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Effects of innovation on wages: Evidence from Estonian linked employer employee data

Master's thesis

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Abstract

This paper contributes to the less explored literature on the effects of firm level innovation on wage heterogeneity using linked employer employee data. Using CIS innovation survey data, I identify 3453 Estonian firms to investigate wage variation brought forth by different types of innovation, namely product, process and organisational innovation. It is found that both product and process innovations associate positively with wages, whereas organisational innovation seems to have a negative impression. Additionally, I focus on worker skill levels to analyse varying innovation effects on different skill categories. The results show that in firms that introduce product innovation low skilled employees seem to earn the largest wage premium. On the other hand, high skilled employees gain more premium in firms introducing process innovation.

Introduction

For long, innovation at the firm has been an area of interest for researchers to better understand outcomes with respect to firm's organizational dynamics, labour structure and compensation changes (see for e.g. Autor et al., 1998, Hottman et al. 2016, Akcigit & Kerr, 2018). This way we can have a better understanding on a firm's decision to innovate and its implications on its employees, which can in turn serve as a valuable input for policy development. In the fast-changing global order, there are important inferences to be obtained from the different kinds of innovation activities, each motivated by different factors, and their effects on the employment dynamics. In this paper I am interested in studying the wage premiums of employees in firms where different innovation activities were introduced, and how these wage changes vary with employees' skill levels.

The foundational concepts of innovation can be sought from various disciplines, where of interest to us is the economics of innovation. Through the economic lens the vast literature has explored the drivers of innovation decisions, the factors that hinder its implementation (e.g. Aghion et al., 2018, Acemoglu et al., 2015) and the eventual effects of such innovations when applied on an industry, market and firm (Broda & Weinstein, 2010). Of pertinent value to these theories of innovation is Joseph Schumpeter's "creative destruction" (Schumpeter, 1942) that posits firms have incentives to disrupt existing economic activity so as to innovate and gain competitive advantage in the market. Joseph Schumpeter identified the broad umbrella term of innovation as (with the additions of the indicators put forth by Kline and Rosenberg, 1986) :

creation of a new product, a novel process of production, inventiveness in employing cheaper raw materials to production, reorganization of production so as to enhance productivity or distribution systems, an improvement in the methods of applying innovation or some combination of these activities.

My contribution in this paper is twofold: Firstly, I have studied firms over a period of 9 years using a linked employer-employee data from Estonia to establish a relationship between different innovation activities in the firm and employee wages. Secondly, I have tested for this relationship for different employee skill categories and found some interesting insights. It was found that low skilled blue-collar (lowest skilled) employees in firms that have introduced product innovation have received higher wage premiums than employees in other skill categories. This is in contrast to the large literature that suggests high skilled workers benefitting more from technological change. This in turn provokes some discussion on the complementarities between lower and high skilled workers, as well as providing some evidence to the presence of some “soft skills”, as established in Aghion et. al. (2019), which seems to have strong productivity effects, and in turn a positive impact on wages. Further, the results on process innovation seem to complement the larger literature, where it is suggested that only higher skilled workers gain wage premium from technological change. Additionally, I have considered organizational innovation alongside product and process innovations, which has been less studied before to estimate wage equation, to find that it has significant negative impact on wages. This in turn provokes questions on the quality of such innovation, whether it leads to productivity gains, and whether there are some positive effects that are to be seen only over a longer period of time.

Innovation in itself is an expansive subject of measurement and the decision to innovate is driven by economic factors. Firm surveys are a traditional method to account for innovation activity and technological improvements, both at the industry and the firm level. In Europe, two innovation surveys are chiefly known and used, among which my paper uses one- the Community Innovation Survey (CIS). In this paper I have used CIS data, which is a survey mostly conducted in the member states of European Union (EU) to collect information on innovation activities, providing a broad range of indicators that account for innovation spending, inputs, barriers and cooperation. Nathan Rosenberg’s work also influenced the Oslo Manual (Innovation Manuals of OECD (OECD (1992,1997)) which broadly dealt with drafting periodic revisions on standardized innovation surveys.

Traditionally, product and process innovations are the innovations considered for analysing the effects of innovative activities on employment and wage outcomes (Angelini et al., 2009, Pianta & Tancioni, 2008). Product and process innovations are associated with the technological components of the firm's innovativeness, where the former is the introduction of newer products or significant improvements in existing ones, and the latter is identified as changes brought in the production or delivery processes in the firm. In addition to these, another type of innovation is gaining interest, which is organizational innovation (see e.g. Rennings, 2000). The Oslo Manual of innovation, which is OECD's initiative to lay down guidelines for innovation measurement and analysis, has recognised organizational innovation (OECD, 2005) as an addition to capturing firm's performance and as an essential indicator of knowledge creation. Generally speaking, organizational innovation is identified as the decision to create or adopt a workspace culture, behaviour, that are new to an organization (Lam, 2005). More specifically, it could be a change brought in to a firm's external relations, workplace environment or it's day-to-day business practises (OECD,2005). There are different strands of literature in this area, of significance to us is the one concerning changes in a firm's organization, adoption of newer structures of operation, and external cooperation. This studies firm's resilience in the face of radical changes in its working environment, whether they lead to more cohesion in economic activity and thus better enhances in the product and process processes (Teece, 1998).

This paper contributes to the less explored literature on the effects of different firm level innovative activities on wages using novel linked employee employer data. I have considered firms over a period of 9 years, from 2006-2014, so that we can overcome the limitation posed by pooled data analysis, where innovation enters in levels– thus promising a better capturing of the dynamic evolution of innovation activities in the firm. This is also in adherence to the vast literature that recognises innovation as a long-term process with feedback and interactions (see e.g. Kline and Rosenberg, 1986, Freeman, 1987, Lundvall, 1992, & Nelson [ed.], 1993; OECD, 1997). I have used fixed effects models to account for person effects as well as firm effects for modelling wage equations for Estonian firms. I have found larger wage premiums for firms that introduce product and process innovations. To the contrary, it is found that firms introducing organizational innovations have experienced a depressing effect of innovation on wages.

To my surprise, I find product innovations to have the highest positive association with the wages of low skilled blue workers (lowest skilled), that calls for some discussion on the involvement of lower skilled workers in providing inputs for newer products, or for revisions in already existing products, and in their potential indispensability. High skill workers in firms that undertake process innovation benefit from large premiums. Another interesting finding is with respect to organizational innovations which seems to suggest a negative association of innovation with wages for all skill-categories save one, with the lowest skilled employees affected the most. This perhaps hints at an adverse response to organizational innovation among employees of the firm, which poses questions on the role of such innovations in bringing alleged cohesion to the economic activities of the firm.

Among this vast literature that explains wage dispersion by innovativeness at the firm level, I find my study to have drawn great insights from Aghion et al. (2019), where they have studied the effects of research and development on the wage heterogeneity using linked employer employee level data by developing a model that considers complementarities between worker skill levels. My paper complements this literature by studying the effects of three types of innovation: Process, Product and Organizational innovation.

The rest of the thesis is organized as follows.

2. Literature

The consensus on developed economies has largely been that innovation activities have a positive effect on the labour wage in the industrial level, though in varying degree. This is shared by the traditional literature on rent sharing (Card et al., 2018) which argues that innovation promises prosperity to the firm in terms of larger surplus, which in turn is divided among workers and employers through virtue of bargaining. However, there is higher cost involved with adoption of newer techniques which has a depressing effect on worker premiums.

Moreover, within the firm there is a long-standing discussion on skill biased technological change, that argues in favour of differing effects of technology on differently skilled workers (e.g. Berman et al., 1994, Katz and Autor, 1999, Goldin and Katz, 2010, Acemoglu and Autor, 2011). The literature finds demand for workers to be higher in the case of educated, high skilled workers in the face of technological change, which in turns leads to wage inequality. Some of the older papers in this area studied the advent of microcomputers and the hastening of the technological process, which was suggested to have significant effects on wage changes that favoured more the skilled workers (e.g. Bound and Johnson, 1992, Pierce et. al., 1993), or that workers who were adept at using computers earned higher wage as a consequence of possessing such a skill (e.g. Krueger, 1993). However, though the Skill Biased Technological Change (SBTC) hypothesis held true for various reasons in the 1970s, from the late 1980s other dimensions of wage inequalities were on the rise and it was clear that SBTC alone could not account for such variations (see Card & DiNardo, 2002) This briefly brought the discussion to Routine Biased Technical Change which posited that the more recent changes in technology pull down the demand for labour employed in tasks that are deemed routine. Add to this task offshoring (also partly influenced by technical change), the result is a decline in demand for low-skilled occupations (Goos et al., 2014). The findings of this paper are partly in line with the overarching theory of these literatures, that technical change has been biased toward higher skill categories in the case of process innovations. But a slightly different result is found for product innovation, where low skilled workers in innovative firms earn higher premium in comparison to their higher skilled counterparts. This is explained by employing a model such as that established in Aghion et al. (2019) where it is argued that in innovative firms there is larger complementarities between high skilled worker and those low skilled workers who possess "soft skills". They reason that these "soft skills" are difficult to detect and constitute a major proportion of the abilities of low-skilled workers, contrary to their higher-skilled counterparts. In effect they stand to gain more wage bargaining power since it becomes difficult for the firms to replace these workers.

