Descriptive Summary (continue)

Variable	Mean	Standard Deviation
Other Independent Variables (Within Skilled Groups) (Percentage from the total sample Group)		
Highly Skilled Natives Labour	0.2373	0.0908
Low-Skilled Natives Labour	0.1141	0.0517
Highly Skilled Immigrants Labour	0.0184	0.0394
Low-Skilled Immigrants Labour	0.0364	0.0623
Other Independent Variables (Between Skilled Groups)		
Highly skilled Natives/Low-skilled Immigrants	2.8976	2.6360
Highly skilled Immigrants/Low skilled Natives	2.9376	2.6338

Table (A1.7) Relevance and Reliability (GMM & TSLS Heteroskedasticity)

Method	Sargan-J (P-Value)	F-First-Stage (P-value)
GMM – Within Groups (without Interaction Term)		
Gini Index	0.6753	0.0000
Atkinson	0.7379	0.0000
Mean Log Deviation	0.9485	0.0000
Theil	0.553	0.0000
GMM – Within Groups (with Interaction Term)		
Gini Index	0.7126	0.0004
90%-10% wage inequality	0.2556	0.0006
75%-25% wage inequality	0.1405	0.0001
Top 1%	0.4027	0.0090
Top 10%	0.6873	0.0011
Bottom 10%	0.8548	0.0000
GMM- Between Groups (with Interaction Term)		
Gini Index	0.7892	0.0002
Heteroskedasticity- Within Groups (with Interaction Term)		
Gini Index	0.1006	0.0000
Top 1%	0.4211	0.0000
Top 10%	0.6969	0.0000
Bottom 10%	0.6551	0.0000
Heteroskedasticity- Between Groups (with Interaction Term)		
Gini Index	0.1467	0.0000
European Regions		
Gini Index-All European regions	0.3251	0.0000
Gini Index- European regions excluding (UK, Germany, and Sweden)	0.4078	0.0000

A2. Methodology of measuring wage inequality

To estimate the measures of wage inequality percentile shares, we follow the method developed by (Binder and Kovacevi, 1995). This method is easy to use and applicable to different sampling designs. The percentile shares for a sample of size (N), wage (W), and observation (i) are estimated by the following function: -

$$S^{\wedge}(p_1, p_2) = L_N^{\wedge}(p_2) - L_N^{\wedge}(p_1)$$

Where $L_N^{\wedge}(p)$ represents the estimation of Lorenz Ordinates and equals $[(1-\gamma)W_i^{\sim} + \gamma W_{i+1}^{\sim}]$. Note that $p_i^{\wedge} \le p \le p_{i+1}^{\wedge}$, with $p_i^{\wedge} = \frac{i}{N}$, $\gamma = \frac{p-p_i^{\wedge}}{p_{i+1}^{\wedge}-p_i^{\wedge}}$, and $W_i^{\sim} = \frac{W_i}{\sum_i^N W_i}$. By constructing these estimates, we end with different percentiles of wage distribution that include the middle 80%, middle 50%, top 10%, top1%, and bottom 10% of the distribution.

Another most used measure of inequality is the Gini coefficient, mainly based on Lorenz Curve. It is calculated by utilizing the following formula (Cowell, 2000): -

$$I_{Gini}(F) = \frac{1}{2\mu(F)} \int \int |w - w'| \, dF(w) dF(w')$$

This coefficient has many advantages, one of them is its ability to solve the negative values of wages (Stich, 1996), which is considered a problem in measuring wage inequality. We follow (Ourti and Clarke, 2011) to reduce the downward bias in such estimates. The methodology used in this paper depends on the number of individuals in each group, in which downward bias is reduced by taking the first-order correction term.

Finally, we estimate two other measures (Generalized Entropy Index (G.E.) and Atkinson Index) that are clarified by (Biewen and Jenkins,2006) as follows: -

$$I_{GE}{}^{\alpha}(F) = \frac{1}{\alpha^2 - \alpha} \int \left[\left[\frac{w}{\mu(F)} \right]^{\alpha} - 1 \right] dF(w) \ , \forall \ \alpha \neq 0{,}1$$

$$I_{Atkinson}^{\varepsilon}(F) = 1 - \frac{1}{\mu(F)} \left[\int w^{1-\varepsilon} dF(w) \right]^{\frac{1}{1-\varepsilon}},$$

Where ε is the inequality aversion parameter and α is the weight of the distances between wages at different parts of the distribution, it is worth mentioning that Theil Index and Mean Log Deviation are particular cases of the Generalized Entropy Index. The Theil Index represents $(\alpha \to 1)$, and the Mean Log Deviation represents $(\alpha \to 0)$.

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