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Innovation and skill premium*

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Abstract

The relationship between innovation and skill premium is analysed on a panel of 12 countries for a 16 year span (2000-2015). According to a Schumpeterian view, a non–linear relationship between innovation and skill premium is found showing a threshold effect that reverses the relationship for relatively high levels of innovative activity. Moreover, the relationships change from convex to concave when variables representing different types of innovative activity are considered. In fact, with R&D a positive relationship with skill premium reverses once a threshold is exceeded, while the opposite holds for patents, for which the relationship is initially negative and then becomes positive. We argue that this is due to the different degrees of approriability of the knowledge produced by innovators with these activities. We then show how to exploit these different patterns to provide a truly innovation–based analysis of the patterns of skill premium for United States, France, Germany and Great Britain.

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1 Introduction

Since the seminal contribution of Kuznets (1955), the analysis of inequality has become a central topic in the economic literature. As capitalism progresses through successive waves of development, inequality emerges from the structural change caused by transition patterns between sectors with different productivity as result of differential innovative capacity. Although Kuznets himself was well aware[1] of its limits, his model had a wide impact on the literature on inequality and growth, becoming the centrepiece of the debate aimed at empirically assessing a sort of 'natural' association between stages of growth and levels of inequality.

The relationships between innovation and inequality is the core of a very important research program (for a thorough account see Saint-Paul, 2008) on the skill–biased technical change hypothesis, started by the seminal work of Krueger (1993). The stream of literature that followed (Acemoglu, 1998; Goldin and Katz, 1998; Autor, Katz, and Krueger, 1998; Caselli and Coleman, 2002) stressed that as the level of technological change of an economic system increases, firms will need workers with a higher skill level to deal with the new technology (see Levy and Murnane, 1992, for an early survey). As the relative demand for highly-skilled workers with respect to low-skilled ones increases, the wage gap between these two categories of workers is expected to widen.

In the period 1970-1989, in front of an average growth of weekly wages of working men in US of about 20%, the least skilled ones obtained a 5% increase, to be compared to the 40% increased obtained by the most skilled workers. As a result, in 1989 wages were 15% higher than in 1970 for the latter category of workers, and 5% lower for the former one (Juhn, Murphy, and Pierce, 1993).

In these contributions, technical change was conceived predominantly as the adoption and the use of personal computers: thus, a skill bias technical change emerged as computers became widely adopted, favouring skilled workers able to work with them (Katz and Murphy, 1992). As a consequence,

[1] "This is perhaps 5% empirical information and 95% speculation, some of it possibly tainted by wishful thinking" (Kuznets, 1955, p. 26).

in the period 1984-89, Krueger (1993) estimated that the impact of the increasing utilisation of computer–based technical change increased the wage of the workers using it by 10 to 15 percent. Hence, the diffusion of computers contributed from 1/3 to 1/2 of the rate of return to skilled workers.

A more recent set of contributions has emphasised the differences in job tasks rather than in skills in explaining inequality patterns in wages (Autor, Levy, and Murnane, 2003; Acemoglu and Autor, 2011; Autor and Dorn, 2013; Beaudry, Green, and Sand, 2014). The model proposed explained a large fraction of the shift in demand triggered by decreasing computer prices in the task composition, although with nominally unchanged occupations (Autor, Levy, and Murnane, 2003, p. 1321). The rationale is that technology (i.e. computers) can replace workers employed in professions that are characterised by relatively more routinised tasks (or associated with lower cognitive contents), and is complementary to workers employed in non–routinised jobs, with higher (or more complex) cognitive content associated to their constituent tasks. If the two types of tasks cannot substitute one for another, then the effect of technological change is to reduce the need for routine–based tasks that can be substituted by 'machine programmed rules'. On the contrary, it will increase non routine problem–solving creative and complex tasks. As evidenced by Autor and Dorn (2013) and Goos, Manning, and Salomons (2014), these dynamics have brought about the polarisation of labour markets in both Europe and the US with an increase in the employment and wages of the tails of the occupational skill distribution.[2]

However, it has been pointed out that also the structure of the labour market, especially the relative weight of skilled workers with respect to the overall labour supply, affects the behaviour of employers in the adoption of technologies. On the one hand, if there is an increase in low-skilled labour supply, as it happened in the XIX century, then the technologies adopted tend to be skill–replacing. On the other hand, when one observes a surge in skilled labour supply, as it happened in the XX century, employers pushed for the adoption of skill–biased techniques (Acemoglu, 2002). In this approach, changes in relative prices will induce the adoption of new production processes; the now more expensive production factor (labour) will boost the process of introducing inventions aimed at decreasing its

[2]It is also worth stressing that task offshoring can have similar restructuring effects to those stemming from the extensive introduction of computers (Grossman and Rossi-Hansberg, 2008).

use. These mechanisms of induced technological change have been recently embedded within a Schumpeterian framework of analysis based on the notions of both creative destruction and localised knowledge as key production factors (Antonelli and Feder, 2020; Antonelli and Tubiana, 2020). Accordingly, the efficiency wage approach (Shapiro and Stiglitz, 1984; Antonelli and Scellato, 2019) shows that the bigger the firm size the higher the effort-inducing wage. As a result, assuming a non–zero elasticity of substitution production function, the bigger the firm, the higher its propensity to invest in capital intensive production processes aimed at economising the use of labour.

Overall, evidence of increasing inequality levels between differently skilled occupations due to technical progress have been investigated by a vast and diverse stream of the economic literature, both theoretically and empirically. However, when it comes to measure technical progress, these studies tend to restrict the analysis to the introduction of computers thus somewhat neglecting the role played by different innovative activities, such as R&D and patenting.

It is also worth noticing that this stream of the economic literature has often missed to test the hypothesis of a non-linear relationship between innovative proxies and inequality. Indeed, for instance, Aghion, Akcigit, Bergeaud, Blundell, and Hémous (2019) highlight a positive correlation between top income shares and innovation as proxied by flows of granted patents per capita. In this case, the estimated coefficients associated with patents show a positive and a statistically significant sign, although the possible prevailing of a non linear relationship between these two variables is not addressed.

Even the literature on skill–biased technical change does not address possible non linearities in the relationship between R&D and wage inequality.[3] In this stream of the literature the link between wage/income inequality and R&D, used as a proxy of technical change, always turns out to be monotonic and positive.

However, in diverse strands of the literature different innovative activities are found to bring about different microeconomic implications on inequality. Hatipoglu (2012) estimates the impact of income inequality on innovative activity as proxied by the amount of patents granted and addresses the potential non-linearity of this relationship, by finding a threshold at which

[3] See, among the others, Aghion, Caroli, and Garcìa-Penãlosa (1999), Nolan, Richiardi, and Valenzuela (2019) and Chusseau, Dumont, and Hellier (2008).

the relation reverses sign.

Chu and Cozzi (2020) find, within a Schumpeterian approach, that increased R&D levels spurred by subsidies have less univocal effects, possibly resulting in a non-linear relationship. In fact, on the one hand increased R&D spending can boost economic growth, causing interest rates to rise. This generates an asset-value effect capable to affect inequality. On the other hand, R&D spending is also likely to negatively affect asset income via creative destruction. Interestingly, similar evidences concerning the relationship between R&D and income inequality were found also by making reference to further non-monetary factors such as the segmentation of labour markets. Osorio and Pinto (2020) find a positive relationship between R&D spending supported by public incentives and inequality due to differential remuneration between high and low skilled workers. In their model, knowledge spillovers are expected to turn this relationship into a non-linear one although this effect is described as "less clear-cut". Finally, skill heterogeneity can explain the non-linear nature of this relationship also when reference is made to a quality-ladder growth model a la Acemoglu (Chan, Yang, and Zheng, 2022).

As technology is a crucial element for the wage structure (see Lemieux (2008) for a sceptical view), other factors must be accounted for in order to fully understand it (Acemoglu, 2002; Aghion, Caroli, and Garcìa-Penãlosa, 1999). These factors affect the mechanisms regulating not only the wage structure but also, more generally, income distribution. We refer, in particular, to globalisation (Van Reenen, 2011) and to institutional factors, especially those affecting the working of the labour market (see, for instance, Huber and Stephens (2014); Lamont, Beljean, and Clair (2014)).

As for the former, the analysis of the effects of globalisation on wage inequality parallels that on the analysis of the consequences of the intensive introduction of computers in production of goods and services. In two seminal papers, Wood (1995, 1998) claims a negative impact of the expansion of trade with developing countries on low-skilled workers' wage in developed countries. However, Milanovic and Squire (2005) state that the effects of trade tariffs reduction on wage inequality, measured as education premium, are positive despite a rather weak and not conclusive evidence from an econometric point of view. One of the problems pointed out by the authors is the difficulty to disentangle the consequences of globalisation with the effects brought about by some radical changes such as the introduction of labour reforms and pervasive technological change. In accordance with Milanovic and Squire (2005), Helpman (2016) maintains that globalisation can explain only a fraction of the increase in wage inequality and that skill–biased technical change might play a bigger role in the widening of the gap between high and low-skilled workers' wage.

As for the latter, we can identify several different, even though not mutually exclusive, approaches to the analysis of the wage gap between skilled and unskilled workers.

The human capital approach provides a supply–side perspective to the determination of the wage gap between skilled and unskilled workers based on the years spent in both school and training. According to this model (Becker, 1964; Mincer, 1974) workers' earnings are positively related to school education, training in the workplace and a set of individual characteristics — such as individual ability, length of working experience and the so–called soft skills (such as teamwork, personal habits, time management, etc.). In short, within this approach the wage gap depends on the investments in schooling and on–the–job training as well as individual ability.