2.1. Innovation and Employment

Firms innovate in the market with the incentive of gaining a larger share in the market, and subsequently increased profits as a result. Now whether such initiations accrue to increase or decrease in jobs in the firm plant depends on the type of innovation in question. Product innovation though translates to newer products entering the consumer market, the temporary monopoly power that it exercises would demand increased profits at the cost of employment cut. At the same time, there is the potential increased demand brought in by the new product. Thus, theoretically the overall effect of product innovation remains unclear (Peters et al., 2014, Jaumandreu & Mairesse, 2017). However, there is also ample literature both older and from the recent past that suggests a clear positive effect on employment (e.g. Van Reenen, 1997, Greenan & Guellec, 2003, Harrison et. al., 2014). Similarly, though process innovation enhances the production process and in effect its productivity, the firm would need fewer workers to produce the same amount of goods or services, but at the same time can exploit the advantage to further expand production and thus employ more workers. So, on the one hand in an imperfect market an increase in production efficiency will translate to higher profits, thus more investment by the firm, and eventually more labour demand, hinting to a labour-saving phenomenon of process innovations (e.g. Vivarelli, 2012). But on the other hand, there is a burgeoning strand of literature, in particular to do with artificial intelligence, that lays speculations on the changing production technology (process), with an increased adoption of automation, and the growing incentive to outsource low skilled work in the firm, thus offsetting the positive effect on employment (Aghion et. al., 2018). Thus, as with product innovation, the eventual effects of process innovation are ambiguous (see e.g. Dachs & Peters, 2014). As for organizational innovation, though the literature is limited owing to its more recent academic interest, there is a positive trend that is expected, of which benefits are promised to be biased toward the high skilled workers (see Adler, 1992). That is, broadly productivity has been found to be positively linked with organizational innovation (see e.g. Appelbaum & Batt, 1994, Black and Lynch, 2004).

Drawing away from the theories, at this point it is imperative to analyse some empirical papers so as to find common ground with the findings of our paper, and to contrast dissimilarities in methodologies and conclusions. The papers could be largely divided into those who have studied short- or medium-term employment changes, thus going for a year-to-year employment processes, and those who have considered longer term changes. To begin with, in Greenan & Guellec (2003), innovation categorical variables were employed to study French firms for the period 1986-90 for firms which implemented at least one innovation (innovation survey). They found a strong relationship between innovation and employment change (annual mean of employment) in the medium term, with a more pronounced impact in firms that perform process innovation as compared to product innovation, 1.3% and 0.6% respectively, which are both statistically significant. Along similar lines Van Reenen (1997) previously studied the influence of innovation on short term employment growth in UK firms and found slightly different results. That is, they found a positive impact of technological innovation (product and process innovations) on employment, of which more innovations were in product rather than process innovations. However, this study unlike Greenan & Guellec (2003), took innovation headcount data as a measure of innovation, owing to the nature of data that was used.

Covering a larger time span of 20 years, Lachenmaier & Rottmann (2011) uses German firm data to conclude that employment responds more to process innovation than product innovation. They find that only the second lag of product innovation shows weakly significant positive effect, argued by them to be owing to a gradual effect of product innovation on employment.

On the whole, although there is an overall established positive relationship between types of innovation and employment pointed out by the overwhelming stretch of literature, there are some notable exceptions. For instance, Ross and Zimmerman (1993), find process innovation to have a negative effect on employment, while Jaumandreu et al. (2004), find a weak positive effect of such innovation in the case of Spanish manufacturing firms from the period 1990-1998. Surprisingly, in the case of Chile for the short period 1998-2001, Benavente & Lauterbach (2008) found that there is no statistically significant effect of process innovation on employment.

The links between employment and wage have been well documented through various approaches in the literature. Earlier studies have suggested that wage differentials are largely explained by firm heterogeneity (e.g. Gibbons & Katz, 1992 & Abowd et al.,1999). This is further explored by the productivity studies, which find strong linkages between productivity and wages (e.g. Cahuc et al., 2006, Barth et. al., 2016).[1] Further papers such as Card et al. (2016) have used linked employer employee data to test for whether such correlations hold true between workers and the productivity of their employers (firms) as well as with the wage pay policies of the firm, and found quite strong relationships in both cases. This, in turn, has shifted the discussion of explaining wage differentials by measures other than human capital, such as innovation systems and capital (Drahokoupil & Piasna, 2018). [2]This is followed by recent empirical studies on innovation and income inequality which found high wage polarisation owing to innovation activities at the industry level (Angelini et al., 2009, Akcigit et al., 2017).

2.2 Innovation and wages

Innovation is associated with higher productivity, which other than improving the complementarities of human capital also enhances the quality of labour output and in effect pushes up the returns to labour. Through innovative activities the firm tries to gain certain surplus, and a part of that rent is shared with the workers. The typical literature pertaining in this regard is that of rent sharing that puts forth the idea that there is measurable relationship between employee wages and employer rents (e.g. Van Reenen, 1993, Goldberg & Hellerstein,

[1] One more proposition that emerges is that of technical change, which creates ‘rents’ through innovation led growth (see Romer, 1990).

2013). In the process of workers attempting to seek rent (produced by innovation) through bargaining power, there needs to be made a distinction between the effects of product innovation, process innovation, and organizational innovation since they have differing effects over output and employment, as we previously discussed, and in effect on wages.

The literature concerning wages and innovation has been largely explored from the standpoint of technology and its effects on wage differentials, between say high and low skilled workers. One of the early investigations of computers in the study of innovation is that of Krueger (1993), which leans on to the erstwhile mentioned literature on skilled biased technological change as well as on the novelty of computers to study innovation processes. The paper uses both OLS and TSLS (two stage least squares) to estimate log hourly wages by computer usage using a pooled sample of individuals. The author found that workers who used computer on their job in the 1980s had roughly 10 to 15 percent higher wage rate on average.

This is also followed by Bartel & Lichtenberg (1988) where the overall effects of technological change on wage rate has been investigated given that the education, age and sex of each employee is kept constant in a pooled industrial level data. They estimated a wage equation with a fixed effects model using three technology measures and other industrial characteristics. They found that all workers in industries with new technology have higher wages on average. Further, they found that the wages of college graduates increase more than those of less educated workers, though this difference seems to decline with the age of workers.

In order to address the unobserved heterogeneity brought in by individual workers that the Bartel & Lichtenberg (1988) paper omits, Bartel & Sicherman (1999) uses the National Longitudinal Survey of Labour Market Experience of Youth aged 14-21 data in addition to the industry level data to test for the effects of technological change by accounting for individual fixed effects. Using six proxies for the industry rate of technological change, they find that erstwhile correlation between technological change and industry wages reduces significantly with respect to the results found in Bartel & Lichtenberg (1988). In addition, they found more significant correlations between individual wage premium, which is the component of the wage that is not explained by individual’s observed characteristics or by industry affiliations as opposed to just fixed effects, and technological change. They concluded that the observed effects of technological change on wage structure are due to the sorting of individuals on the basis of their unobserved characteristics into industries with differing technological change. Similar to these were other empirical papers such as: Casavola et al. (1996) that studied the firms in Italy and found that the radical use of new technology contributed to a higher blue collar - white collar job earnings ratio.

Chennels & Reenen (1999) conclude for there to be a strong effect of technological diffusion, in the cross-section data, and that product innovation seems to have a larger impact on rise in employment than other innovations do. As for more recently, Cirrilo (2014) implemented a multivariate analysis of Chilean firms to investigate the effects of innovation on wages. They confirmed previous theories on positive effects of product innovation on wages, albeit finding a negative effect on unskilled manual labour wages, though on average firms indulging in process innovation pay higher wages.

Unlike most of its predecessors, Allen (1996) used population survey data in addition to the industry level data, recorded at two decades, namely 1979 and 1989, to map changes in wage structure across industry. Estimating a conventional log wage equation, the author first accounts for industry level differences, and found that there was considerable variation in wage structure across industries and also over time. However, the evident twin limitation of this paper remained to be of endogeneity and selection bias. Reenan (1996) too examined the impact of technological innovation on wages using a panel data of British firms and found innovating firms to have higher wages on average, although it was theorized that the innovation activities conducted by rival firms tend to depress firm's own wages. This is in accordance to the traditional model where wages are determined by rent sharing consequence of innovation, and an increase in competitiveness threatens the bargaining power of workers.

Unlike the aforementioned studies, there are more recent contributions to this literature which have undertaken panel data analysis as opposed to cross-sectional pooled data analysis and looked more specifically at innovation strategies, namely product and process innovations. This is more relevant to our paper since we believe that the usage of panel data facilitates a better understanding of the effects of firm level innovation as these innovation changes are not merely one-offs, and are longer term processes.

In order to account for different innovation processes and their individual effects Martinez-Ros (2001) took Spanish manufacturing firms from 1990-94. The author found that in general, process innovation causes a larger and more significant impact on wages than product innovation, which is insignificant. Thus, only when firms introduce process innovation or both process and product innovations simultaneously will employees gain a wage premium (7% and 20%, respectively).

However, a different result is found in Castillo, V. et al (2014), where the authors were able to evaluate the effects of innovation programs on employment and labour wage, undertaken at the firm level in Argentina. Although the effect on employment was larger, they found strong effects on wage, predominantly the impact of product innovation, but also significant impact of process innovation. The authors have used propensity score matchings to first evaluate the similarity of characteristics between treated (innovation support received) and control (no support received) firms, after which they have studied the effectiveness of innovation in pushing labour wage with difference-in-differences estimator. It is imperative to note that in this paper innovation is taken to be exogeneous unlike Martinez-Ros (2001) where instruments of lagged innovations clearly led to a drastic drop in the effect of innovations in explaining wage rates.

Pianta & Tancioni (2008) analyses 11 industrial sectors and 10 European countries to inspect changes in annual wage compensation brought forth by innovation from two waves of CIS innovation data(1994-1996 & 1998-2000 surveys), and found that innovation effects were weaker in less innovative firms than in highly innovative firms, and propose the inference that technological competitiveness drives wage growth, hinting at "Schumpeterian effects of new products". They conclude that on one hand industries with new products push wages, but on the other new processes dampen wages.

Although, organizational innovation hasn't been previously studied for its direct effects on real wages, it has been found to have significant effects on the general innovative activity at the firm level. For both product and process innovations Cozzarin (2016) found that organizational innovation led to 1.7 times and 1.5 times increase in these innovations respectively. A similar complementary effect of organizational innovation on these innovations are found in Leeuwen et. al. (2010).

