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INNOVATION AS A FIRM-LEVEL FACTOR OF THE GENDER WAGE GAP

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Innovation as a firm-level factor of the gender wage gap

Jaan Masso, Priit Vahter*

Abstract

Although much research has investigated how innovation affects wages and wage inequality in general, less is still known on how innovation in firms affects the gender wage gap. We show, using matched employer-employee data from Estonia, that technological (product and process) and non-technological (organizational and marketing) innovation, as well as the firm's own R&D and innovation-related collaboration with external partners are, on average, associated with a larger gender wage gap in the firm. The positive effect of innovation on wages is about 3–5 percentage points smaller for women compared to men. The relationship between innovation and gender wage gap is stronger in the case of managers and plant and machine operators; therefore, both at the higher and lower end of the wage distribution, potentially indicating the importance of routine-biased technological change. We further show based on propensity score matching that men gain more from taking up a job at an innovative firm than women. The effect of innovation on men's wages and on the gender wage gap is significantly larger among newly hired employees compared to incumbent employees. Among the newly hired employees at innovative firms, taking up a job at a more 'open' innovator appears to be associated with especially strong gains for newly hired women. However, even in this case the gains fall short of the gains for men.

JEL Classification: J31, J71, J16, D22.

Keywords: innovation, gender wage gap, wage inequality.

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1. INTRODUCTION

The ability of traditional "old" factors of the gender wage gap, such as education and various individual-level characteristics to explain the gender wage gap has diminished over time (Goldin 2014, Bertrand 2010, Blau and Kahn 2017). Recent literature in labour economics has emphasized the importance of firm-level heterogeneity as a determinant of the gender wage gap. In particular, recent research has shown that firm productivity matters for the gender wage gap, with men and women sorting to a different extent into high-productivity firms and also receiving different wages within these firms after being hired (Card et al. 2016, Coudin et al. 2018). For example, the heterogeneity of firms explains 20 per cent of the overall gender wage gap in the case of Portugal (Card et al. 2016) and even 35 per cent in the case of Estonia (Masso et al. 2020).

This paper addresses an important and less studied aspect of firm heterogeneity affecting gender pay differences. We focus on a key driver of productivity differences at firms – the role of firm-level innovation. First, we show the effects of technological (product and process) and non-technological (organizational and marketing) innovation – the effect of key innovation output indicators. Second, we focus on two key innovation input indicators, firm's innovation-related collaboration with external partners (as an indicator of 'openness' in innovation) and R&D, and their effects on the gender wage gap. There is a clear need to understand in greater detail the link between innovation and gender wage inequality, and how similar or heterogeneous are the effects of innovation activities. Much of the relevant prior analysis focuses on the effects of technological novelties, especially on the effects of automation (e.g. Aksoy et al. 2020) and IT on wages or gender related labour market outcomes.

We add to the literature by investigating the effects of various core innovation indicators on the gender pay gap. In particular, we contribute by complementing the analysis of the effects of technological innovation and R&D with those of non-technological innovation and firm 'openness' in innovation. This enables us to observe whether the recent evidence (Aksoy et al. 2020) that the adoption of some key technologies, such as automation, are associated with higher gender pay gaps, is specific to a certain type of innovation, or whether such effects of innovation are more general and visible across different types of innovation indicators and key innovation activities.

We show, based on micro level data from Estonia and the estimation of Mincerian wage equations, that innovation at firm-level is associated with a greater gender wage gap in firms, in the case of each of the innovation indicators that we have used. Next, we add a more in-depth analysis using propensity score matching (PSM) in order to address to some extent the endogeneity of treatment variables, with a focus on the effects of the movement of men and women into innovative firms and how that shapes the gender wage gap. We observe that men gain more from such mobility than women, increasing thus the difference between the pay for men and women. We further outline whether the contribution of innovation to the gender pay gap differs depending on the occupational group of the individual and how, distinguishing in particular the relationship with managers' wages. The effects of innovation vary between different occupational groups, and managers are likely to be among the most affected occupations. Further, due to the segregation of men and women into different occupational groups, this can also materialise in effects on the overall gender wage gap in firms. In the case of managers, the association between innovation and the gender wage gap turns out to be larger than among most other occupation groups, except in the case of plant and machine operators.