In a similar vein as the human capital theory, but within the institutionalist approach, Thurow (1975) worked out the queue theory. Conversely from the human capital theory, wage fixing is not only the result of an appraisal of marginal productivity but it is also set by a process of wage bargaining between the employer and the unions. Accordingly, the wage gap has two main determinants. At a macro level, centralised negotiation between unions and the representatives of employers regulates the gap; at a micro level, the wage gap is tuned within the firm according to the idiosyncratic evaluation of marginal productivity differentials between skilled and unskilled workers. In another contribution emphasising the role of labour demand, Doeringer and Piore (1971) maintain that, in comparison to small firms, in large firms the structuring of internal labour markets allows for longer career paths and favours upward mobility, especially for skilled workers. Accordingly, the wage gap between high and low-skilled workers is likely to be wider in large firms.

The literature about the skill mismatch in labour markets is huge and would deserve at least a whole paper to survey it thoroughly (see, for instance, Brunello and Wruuck, 2019). Although this literature is still in evolution and has not reached a wide consensus on a substantial amount of research questions yet, a few contributions in this field of analysis can provide useful hints about the determination of the wage gap between skilled and unskilled workers. In this case, wage inequality does not depend on individual skills only, but also on the operation and the structure of labour markets and hence on how the market for skills reacts to unbalances between demand and supply. Whenever demand for skills exceeds supply, wage inequality between skilled and unskilled workers soars, while when the skill supply keeps up with demand, this gap attenuates.

Another set of factors can be identified, namely, the minimum wage and the process of de–unionisation. As far as the minimum wage is concerned, OECD (2015) surveys the huge amount of literature evidencing the negative role played by statutory minimum wage on wage inequality by pushing up remunerations at the bottom of the wage distribution. This effect heightens if firms enjoy monopsonistic power in the labour market. As to the process of de–unionisation of wage bargaining, Jaumotte and Osorio (2015) produce evidence of both de–unionisation in advanced economies and of its positive effects on skill premium. Following this line of reasoning, further empirical evidence is provided by Belloc, Burdin, Cattani, Ellis, and Landini (2022) who highlight the interplay between job design and employee representation at a firm level, finding a negative relationship between the latter one and automation risk. It seems plausible to claim that, as the low-skilled workers have a lower individual bargaining power, their wages has been more severely hit than the highly skilled workers' wages.

Finally, the rent–sharing approach (Juhn, McCue, Monti, and Pierce, 2018; Card, Cardoso, Heining, and Kline, 2018) outlines another possible source of thickening of the wage gap between skilled and unskilled workers. Within a monopsonistic setting, Card, Cardoso, Heining, and Kline (2018) show that more profitable firms hire not only more productive workers but they tend to award higher wage premium than less productive firms. However, this rent–sharing process between employers and workers is not equally distributed among workers with different skill levels. Juhn, McCue, Monti, and Pierce (2018) estimate that higher–skilled workers appropriate a higher quota of the firm's rent as they possibly enjoy a higher capability to create a potential hold–up inducing firm's under investment (Card, Devicienti, and Maida, 2014).

The literature review has thus highlighted a non-linear relationship between innovation and skill premium. However, the are two main gaps in the literature that this paper will address.

The first is related to the qualification of the innovative proxies. We posit that different proxies have different meanings and thus different impacts. If we consider the knowledge production function, we easily see that while R&D is an input of this function, patenting activity is an output of this same function. Therefore, the use of one or another is not neutral in terms of the way innovative activity in broad terms enters the picture. We thus reckon that this is a relevant gap in the literature that we will address both theoretically, by building a model that account for their different roles, and empirically, by estimating a two-step model of the knowledge production function.

The second gap in the literature that is addressed in this paper is related to the fact that non-linearity must be better qualified. Indeed, we posit that different types of innovative activity impact differently on the skill premium, depending on their non–linear relationship with the quasi-rents they deliver to firms. We build our hypotheses starting from the rent-sharing framework thus arguing that skilled workers enjoy higher levels of bargaining power compared to their unskilled peers thus allowing them to obtain larger shares of the quasi-rents deriving from innovative activities and distributed between employers and employees within innovative firms.

Moreover, from the theoretical model we derive different patterns in the non-linear relationships, because of the different degree of appropriability of the knowledge produced with the innovative activity. Namely, when R&D intensity is relatively low, an expansion of R&D spending is associated with larger skill premiums while this correlation turns negative for relatively high levels R&D. The opposite holds for patents, for which the relationship is initially negative and then becomes positive.

We thus empirically test the non-linear relationship between innovation and skill premium on a panel of 12 OECD countries over a 16 year span (2000-2015), finding that the relationship changes from convex to concave when variables representing different types of innovative effort are considered. We then show how to exploit these different patterns to provide a truly innovation–based analysis of the patterns of skill premium for United States, France, Germany, and Great Britain.

The paper is organised as follows. Section 2 will present a model of innovation and the skill premium, and the identification strategy. Section 3 will detail the main characteristics of the dataset and of the methodology adopted. Section 4 will offer an articulated discussion of the results, and section 5 will provide a consequent vision of the relationships between innovation and skill premium. Finally, section 6 will provide some concluding remarks.

2 The model

2.1 Wage gap and innovative activity

The literature quoted above is unanimous in highlighting the role of technological change in producing wage disparities between skilled and unskilled workers. However, as sketched in the introduction, the results do not seem very robust because in many of these contributions the role of innovative activity is treated unsatisfactorily. On the one side, the use of innovative activity is often limited to the introduction of computers, or technologically advanced machinery, on the other side, either inputs or outputs of the innovative process are used to proximate innovative activity, without making proper distinctions among them. Finally, even the direction of the relationships is difficult to understand. Therefore, we propose to approach this problem adopting a Schumpeterian perspective to understand the relationship between technological change and the wage structure.

At this regard, Schumpeter worked out two frameworks in two different contributions (Schumpeter, 1934, 1947). Innovation is the engine of economic progress and is the main determinant of the structural dynamics of economic systems. At first, innovation acts in favour of the first mover (the entrepreneur) who can thus appropriate higher income levels because of her capacity to exploit her innovative ability (i.e. she will be the most talented or, in Schumpeter words, a "leader"). One can assume that a fraction of this augmented income will be distributed to the entrepreneur's high–skilled workers. Innovation activities need high–skilled workers. The surplus generated by innovation can flow towards either profits or wages. On the one side, higher wages to high–skill workers are paying their higher productivity, on the other side, the entrepreneur will be willing to pay higher wages to the high–skilled workers to give them incentives to update the skills necessary to the development of innovative activities.

For the purpose of this paper, we distinguish between the so called Schumpeter Mark I and Mark II. Schumpeter Mark I refers to Schumpeter early work (Schumpeter, 1934), in which innovation is brought into a (general) equilibrium setting by the entrepreneur. This behaviour, by destroying the prevalent equilibrium (the so–called creative destruction), confers to the entrepreneur a monopoly profit, that will create better conditions for the high–skilled workers thus widening the wage gap with the low-skilled ones. The process of creative destruction promotes a wave of imitative behaviour that will cause the innovator's rents to be eroded. This reduces the surplus that can be handed out to workers. The speed of this process depends on the industrial structure of the economic system; the higher the number of imitators, the quicker the catching–up process.

Technological change is thus ultimately responsible for the introduction of more efficient production processes. However, the effect on the structure of wages follows a non linear and non monotonic path as a result of the amount of surplus (profit) generated by the technological change. In the first stage, as the surplus raises, the wage divide enlarges. In the second stage, when the operation of competition brings about a contraction of the surplus, the wage gap narrows (e.g. Antonelli and Gehringer, 2017).

In this case, as no protection for the use of ideas is in place, we can think of this model as pulled by pure knowledge and that this knowledge, embodied in goods, becomes public knowledge available to the stream of imitators. We thus expect that a small amount of knowledge can confer a competitive advantage, while a bigger one is more easily appropriable by imitators as it generates larger externalities. This is particularly the case for knowledge that is produced with R&D investments.

The late Schumpeter witnessed the establishment of giant corporations with large amounts of investments in innovative knowledge (Schumpeter, 1947). In this case, innovative knowledge is produced in cost centres with the aim of continuously innovating either products or production processes (Schumpeter Mark II). The conversion of this knowledge into an appropriable innovative commodity becomes reason for legal protection through the use of registered patents. In this way, this knowledge favours the establishment of competitive advantage for the innovative firm.

Indeed, when patents are very little diffused, the knowledge regarding an innovation can be relatively easy to understand and thus even in the presence of a patent, it is still possible to appropriate the results of it by trying to circumvent the barriers to appropriability posed by the patent itself. However, as the number of patents increases, the innovation process becomes more and more complex. Hence, the many patents that are now defending the original idea constitute a "protective belt" that is very difficult to overcome, because of (i) the complexity of the technology, (ii) the strategic use of the knowledge 'around' it, (iii) the legally binding difficulties that are created by the high number of patents.[4]

[4] This is confirmed by the recent explosion of the strategic use of patents (Hall, 2004),

In order to work out a rationale for these stylised facts it is useful to set up a heuristic model to spell out the complex relationships among the technological change, the resulting firm's rent and the gap between skilled and unskilled workers' earnings.