Lastly, when it comes to innovation, there is certainly the problem of high-skilled workers selecting higher quality firms, which might be in tandem to higher innovation, thus causing some selection bias in the model. In Aghion et al. (2019) this is captured with individual worker effects along with firm fixed effects in the estimation, so identification comes off individuals who move jobs between firms that do more and less R&D. It is a study based on the UK firm level data, where using linked employee employer data the authors have been able to establish a robust relationship between higher innovativeness, or in this case R&D expenditures, and higher wages on average. Moreover, the premium in working in an R&D intensive firm has been found to be higher for low skilled workers than high skilled workers. This paper is crucial to us in pointing out the effects of innovation on the complementarities and substitutability between workers in occupations with different skill levels within the firm. Firms with different levels of innovation have disparate characteristics, and behave differently in terms of labour compensation over longer period of time.

2 Data

In this paper I establish a relationship between innovation initiatives taken within the firm and the individual's firm level wages, and how such innovation decisions may influence wage structure for the different worker skill levels. I use novel linked employer-employee data for Estonia. The individual level data comes from the Estonian Population and Housing Census 2011 data and the Estonian Tax and Customs Office payroll taxes data for the period 2006 to 2014. The data on employer's financial and other information, such as ownership and sales turnover, comes from Business Registry data, that contains information of all registered firms in Estonia, and is linked with the employee wage data that is available for the years 2006 to 2017. This is linked to the Community Innovation Survey data which is an innovation survey widely used by EU member states conducted in two-year frequencies, for enterprises to respond to questions relating to different kinds of innovation activities that have been conducted in the organization, the varying aspects to these innovations, public funding to innovations, patents, as well as expenditures that have accrued to such initiatives. In the case of Estonia this data is readily available for each wave, 2 years apart, from 1998 to 2014. In addition to these datasets, I also use some inputs from the Population and Housing Census data of 2011 for information on individual worker's occupations and educational qualifications.

In this analysis I have considered years from 2006 to 2014 in which the firms have responded to the survey every three years, that is namely starting 2006, namely 4 CIS waves: 2006-2008, 2008-2010, 2010-2012 & 2012-14. While the questions on companies' innovativeness consider the 3-year period, I extended the response to all the years, e.g. a company reporting to have conducted product innovation in the 2008-2010 CIS wave is considered to have product innovation in years 2008, 2009 and 2010. This helps in being able to track individuals across firms more continuously and consistently, for a longer period of time.

The data that I thus have is longitudinal, with workers being followed over time. Owing to the limitations in our dataset we have not been able to ascertain if the workers considered are full time or part time workers. I have excluded in our analysis all individuals aged below 18 (non-adults) and above 70. Thus, in our final analysis I have considered 3,453 firms and 280,393 individual employees over a period of 9 years. In this period, a total of 858 firms indulged in product innovation, 996 firms in process innovation and 844 adopted organizational innovation at least once. Due to my dependence on Population and Housing Census data of 2011 to ascertain individual worker's background, the educational qualifications of 173,118 individual workers is known as of 2011. All of the firms included in the data have responded to the question of innovation and R&D expenditure, hence we have identified firms that innovate and those which don't (as in table 1).

Table 1. Number of observations in our linked employer – employee data according to the reported CIS innovation decisions of firms:

	Product Innovation		Process Innovation		Organizational Innovation		Innovative firms*	Non-innovative firms
	Yes	No	Yes	No	Yes	No		
Workers	114,340	162,349	147,599	129,090	117,335	166,048	148,077	135,306
Firms	845	2469	998	2,316	858	2,594	1,078	2374
Firm years	4,250	11,601	5242	10,609	4,107	12,167	5,542	10,732
Worker-firm-years	460,148	644,481	613,234	491,395	471,166	656,298	613,628	513,836

Source: Business Registry, CIS data, Estonian Tax and Customs Office payroll taxes data, period 2006-2014. *Here innovative firms are those that report positive innovation expenditure, whereas non-innovative firms are those that have reported no innovation expenditure.

Further, the occupational details of 160,627 individual workers are known. These have been further classified into four skill categories according to ISCO-088 classification, namely high skilled white collar, low skilled white collar, high skilled blue collar and low skilled blue-collar workers. It is to be noted here that these are time variant occupational details that have been taken from the Population and Household Census of 2011, and thus have been assumed to have remained unchanged all throughout our analysis period. That is, I have extrapolated the skill levels of individuals across the analysis period 2006-2014. Since occupational details are known only for one year, namely 2011, naturally the criticism that employees' move between occupations is a valid concern. However, I argue that worker mobility is not very high in the period of our analysis. Firstly, we find the average wage in both innovative and non-innovative firms to be approximately 41 and 43 respectively (which are on the higher side when compared to other developing economies). More importantly for this paper, it makes a less probable case for employees to change occupations mid-life. Secondly, I have conducted a robustness check for this assumption by considering for analysis only three years, namely 2010, 2011 and 2012. I find the estimates from this period to be consistent with my overall regressions on various employee skill levels for 2006-2014 (see results section, Table).

Table 2. Comparison of innovative and non-innovative firms, as well as firms with different innovation activities

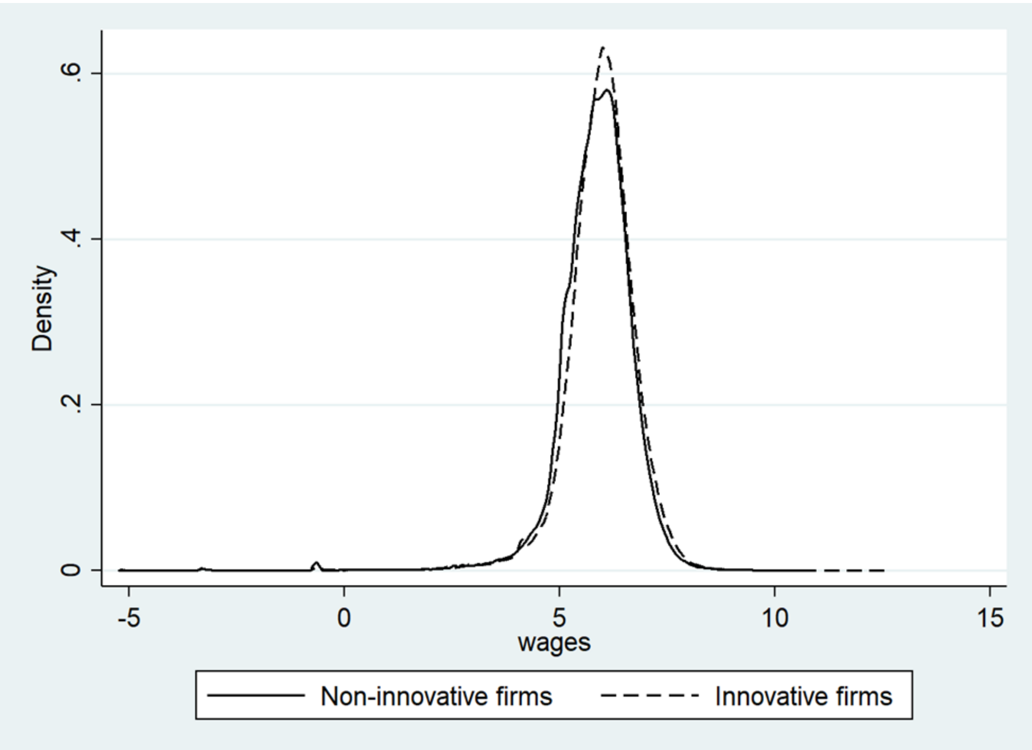
	Product		Process		Organizational		Innovative firms	Non-innovative firm
	Yes	No	Yes	No	Yes	No		
Employment (Average workers in firms)	92.40	48.40	102.83	41	90.35	48.17	95.11	42.10
Log (Real wages)	5.98	5.80	5.90	5.82	5.96	5.81	5.94	5.81
Male (in percentage terms)	47.03	58.46	50.92	57.17	50.17	56.52	51.07	57.20
Tenure (of workers)	2.98	3.33	2.95	3.47	2.82	3.44	2.99	3.40
Foreign ownership (average number of firm)	34.66	22.24	33.31	22.35	34.24	22.99	34.03	21.61
Age (averages)	41.25	43.49	42.02	43.23	41.60	43.24	41.84	43.42
Innovation expenditure (average)	375,276	106352	472453	36969	432265	80093	521,037.40	.

Source: Business Registry, CIS, Estonian Tax and Customs Office payroll taxes data; Period 2006-2014. *Worker wages refers to log wages, calculated by taking log of real wages, and also contains negative log wage values. Foreign ownership is an identification of firms that have at least 51% of their ownership belonging to a foreign company/corporation.

In addition, I have used 3-digit Estonian Classification of Economic Activities (EMTAK) indicators to identify firms that belong to the manufacturing and services sector, wherein firms with industry code between 101 and 451(not included) are taken to be manufacturing, and those with industry codes above 451 are taken to belong to the services sector.

In Table 2. I have summarised some variables contingent on the firm's decisions to innovate, and on the kind of innovation that is initiated. As was expected from the large literature I find innovative firms having a much larger workforce on average, more than double that of non-innovative firms(108.6 as opposed to 47.47), and they seem to be employing a younger pool of workforce on average (lower average age of employees), both of which may hint to higher wages of employees in innovative companies than in non-innovative companies as is evident from our data in Table 2. Similarly, innovative firms are more frequently foreign-owned on average than non-innovative firms, which may explain a foreign-owned company's supposed competitive advantage over domestic companies, and better access to technology. However, one matter of surprise is the tenure of workers in innovative firms which seems to be lower than non-innovative firms on average, perhaps hinting to more mobility of workers between firms in such enterprises since they are younger on average and pick up skills and wage bargaining powers by virtue of being in innovative firms. Additionally, we also find more gender parity on average in innovative firms as compared to non-innovative firms.

Figure 1. Kernel density graph of log (real) wages.



Source: Estonian Tax and Customs Office payroll taxes data, CIS. Period 2006-2014.

As for the various types of innovation, we find the overall mean wages in firms that introduce product, process or organizational innovations to be statistically different from firms that don't.