Our analysis builds on various theoretical contributions that help to outline why innovative firms may have higher wages in general, and in particular for certain groups of employees. Some models and empirical papers suggest potential effects on the gender wage gap due to the segregation of men and women into different skill groups, tasks and occupations (Acemoglu 2002, Acemoglu and Autor 2011, Blanas et al. 2019, Acemoglu and Restrepo 2018). Others can be used to assist in addressing why men and women with similar skills and from similar occupation groups, and with similar tasks, may receive different wages in firms due to different pay policies or other reasons (e.g. van Reenen 1996). We rely on the reasoning from various different models and theories, not one specific model in our empirical analysis. These include studies on skill-biased technical change (Acemoglu 2002) or routine-biased technical change (Acemoglu and Autor 2011). These also include models investigating rent sharing between owners and employees (van Reenen 1996), the shirking model (Lazear and Rosen 1981), as well as recent work on firm heterogeneity and the gender wage gap (Card et al. 2016) or models suggesting complementarities between the adoption of new technology by firms and the ability of the employee to provide 'commitment' to work (e.g. 24/7 availability for work), such as in an extension of Melitz (2003) type heterogeneous producer model by Ben Yahmed (2013).

Our study uses matched employer-employee level data from Estonia. Estonia is an interesting case. It has the largest gender pay gap in the European Union, that is close to 23% and has been even more in the past (Anspal 2015, Eurostat 2020, the very long-term dynamics of the gender wage gap are explained in detail in Meriküll and Tverdostup 2020). According to Eurostat, it varied between 2009 and 2018, ranging from a low of 21.8% (in 2018) to a high of 29.9% (in 2012) (Eurostat, table earn_gr_gpgr2). A high proportion of this large gap is not explained by 'old' supply side factors such as the education and occupation of the individual or other observable characteristics of the individual. Several studies have by now also assessed the size of the firm-specific component in the aggregate gender wage gap (Card et al. 2016, Coudin 2018, Masso et al. 2020). Among the countries investigated so far, the largest role for firm-level heterogeneity (productivity differences) is found in Estonia (Masso et al. 2020). The firm-specific (productivity) differences, such as different sorting of men and women into higher productivity firms and the residual within-firm differences in the gender wage gap, account for about 35% of the aggregate gender pay gap in Estonia.

We make use of innovation indicators of firms from a matched and partially overlapping series of Community Innovation Surveys (CIS), matching the CIS with other firm-level indicators from various datasets as well as employee-level data on wages and characteristics of individuals. The employer-employee level dataset also enables us to track the mobility of individuals between firms, including movement from non-innovative to innovative firms. The dataset covers the period 2006–2018 and both manufacturing and services sector firms.

Our analysis is related to the wider literature on firm-level innovation and wage inequality (e.g. Cirillo et al. 2017) and recent advances in the analysis of the role of firm heterogeneity for the gender wage gap (Card et al. 2016, Masso et al. 2020). We contribute to the analysis of the effects of innovation on wages and wage inequality (e.g. Cirillo et al. 2017, Cirera and Martins-

Neto 2020, among others) by focusing on links between various key innovation indicators and the gender wage gap. For example, a recent paper by Laursen and Salter (2020) points to a rather neglected research question: To what extent do the employees of the firm capture value from open innovation by firms? We address this specific gap through empirical analysis of the different effects of firm collaboration in innovation on the wages of men and women. We observe that among the newly hired employees at innovative firms, taking up a job at a more 'open' innovator appears to be associated with especially strong gains for the newly hired women. However, even in this case the gains for women still fall short of the gains for newly hired men.

There is mixed prior evidence for how different new technologies and innovation in general affect the gender wage gap. For example, there is some evidence suggesting that adoption of IT has historically favoured women on the labour market, due to changes in the task structure (Black and Spitz-Oener 2010, Yamaguchi 2018) and the reduced relevance of physical skills (Weinberg 2000). At the same time, recent evidence on another key technology, on the effects of automation in the labour market, suggests that automation is associated with increasing gender gaps (Brussevich et al. 2019, Blanas et al. 2019), including a higher gender wage gap (Aksoy et al. 2020). These effects have been argued to be the result of the different distribution of routine and non-routine tasks among men and women (Brussevich et al. 2019).

The rest of the paper is structured as follows. Section 2 presents a literature review on the links between innovation and the gender wage gap, Section 3 outlines the employer-employee level data used in the paper, Section 4 discusses the methods used, Section 5 presents the results of the estimation of Mincerian wage equations and the application of PSM, Section 6 presents a robustness test and Section 7 concludes.

2. LITERATURE REVIEW

A number of theoretical contributions are relevant for explaining the channels through which innovation at firms affects wage inequality in general or the gender wage gap in particular. Here we review the core mechanisms of these effects.

A first simple reason why innovators may have a larger gender wage gap comes from Becker's (1957) theory of taste-based discrimination, where more profitable firms can more easily cover the costs of costly discrimination between men and women. Innovation, despite the great uncertainty about its outcomes, is associated on average with higher expected ex-post profits. Therefore, based on this reasoning alone, one would expect innovators to have on average a larger gender wage gap compared to non-innovators. We note that, given that different types of innovation can increase profits, this reasoning points to a potential general effect of innovation on gender inequality, which may hold both in the case of technological and non-technological (e.g. organisational) innovation.