2.2 Heuristic model

We introduce a heuristic model aimed at synthesizing the theoretical intuition behind our empirical analyses. To this end, the association between wage inequality, skilled and unskilled workers and technological change will be discussed from two different but not mutually exclusive perspectives. First, one can consider R&D as an output of the knowledge endowment of employment measured through the employees' skills. Starting with Terleckyj (1980), R&D expenditure is considered as a proxy for technological change and for the potential of the productive fabric of a country to introduce innovations aimed at gaining productivity growth. Second, one can consider R&D as an input of a knowledge production function (Griliches, 1979), whose output is measured through patenting activity. An indicator of this activity is another useful quantitative tool for the analysis of technologically induced productivity gains. Besides, one has to take into account that as patenting activity becomes more and more intense, it can also be used strategically to make imitation of innovation more and more complicated.

According to this framework of analysis R&D can be considered as a pure indicator of the pursuit of technological change, which can generate the potential for the creation of quasi-rent. On the contrary, patenting activity can be considered as an indicator of attainment of technological change. R&D and patenting activity also differ as far as their appropriability is concerned. As a matter of fact, while one can easily appropriate the results of R&D, for example through human capital poaching, IPR protection makes the appropriability of patenting activities rather problematic, especially when these activities exceed a given threshold (Hurmelinna-Laukkanen and Yang, 2022).

In non-perfectly competitive product markets, these processes of technologically induced productivity growth yield a quasi-rent to be shared between

which are put in place for reasons that are far from the protection of knowledge as a public good. See, for instance, Cohen, Gurun, and Kominers (2016) about the so–called patent trolls.

employers and employees. Then, the share of the rent accruing to workers is split in turn between skilled and unskilled workers.

2.2.1 R&D as an output

As discussed in the previous section, Schumpeter Mark I claims that innovative activities generate an appreciable amount of surplus, which can be split between profits and wages. Surplus may well have the nature of quasi-rent, as it derives from the productivity gains resulting from R&D and is distributed between employees and employers. Starting from Van Reenen (1996) contribution, which highlights the positive association between wages and successful innovations, Card, Devicienti, and Maida (2014) develop a theoretical setting in which the process of wage determination is affected by the size of the quasi-rent arising in the market for product. In a framework with irreversibility of investments, such as those in R&D, and where capital accumulation is a time-consuming process, the hold-up problem comes out and the distribution of the quasi-rent is bargained between employers and employees. As a result, wage becomes:

$$W = m_1 + c\frac{Q}{L} \tag{1}$$

where W is the wage, m_1 is the alternative wage, Q is the amount of the quasi-rent and c is the workers' bargaining power ($c \in [0, 1]$).

Additionally, if one considers a framework of employment segmented along the skilled/unskilled divide, on the basis of Piekkola and Kauhanen (2003), Fukao, Perugini, and Pompei (2020), Cirillo, Sostero, and Tamagni (2017), Mueller, Ouimet, and Simintzi (2017) and Appelbaum (2017) one can assume that high-skilled employees can appropriate a share of the rent higher than their low-skilled colleagues due to their higher bargaining power. Skill–biased technical change slacks the demand for unskilled workers and, hence, it weakens the bargaining power of this tier of the workforce. Consequently, the high-skilled employees wage encompasses a higher share of rent than the low-skilled workers' wage. In this way the ability of unskilled workers to appropriate a share of the quasi-rent is weak. As a result, these workers receive a wage that is either very close to the statutory minimum wage (e.g., France, Germany) or to the minimum centrally bargained (e.g., Italy, Sweden).

We can thus complement equation (1) to account for two distinct workers' groups with different bargaining power levels, by simply specifying the composition of workers' total bargaining power:

$$c = c_S + c_U \tag{2}$$

where c_S is skilled workers' bargaining power ($c_S \in [0, c]$), c_U is unskilled workers' bargaining power ($c_U \in [0, c]$) and $c_S > c_U$. From this, we can rewrite equation (1) to differentiate for skilled and unskilled workers, separately:

$$W_\lambda = m_1 + c_\lambda \frac{Q}{L} \tag{3}$$

where the subscript $\lambda \in [S, U]$ indicates the type of workers, either skilled (S) or unskilled (U). Consequently, the ratio between W_S and W_U rises when either Q or c are increasing. On the contrary, the ratio between W_S and W_U falls when either Q or c are decreasing. Formally, this means that:

$$\frac{\partial \frac{W_S}{W_U}}{\partial Q} > 0 \tag{4}$$

Having made explicit how the quasi-rent is distributed between employers and employees, thus further discriminating between skilled and unskilled employees, we can now have a closer look at how the quasi-rent is affected by different innovative efforts in the first place. As far as R&D is concerned, one can assume that the quasi-rent rises as firms engage in their innovative efforts starting from scratch. The underlying assumption is that R&D has the nature of a public good thus generating positive externalities for potential imitators. As a consequence, for low levels of R&D these externalities are relatively limited in scope and do not bring about severe appropriability issues.

One can assume that, for low levels of R&D, as this variable increases the production of quasi-rent rises, as well. However, given that R&D results can be replicated relatively easily, the catching up process starts to operate effectively and, hence, one can observe that depending on the value of $R\&D$ being below a certain threshold ($\widehat{R\&D}$), we have:

$$R\&D = \underline{R\&D} \text{ if } R\&D < \widehat{R\&D} \tag{5}$$

which implies that

$$\frac{\partial Q}{\partial \underline{R\&D}} > 0 \tag{6}$$

However, when firms expand their innovative efforts beyond the threshold $\widehat{R\&D}$ starting from relatively higher levels of R&D, the larger knowledge base is more easily appropriable by imitators as it generates larger externalities thus obliterating the initial competitive advantage of the leading firms. As a consequence, further expansions of investments in R&D have a negative impact on the quasi-rent at this stage. We thus have:

$$R\&D = \overline{R\&D} \text{ if } R\&D > \widehat{R\&D} \tag{7}$$

which in turn implies:

$$\frac{\partial Q}{\partial \overline{R\&D}} < 0 \tag{8}$$

Following equations (3) and (4), we note that the ratio $\frac{W_S}{W_U}$ proceeds along with the amount of the quasi-rent, Q. This implies that, for low levels of R&D:

$$\frac{\partial \frac{W_S}{W_U}}{\partial \underline{R\&D}} > 0 \tag{9}$$

while the opposite is true when firms engage in R&D activities starting from a relatively larger knowledge base:

$$\frac{\partial \frac{W_S}{W_U}}{\partial \overline{R\&D}} < 0 \tag{10}$$

2.2.2 R&D as an input

Griliches (1979) introduced the knowledge production function in which a measurement of productivity is associated with an indicator of knowledge capital. Audretsch and Feldman (2004) develop this approach and represent the knowledge production function as a standard Cobb-Douglas function given by:

$$I = R^{\alpha} HC^{\beta} \tag{11}$$

where I is an indicator of innovative output, R is expenditure in research activities and HK stands for some measurement of human capital. Borrowing from Kang and Dall'erba (2016) we use patents as indicator of innovative outputs and R&D as an input. Hence we can rewrite the knowledge production function as follows:

$$ln(Pat) = \alpha ln(R\&D) + \beta ln(HC) \tag{12}$$

Following Crepon, Duguet, and Mairesse (1998), we also model labour productivity within the framework of an augmented Cobb-Douglas production function accounting for employment, patents as proxies of innovative activities, skill composition and physical capital. From this one obtains:

$$ln(y) = ln(\alpha) + \beta ln(K) + \gamma ln(L_U + eL_S) + \delta ln(Pat) \tag{13}$$

where y is labour productivity, α is a constant, K is the level of capital intensity, L_U and L_S are the level of unskilled and skilled labour, respectively, e is an indicator of the efficiency of skilled labour.

As outlined in section 2.1, Schumpeter Mark II devised an analytical framework in which the economic exploitation of patenting activity follows a non-linear path. Kline, Petkova, Williams, and Zidar (2019) maintains that patent activity increases within-firm inequality. This can be true as long as the amount of patenting is high enough to hinder imitation and to favour the extraction of quasi-rent. As a matter of fact, when patenting activity remains low, imitation turns out to be quite simple and, therefore, the extraction of quasi-rent rather problematic. For this reason firms adopt the strategy of inflating patenting activity. Van Pottelsberghe de la Potterie and Van Zeebroeck (2008) show that between 1980 and 1998 firms have split single patents into more narrow breadth ones. Of course, this strategy devalues the single patent but it inflates the patenting activity, discourages imitation and helps protecting quasi-rent gains. This evidence is also confirmed by Forman and Goldfarb (2020) who show that, since the 80s in the overall economy patenting activities in IT has grown considerably despite a decrease in the number of patenting firms. The combination of these two events has resulted into an increase in firm concentration in patenting.

In brief, when patenting activity is not intense and can be easily imitated by competitors, the quasi-rent earned by the leading firms is negatively associated with further patents, as the knowledge encapsulated in them is easily replicable, generates externalities and it is not effectively shielded by legal protection. However, when leading firms engage in further patenting activities and these exceed a given threshold the quasi-rent will start to rise due to ever growing difficulties for imitators to take advantage of the positive externalities linked with the enlarged knowledge base, which will be progressively more and more shielded by legal protections. Therefore, following equation (5) to (8), the quasi-rent function (Q) presents the following properties. If patenting activity is below a certain threshold ($\widehat{Pat}$) we have:

$$Pat = \underline{Pat} \text{ if } Pat < \widehat{Pat} \tag{14}$$

then we get:

$$\frac{\partial Q}{\partial \underline{Pat}} < 0 \tag{15}$$

Conversely, when Patenting activity overcomes the threshold ($\widehat{Pat}$), we get:

$$Pat = \overline{Pat} \text{ if } Pat > \widehat{Pat} \tag{16}$$

that implies:

$$\frac{\partial Q}{\partial \overline{Pat}} > 0 \tag{17}$$

Based on the framework of analysis of rent-sharing among employees and employers discussed in the previous section, one can outline the relation between patenting activity and the ratio between W_S and W_U. As patenting activity and quasi-rent are negatively associated, the ratio between W_S and W_U declines, whereas when patenting activity and quasi-rent are positively associated this ratio rises.