(Also see Figure 1.) This, though expected, only points to a need to study further the effect such innovation decisions may have on wage differentials in firms. Since we have previously discussed skill biased technical change literature, in this paper we are also interested in studying the effects of innovation on various skill levels in firms.

Table 3. Comparison of innovative and non-innovative firm's worker wages, according to worker skill levels.

Worker Skill levels	Individuals whose skills known	Innovative firms		Non-innovative firms	
		Mean log(real) wages	Standard deviation	Mean log(real) wages	Standard deviation
High skilled White collar	58,306	6.38	0.72	5.75	0.77
Low skilled White collar	23,925	5.83	0.69	5.92	0.82
High skilled Blue collar	31,704	5.86	0.66	5.93	0.83
Low skilled Blue collar	45,552	5.69	0.69	5.98	0.83

Source: Estonian Tax and Customs Office payroll taxes, CIS, Population and Housing Census data 2011; Period 2006-2014

In our descriptive statistics we find differences in wages for all four categories, which are also different statistically (t test of means) for workers in innovative and non-innovative firms. On average, we find innovative firms to have higher wages only for high skilled white-collar workers and surprisingly, we find average wages to be statistically lower for all the other three skill categories in innovative firms, which have been summarised in Table 3.

Table 4. Correlations between different innovation activities in the firm.

	Product innovation	Process innovation	Organizational innovation
Product innovation	1		
Process innovation	0.3947	1	
Organizational innovation	0.3353	0.3701	1

Source: CIS data, 2006-2014. No of observations = 19,557

And since, these innovation decisions are not stand-alone events in the firm's life and are often used for complementing each other, especially in the case of product and process innovations as the literature suggests. There is thus some palpable correlation between these decisions that needs to be considered to better understand their outcomes (see Table 4).

3. Methodology

This paper uses a fixed effects model that has been adopted by Aghion et al. (2019), by employing it to explain log wages by innovation activities, as well as firm and individual characteristics. Unlike Aghion et. al (2019) I use innovation categorical variables instead of R&D intensity, and the estimated wage equation looks as follows:

$$\log\left(w_{ikft}\right) = \beta_1 I_{(prod)_{ft}} + \beta_2 I_{(proc)_{ft}} + \beta_3 I_{(org)_{ft}} + \beta_4 A_{it} + \beta_5 A_{it}^2 + \beta_6 (S_{ft} + F_{ft}) + \gamma_i + \sigma_t + \tau_k + \vartheta_{ikft} \qquad (1)$$

where *i* indexes individual which is found by individual identifiers from the tax information of individuals, *k* is industry identifier, *f* firm and *t* years. Further, $I_{(prod)}, I_{(proc)}$ & I_{org} are indicator variables for product, process and organizational innovation, that are reported in 4 Community Innovation Survey waves. 'A' is the variable for worker's age, information on which comes from the Estonian Tax and Customs Office payroll taxes data. *S* is for firm size, which is measured by the number of workers employed in the firm, *F* for foreign ownership, both of which information comes from the Estonian business registry. γ accounts for individual worker effects, σ is common time effects, σ is industry effects, and ϑ represents the error term.

The estimation of this equation has proceeded in the following way. To begin with, in Table 6, I have estimated log (real) wages by using a fixed effects model since I understand that such a panel data is not suited for pooled OLS. However, in order to decide on whether to go for random effects or fixed effects model I ran a Hausman test with the null hypothesis that individual fixed effects was adequately suited to be explained by a random effects model in the data. We reject this hypothesis, thus choosing a fixed effects model. This result was further confirmed by a Breusch Pagan test. In the same table I estimated an individual fixed effect model with various controls such as year controls in (1) to (4), industry controls in (1), (2), (3) and firm fixed effects in (3), to compare my results.

Then I have considered firms as part of two separate industries, as manufacturing and services firms in Table 7, identified as such by 3-digit industry EMTAK classifier, so that I am able to investigate innovation effects in different industries. Innovations takes up a different nature in these two defining industries, and this is only complemented by my results (see Table7.). For instance, product innovations in a manufacturing firm are primarily tangible in nature, such as e.g. the introduction of a new product or development of an already existent product. However, a service sector firm's 'product' in itself entails a different definition such as e.g. the introduction of a new customer interface.

Further, in order to study wage premiums for different skill and educational categories I run fixed effect regression for workers by dividing them according to different skill categories. Additionally, I have also dividing them into different education levels and run a separate regression. These tables have been summarised as Table 8 & Table 9 respectively. I identify employee skill levels from their occupation information, which is as reported in the Population and Housing Census data of 2011, and classified them by the ISCO-O88 classification of occupations (See Appendix). Similarly, the classification of individuals into three educational categories -primary, secondary and higher education- is also as reported in the same census. It is to be noted that since like the skill information the educational qualifications of an individual are also known for just one year, I have extrapolated this information for the whole period. This is a drawback I concede, that doesn't account for individual's having acquired more education. However, I argue that average age of employees (see Table 2.) in firms is very high, ranging from 41-43 in innovative and non-innovative firms, hence there is less possibility for individuals to be acquiring higher education.

In the last section I tried to deal with the potential issue of innovation endogeneity. Since wages and innovation decisions are both measured at the firm level, and the literature suggests a lag in the adjustment process of innovation (see for e.g. Van Reenen, 1997, Piva & Vivarelli, 2004 there is reason to believe that both these decisions may be taken simultaneously. That is, previous period innovations may have an effect on the present decision to innovate, which in turn may have an influence on present period wage determination. Thus, we are sceptical of the decision to innovate to be entirely exogeneous. Aside from the briefly discussed complementarities between innovation activities, especially the cohesive properties of organizational innovation. If we consider a firm's decision to innovate to being correlated with the error terms, we could use the lagged variables of innovation as instruments for our contemporaneous innovation variable(s).

Thus, to address this endogeneity problem, I employed a two-step System GMM estimator as proposed by Blundell and Bond (1998) to estimate dynamic panel data for large number of observations in small periods of time. This method has largely been used to account for innovation endogeneity in the case of employment studies (Van Reenen, 1997, Lachenmaier

& Rottmann, 2011). In my base specification, which is the differenced equation, I have all the specifications that have been used until now, with the addition of a one-period lagged wage variable and a three-period lag of process innovation as instrument. The differences obtained thus are then used in the levels equation. In my analysis, the estimation doesn't qualify the Sargan test for valid instruments. However, since the GMM coefficient of lagged dependant variable is close to the fixed effects estimate, and lies between fixed effects and OLS estimates (see Appendix), it serves as a robustness test at the very least for my innovation estimates.

4. Results

I have estimated the wage equation as previously specified in equation (1) with varying controls. To begin with, consider the results in Table 5. In the (1) column, I have estimated a fixed effects model with individual fixed effects and industry effects. In this estimation, we find that all three types of innovation are strongly significant for explaining wages. Product and process innovations have a similar positive relationship, whereas organizational innovation has a negative relationship with wages which is larger than the coefficients of both the former activities. To be more precise, we find that when firms adopt process innovation employees gain by 2.9%[3] increase in their real wages on average.

In the estimation of column (2), I have included year effects that alongside the individual fixed effects will which help us in eliminating bias from unobservables that are constant over individuals, but change over time, like the business cycle effects. The estimation resulted in a marginal increase in R squared, while maintaining the statistical significance at all levels for the innovation variables in our model. The nature of these relationships still holds the same as in column (1), though the coefficients have become smaller, with a pronounced decline in the positive coefficient value of process innovation, indicating lesser wage premiums, as well as a notable fall in the negative coefficient of organizational innovation.

In the (3) column we have the estimations with only firm fixed effects, as well as year and industry controls. We find the estimation to have made the coefficient of organizational innovation less significant, being statistically significant only at 5%, and with a smaller

[3] This is [exp (0.0285)-1] *100=2.89

negative coefficient. With this specification, not controlling for the individual level fixed effects, we also find a relatively stronger positive effect of product innovation.

Table 5. Relationship between Wages and Innovation variables (decisions).

	Dependant variable $\log(w_{ikft})$			
	(1)	(2)	(3)	(4)
Product Innovation	0.0210***	0.0181***	0.0248***	0.0189***
	(0.001)	(0.001)	(0.002)	(0.001)
Process Innovation	0.0285***	0.0170***	0.0154***	0.0185***
	(0.001)	(0.001)	(0.002)	(0.001)
Organizational Innovation	-0.0288***	-0.0109***	-0.0167*	-0.0136***
	(0.001)	(0.001)	(0.002)	(0.001)
Firm size	0.0668***	0.0616***	0.0351***	0.1460***
	(0.001)	(0.001)	(0.003)	(0.002)
Age	0.0929***	0.152***	0.0640***	0.1032***
	(0.000)	(0.002)	(0.000)	(0.001)
Age squared	-0.0008***	-0.0008***	-0.0007***	0.0007***
	(0.000)	(0.000)	(0.000)	(0.000)
Foreign ownership	0.0093***	0.0125***	-0.0029	0.0034
	(0.002)	(0.002)	(0.002)	(0.002)
Individual fixed effects	✓	✓		✓
Industry effects	✓	✓	✓	
Year effects		✓	✓	✓
Firm fixed effects			✓	✓
R- squared	0.0267	0.0363	0.3196	0.0633
Observations	1,104,629	1,104,629	1,104,629	1,104,629
Individuals	280,393	280,393	.	280,393

Note: (1)-(3) estimated OLS with fixed effects model, (4) estimated a two-way fixed effects model, for period 2006-14. Source of data: Estonian Tax and Customs Office payroll taxes, CIS, Business Registry 2011. Here t test of significance is given by * p<0.05, ** p<0.01, *** p<0.001.

Lastly, in the (4) column I have considered a two-way fixed effect model, with firm fixed effects and individual fixed effects, while maintaining our erstwhile year controls. As one is to understand from the literature, in the process of being more innovative, firms are bound to attract potential workers from other less-innovative firms, since these workers can benefit out of the wage premia increases from firm level innovations. Further, our discussions on skill biased technical change also hinted at demand for labour being skewed in favour of more skilled workers as against workers in routine jobs in firms that undertake technical change. Thus, there is a need to account for worker mobility between firms. I believe the specifications of (4) achieves this task of eliminating endogenous selection of and by workers between firms, by taking both firm and individual fixed effects, since we also see about 25% of the total workers considered having changed their firm of employment in the time period 2006-14 (see Table 5).