However, there are many factors that affect the gender pay gap in different types of firm and Becker's type of discrimination is not necessarily the core explanation. Arguably, statistical discrimination is also relevant in the context of innovation and the gender pay gap. Employers may have imperfect information about the skills of their employees and base their judgements on the gender-based average levels. One example: the lower average skills of women in mathematics have been shown to affect the gender wage gap (Hanushek et al. 2015, Altonji and Blank 1999). Math skills are especially relevant for R&D and in technology rich environment. The lower average skills of women in mathematics may cause statistical discrimination in these contexts where analytical skills are especially important (Brussevich et al. 2019) and valued by the employer. This in turn might cause women to invest less in these skills and to apply less frequently for jobs where these skills are required.

Apart from any direct discrimination, the gender wage gap differences between innovators and non-innovators can be due to the segregation of men and women in the labour market and the firm or due to productivity differences of otherwise similar employees in a firm. The first broad class of theoretical reasons for the links between innovation and the gender wage gap has to do with the structural effects of innovation, which can affect the aggregate gender pay gap through changes in demand for certain skills (skills that are complementary to technological change), tasks or occupations. If there is segregation by gender in skill groups, occupation groups and within occupations by job tasks, then these structural effects can result in widening the aggregate gender wage gap. This type of classical theoretical reasoning starts from the hypothesis of skill-biased technical change (SBTC) (Acemoglu 2002, Aghion 2002, Hornstein et al. 2005). Skill-biased technical change means that a change in the production technology favours high-skilled labour that is more educated or more experienced over unskilled labour. In the case of SBTC, the technological change raises the productivity of skilled employees relative to others, and thus (ceteris paribus) the relative demand for them, leading to growth in the skill premium in wages (Acemoglu 2002, Violante 2008). A related reasoning is the routine-biased technical change (RBTC) hypothesis (Acemoglu and Autor 2011, Goos and Manning 2007, among others). It implies that technological change has different effects on demand and rewards for routine and non-routine tasks, with new technology having more complementarity with the latter, resulting in higher demand for non-routine tasks and higher relative rewards for these.

There is somewhat contrasting evidence for how the new technologies and innovation in general affect the gender wage gap through the SBTC and RBTC channels. For example, there is some evidence suggesting that the adoption of IT has historically favoured more women on the labour market, due to changes in task structure (Black and Spitz-Oener 2010, Yamaguchi 2018) and the smaller relevance of physical skills (Weinberg 2000). At the same time, recent evidence on the effects of another key technology, automation, in the labour market suggests that automation is associated with increasing gender gaps in the labour market (Brussevich et al. 2019), including a higher gender-based wage gap in Europe (Aksoy et al. 2020). These effects have been argued to be the result of a different distribution of routine and non-routine tasks among jobs for men and women (Aksoy et al. 2020, Brussevich et al. 2019). Automation and robotization decrease the relative demand for services in those labour groups that engage more in routine tasks (Brussevich et al. 2019, Blanas et al. 2019).[1]

[1] Some recent empirical and theoretical research by Aghion et al. (2019) points to complementarities between firm R&D and the soft skills of some 'low-skilled category' employees. They point out, based on their model and data from the UK, that low-skilled employees with soft skills related to coordination, communication and managerial competences, the ability to adjust actions in relation to others, the ability to work in teams, being highly accurate at the task, and so on, can reap especially large wage premiums in innovative firms. However, there is little reason to

Further, theories that introduce labour market imperfections and asymmetric information between the employer and employees point to reasons to set different wages for different jobs or for employees with similar skills that have different job tasks. For example, the shirking model in labour economics suggests that wages may be higher for those employees whose tasks are difficult to measure in terms of employee effort spent on the task (Lazear and Rosen 1981). If men at a firm work more on knowledge intensive and managerial tasks that are more complex to assess in terms of effort, then this would drive up the gender wage gap within the firm. Also, innovative firms may want to pay higher wages to their key employees who contribute especially to their innovation process, in order to hinder their movement away from the firm and taking the acquired firm-specific tacit knowledge capital to their competitors (see the discussion in Laursen and Salter 2020). That may also result in a greater gender pay gap if men more frequently fill such positions.

A standard assumption is also that there is a direct link between the productivity of the firm and the employees and wages at the firm.[2] This has its theoretical basis in the rent-sharing hypothesis, where wages are expected, due to the bargaining power of employees and higher 'rents', to be higher at firms with greater productivity (van Reenen 1996). The division of the rents of innovation depends on the relative bargaining power of the employees and owners of the firm. It can similarly depend on the relative bargaining power and attitudes to risk taking and wage negotiation of men and women at the firm. As the attitudes towards negotiation and risk taking are on average different between men and women (see the literature review in Bertrand 2018), this can be one mechanism for how men can reap more rewards from working at innovative firms compared to women.