Therefore, if one considers R&D as an output (Schumpeter Mark I), the relationship between technical change and the generation of the quasi-rent comes out as an inverse U-shaped relationship. As a result, since wage inequality proceeds alongside quasi-rent, the relationship between $\frac{W_S}{W_U}$ and R&D presents the same inverse U-shaped profile. However, if one considers R&D as an input of patent activities (Schumpeter Mark II), then the relationship between the latter and the quasi-rent comes out as a U-shaped curve and likewise the relationship between $\frac{W_S}{W_U}$ and patenting activity.

Summarising our insights based on the Schumpeterian approaches Mark I and Mark II one can conclude that the relationship between the skill premium and the expenditure in R&D can be depicted by an inverse U-shaped curve (see Figure 1), whereas the relationship between the wage premium and the number of patents can be represented by a U-shaped curve (see Figure 2).

[Figure 1 about here.]

[Figure 2 about here.]

Our heuristic model is a refinement of the Crepon, Duguet, and Mairesse (1998) framework of analysis. In their heuristic model, R&D and knowledge capital elicit the production of innovative activities which, in turn, fosters labour productivity. The latter is also affected by labour quality. We develop Crepon, Duguet, and Mairesse (1998) approach by introducing a rent-sharing equation that specifies how the surplus is distributed between workers and entrepreneurs. Furthermore, we point out the key role played by technology as a determinant of the wage gap between the skilled and the unskilled workers. R&D and the amount of patents granted are the two technological indicators used in this paper

Two questions deserve special attention in the identification strategy. First, despite R&D and patents granted are both indicators of the intensity of technological innovation in a country, as outlined in the previous section the relationship between each variable and the wage gap is substantially different. Second, the estimate of the relationship between the wage gap and the amount of patents granted can give rise to a problem of reverse causality and endogeneity. As a matter of fact, the wage gap can be the result of patenting activities, as discussed in Schumpeter Mark II. However one can conceive patenting activity as the upshot of a wage gulf that awards considerably the high-skilled workers pushing this component of the workforce to exert more efforts in their search for technological innovation. In order to address this potential source of endogeneity we have resorted to a two-step estimation procedure.

2.2.3 A set of testable hypotheses

Based on the rent-sharing framework, we can thus derive from the Schumpeterian approach to innovation rents two hypotheses that can be empirically tested:

H1. The relation between $\frac{W_S}{W_U}$ and R&D is non linear and convex, and an be graphed by a reverse U-shaped curve

H2. The relation between $\frac{W_S}{W_U}$ and patents granted is non linear and concave.

It can be graphed by a U shaped curve.

It is important to emphasise that these two relationships proceed in parallel. The first hypothesis points out the relation between the relative wage and the pure innovation effort exerted by firms regardless of the results achieved. The second hypothesis points out the relation between the relative wage and the achievement in innovation activities as measured by the set of patents granted to the productive system of a country.

3 Data and estimation strategy

3.1 Dataset and variables

The dataset is a longitudinal panel made of 12 OECD countries (Austria, Belgium, Czech Republic, Finland, France, Germany, Italy, the Netherlands, Spain, Sweden, United Kingdom and the United States) along a 16 years time span (2000-2015), with a potential of 192 total observations that, due to missing values, are restricted to 168 in the estimates obtained from the OLS, fixed effects and two steps specifications described later in this section.

As the selected countries share a more or less common institutional structure and a common set of both formal and informal rules regulating their political and social interactions, this homogeneity guarantees that the main differences in our results are (almost) exclusively due to the techno–economic performance, as evidenced in our heuristic model.

The model used for the regression is the following:

$$\mathbf{SP_{it}} = \mathbf{INN_{it}}\beta + \mathbf{INN^2_{it}}\gamma + \mathbf{Z_{it}}\delta + \mathbf{W_{it}}\phi + \epsilon_{it} \tag{18}$$

The dependent variable ($\mathbf{SP_{it}}$) is the skill premium for country i and year t, and is calculated as the ratio between the proportion of labour compensations (LHS) to the hours worked by high–skilled workers (WHS) and the same proportion for low-skilled workers (LLS and WLS respectively): $SP = \frac{LHS}{WHS} / \frac{LLS}{WLS}$. Data concerning the skill premium are retrieved from the EU KLEMS online databank.[5]

[5]The release used is the following: EU KLEMS Growth and Productivity Accounts: Statistical Module, ESA 2010 and ISIC Rev. 4 industry classification — September 2017 release, Revised July 2018.

The main independent variable ($\mathbf{INN_{it}}$) is the innovative effort, either R&D and patents, that is also squared to check for threshold effects. R&D is measured as the total private and public R&D expenditures per employee of country i at time t (the data are retrieved from the World Bank Open Data databank). Patents are included in our model as the total number of patent grants per 10,000 employees (direct and PCT national phase entries, residents and non–residents) issued in country i at time t (data are retrieved from WIPO databank).[6] In this empirical exercise, we restrict patent data to total patent grants as we are interested in the extraction of a quasi rent from innovative outputs, coherently with the Schumpeterian perspective outlined in Section 2. In particular, firms benefit from a competitive advantage only once legal protection has been granted to their innovations. Clearly, including all patent applications would fairly measure innovation, much like the R&D variable, rather than a legal protection from which the firm can extrapolate a quasi-rent.

$\mathbf{Z_{it}}$ is a set of industrial co–variates, representing the different industrial settings determining the techno–economic production structure of country i in year t. As higher concentrations in terms of market shares and market power can substantially affect the way in which innovation impacts onto wage differentials, according to the institutional and rent–sharing approaches introduced in section 2, we control for market concentration, distribution of firms across size groups and the average labour productivity. Market shares concentration is proxied by a standard Herfindahl–Hirschman Index, retrieved from the World Bank (WITS) Databank. As far as the industrial structure is concerned, we also account for firms' size by including the share of large firms (more than 250 employees) on the total number of enterprises operating in country i in year t. In addition, the average labour productivity is measured as the ratio between total value added and total employed persons between 15 and 65 years old in country i in year t[7]. We also included real gross fixed computer equipment capital formation volume of country i at time t expressed

[6] Data concerning patents are retrieved, as stated, from the WIPO Databank and follow standard imputation procedures outlined by, among the others, the World Bank Open Databank. According to these procedures, patent grants are allocated across time based on application date and to countries following standard fractionalised counting imputation techniques. Patent data used in this analysis cover worldwide patent applications filed through the Patent Cooperation Treaty procedure or with a national/regional patent office.

[7] These data have been exported from OECD's SDBS Structural Business Statistics online data–warehouse.

in 2010 prices in order to take into account the role played by capital and investments in ICT[8] of country i at time t. Finally, we added the degree of openness to international trade $(\frac{Export+Import}{GDP})$[9] of country i at time t.

$\mathbf{W_{it}}$ represents the co–variates for the labour market characteristics of each country i at year t. Once again, the rationale behind the inclusion of such control variables relies in the fact that labour market institutions and its dynamics affect the way in which innovation impacts onto wage differentials. In this case, we include the share of workers holding a degree or tertiary educational attainment on the total labour force, the unemployment rate, and a union density measure. In fact, according to Jaumotte and Osorio (2015), de–unionisation processes are suitable to negatively impact onto skill premium and we assess the extent to which these processes are actually taking place by including the union density rate (percentage share of employees who are union members in country i at time t) from the ILO Industrial Relations Data which are available on the online ILO Stat (SDG labour market indicators) data–warehouse. Finally, we retrieved data concerning workers' educational attainments and unemployment rates from the same databank.

3.2 Estimation strategy

Estimates of these fundamental relationships are obtained with a pooled OLS model, controlled for common time trends with yearly time dummies. In order to deal with the potential non–linear nature of these relationships, the dependent variable as well as the explanatory and control variables, are transformed into natural logarithms, while squared terms of R&D and Patent grants are added to the model to control for the threshold effect.

A potential issue arising from our empirical analysis is represented by the endogeneity of R&D expenditures, consisting in either reverse causality and/or omitted variable bias. The former should be partially addressed by the inclusion of R&D expenditures with a one-year lag in all our specifications. As far as omitted variable bias is concerned, we rule out endogeneity that is due to time-invariant unobservable characteristics of the 12 countries included in the analysis by resorting to a panel Fixed Effects (FE) model. We also run

[8]GDP, national account figures and other monetary measures included in our model are retrieved either from the OECD and/or the World Bank databank and are expressed in millions of dollars PPP constant prices, the base year is 2010.

[9]Data on trade are from the World Development Indicators, available on the World Bank Open Databank.

an alternative Random Effects (RE) model with the same specifications to assess the consistency of the FE with respect to the RE estimator by means of a Hausman test.