Table 6. Number of firms that workers were employed in, sample period 2006-2014:

No of Firms	Frequency (of workers)	Percentage (of total)
1	215,676	76.92
2	55,087	19.65
3	8,560	3.05
4	984	0.35
5	76	0.03
6	10	0.00
Total	280,293	100

The results of column (4) are largely consistent with our other estimation results, with marginal decrease in the coefficients of product and process innovations as compared to the estimates of column (1), and a more pronounced decline in the negative coefficient of organizational innovation. Thus, by controlling for worker mobility between firms, we find that firms that indulge in product or process innovations pay significantly higher wages on average respectively as compared to firms that don’t. On the other hand, organizational innovation in firms has a negative effect on wages on average.

This far our estimates complement the broad literature on innovation effects, especially the strong positive relationships between product and process innovation with employee wages. Since empirical papers have less explored the direct effects of organizational innovation on wages, this is an area of some amount of speculation that we face, especially since the literature suggests a positive effect of such innovations on firm productivity by bringing more cohesion and coherence in the day to day activities (e.g. Teece, 1998, Jiang et al.,2006). That is, unlike both the product and process innovations, organizational innovation is often brought in for its objective to ease, and complement, the former innovations, with some role to play in innovation persistence in firms (see Mothe et. al.,2015). However, since we find a strong negative relationship throughout out estimations, I am compelled to believe that organization's incentives to innovate in areas such as for instance workplace groups, revisions in external relations etc., is at loggerheads with their ability to gain wage premiums. This must be an inability to adjust perhaps, since we find worker mobility to be quite high in the firms in our analysis period (see Table 6.), thus indicating lesser time to adapt. We find almost 25% of the employees considered in our study to have changed their employer atleast once in our analysis period 2006-2014, and thus also indicating lesser time available to learn and replicate. However, we cannot jump to conclusions. Thus, we leave room to suspect other undetected reasons for such adverse effects of organizational innovation, which follow throughout all our estimates. Perhaps it also owes to the quality of such innovations, top-down implementation and the frictions in the levels of management that follow. As we have come to understand from the literature, organizational innovations are by nature more prone to being influenced by external ideas that may have less to do with the existing working environment, as compared to the technological innovations (product and process). That is, organizations are often heavily influenced by external sources of knowledge to decide on such innovations (see for e.g. Lurdes & Mario, 2018). Although they may have positive effects on other innovative activities, their subsequent effects on wages may be different. Previously, the literature on productivity gains of organizational innovation had led us to expect positive wage benefits to employees. However, since that is not the case, there is a possible gap in the effects of organizational innovation on productivity and in its effect on wages that needs to be more deeply studied, which is beyond the scope of this paper.

Now we consider the same specifications as in equation (1) separately for manufacturing and services industry, thus summarised in Table 7. As for wage differentials in industries, traditionally the wage literature takes it as an undisputed fact that there is persistence of inter-industry wage differentials. Various strands in literature attributes these differences to capital-labour ratios, union behaviour, unobserved worker characteristics and industry profitability (see e.g. D. Montgomery, 1991 and Gibbons & Katz, 1992). In the context of our fixed effect model, we are thus interested in analysing the manufacturing industry separately from others, namely services, whom we identify from the 3-digit EMTAK industry classifications.

Table 7. Relationship between Wages and Innovation variables(decisions): Comparison between two sectors.

	Dependant variable $\log(w_{ikft})$	
	Manufacturing firms	Services firms
Product Innovation	0.0119** (0.002)	0.0165*** (0.003)
Process Innovation	0.0218*** (0.002)	-0.0016 (0.002)
Organizational Innovation	-0.0060** (0.002)	-0.0164*** (0.002)
Firm size	0.0714*** (0.003)	0.0665*** (0.003)
Age	0.1580*** (0.003)	0.1482*** (0.002)
Age squared	-0.0007*** (0.000)	-0.0009*** (0.000)
Foreign ownership	0.0032 (0.000)	0.0124** (0.000)
Individual fixed effects	✓	✓
Industry effects	✓	✓
Year effects	✓	✓
R- squared	0.0367	0.0929
Observations	597,131	478,745
Individuals	162,156	134,290

Note: OLS with fixed effects model for 2006-14. Source of data: Estonian Tax and Customs Office payroll taxes, CIS, Business Registry 2011.Here t test of significance is given by * p<0.05, ** p<0.01, *** p<0.001

To begin with, we find statistically significant differences in the average wages in both these industries, with lesser variation in log real wages within the manufacturing industry (s.d.= .7700) as compared to others (s.d.= .8172). This we followed by our estimations from the erstwhile proposed fixed model with individual fixed effects, as well as keeping our year and industry controls. A cursory glance at the results in Table 7., and we find workers are more or less equally spread among these two industry groups.

Here, we find to one's surprise stronger effects of product innovation in driving up wages in service sector firms more as compared to the wages in manufacturing firms, where one expects to indulge more closely in product innovations to meet competitive market demands (for e.g. Göran Roos, 2016). It is suggested in the literature that perhaps services sector is able to better exploit the profits from novel products (Ettlie & Rosenthal, 2011). Another interesting result is the statistically insignificant coefficient of process innovation for service sector firms. We expect innovations in processes in this industry that may include changes in delivery systems, software changes & advancements in equipment to enhance the production or service rendering process. This in turn should lead to efficiency gains, and also help expand a customer base. However, it seems that either such efficiency gains are not true for service sectors, or that they do not translate, at least immediately, to wage premia. Also, innovation decisions in service sectors are seen to be more closely linked to customer specific demand (see for e.g. Grupp & Hipp, 2005). However, this is where I must draw a different inference from the literature. It is argued that innovations in services are easily copied, and thus is a continuous process, with an incremental nature (Sundbo, 1997). This is a pertinent point, since in our analysis only contemporaneous innovation variables have been considered, and thus we are unable to tell whether there exist more gradual positive effects of such innovation.

I may also speculate that service sectors, be it tourism, banking, communications etc. are more dependent on the use of IT and software. It is likely that changes in these processes take more time to adjust and be accustomed to, so as to workers to gain from them. These changes may also take more time to attract customers, since they need to get used to it (Grupp & Hipp, 2005) These innovation decisions also depend on the nature of the organization in question (see for e.g. Sirilli & Evangelista, 1998). On the contrary, changes in production processes (as in manufacturing firms) that are handled by technical workers trained by foremen and in-house workshops that demand lesser skill-acquiring may arguably be more immediate in nature. In fact, in manufacturing firms the real wage increases by approximately 2.20% on average[4] when process innovation is undertaken. That said, organizational innovation maintains its adverse effects on wages with a larger coefficient for services sector firms.

Table 8. Innovation and wage relationships at different skill levels.

	Dependant variable $\log(w_{ikft})$			
	High Skilled White	Low Skilled White	High Skilled Blue	Low Skilled Blue
	(1)	(2)	(3)	(4)
Product Innovation	0.0187***	0.0145**	-0.0002	0.0260***
	(0.003)	(0.005)	(0.004)	(0.006)
Process Innovation	0.0256***	0.0016	0.0248***	-0.007***
	(0.003)	(0.005)	(0.004)	(0.003)
Organizational Innovation	-0.0135***	-0.0139**	-0.0013	-0.0164***
	(0.003)	(0.005)	(0.004)	(0.003)
Firm size	0.0477***	0.0975***	0.0614***	0.0665***
	(0.003)	(0.006)	(0.004)	(0.004)
Age	0.1553***	0.1286***	0.1434***	0.1295***
	(0.003)	(0.006)	(0.005)	(0.005)
Age squared	-0.0011***	-0.0008***	-0.0006***	-0.0006***
	(0.000)	(0.000)	(0.000)	(0.000)
Foreign ownership	0.0129***	-0.0050	-0.0002	0.0132***
	(0.004)	(0.007)	(0.005)	(0.004)
Individual fixed effects	✓	✓	✓	✓
Industry effects	✓	✓	✓	✓
Year effects	✓	✓	✓	✓
R- squared (within)	0.0628	0.0750	0.0347	0.0294
Observations	294,272	102,616	164,658	233,664
Individuals	58,306	23,925	31,704	45,552

Note: OLS with fixed effects model for 2006-14. Source of data: Estonian Tax and Customs Office payroll taxes, CIS, Business Registry 2011, Population and Housing Census data 2011. Here t test of significance is given by * p<0.05, ** p<0.01, *** p<0.001.

[4] [exp (0.0218)-1] *100 =2.20

We understand that worker's productivity is dependant on their skill levels, but unsure how it translates to wages. Hence, we are interested in analysing varying skilled-levels employees at the firm, and the wage differentials brought in by innovations thereof. There are strong hints in wage and skill literature on the fact that high skill workers earn higher wages on average than low skilled workers in innovative firms (see for e.g. Goldin and Katz, 2010, Acemoglu and Autor, 2011). This is because the literature suggests that technological change favours skilled workers by improving their relative productivity, thus pushing up their demand, and in effect wage bargaining power. Further it is also contended that firms that innovate tend to hire more high skilled workers than low skilled workers. Thus, it is imperative to estimate the wage equation (1) separately for each skill level and see the varying effects of innovation on the wages in these categories, and to test whether the skill bias of innovations hold.

In Table 8., we estimate our results for each employee skill levels, derived from the ISCO-88 classification of workers where column (1) refers to high skilled white-collar workers, (2) to low skilled white-collar workers, (3) to high skilled blue-collar workers and (4) low skilled blue-collar workers. I have estimated a fixed effects regression model regression like previously, including year, industry and individual fixed effects. The positive coefficients of product and process innovations still largely holds for all four different skill categories, apart from the negative coefficient of process innovations for low-skilled blue-collar employees. Also, the coefficients for product innovation for high skilled blue-collar workers and process innovation coefficients for low-skilled white-collar employees appear to be insignificant.