The differences in the bargaining power of men and women at firms constitute one core aspect in recent advances in the analysis of the role of firm-level heterogeneity and in particular firm productivity in shaping the gender wage gap.[3] This strand of literature points to two core channels of how firm productivity differences or firm-specific fixed effects affect the gender wage gap (Card et al. 2016, Coudin 2018). The authors disentangle the overall firm-heterogeneity effect on the gender wage gap into the sorting and bargaining channels (Card et al. 2016). Part of the firm-heterogeneity effect reflects the fact that women are less likely to sort to working at high-productivity firms (sorting channel), and if women take up a job at a high-productivity firm they still earn less than men with similar skills (the bargaining channel). The empirical literature tends to show that the sorting channel is especially important in Western European countries. However, in our studied country Estonia, the two effects have been previously shown to be roughly similar in terms of their size (Masso et al. 2020), emphasizing the importance of the bargaining effect on wages in the Estonian context.

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expect this to lead to a lower gender wage gap, as many of these characteristics are not likely to be more represented among women compared to men (or may even reflect the routine vs non-routine distinction already mentioned above).

[2] For example, marketing innovation has been shown to also have sizable effects on productivity (Peters et al. 2018). Thus, similarly to other types of innovation it may affect wages and wage dispersion at the firm through productivity related effects.

[3] The differences in bargaining power or willingness to bargain by men and women have been suggested as important factors of the gender wage gap by prior research in Estonia (Meriküll and Mõtsmees 2017, Masso et al. 2020).

In addition to complementarity between innovation and skills or between innovation and non-routine tasks, innovation may also favour categories of employees who can offer more flexibility of 'commitment' for job purposes (or are perceived to be on average more committed by the managers of firms). This can be a further reason why firms in high competition environments and in rapidly developing firms may on average favour men over women with children. Goldin (2014) suggests that lower (temporal) flexibility for job purposes among women compared to men and more work interruptions for women due to children and more non-market work (e.g. taking care of elderly relatives) is one powerful reason explaining the remaining gender wage gap in advanced economies.

The temporal flexibility of an individual in terms of availability 24/7 for job purposes creates productivity advantages especially in certain occupations (e.g. lawyers, management consultants, business professions in general) and high-performance organizations, such as in innovative firms and internationalised firms. These are firms that operate in a more uncertain and rapidly changing context compared to non-innovative firms or firms that are active only in their home market. In such organizations there can be disproportionate strong rewards for working longer hours, doing overtime and in general 24/7 availability for job purposes (to travel at short notice, to take work tasks and calls also at weekends and after hours). Individuals who are able to offer this kind of flexibility are remunerated disproportionally well in such high-performance contexts. The fact that men are on average more likely (or perceived as more likely by managers) to offer this kind of temporal flexibility compared to women with children, can lead to a larger gender wage gap in more innovative firms. The theoretical basis for such effects among innovators compared to non-innovators is developed in a heterogeneous producer Melitz-type model by Ben Yahmed (2013), where she introduces a complementarity between the adoption of advanced technology at the firm and the high levels of commitment (temporal flexibility for job purposes) needed from its employees (especially during the setup of new technology). Such complementarities create an incentive for high-performance firms to favour hiring and remunerating more men compared to women.

Much of the empirical analysis on innovation and the gender wage gap focuses on the role of technological innovations such as IT (Weinberg 2000) or automation (Aksoy et al. 2020). Some research has also focused on the role of investments in intangibles (Asplund and Napari 2011), or specific organisational practices, such as various high-performance work practices, such as job rotation, incentive pay, self-managed teams and project based teams (Datta Gupta and Eriksson 2012, Davies et al. 2015).

There are some reasons why organisational innovation, such as, for example, the adoption of high-powered work practices might be expected to lower the gender wage gap (Davies et al. 2015). Datta Gupta and Eriksson (2012) point out that the traditional occupational types and occupation specific barriers for women may change due to the adoption of human resource management practices such as job rotation or quality control circles. The reason is that these practices could in principle allow the easier entry of women to those tasks and jobs that were traditionally more a man's realm, and allow building skills in women by doing tasks that are associated with higher wages at the firm. Further, increased involvement in decision-making and more decentralised decision-making due to some of these practices might support the relative bargaining power of women.