Consequently, we alter equation (1) to account for unobserved time–invariant individual effects (α_i) and time effects ($\mathbf{T_t}\tau$):

$$\mathbf{SP_{it}} = \mathbf{INN_{it}}\beta + \mathbf{INN^2_{it}}\gamma + \mathbf{Z_{it}}\delta + \mathbf{W_{it}}\phi + \alpha_i + \mathbf{T_t}\tau + \epsilon_{it} \tag{19}$$

Finally, we follow the methodology developed in Crepon, Duguet, and Mairesse (1998), and run a pooled 2 steps OLS procedure to model, in the first stage, the production of innovation, and then, the relationship between innovation and skill premium, by plugging the predicted values of the first stage as a co–variate into the second stage. Therefore, in the first stage, we estimate a knowledge production function, in which the main innovative output (i.e. patents granted) is function of innovative input (i.e. R&D) and other co–variates ($\mathbf{Z_t}$):

$$\mathbf{PAT_{it}} = \alpha + \mathbf{R\&D_{t-1}}\beta + \mathbf{Z_{it}}\delta + \mathbf{W_{it}}\phi + \mathbf{T_t}\tau + \eta \tag{20}$$

In the second stage, we estimate the skill premium on the same set of co–variates, with the exception of innovation, which is substituted by the predicted value of innovative output obtained in the first stage:

$$\mathbf{SP_{it}} = \delta + \widehat{\mathbf{PAT}}_{\mathbf{it}}\beta + \widehat{\mathbf{PAT}}^{\mathbf{2}}_{\mathbf{it}}\psi + \mathbf{Z_{it}}\delta + \mathbf{W_{it}}\phi + \mathbf{T_t}\tau + \mu \tag{21}$$

Table 1 displays the values of the skill premium for the 12 OECD countries included in the sample for the whole time span (2000-2015). In order to make the data on skill premium easier to compare, data in Table 1 are in percentages. Hence, for instance, highly skilled workers in year 2000 in Austria earned 67.25% more than their non–graduate peers. However, the dependent variable included in our model is expressed as a ratio and, for instance, the relative skill premium for Austria in year 2000 is equal to 1.6725.

It is clear from the figures in Table 1 that no common pattern is shared by all the 12 countries included in the panel where persistence and variability in the series of the outcome variable differ greatly from case to case. Broadly speaking, skill premium increased in Belgium, Finland, Spain, Sweden whereas in the USA and Czech Republic it fluctuated around the mean. However, skill premium associated with holding at least an undergraduate degree shrunk in the period of interest in the Netherlands and, quite dramatically, in Austria, Germany and Italy (from 83% in 2003 to 7% in 2014) especially.

[Table 1 about here.]

Divergent patterns of evolution are displayed when the skill premium is plotted against time individually (Figure 3). Its minimum and maximum ranged in 2000 from 50% (Finland and the Netherlands) to 116% (USA) whereas at the end of the period its minimum reached as low as 12% (Italy) while its maximum remained fairly the same at 110% (USA).

[Figure 3 about here.]

Table 2 shows the main descriptive statistics.

[Table 2 about here.]

Finally, the analysis of the correlation matrix (Table 3) does not reveal multicollinearity problems among the selected co–variates and shows only a correlation between the dependent variables (skill premium) and one of our main explanatory variables (patent grants). In addition, R&D expenditure is only weakly correlated with the output variable, suggesting the need for a more in depth analysis of this relationship.

As far as the co–variates are concerned, the share of large firms and the share of highly skilled and unionised workers reveal interesting correlations with patents and R&D intensity. In fact, either input and output measures of innovative activity tend to increase with shares of large enterprises and skilled workers, whereas the union density plays a differential role showing a negative relationship with patents and a positive one with R&D. As expected, employment representation (i.e., union density) is negatively correlated with the skill premium thus reducing wage differentials among different categories of workers.

[Table 3 about here.]

4 Main results

The model used for our main estimation results is a pooled OLS regression with time dummies: we have estimated three different specifications of the same model allowing alternative and joint inclusion of different types of proxies for innovative activities. Estimates are reported in Table 4: Column

1 displays estimates from the first specification of the model, with inclusion of the R&D intensity variable only; Column 2 displays estimates of the same model including solely patent intensity; Column 3 displays estimates obtained by including both proxies. On the other hand, the three specifications are identical as far as the dependent variable and the sets of controls are concerned.

[Table 4 about here.]

As far as our empirical tests are concerned, the main result we obtained is the strong differentiation between the two variables for the innovative activity (columns 1 and 2 of Table 4 and Table 5). While both R&D and patents granted are statistically significant, their coefficients are rather different. In fact, while the coefficient for R&D is positive (i.e., an increase in R&D intensity produces an increase in the skill premium), that for patent granted is negative.

A partial exception is represented by estimates from the pooled OLS in Table 4, where patent density loses its significance, with P(X)=0.11. Nonetheless, when FE are employed in Table 5 the coefficients associated with R&D and patent density are fairly significant and exhibit the expected signs: positive and negative, respectively.

However, for both R&D and patents a strong non–linearity is present as their respective squared terms are significant and exhibit inverted signs across all specifications both in Table 4 and Table 5, thus revealing a threshold effect. We thus have that the impact of R&D on skill premium is positive until a certain threshold, from which it turns negative. This is in line with our expectations based on the Schumpeterian idea that a little amount of knowledge is rather appropriable (mainly because the externalities produced are small, and thus the knowledge produced spreads relatively thinly). As more knowledge is put at use into the techno–economic system, externalities increase, thus making appropriability to decrease. As a consequence, skill premium declines as well. Indeed, for a firm that can appropriate the knowledge content of its innovative effort, it is easier to make supra normal profits, and thus to benefit more the skilled employees that can produce quality output in line with its innovative content.

What happens for R&D is turned upside down when we consider patent intensity. A little amount of patenting activity produces little innovative knowledge, for which the degree of appropriability turns out to be small, as imitation can easily circumvent the small legal barrier. Firms can try to imitate innovation that are not very intensive of knowledge, and that result to be quite simple to understand, to be reverse–engineered and to be reproduced in a "legal" way. As patenting activity increases, so increases technological complexity (either true or strategic), for which a high level of absorptive capacity is needed, and thus a higher levels of dynamic capabilities in order to be able to understand and reproduce the innovation without violating the legal protection.

This different impact is perfectly in line with our Schumpeterian interpretation of the innovative activity, and fits the idea that the impact of innovative input must be different from that of innovative output, in particular because while one has a direct impact on innovative output performance, and thus on both the labour market and the markets for goods and services, the other has an effect that is mediated by a complex set of other variables.

This impact is robust to an additional estimation obtained with a panel regression with Fixed Effects to account for time–invariant unobservable characteristics across individual countries. The Hausman test confirms this hypothesis as the $\chi^2(8) = 41,86$ strongly rejects the null that the Random Effect model provides consistent estimates. The main results are shown in Table 5.

[Table 5 about here.]

A couple of interesting insights derives from the scrutiny of the controls across Table 4 and Table 5. First, labour markets, as we expected, have a strong influence on the skill premium. Indeed, while higher levels of unemployment increase the skill premium, stronger unions can protect the low–skill employees and make the skill premium to decrease. However, this effect is not significant. The same effect (i.e. to make the skill premium to decrease), although to a smaller extent, is obtained by the increase of the proportion of high–skilled workers. In this case, nonetheless, we obtain very different results according to the types of estimators deployed. In fact, the relationship between the share of HE workers on the total labour force and the Skill premium turns out to be positive in the pooled OLS model (although not significant) whereas the same relationship is negative under the FE estimator. Apparently, this may be due to a sort of scale effect, with relatively rich countries with relatively high shares of HE workers also displaying wider wage gaps. Once fixed effects are included, however, this relationship is read through the lens of the within variability thus showing how *ceteris paribus* a relative increase over time of HE workers is suitable to deflate the Skill Premium. This possible explanation seems especially plausible in case the supply of highly qualified workers outpaces its relative demand. A similar degree of ambiguity emerges with evidences on the openness to international trade, which has a negative effect on the skill premium only in the panel estimation with fixed effects. Also in this case the scale effect seems to be a plausible cause. Positive and significant impacts of the unemployment rate and the endowment of total PC assets are robust across the three specifications in both sets of estimates, with the only exception represented by the loss of significance of the coefficient associated with PC assets when reference is made to the last specification of the FE model. Quite surprisingly, the concentration in the end market for goods and services as proxied by the HH index and the average labour productivity do not seem to play a major role in shaping the wage divide between skilled and unskilled, as witnessed by poor significances and some inversion of signs. In addition, the share of large firms on the total number of firms in a country does have a positive relationship with the skill premium, even if it is significant only in the pooled OLS estimates.

To validate the U-shaped and inverted U-shape relationships, we resort to tests first proposed by Haans, Pieters, and He (2016); Lind and Mehlum (2010) to assess that the turning point of each relationship falls within the range of the relative independent variable and to test the presence of the non-linear relationship, respectively. The first test implies computing the turning point by applying the standard formula for the maximum/minimum of a curve that takes the following form

$$Y = \beta_0 + \beta_1 X + \beta_2 X^2 \tag{22}$$

where the turning point is given by:

$$MAX/min = -\frac{\beta_1}{2\beta_2} \tag{23}$$

In our case, the maximum for the R&D curve is 11.578 while the minimum for the patent density curve is 1.701 when reference is made to last specification in Table 5. Both values fall within the range of these variables in the dataset, as showed in Table 2. As far as the second test is concerned, we implemented the test suggested by Lind and Mehlum (2010) resorting to Stata command utest: when reference is made to the R&D curve, we reject the null hypothesis that the relationship is monotone or U-shaped with T-statistic equal to 1.67 and p-value equal to 0.0616; when reference is made to the patent density and skill premium relationship, we equally reject the null hypothesis that this is monotone or inverse U-shaped with T-statistic 1.62 and p-value 0.0662.