The highest wage premia from product innovation is found for the lowest skilled (low skilled blue-collar) workers which is an interesting observation to maintain since newer products are essentially manufactured by these blue collared workers. This is a particularly pertinent result for us as it complements with the findings of Aghion et. al. (2019), where they found certain low skilled workers with "soft skills" having more bargaining power than high-skilled employees, and thus potentially benefitting more from innovative activities. In our estimation we find that white collared employees (high and low skilled) also gain a premium from product innovation, which perhaps owes to their role in product ideations, and is consistent with the findings of our estimations before.

As for process innovation we find that high skilled workers, both white and blue collared, gain a wage premium from such activities, which is congruent to the skill-biased technical change literature where higher skilled workers benefit from technological innovations. The reasoning behind our result can also be borrowed from the Routine Biased Technical Change literature (Goos et al. 2014) that suggests lower skilled workers are more dispensable to the firm because of the specific nature of their work and the skills that pertain to them, as compared to their higher skilled counterparts, where higher skilled “abstract” work benefits from technical change. Of interest to us is also why these process innovations, adopted namely in the production place, have a small but statistically significant negative effect on wages of the lowest skilled workers (low skilled blue-collar). This finds credence in the literature studying capital and skill complementarities, which finds capital changes to be complementary with high skilled workers, and actually substituting low skilled workers (see e.g. Ethan Lewis, 2011 & Duffy et. al., 2006). This is because with changing production processes, better machinery and more suitable labour-capital ratio, the demand for these workers falls, and thus adversely affects their wage bargaining power.

Organizational innovation once again relates to wages negatively, and seems to have a larger negative coefficient for low-skilled blue-collar workers. As has been the results of our earlier estimations, white collared employees’ wages are also adversely affected. This points to unreceptiveness among white collar employees to change in organizational structure and in being unable to gain from efficiency gains thereof. Perhaps these changes in the higher organizational rung go against worker spirits, and are more arbitrary and external than the innovations in the production process.

At this point, I must also address the criticism of skill information of individuals having been assumed to remain static for the period of analysis 2006-2014, since individual’s occupational information is only available for 2011, from the Population and Housing Census Data, and has been extrapolated for the whole period. In order to test for the robustness of my results I run the same regression for the periods 2010, 2011 and 2012, and the results have been summarised in Table 9.

Here again we find product innovations to have a positive effect on wages for almost all skill categories, except low skilled white-collar employees for whom it is insignificant. This is similar to our earlier finding that low skilled workers with “soft” skills benefit the most, with the lowest skilled workers having the largest product innovation coefficient. However, unlike in our previous estimation, process innovation seems to be insignificant for almost all categories of employees, except for the high skilled white collar, for whom the premium seems to be quite similar to the estimate of Table 8. This is in line with the skill-biased technical change and routine biased technical change literature.

Table 9. Innovation and wage relationships at different skill levels (period 2010-2012).

	Dependant variable $\log(w_{ikft})$			
	High Skilled White	Low Skilled White	High Skilled Blue	Low Skilled Blue
	(1)	(2)	(3)	4
Product Innovation	0.01228**	0.0151	0.0207*	0.0286***
	(0.006)	(0.012)	(0.012)	(0.008)
Process Innovation	0.02812***	0.0110	0.0012	0.007
	(0.006)	(0.016)	(0.012)	(0.008)
Organizational Innovation	-0.060***	-0.037***	-0.028**	-0.011
	(0.007)	(0.014)	(0.011)	(0.088)
Firm size	0.1148***	0.1743***	0.201***	0.188***
	(0.012)	(0.020)	(0.026)	(0.019)
Age	0.171***	0.122***	0.147***	0.106***
	(0.007)	(0.000)	(0.012)	(0.011)
Age squared	-0.001***	-0.001***	-0.001**	-0.0009**
	(0.000)	(0.000)	(0.000)	(0.000)
Foreign ownership	-0.0272**	-0.028*	0.0177	0.023**
	(0.009)	(0.015)	(0.000)	(0.01)
Individual fixed effects	✓	✓	✓	✓
Industry effects	✓	✓	✓	✓
Year effects	✓	✓	✓	✓
R- squared	0.025	0.026	0.024	0.0158
Observations	103,161	33,950	56,224	80,272
Individuals	43,382	14,467	24,526	34,702

Note: OLS with fixed effects model for 2010-12. Source of data: Estonian Tax and Customs Office payroll taxes, CIS, Business Registry 2011, Population and Housing Census data 2011.Here t test of significance is given by * p<0.05, ** p<0.01, *** p<0.001

It is to be noted here that since we have only taken 3-years in this estimation, I have only considered one CIS wave, that is CIS 2010-2012. Thus, the number of individuals considered dropped, as did the firms in our analysis. So, the insignificance of process innovation, can be in part attributed to this drawback. Additionally, the direction of the movement of wages with respect to organizational innovation remains the same.

Table 10. Innovation and wage relationships at different worker education levels.

	Dependant variable $\log(w_{ikft})$		
	Higher	Secondary	Primary
	(1)	(2)	(3)
Product Innovation	0.0121***	0.0203***	0.0096
	(0.004)	(0.002)	(0.006)
Process Innovation	0.0214***	0.01492***	0.0230***
	(0.003)	(0.002)	(0.006)
Organizational Innovation	-0.0145***	-0.0134***	-0.0027
	(0.003)	(0.002)	(0.006)
Firm size	0.0469***	0.0678***	0.0763***
	(0.003)	(0.002)	(0.006)
Age	0.1749***	0.1325***	0.1444***
	(0.004)	(0.003)	(0.008)
Age squared	-0.0012***	0.0007***	0.0006***
	(0.000)	(0.000)	(0.000)
Individual fixed effects	✓	✓	✓
Industry effects	✓	✓	✓
Year effects	✓	✓	✓
R- squared	0.0618	0.0389	0.0324
Observations	211,007	533,495	97,143
Individuals	43,163	107,156	21,555

Note: OLS with fixed effects model for 2006-14. Source of data: Estonian Tax and Customs Office payroll taxes, CIS, Business Registry 2011, Population and Housing Census data 2011. Here t test of significance is given by * p<0.05, ** p<0.01, *** p<0.001.

Now, although worker skills are a more imperative and traditionally used classification to understand existing wage differentials brought in by technology and innovation, we want to view these innovation wage effects from a worker's background point of view. Thus, we use the fixed effect model by classifying workers into three educational categories, namely, primary, secondary and higher education, and running separate regressions. Information of individual's educational qualifications has been obtained from the Population Census and Housing Data 2011, and is extrapolated for the whole period, 2006-2014, even though it is static information. However, even though it doesn't cover for the changes in educational qualifications after 2011, since our study is limited till 2014, we argue that very few individual's qualification changes are unaccounted for since we also found the average age of workers in firms to be in the range 41-43 (see Table 5). I also borrow from the case I made previously that occupational mobility is not that high in Estonia.

The results of this analysis are summarised in Table 10. As we can see from the table, there is an insignificant coefficient for product innovation in the case of primary educated workers. Since this educational information pertains to 2011, and our last year of analysis is 2014, it is not too far an assumption to make that these individuals have maintained this educational qualification throughout the period of our study on average. Then we can reason that these individuals make it to blue collar jobs where because of lack of education they face some dispensability in the firm. However, since process innovation pertains more to the production process in general, the large coefficient for primary-schooled individuals also indicates how these perhaps possess "soft skills", and have higher complementary with their more skilled counterparts in the higher echelons of the workplace.

Clearly, more educated individuals benefit from technological innovations- both product and process. We find the coefficient of product innovation to be higher in the case of secondary-school educated individuals as compared to the highly-educated. At first glance this is a bit surprising. But it is less so when we consider the problem of overeducation, especially in the Estonian case[5] where about one-third of Estonians are over-educated. This may have a negative effect on wages, as it hints at a gap at employers being unable to recognise and commensurately remunerate highly skilled individuals.

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[5] Vivika Halapuu. Skills Mismatch on the Estonian Labour Market, 7th Thematic Report. Link: https://www.hm.ee/sites/default/files/mismatch.pdf

The wage depressing effects of organizational innovation still holds for all individuals except those only primary-schooled where the coefficient is insignificant. The latter fits in with our estimates from Table 9 where the lowest skilled employees are unaffected by organizational innovations.

Lastly, in accounting for innovation endogeneity I employed a System GMM model, with the following specifications: the first lag of log wages, year variables, organizational innovation, product innovation, and all firm variables used in our fixed effect models to be exogeneous; only process innovation is taken to be endogenous (since innovation activities are correlated, thus only one is taken as endogenous), and its first lag is used. The result is summarised in Appendix (see Table 12.). Since by Sargan test we reject the Null hypothesis that instruments are valid, we cannot rely on these estimates. However, we find that the lagged variable of the dependant variable from GMM-SYS is between the coefficient of OLS and Fixed effect estimations which serves its purpose as a robustness check for our estimations, even though we do not seem to have ideally solved the endogeneity problem.

Conclusion

In this paper I have used a novel employer-employee data from Estonia to analyse the relationship between firm level innovation activities and real wages. For this I employed a individual fixed effects model with varying controls: year, industry and firm. My first finding was that there are significant positive effects of product and process innovations on wages, which complements the results of existing literature. That is, the wage differentials brought forth by innovation (in-between firms) is statistically significant, and that employees working in firms that conduct product and process innovations gain wage premium. What was particularly a surprising result was that organizational innovation has wage depressing effects. This I argue is because of the distinct nature of these innovations. Unlike the technological innovations that have more scope for review and stem out of the internal workings of a firm, organizational innovations may be either externally designed, and inspired, with being more difficult to assess immediate outcomes of. Thus, there is reason to pose questions on the quality of these innovations in bringing productivity gains in a short period of time. We also see a relatively middle-aged worker pool, with high mobility between firms in our period of study, which may suggest recalcitrant response and supposed adjustment issues among employees with the introduction of organizational innovations. This may also be the reason why they do not translate into wage premiums.