However, there are also reasons why organisational innovation in the form of high-powered work practices may be associated with an increase in the gender wage gap (Davies et al. 2015, Datta Gupta and Eriksson 2012). Some of these organizational practices introduced at firms may require, as mentioned above, more commitment from employees and demand more temporal flexibility for job purposes, such as being ‘on call’ for work purposes and ready to take on tasks at short notice outside normal work hours, or in general if these introduce a more competitive environment at the workplace. Performance based pay may in fact increase the wage differentials resulting from the real or perceived differences in characteristics of employees (Albanesi et al. 2015).[4]

There is some evidence from Datta Gupta and Eriksson (2012) using Danish data that high-powered HR management practices (including incentive pay and job rotation) can have stronger wage benefits in the case of men, although there appears to be heterogeneity in these effects by type of practice, as the organization of work into project based work was in their analysis associated with a lower gender pay gap. Davies et al. (2015) find, using data from the UK, that while wages in general are higher among firms that have introduced high-performance work practices, the adoption of these is not associated with a lower gender wage gap, and may in fact even increase the gap.

There are further aspects of innovation in firms that are much less investigated in relation to gendered labour market outcomes, compared to technological innovation or high-performance work practices. In particular, there appears to be a significant need for studies on gender related outcomes and gender wage gaps related to open innovation (Chesbrough 2003) in firms. Open innovation emphasizes the role of combining external knowledge from outside the firm with internally created knowledge in innovation and can be defined as “a distributed innovation process based on purposively managed knowledge flows across organizational boundaries, using pecuniary and non-pecuniary mechanisms in line with the organisation’s business model” (Chesbrough and Bogers 2014, p. 17).

There is much literature on open innovation and firm performance, with Laursen and Salter (2006) being a most influential empirical study. There is much less literature on the competences needed for open innovation in firms (see Podmetina et al. 2017) or on the challenges it poses to individuals at the firm (Bogers et al. 2017). Literature on open innovation has paid rather limited attention to various social issues, and this limitation is especially evident on perspectives concerning links between open innovation and gender (Wikhamn and Knights 2013) or its effects on gendered labour market outcomes, with the latter topic essentially missing in the literature.

A recent conceptual paper by Laursen and Salter (2020) on open innovation points to the rather neglected general research question: To what extent do the employees of the firm capture value from open innovation (incl. collaboration in innovation with external partners and knowledge sourcing from outside the firm) in firms? We address this specific gap via empirical analysis of

[4] Additionally, there are simple structural factors at work. If the firm successfully introduces complex productivity enhancing organizational innovations and if managerial positions and supervisor positions at the firm are held predominantly by men, then the likely pay rewards to different managers and supervisors for good organization of the introduction of the new practices may also exacerbate the gender pay gap.

the different effects of innovation-related collaboration in firms on the wages for men and women.

A standard expectation, as discussed in Wikhamn and Knights (2013), can be that strategic change in the firm from a 'closed' innovation model relying only on their own R&D towards combining internal R&D with external knowledge sources could mean a disruption in management practices by putting emphasis in the firm on "openness", "sharing and trust", "creativity", "communication" and "collaboration" – terms that are classically associated with femininity (Vetterling-Braggin et al. 1977), and could create opportunities for change in terms of gendered work practices at the firm towards a more equal treatment of women. However, this does not need to be the case. Based on a case study of Volvo, Wikhamn and Knights (2013) demonstrate how the introduction of open innovation practices, if governed by the existing masculine norms at the firm level, may be much more likely to reinforce the existing norms rather than challenge them. Furthermore, the set of competencies needed for open innovation, as outlined, for example, in Podmetina et al. (2017), does not appear to be necessarily associated with a higher relative demand for women in the labour market.

3. DATA

In our study we used Estonian matched employer-employee data for 2006–2018, combining individual and firm-level variables from different sources. The source of the data on the key variable "wages", is the Estonian Tax and Customs office monthly data on paid payroll taxes disaggregated both across individuals and companies. We use the wages from January for each of the sample years and have limited the focus to employees' main job (as in Vahter and Masso 2019).[5] The Tax and Customs Office data includes only two types of individuals' characteristics: date of birth (used to construct employee age) and gender. Therefore, the other datasets are used for additional socio-demographic characteristics: Population and Housing Census of 2011 (used for data on number of children, education, occupation), Structure of Earnings Survey 2014 and 2018 waves covering approximately 20 per cent of the Estonian workforce (education and occupation variables for 2014 and 2018), Employment Registry data since 2019 (for occupation). The 4-digit ISCO occupation codes are analysed at the 1-digit level and the educational variable is transformed to a form with 3 values (primary, secondary, tertiary education). Therefore, while we do not have data on education and occupation for all of the years, we will use the values from the closest year for the years with missing data (either 2011, 2014, 2018 or 2019).