The relationships between innovation and skill premium seems thus to sit comfortably well with our model expectations. Here, what we have is that the more firms invest in their patents portfolio (i.e. innovative output), the more their innovative activity becomes difficult to imitate and the more it is difficult to imitate the more it remains appropriable. Thus a high level of patenting activity implies that the firms can maintain their competitive advantage over the others and if this maintains their level of reward (i.e their monopoly rent) high, it will also maintain a low level of welfare for the rest of the economy, and thus a high level of skill premium.

However, if we evaluate the impact of the innovative input (R&D), it appears to show an opposite impact: it increases the skill premium up to a certain point, after which its impact starts decreasing. The knowledge incorporated into the R&D gets diffused into the techno–economic system as its level increases, and this is in accord with the vision that as soon as an innovation has earned its monopoly rent, the subsequent wave of imitators erode it through a process of imitation and of diffusion of the innovation within the economic system. The erosion of the monopolistic rent in favour of the imitators allows also for an increase of the system welfare, as profits from the innovation get diffused and are beneficial to an increasing number of agents.

These results help clarifying how innovative activity impacts wage inequality through a coherent supply–driven mechanism, with both the inner nature of the innovative activity and the true dynamics determining the skill premium patterns. Indeed, on the one side, innovative activity should not be thought in aggregated terms, but rather in terms of the main elements constituting the so–called knowledge production function (Pakes and Griliches, 1984), Moreover, innovative activity should not be confined to the adoption/diffusion stages only (such as the diffusion of PCs in the economy), but more correctly should be seen in all its components, especially the disembodied ones. From this point of view, that is by looking at a more complete picture, we can also expect firms to adapt their strategies very quickly to changes in the outer environment.

On the other side, firm do not simply adopt superior technologies (such as computers), but work to improve them through complex patterns of both adaptation, marginal and radical modifications. In turn these innovations usually require organisational innovation. Thus, firms are a more complex agent of innovative activity, and this has been (although still partially) captured by the different types of innovative activity introduced in this paper. Firms differ in size, capitalisation, industrial sector, position in the value chain, an so on, and all these differences call forth for idiosyncratic behaviours.

We have also considered that our model could be identified by following the procedure put forward by Crepon, Duguet, and Mairesse (1998). We therefore performed a pooled 2 steps OLS procedure in which we first provided an estimation of the "knowledge production function", and then we plugged the estimated output of the first step in a performance equation linking innovation to skill premium.

In particular, we first regressed the innovation output (i.e. patents) on lagged innovation input (i.e. R&D expenditure) plus a host of co–variates to control for the industrial and labour market conditions, the results of which are presented in column 1 of Table 6.

As expected, in the first stage of our model when innovation output (patents) is the dependent variable, innovative input (R&D) is positive and highly significant. Interestingly, total assets (a proxy for capital), openness, average productivity, share of educated employees all negatively impact (and significantly) patenting activity.

[Table 6 about here.]

The second stage shows that by changing the estimation strategy and by using the predicted patents rather than their effective values, the explanatory power of our model gets even better. Our main explanatory variables are statistically significant and their signs are still coherent with our identification strategy. Patents still have a negative and non–linear impact on the skill premium.

5 A new look at the skill premium

We now show how the results obtained so far can help in shedding some light on the relationship between innovative activity and skill premium.[10]

[10]The data on the skill premium used in this paragraph differ from those used in the previous one. Indeed, on the one side, for France, Germany and Great Britain we used the

In particular, for 4 countries, we plot the skill premium against the ratio between R&D and patents. This ratio shows high values when R&D is high and/or patents are low, and low values when the opposite holds. As outlined in our heuristic model, high value of this ratio should imply, *ceteris paribus*, relatively low levels of wage inequality, as this ratio would pick values for R&D at the right of the turning point and values for patents at the left of the turning point. Contrary wise, low values of the R&D/patents ratio would imply, *ceteris paribus*, higher levels of skill premium, as in this case R&D would gravitate on the left of the turning point and patents on the right of the turning point.

[Figure 4 about here.]

Figure 4 replicate the usual skill premium pattern for US from 1962 to 1997 together with the R&D/patent ratio. The picture that emerges is quite revealing, as the two variables show a clear and robust inverse correlation. The ratio of R&D to patents seems quite able to depict not only the patterns of the skill premium over time, but also its turning points (marked by vertical lines). When the ratio is declining, firms tend to patent more than they research. This in turn allows firms to more than appropriate their innovative effort and thus to benefit from the possible competitive advantage they are able to create with their innovation. This creates a market pressure toward increasing quality products that will benefit skilled workers. The opposite holds when firms are producing more R&D than patents that, being less appropriable, allows for imitative efforts to be more successful and thus constitute a powerful re–equilibrating element for the wages of less technological firms and thus for their less skilled workers.

[Figure 5 about here.]

The graphs for France (Figure 5), Germany (Figure 6) and Great Britain (Figure 7) follow similar patterns. Also in these cases it seems quite clear how the skill premium patterns are very much in (inverse) line with the ratio between R&D and Patents. In particular, also for these three other countries

same source as before (i.e. the EU KLEMS Growth and Productivity Accounts), but we exploited the availability of a longer series, which is taken from the March 2008 Release of that same dataset. On the other side, for US we used the data taken from the publicly available Acemoglu dataset. This obtains two results: i) we have a longer series; and ii) we can make a comparison with the Acemoglu results.

there quite clearly appear to be the same characteristics of the US case: the pattern of skill premium is almost everywhere following the inverse one of the innovative activity, and the turning point seems to be even here almost always coincident (as in 2000 for France, 1997/98 for Germany and 2004 for Great Britain).

[Figure 6 about here.]

[Figure 7 about here.]

6 Conclusions

This paper provides a novel empirical evidence on the relationships between innovation and the skill premium. The relevance of this topic is clearly witnessed by the huge and differentiated literature produced over a very long time span since the seminal contribution of Krueger (1993).

The main drivers of this dynamic process can be identified in the co–evolution of technology, institutional change and globalisation. Technological innovation determines patterns of structural change through the intertwining of the two well–known Schumpeterian mechanisms of, respectively, creative destruction (that increases the skill premium in the economy) and imitative behaviour (that decreases that level). The two are forged by the degree of appropriability of the technological knowledge that has been shown to have a fundamental role in engendering this kind of dynamics. Depending on the way in which innovation production is considered, either as an input or as an output of a knowledge production function, different outcomes result.

The main result of this paper is thus that a non–linear relationship exists between innovation and skill premium, and the nature of this non linearity is different whether innovative input or output are considered. Innovative inputs increase the skill premium up to a point where knowledge spillovers allow imitative efforts that, by increasing the productivity level of the systems, start decreasing it. On the contrary, innovative output decreases the skill premium as long as it is possible to understand its knowledge content, up to the point where the number of patents become so large that either their strategic use or the impossibility to appropriate even part of the knowledge embodied in them allows only the owner to innovate and consequently to increase the wage inequality of the system.

Globalisation impacts the skill premium in different ways, as economic restrictions seem to affect more the production of innovative inputs than that of innovative outputs. Also the labour market institutions have a role as they directly target particular types of employees who can thus benefit more from them.

Finally, the model presented allows to gain fresh insights on the patterns of skill premium. Indeed, there seems to be a close relationship between the direction of the skill premium and that of the innovative activity. Moreover, there seems to be a relationships with the way in which the inputs and outputs of innovative activity happen to be combined within an economic system. Hence, the skill premium is the result of how the different patterns of innovative activity are produced by the different meshing of innovative inputs and outputs. When the ratio of R&D to patenting activity is low, we expect relatively high appropriability for both, thus determining the skill gap to widen. The opposite happens when the ratio is high, implying relatively low appropriability, thus determining a decrease in the skill premium.

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Figure 1: Skill premium and R&D expenditure (per employee)

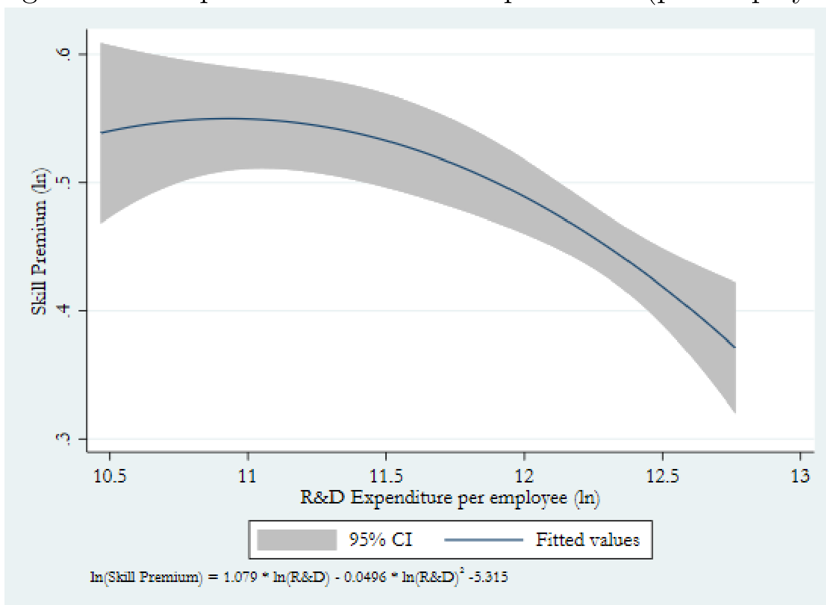

Figure 2: Skill premium and patent grants

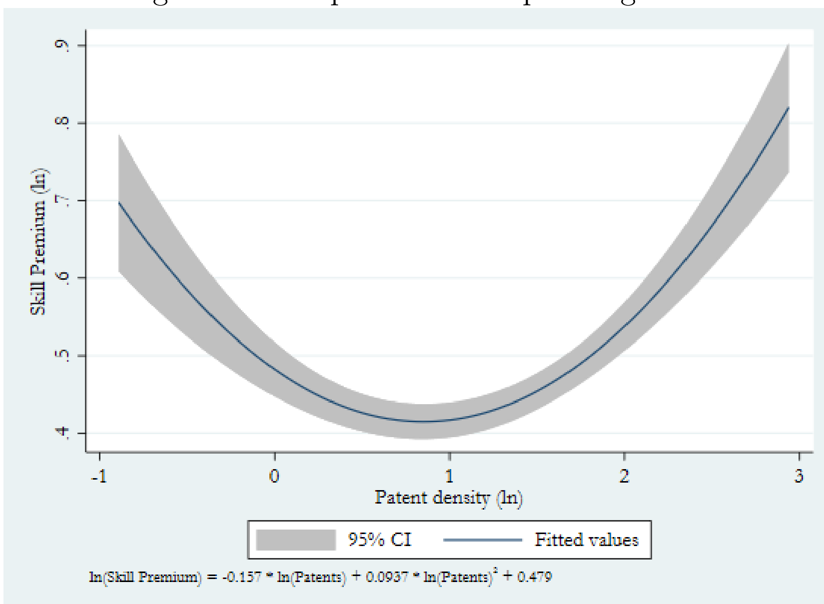

Figure 3: Skill premium over time by country (2000-2015)