I also looked at the wage estimations separately for two different industries, namely manufacturing and services sector, since the nature of innovation, and their source, differs in these sectors (see for e.g. Evangelista, 2000) That is, for instance, service sector 'products' are more intangible, require less dependence on R&D and fixed asset investments (e.g. Grupp & Hipp, 2005, Miles, 2007), as compared to the manufacturing sector. With this background in mind, in my analysis I found that product innovations are more positively related to wages in the services sector. However, process innovations do not seem to relate to wages in the case of services sector.

Thirdly I used a fixed effects model to analyse worker wage for different skill levels. At the very outset I admitted to the drawback that a static occupational information on individuals poses (available only for 2011, which we have extrapolated throughout the whole period). To check for it's the robustness of these results, I made a separate analysis for years 2010-12. The results were largely similar. Of notable mention is the bias of process innovation in favour of higher skilled workers in giving wage premium, which is suitably skilled biased technical change literature. On the other hand, product innovation promises higher premium for workers at almost all skills, with the lowest skilled workers (low skilled blue collar) benefitting the most. This is an interesting result, and finds reasoning in Aghion et. al. (2019) where the authors present the case that complementarities between different skilled workers increases with the degree of innovativeness. In this backdrop they find that low skilled workers stand to gain the most wage premia, since they possess 'soft skills' which makes it difficult to replace them.

When similar fixed effects model was used to estimate separately individuals with different educational qualifications – primary, secondary and higher education, we found that highly educated individuals gain less wage premium on product innovation – possibly because of education-skill mismatch, owing to over-education.

In conclusion, overall these results provide some useful insights into the nature of employee wage premium from innovative activities at the firm. This has various policy implications. Firstly, it provides some incentive to push innovation programs at the firm level, especially product and process innovations, as they seem to associate positively with the employee wages on average. Secondly, it distinguishes the effects of product and process innovations on different skill-levels, provoking more research on the source of such distinction, and whether these differences rise in the long term. Lastly, I have observed a surprisingly different presence of organizational innovation on wages as opposed to the suggestion of the literature. These estimations of organizational innovation seek broader research on the overall management practises at the firm, the nature of these innovations, and whether they are indeed incongruent with the workplace efficiency of firms' employees.

Appendix

Table 11. Skill classification by ISCO-088, 1 digit.

Skill category	Types of Occupation	ISCO codes
High skilled white collar	Managers, professionals, technicians	1,2 & 3
Low skilled white collar	Clerks, sales and service workers	4 & 5
High skilled blue collar	Agricultural workers, craftsmen, traders	6& 7
Low skilled blue collar	Plant/machine operators, elementary occupations	8 & 9

Table 12. GMM estimations alongside FE & OLS estimations from the same specifications

	Dependant variable $\log(w_{ikft})$		
	OLS	GMM	FE
Log wages(t-1)	0.665***	0.093***	-0.0362***
	(0.044)	(0.003)	(0.002)
Product Innovation	0.0013	0.013**	0.012***
	(0.001)	(0.004)	(0.002)
Process Innovation	0.014***	-0.022***	0.014***
	(0.001)	(0.003)	(0.002)
Organizational Innovation	0.046***	-0.025***	-0.008***
	(0.001)	(0.003)	(0.002)
Firm size	0.001***	0.065***	0.039***
	(0.001)	(0.006)	(0.003)
Age	0.006***	-0.014**	0.134***
	(0.000)	(0.003)	(0.002)
Age squared	-0.00001***	-0.0005***	-0.0007***
	(0.000)	0.001	(0.000)
Foreign	0.022***	-0.016***	0.013***
	(0.001)	(0.003)	(0.002)
Year.2007	-0.034***	-0.143***	0.368
	(0.002)	(0.014)	(0.014)
Year.2008	-0.634***	-0.129***	0.357***
	(0.002)	(0.011)	(0.012)
Year.2009	0.092***	-0.108***	0.285***
	(0.002)	(0.009)	(0.010)
Year.2010	-0.131***	-0.130***	0.165***
	(0.002)	(0.007)	(0.008)
Year.2011	-0.092	-0.108***	0.085***
	(0.002)	(0.009)	(0.010)
Year.2012	-0.474***	-0.040***	0.055***
	(0.002)	(0.003)	(0.003)
Year.2013	0.056***		
	(0.002)		
Year.2014	0.137***	-0.095***	
	(0.010)	(0.003)	
Cons.	2.037	5.69	1.45

Observations	753,163	738,693	753,163

Here t test of significance is given by * p<0.05, ** p<0.01, *** p<0.001.

References

Acemoglu, D and Autor, D. (2010). *Skills, Tasks and Technologies: Implications for Employment and Earnings*. Handbook of Labor Economics. Vol. 4, Part B. Pages 1043-1171. Amsterdam: Elsevier B.V.

Acemoglu, D., Akcigit, U and Celik, M. A. "Young, Restless and Creative: Openness to Disruption and Creative Innovations". NBER Working Paper No. 19894. Revised in August 2015.

Adler, Paul S. (1992). *Technology and the future of work*, New York: Oxford University Press

Aghion, P., Bergeaud, A., Blundell, R & Griffith, R. "The Innovation Premium to Soft Skills in Low-Skilled Occupations". Working Paper Series no. 739. 2019.

Aghion, P., Akcigit, U., Bergeaud, A., Blundell, R. and Hémous, D. (2019). "Innovation and Top Income Inequality." *The Review of Economic Studies*, Volume 86, Issue 1, (January): Pages 1–45.

Aghion, P, Bergeaud, A., Melitz, M. J. and Lequien, Matthieu. "The Impact of Exports on Innovation: Theory and Evidence". NBER Working Paper 24600. 2018

Aghion, Philippe., Jones, Benjamin. & Jones, Charles. (2018). *Artificial Intelligence and Economic Growth*. The Economics of Artificial Intelligence: An Agenda, NBER Book p. 237-282.

Akcigit, U. & Kerr, William R. (2018). "Growth through Heterogeneous Innovations". *Journal of Political Economy* 126, no. 4 (August 2018): 1374-1443.

Akcigit, Ufuk., Grigsby, John and Nicholas, Tom. "Immigration and the rise of American ingenuity". NBER Working Paper No. 23137. Issued in February 2017, Revised in October 2017.

Allen, Steven G. (1996). “Technology and the wage structure”. *Journal of Labour Economics* 19, no. 2 (April): 440-483.

Angelini, Elisabetta C., Francesco, Farina and Mario, Pianta. (2009). “Innovation and wage polarisation in Europe”. *International Review of Applied Economics*. 23. 309-325. 10.1080/02692170902811736.

Appelbaum E and Batt, R. (1994). *The New American Workplace: Transforming Work Systems in the United States*. ILR Press Books.

Arellano, M., and S. Bond. (1991). “Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations”. *Review of Economic Studies* 58: 277–297.

Autor, D., Katz, L., and Krueger, A. (1998). “Computing Inequality: Have Computers Changed the Labor Market?” *Quarterly Journal of Economics*. November 1998, 113(4), 1169–1214.

Bartel, A. and Lichtenberg, F. “Technical change, learning and wages”. NBER Working Paper 2732 (October). 1988.

Bartel, A. and Sicherman, N. (1999). “Technological change and wages: An inter-industry analysis”. *Journal of Political Economy*. Vol. 107, No. 2 (April), pp. 285-325 (41 pages)

Barth, E., A. Bryson, J. C. Davis, and R. Freeman. (2016). “It’s where you work: Increases in the dispersion of earnings across establishments and individuals in the united states”. *Journal of Labor Economics* 34(S2), S67–S97.

Benavente, José M and Lauterbach, Rodolfo. (2008). “Technological innovation and employment: complements or substitutes?” *The European Journal of Development Research*, 20:2, 318-329 (June)

Berman, Eli., Bound, John. and Griliches, Zvi. (1994). “Changes in the Demand for Skilled Labor within U.S. Manufacturing: Evidence from the Annual Survey of Manufacturers”. *The Quarterly Journal of Economics*, Vol. 109, No. 2 (May), pp. 367-397

Black, Sandra E. and Lynch, Lisa M. (2004). “What’s driving the new economy? The benefits of workplace innovation”. *Economic Journal*, 2004, v114(493, Feb), 97-116.

Blundell, R. and S. Bond. (1998). “Initial Conditions and Moment Restrictions in Dynamic Panel Data Models”. *Journal of Econometrics*. Volume 87, Issue 1, Pages 115-143, ISSN 0304-4076. https://doi.org/10.1016/S0304-4076(98)00009-8.

Bound, J., & Johnson, G. (1992). "Changes in the Structure of Wages in the 1980's: An Evaluation of Alternative Explanations". *The American Economic Review*, 82(3), 371-392. Retrieved from http://www.jstor.org/stable/2117311.

Broda, Christian & Weinstein, David E. (2010). "Product Creation and Destruction: Evidence and Price Implications". *American Economic Review*, American Economic Association, vol. 100(3), pages 691-723.

Cahuc, P., F. Postel-Vinay, and J.-M. Robin. (2006). "Wage bargaining with on-the-job search: Theory and evidence". *Econometrica* 74(2), 323–364.

Card, David and DiNardo, John E. (2002). "Skill-Biased Technological Change and Rising Wage Inequality: Some Problems and Puzzles". *Journal of Labor Economics*. University of Chicago Press, vol. 20(4), pages 733-783.

Card, David and Cardoso, A Rute and Heining, Joerg and Kline, Patrick. (2018). "Firms and Labor Market Inequality: Evidence and Some Theory". *Journal of Labor Economics*, vol. 36, no. S1.

Casavola, P., Gavosto, A and Sesisto, P. (1996). "Technical Progress and Wage Dispersion in Italy: Evidence from Firms' Data". *Annales D'Économie Et De Statistique*, no. 41/42, pp. 387–412 (June).