The above individual-level datasets are combined with firm-level variables among which the key for the purpose of our study is the innovation data from the 6 waves of the Community Innovation Survey: 2004–2006 (CIS2016), 2006–2008 (CIS2006), 2008–2010 (CIS2008), 2010–2012 (CIS2010), 2012–2014 (CIS2012), 2014–2016 (CIS2014), 2016–2018 (CIS2016). The CIS

[5] The potential drawback of the dataset is the lack of the data on working hours; even though the data includes since 2015 the information on the degree of working time (*tööaja määr*, a variable within the range of 0 to 1), as the latter information is often missing and of low quality. However, we argue that the shortage of data on working time and hours is a relatively minor issue given the very limited part-time working in Estonia (as in other Central and Eastern European countries) even among females.

datasets cover annually approximately 1,600 firms with more than 10 employees with major overlap across the waves, so that the innovation data is effectively unbalanced panel data. The difficulty in merging the CIS data with other firm-level or individual-level datasets is that each of the CIS waves covers a 3-year period (e.g. in the case of CIS2014, 2012–2014 for the innovation output variables like product or process innovation). Naturally, we may then attach the values of CIS2014 to all of the years 2012–2014, but then we need to consider that the periods of the different CIS waves also overlap (e.g. CIS2016 covers 2014–2016); therefore, in our example, we have two values for CIS2014, one from CIS2014 and the other from CIS2016. In that case, we decided to use the values of the earlier survey for the overlapping years, such as 2014 here, as the moment of the survey was closer to the particular year, and thus that value should be more accurate (more likely to equal the true value). Therefore, if we suppose that some firm is innovative (value 1 of the dummy variable) in CIS2014 and non-innovative (value 0) in CIS2016, the time series is as follows: 2012 – 1; 2013 – 1; 2014 – 1; 2015 – 0; 2016 – 0.

To investigate how general the effects of innovation on the gender wage gap are, we study various standard measurers of innovation in firms. These are as follows: 1) dummies for being a technological innovator (with either product or process innovation); 2) dummies for having non-technological innovation introduced in the firms (with either organisational or marketing innovation); 3) two measurers of innovation inputs – a dummy for innovation-related cooperation with external partners and a dummy for continuous engagement in R&D.

The innovation indicators that we use have been widely used in relevant literature to analyse the firm-level effects of innovation on performance (Mairesse and Mohnen 2010). The innovation variables follow the definitions from the OECD Oslo Manual (2005). The four innovation output indicators – product, process, organizational and marketing innovation – reflect innovation that is new to the firm but not necessarily new to the market in general.

A process innovation is the "application of new or significantly improved methods for the production or delivery/distribution of a good or service" (Oslo Manual 2005, p. 48). Product innovation is the provision of new or significantly improved goods or services. Organisational innovation includes "new or significantly changed business practices in the organisation of work, business structure and decision-making or in ways to manage external relations" (Oslo Manual 2005, p. 49). Research and experimental development (R&D) "comprises creative work undertaken on a systematic basis in order to increase the stock of knowledge, including knowledge of man, culture and society, and the use of this stock of knowledge to devise new applications (as defined in the Frascati Manual)" (Oslo Manual p. 92). In-house continuous R&D includes creative work continuously "undertaken within the enterprise to increase the stock of knowledge for developing new and improved products and processes (including software development in-house that meets this requirement)" (CIS2008 questionnaire p. 5). Innovation collaboration is defined based on a "Yes" answer in the CIS survey to the following question: "During the three years … to …, did your enterprise co-operate on any of your innovation activities with other enterprises or institutions?"[6] (CIS2008 questionnaire, p. 7).

[6] A clarification is added: "Innovation co-operation is active participation with other enterprises or non-commercial institutions on innovation activities. Both partners do not need to commercially benefit. Exclude pure contracting out of work with no active co-operation." (CIS2008 questionnaire, p. 7).

Some other firm-level datasets[7] were used as a source of the necessary control variables related to firm performance and characteristics, these were the Estonian Business Registry for financial information, location, as well as ownership of firms, as multinational firms have been shown to have a strong positive effect on the size of the gender pay gap (Vahter and Masso 2019). The Statistics Estonia international goods trade dataset and Bank of Estonia services trade datasets are used to control for the exporting status of firms in the wage analysis, as exporting has been shown to be associated with a higher gender pay gap (Boler et al. 2018).

The key descriptive statistics of the key variables used in our analysis, separately for men and women, are shown in Annex 1. In Estonia, as evident also from Annex 1, women have more frequently on average a higher education than men; men have more frequently secondary or primary education only. In our sample, the share of women is higher in the capital region and that of men is higher in the industrial Ida-Virumaa county in the east.