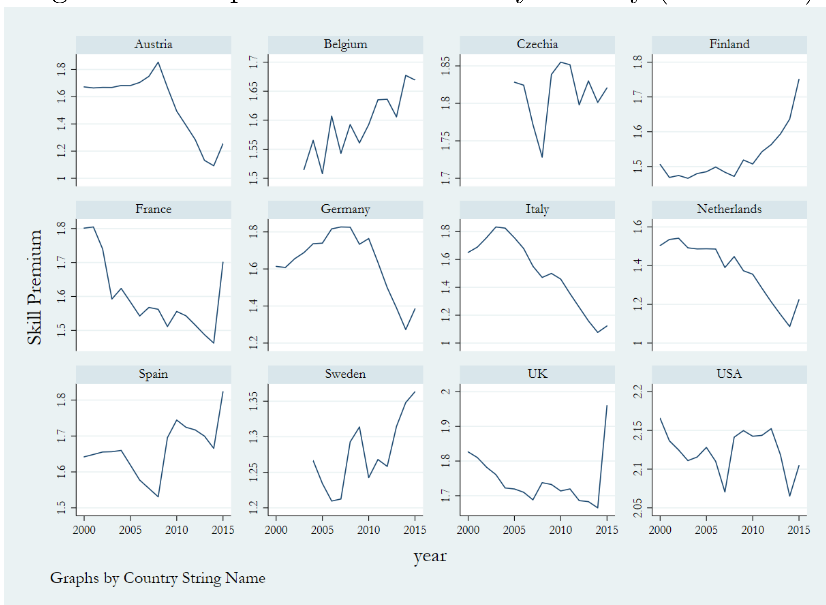

Figure 4: Innovative activity and skill premium in US

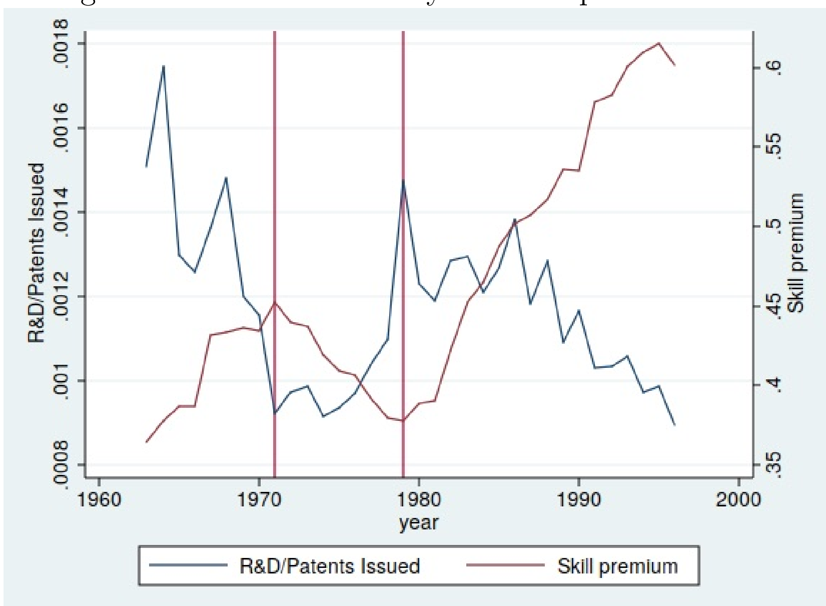

Figure 5: Innovative activity and skill premium in France

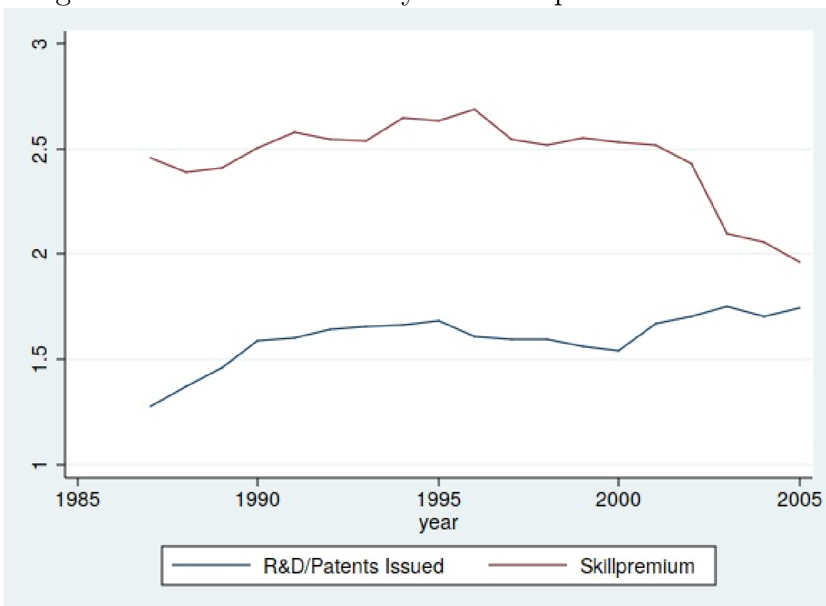

Figure 6: Innovative activity and skill premium in Germany

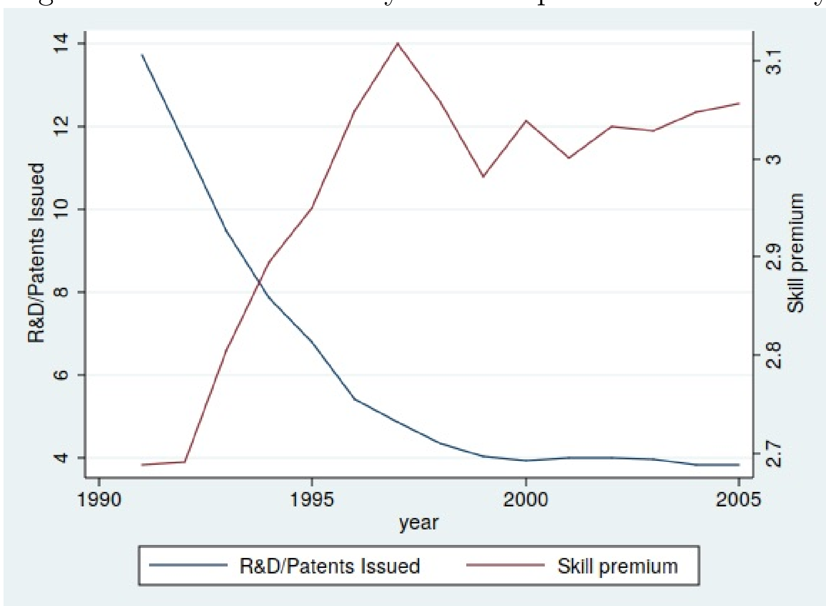

Figure 7: Innovative activity and skill premium in Great Britain

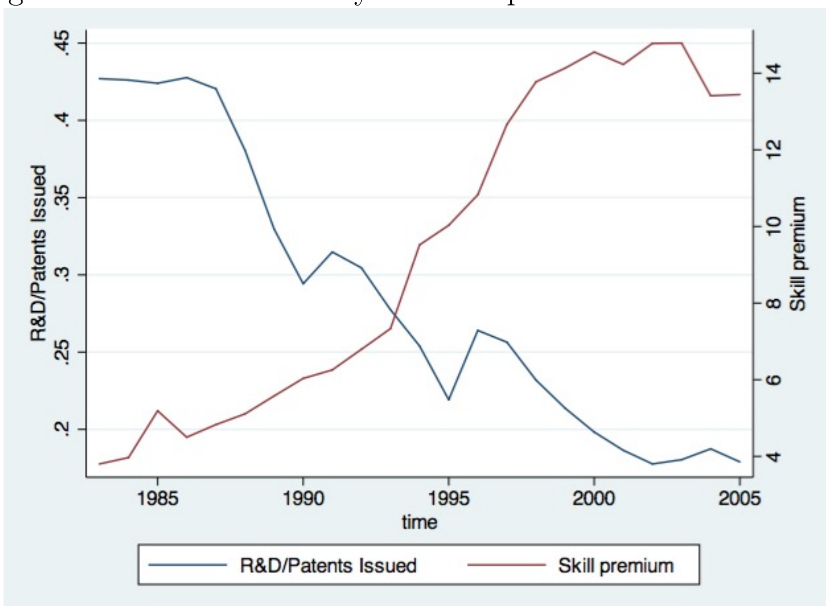

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Table 1: Skill Premium by country (2000-2015)