Castillo, V., Maffioli, A., Rojo, S. and Stucchi, R. (2014). "The effect of innovation policy on SMEs' employment and wages in Argentina". *Small Business Economics* (February) 42: 387. https://doi.org/10.1007/s11187-013-9485-9

Chennels, L & Reenen, John V. "Has technology hurt less skilled workers? An econometric survey of the effects of technical change on the structure of pay and jobs". The institute for Fiscal Studies. Working Paper Series No. W99/27. 1999.

Cirillo, V. (2014). "Patterns of innovation and wage distribution. Do 'innovative firms' pay higher wages? Evidence from Chile". *Eurasian Business Review*. Dec2014, Vol. 4 Issue 2, p181-206. 26p.

Cozzarin, Brian Paul. (2016). "Impact of Organizational Innovation on Product & Process Innovation". *Economics of Innovation and New Technology*. Pages 405-417. https://doi.org/10.1080/10438599.2016.1204779.

Dachs, Bernhard and Peters, Bettina. (2014). “Innovation, Employment Growth, and Foreign Ownership of Firms - A European Perspective”. *Research Policy*. 43. 10.2139/ssrn.2256511.

Drahokoupil, J and Piasna, A. (2018). “What is behind low wages in central and eastern Europe?” *Post-Communist Economies*, 30:4, 421-439, DOI: 10.1080/14631377.2018.1442037.

Duffy, John., Papageorgiou, Chris and Perez-Sebastian, Fidel. (2004). “Capital-Skill Complementarity? Evidence from a Panel of Countries”. *The Review of Economics and Statistics.* 2004 86:1, 327-344.

Ettlie, John E. and. Rosenthal, Stephen R. (2011). “Service versus Manufacturing Innovation”. *The Journal of Product Innovation Management*. Volume 28, Issue 2, pages 285-299.

Evangelista, Rinaldo. (2000). “Sectoral Patterns Of Technological Change In Services”. *Economics of Innovation and New Technology*, Taylor & Francis Journals, vol. 9(3), pages 183-222.

Freeman, C. (1987). *Technology Policy and Economic Performance: Lessons from Japan,* Pinter, London.

Gibbons, Robert, and Katz, Lawrence. (1992). “Does Unmeasured Ability Explain Inter-Industry Wage Differentials?” *The Review of Economic Studies* 59, no. 3 (1992): 515-35. http://www.jstor.org/stable/2297862.

Goldberg, P., and Hellerstein, R. (2013). “A Structural Approach to Identifying the Sources of Local Currency Price Stability”. *The Review of Economic Studies*, 80(1), 175-210. Retrieved from http://www.jstor.org/stable/23355777

Goldin, C. and L. F. Katz (2010). *The Race between Education and Technology*. Belknap Press.

Greenan, Nathalie and Guellec, Dominique. (2003). “Technological innovation and employment reallocation”. *Labour.* 14: 547–590 (February)

Grupp Hariolf and Hipp, Christiane, (2005). “Innovation in the service sector: The demand for service-specific innovation measurement concepts and typologies”. *Research Policy*, Volume 34, Issue 4, Pages 517-535, ISSN 0048-7333.

Harrison, R, Jaumandreu, J, Mairesse, J and Peters, B. (2014). “Does innovation stimulate employment? A firm-level analysis using comparable microdata from four European countries”. *International Journal of Industrial Organization*, 35, issue C, p. 29-43.

Hottman, Colin J., Redding, Stephen J., Weinstein and David E. (2016). “Quantifying the Sources of Firm Heterogeneity.” *The Quarterly Journal of Economics*, 131(3): 1291–1364.

Jaumandreua, J. and Mairessec, J. (2017). “Disentangling the effects of process and product innovation on cost and demand”. *Economics of Innovation and New Technology*. Vol. 26, Nos. 1–2, 150–167.

Jiang, James J., Klein, Gary., Wang, Eric T.G. & Ying, Ta-Chung. (2006). “Group cohesion in organizational innovation: An empirical examination of ERP implementation”. *Information and Software Technology*. Volume 48, Issue 4, 2006, Pages 235-244, ISSN 0950-5849.

Juhn, C., Murphy, K., & Pierce, B. (1993). “Wage Inequality and the Rise in Returns to Skill”. *Journal of Political Economy*, 101(3), 410-442. Retrieved from http://www.jstor.org/stable/2138770

Kline, S. and Rosenber, G. (1986). “An overview of innovation, In: Landau, R., Rosenberg, N. (eds), The Positive Sum Strategy: Harnessing Technology for Economic Growth, Washington, DC, National Academy Press, pp. 275-305.

Krueger, A. (1993). “How Computers Have Changed the Wage Structure: Evidence from Microdata”. 1984-1989. *The Quarterly Journal of Economics*, 108(1), 33-60. Retrieved from http://www.jstor.org/stable/2118494

Lachenmaier, S. and Rottmann, H (2011). “Effects of innovation on employment: A dynamic panel analysis”. *International Journal of Industrial Organization*, vol. 29, issue 2, 210-220 (March).

Lam, A. (2005). *Organizational innovation.* In J. Fagerberg, D. C. Mowery, & R. R. Nelson (Eds.), The Oxford handbook of innovations (pp. 115–147). Oxford: Oxford University Press.

Leeuwen, George Van., Mohnen, Pierre., Polder, Michael and Raymond, Wladimir. (2010). “Product, process and organizational innovation: drivers, complementarity and productivity effects”. CIRANO - Scientific Publications 2010s-28. Available at SSRN: https://ssrn.com/abstract=1626805.

Lewis, Ethan. (2011). “Immigration, Skill Mix, and Capital Skill Complementarity”. *The Quarterly Journal of Economics*, Volume 126, Issue 2, May 2011, Pages 1029–1069.

Lundvall, B.-Å. (ed.) (1992), *National Innovation Systems: Towards a Theory of Innovation and Interactive Learning*, Pinter, London.

Lurdes, Simao & Mario, Franco. (2018). “External knowledge sources as antecedents of organizational innovation in firm workplaces: a knowledge-based perspective”. *Journal of Knowledge Management*, 22(2), 237-256.

Martínez-Ros, Ester (2001). “Wages and innovations in Spanish manufacturing firms”. *Applied Economics*. Vol. 33, No. 1, pp. 81-89.

Miles, Ian (2007). “Research and development (R&D) beyond manufacturing: the strange case of services R&D”. R&D Management. Volume37, Issue3, pages249-268. https://doi.org/10.1111/j.1467-9310.2007.00473.x.

Montgomery, James D. (1991). “Equilibrium Wage Dispersion and Interindustry Wage Differentials”. *The Quarterly Journal of Economics*, Volume 106, Issue 1, February 1991, Pages 163–179.

Mothe, Caroline., Uyen, Nguyen-Thi & Le Bas, Christian. (2015). “Technological innovation persistence: the role of organizational innovation”. *European Journal of Innovation Management*, Emerald, 2015, 18, pp.110 - 127. ff10.1108/EJIM-09-2012-0085.

Nelson, R. (ed.) (1993), *National Innovation Systems. A Comparative Analysis*. Oxford University Press, New York/Oxford

OECD, Oslo Manual, (2004). *The measurement of scientific and technological activities*. Proposed guidelines for collecting and interpreting technological innovation data. European Commission. Retrieved from: http://www.oecd.org/dataoecd/35/61/2367580.pdf

OECD/Eurostat (2018), Oslo Manual 2018: *Guidelines for Collecting, Reporting and Using Data on Innovation*, 4th Edition, The Measurement of Scientific, Technological and Innovation Activities, OECD Publishing, Paris/Eurostat, Luxembourg.

Pianta, Mario & Tancioni, Massimiliano (2008). “Innovations, wages, and profits”. *Journal of Post Keynesian Economics*, 31:1, 101-123.

Piva, Mariacristina and Vivarelli, Marco. (2004). “Technological change and employment: some micro evidence from Italy”. *Applied Economic Letters*. Vol.11, Issue 6, Pages 373-376.

Reenen, John V (1997). “Employment and Technological Innovation: Evidence from U.K. Manufacturing Firms”. *Journal of Labour Economics*, Vol. 15, pp. 255-284. (April).

Reenen, John V. (1996). “The Creation and Capture of Rents: Wages and Innovation in a Panel of UK Companies”. *The Quarterly Journal of Economics*, Volume 111, Issue 1, (February), Pages 195–226.

Rennings, Klaus. (2000). “Redefining innovation — eco-innovation research and the contribution from ecological economics”. *Ecological Economics*, Volume 32, Issue 2, 2000, Pages 319-332, ISSN 0921-8009.

Romer, P. M. (1990). “Endogenous Technological Change”. *Journal of Political Economy* 98(5), 71–102.

Roos, Göran. (2016). “Design-Based Innovation for Manufacturing Firm Success in High-Cost Operating Environments”. *She Ji: The Journal of Design, Economics, and Innovation*, Volume 2, Issue 1, Pages 5-28, ISSN 2405-872.

Ross, David R and Zimmerman, Klaus F (1993*). “*Evaluating reported determinants of labour demand. Labour Economics”. Volume 1, Issue 1, Pages 71-84 (June).

Schumpeter, Joseph A., 1883-1950. (1942). *Capitalism, socialism, and democracy*. Harper & Brothers. ISBN 0061330086.

Sirilli, Giorgio & Evangelista, Rinaldo. (1998) “Technological Innovation in Services and Manufacturing: Results from Italian Surveys”. *Research Policy*, 27, 881-899.

Sundbo, Jon (1997). “Management of Innovation in Services”. *The Service Industries Journal*. 17:3, 432-455, DOI: 10.1080/02642069700000028.

Teece, D. J. (1998). “Capturing Value from Knowledge Assets: The New Economy, Markets for Know-How, and Intangible Assets”. California Management Review, 40(3), 55–79. https://doi.org/10.2307/41165943

Vivarelli, Marco (2012). “Innovation, Employment and Skills in Advanced and Developing Countries: A Survey of Economic Literature”. *Journal of Economic Issues*. 48. 10.2753/JEI0021-3624480106.

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