As observed also in Card et al. (2016), and for Estonia in Masso et al. (2020), men tend to work on average more at firms with higher productivity. This is perhaps surprisingly not reflected in unconditional averages of innovation indicators. In the sample for men in our data, 63.7 per cent of them work in firms that have technological innovation (either new products or production processes), the corresponding number in the sample of women is 70.1 per cent. This pattern is repeated for other indicators of innovation – 25.4 per cent of men work in firms that continuously engage in R&D, the corresponding number for the sample of women is 32.1 per cent. At the same time, women tend to work more in firms that have a lower share of managers and high wage employees, and are employed significantly more in firms with overall lower wage levels. A well-known fact reflected in our dataset is that women tend to be much less likely to work in managerial occupations (7 per cent vs 11 per cent of employees in our sample). Most importantly, there is substantial segregation, the sample of women has a firm-level average of female co-workers of 60.1 per cent, whereas in the men's sample the share of female co-workers is only 32.4 per cent. Previous studies have shown that this segregation contributes considerably to the aggregate gender wage gap, as women tend to select to work at firms with lower productivity and overall wages (Masso et al. 2020).

Unsurprisingly, in the datasets in our study, firms with various innovation activities have higher wage levels in general. For example, in 2012, innovating firms had a wage premium compared to others – a 12.2 per cent wage premium in the case of technological innovation (product or process innovation), and 18.8 per cent in the case of non-technological innovation (organizational or marketing innovation).[8] Obviously, these are unconditional averages and may be driven by structural differences in the use of different skill groups, occupations and the structure of tasks between firms. Wage premiums are also there if we view the firms doing R&D or collaborating with external partners in their innovation process.

A look into the descriptive statistics on the gender wag gap in innovative vs non-innovative firms confirms that the innovative firms have a somewhat higher gender wage gap. However, the

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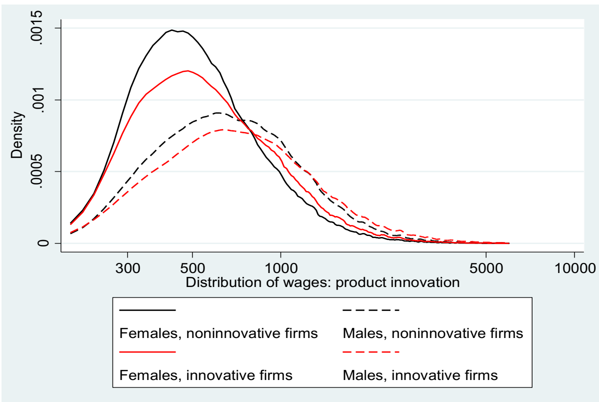
[7] In addition to CIS, we use in an extension of the analysis in Section 6 of the paper also the IT variables from the Information Technology in Enterprises survey for 2015–2019 covering approximately 3,000 firms annually. The following variables were used: 1) Share of employees using computers >=50% (dummy); 2) Share of employees using computers connected to the internet >=50% (dummy); 3) Share of employees using mobile devices.

[8] Note that all these differences are calculated by comparing the corresponding innovator group with non-innovators.

difference is not always large and is heterogeneous in terms of many characteristics of the sector or the firm. Over all the years of the study in our sample, non-innovators had a gender wage gap of 19.3 per cent and technological innovators 21.5 per cent. The corresponding numbers for the manufacturing sector are 21.8 vs 22.3 per cent and in the services sector 17.4 and 22.1 per cent. Firms that have introduced different types of innovation; for example, those with both product and process innovation, show a higher gender wage gap: 23.5 per cent over the studied period.

The differences in the wage distributions across innovating firms and others, as well as across men and women are given in Figure 1, which depicts the kernel density distribution of individual-level wages in our dataset. Figure 1 further confirms that the standard finding of a wage premium at innovative firms (e.g. Cirera and Martins-Neto 2020, Cirillo et al. 2017) holds also in the case of various quantiles of the distribution of wages. It further confirms the standard result of the gender wage gap both at innovative and non-innovative firms.

The Kolmogorov-Smirnov test applied at the standard level of significance (1 and 5%) indicates that the wage distributions of the two groups of firms are different, that of innovative firms lies to the right of the non-innovative firms and stochastically dominates the other. We observe less weight in the left-hand low-wage tail of the distribution in innovative firms, both in the case of men's and women's wages. The descriptive statistics shown in this section may reflect high wage firms' selection into innovation or high-skilled individuals' selection to work at innovative firms, or alternatively the effect of innovation or moving to work at an innovative firm on the wages of men and women.