Year	Austria	Belgium	Czech Republic	Finland	France	Germany	Italy	The Netherlands	Spain	Sweden	UK	US
2000	0,67	-	-	0,51	0,80	0,61	0,65	0,5	0,64	-	0,83	1,17
2001	0,66	-	-	0,47	0,80	0,61	0,69	0,54	0,65	-	0,81	1,14
2002	0,67	-	-	0,47	0,74	0,66	0,76	0,54	0,66	-	0,78	1,12
2003	0,67	0,51	-	0,47	0,59	0,69	0,83	0,49	0,66	-	0,76	1,11
2004	0,68	0,57	-	0,48	0,62	0,74	0,83	0,49	0,66	0,27	0,72	1,12
2005	0,68	0,51	0,83	0,49	0,58	0,74	0,76	0,49	0,62	0,23	0,72	1,13
2006	0,71	0,61	0,82	0,5	0,54	0,82	0,68	0,49	0,58	0,21	0,71	1,11
2007	0,75	0,54	0,77	0,48	0,57	0,83	0,55	0,39	0,55	0,21	0,69	1,07
2008	0,85	0,59	0,73	0,47	0,56	0,83	0,47	0,45	0,53	0,29	0,74	1,14
2009	0,67	0,56	0,84	0,52	0,51	0,73	0,5	0,37	0,7	0,31	0,73	1,15
2010	0,49	0,59	0,85	0,51	0,56	0,76	0,46	0,36	0,74	0,24	0,71	1,14
2011	0,39	0,64	0,85	0,54	0,54	0,64	0,36	0,28	0,72	0,27	0,72	1,14
2012	0,28	0,64	0,8	0,56	0,52	0,5	0,26	0,21	0,72	0,26	0,69	1,15
2013	0,13	0,61	0,83	0,59	0,49	0,39	0,16	0,15	0,7	0,31	0,68	1,12
2014	0,092	0,68	0,8	0,64	0,46	0,27	0,077	0,085	0,67	0,35	0,66	1,07
2015	0,25	0,67	0,82	0,75	0,70	0,38	0,12	0,22	0,82	0,36	0,96	1,10
Mean	0,54	0,59	0,81	0,53	0,60	0,64	0,51	0,38	0,66	0,28	0,74	1,12

Table 2: Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Skill Premium, ln	168	0.469627	0.154537	0.073741	0.766561
R&D Expenditure per employee ($ PPP, OECD b.y, 2010), ln	168	11.93947	.6724256	10.40367	12.76465
Patents Grants per 10k employees, ln	168	3.799125	3.38315	0.411253	18.84123
PC Assets (share of GDP), ln	168	8.302946	1.235071	4.770685	11.44343
Openness to Trade (share of GDP), ln	168	-13.93229	1.312593	-16.93182	-11.96696
Share of large enterprises (250+ eployees), ln	168	-6.0502	0.628688	-7.31887	-4.44373
Average labour productivity, ln	168	-2.55422	0.482096	-3.79527	-1.73078
Herfindhal Index, ln	168	-2.76852	0.37165	-3.21888	-2.04022
Highly skilled workers (share of total labour force), ln	168	3.427634	0.323159	2.617396	3.911423
Unemployment rate, ln	168	1.994888	0.361547	1.131402	3.261935
Union density, ln	168	3.199139	0.657577	2.053415	4.326778

Table 3: Correlation matrix

Variable	1	2	3	4	5	6	7	8	9	10	11
1 Skill Premium	1,00										
2 R&D Expenditure per employee, ln	-0,12	1,00									
3 Patents Grants per 10k employees, ln	0,47	0,05	1,00								
4 Openness to Trade (share of GDP), ln	-0,40	-0,16	-0,54	1,00							
5 PC Assets (share of GDP), ln	0,48	-0,04	0,24	-0,83	1,00						
6 Share of large enterprises (250+ employees), ln	0,42	0,18	0,31	-0,26	0,28	1,00					
7 Average labour productivity, ln	-0,32	0,83	0,50	-0,32	0,04	-0,17	1,00				
8 Herfindhal Index	0,30	-0,45	-0,37	0.32	-0,06	0,20	-0,43	1,00			
9 Highly skilled workers (share of total labour force), ln	0,08	0,37	0,14	-0,25	0,20	0,38	0,15	-0,28	1,00		
10 Unemployment rate, ln	-0,03	-0,06	0,06	-0,12	-0,05	-0,50	0,10	-0,50	-0,04	1,00	
11 Union density, ln	-0,41	0,16	-0,31	0,65	-0,55	-0,18	-0,01	-0,14	-0,03	-0,04	1,00

Table 4: Impact of innovative activity on skill premium — Pooled OLS

	(1)	(2)	(3)
R&D Expenditure per employee (ln)	2.489 ***		2.541***
	(0.658)		(0.603)
R&D Expenditure, square (ln)	-0.107***		-0.113***
	(0.0288)		(0.0263)
Patent density (ln)		-0.0890	-0.0937
		(0.0604)	(0.0592)
Patent density, square (ln)		0.0568**	0.0622***
		(0.0221)	(0.0214)
Total Asset (CPU) (ln)	0.0699***	0.0529**	0.0784***
	(0.0233)	(0.0232)	(0.0222)
Trade (ln)	0.0218	0.0341	0.0823**
	(0.0333)	(0.0327)	(0.0346)
Share of enterprises over 250 employees (ln)	0.0757***	0.0639***	0.0919***
	(0.0269)	(0.0197)	(0.0256)
Average labour productivity (ln)	-0.0663	-0.0206	0.0579
	(0.0519)	(0.0356)	(0.0605)
HH index (ln)	0.103*	0.0842*	0.00828
	(0.0525)	(0.0490)	(0.0558)
Share of HE workers (ln)	0.0742	-0.0537	0.0311
	(0.0495)	(0.0525)	(0.0580)
Unemployment rate (ln)	0.0974***	0.169***	0.0885***
	(0.0350)	(0.0268)	(0.0336)
Union density (ln)	-0.00645	-0.0448	-0.0454
	(0.0239)	(0.0320)	(0.0296)
Constant	-14.05***	1.034**	-12.71***
	(3.803)	(0.461)	(3.521)
Time dummies	Yes	Yes	Yes
N	168	168	168
R^2	0.622	0.632	0.672

Robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Impact of innovative activity on skill premium — Fixed Effects

	(1)	(2)	(3)
R&D Expenditure per employee (ln)	4.575***		3.265**
	(1.318)		(1.128)
R&D Expenditure, square (ln)	-0.198***		-0.141**
	(0.0568)		(0.0492)
Patent density (ln)		-0.234**	-0.199***
		(0.0761)	(0.0596)
Patent density, square (ln)		0.0705**	0.0585**
		(0.0250)	(0.0232)
Total Asset (CPU) (ln)	0.0773*	0.0841**	0.0756
	(0.0428)	(0.0381)	(0.0443)
Trade (ln)	-0.745***	-0.687**	-0.693**
	(0.240)	(0.225)	(0.234)
Share of enterprises over 250 employees (ln)	-0.0493	-0.0480	-0.0517
	(0.0771)	(0.0512)	(0.0583)
Average labour productivity (ln)	-0.123	-0.192	-0.114
	(0.534)	(0.446)	(0.459)
HH index (ln)	0.00548	-0.0658	-0.0753
	(0.0739)	(0.0826)	(0.0774)
Share of HE workers (ln)	-0.620***	-0.510***	-0.644***
	(0.140)	(0.117)	(0.122)
Unemployment rate (ln)	0.190***	0.175**	0.171***
	(0.0521)	(0.0578)	(0.0508)
Union density (ln)	-0.286	-0.236	-0.194
	(0.305)	(0.257)	(0.273)
Constant	-34.75***	-8.523**	-26.89***
	(6.649)	(3.866)	(5.555)
Time dummies	Yes	Yes	Yes
N	168	168	168
R^2	0.577	0.611	0.636

Robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Relationships between innovative activities and the skill premium

	(1) Patents (ln)	(2) Skill Premium (ln)
R&D Expenditure per employee (ln)	1.0119***	1.6332***
	(0.1839)	(0.4916)
R&D Expenditure per employee, square (ln)		-0.0694***
		(0.0206)
Patent density predicted		-0.6237***
		(0.2364)
Patent density square predicted		0.0273***
		(0.0031)
Total Asset (CPU) (ln)	-0.2359***	-0.0166
	(0.0803)	(0.0550)
Trade (ln)	-1.3988***	-0.2074
	(0.1139)	(0.3133)
Share of enterprises over 250 employess (ln)	0.2194**	0.1052**
	(0.1076)	(0.0528)
Average labour productivity (ln)	-1.6641***	-0.2111
	(0.2551)	(0.3754)
HH index (ln)	-0.0143	0.0178
	(0.1502)	(0.0493)
Share of HE workers (ln)	-0.9046***	-0.0911
	(0.1315)	(0.2076)
Unemployment rate (ln)	0.4639***	0.1423
	(0.1294)	(0.1083)
Union density (ln)	-0.1355	-0.0450
	(0.0854)	(0.0397)
Constant	-21.6317***	-8.2770
	(3.9818)	(5.1711)
Time dummies	Yes	Yes
N	168	168
R^2	0.939	0.726

Robust standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$