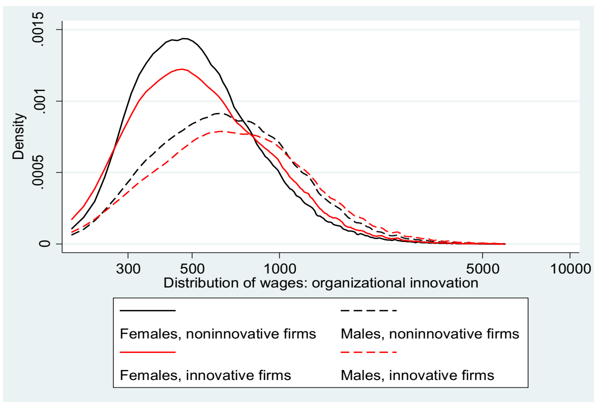


Figure 1. Distribution of wages for different innovators compared to non-innovative firms
Notes: Innovative firms compared to non-innovative firms, 2006–2018, manufacturing and services firms. Kernel density of wages is reported.

4. METHODS

Our empirical approach includes two major methodologies using matched employer-employee level data: the estimation of Mincerian wage equations and application of matching methods. First, as a form of a conditional mean analysis, we estimate the Mincerian wage equations at individual level to study whether, after including the standard determinants of wages, the indicators of innovation in firms are still associated with wages of men and women and the gender wage gap. Second, as a step a bit closer to identifying the causal relationships, we undertake the treatment analysis using the propensity score matching (PSM) approach. Here we focus on employee mobility between firms, and on the effects of this on the wages of the same individual. The treatment is the employee moving from a non-innovative firm to an innovative one. While the innovation is measured in the CIS survey at the level of firms as legal entities, the analysis of the effects of the movement between firms is conducted at the level of employees.

In the Mincerian wage analysis, we account for the observed firm and individual-level covariates. The dependent variable is the log of real monthly wages lnW_{ikt} in January of the year.[9] The wage equations take the following form:

$$lnW_{ikt} = \alpha_0 + \alpha_1 Female_{ikt} + \alpha_2 Innovation_{kt} + \alpha_3 Female_{ikt} \times Innovation_{kt} + \alpha_4 Age_{it} + \alpha_5 Age_{it}^2 + \alpha_6 R_{it} + \alpha_7 Z_{kt} + \alpha_8 \lambda_t + \varepsilon_{ik} \quad (1)$$

In the equation above, i denotes individual, t year and k firm; $Innovation_{kt}$ is a dummy variable denoting whether the individual works at an innovative firm or not; $Female_{ikt}$ is a variable denoting a woman. The key variable for the interpretation is thus the interaction term $Female_{ik} \times Innovation_k$ showing whether a firm's innovation status is associated differently with the wages of the males and females. The parameter $\alpha_3 < 0$ would indicate innovation being associated with a larger gender pay gap.

The set R_{it} of individual level controls includes the individual's age and age squared (proxy also for the length of the job tenure) and education (dummies for primary, secondary and tertiary education). The vector of firm-level control Z_{kt} includes variables that in addition to their general impact on wages have been found or are potentially associated with the gender pay gap. These control variables help account for the possibility that the correlation between firm innovation indicators and gender pay gap is driven by some other characteristics of innovative firms (e.g. innovative firms being also more internationalised). The firm-level control variables are firm size, firm size squared, firm age, firm age squared (controlling for higher wages in

[9] While that wage measure available in the registry data does not account for the working hours and part-time (especially important in the context of a study like ours on gender), it matters relatively little in the context of Central and Eastern European countries like Estonia, where part-time employment even among females has been fairly limited related to relatively low wage levels and historical reasons (full-time employment being a part of the culture both for the employees and the employers). Also, the average wages calculated from our data after excluding outliers closely mimic the average wages in the official statistics (the difference being less than 2 percentage points).

larger and mature firms), share of managers at firms, share of women at the firm, and regional dummies for 5 NUTS3 regions. The dummies for foreign owned firms and exporters (exporting either services or goods) take into account the fact that the internationalisation of firms has been found in past studies to be strongly associated with the gender pay gap (e.g. Vahter and Masso 2019, Boler et al. 2018).

Dummies for different years λ_t and firm-fixed effects υ_k are included in the panel data based specifications of Equation 1. The last term in Equation 1 is an error term, which is assumed to be normally distributed with a zero mean and a constant variance.

In addition to this baseline specification, we estimate several other specifications. One specification included as additional, controls the variable of firm-level labour productivity measured as valued added per employee. This variable endeavoured to account for the possibility that the association between company innovativeness and wages might work through higher productivity. Second, we consider that the above set of individual-level controls could be somewhat small. Therefore we also run the estimates of equation (1) including additional employee-level controls, like the 1-digit occupational ISCO codes as the control variables, originating from the Population Census, Structure of Earnings Survey and Employment Registry. These were not included in the baseline estimations of equation (1), as they are available only for a subset of the study period.

We investigate the association between innovation at firm level and the gender gap in wages also separately for the 1-digit ISCO occupation groups. Prior studies have shown the relevance of other firm-level factors especially at the high end of the wage distribution, as in the case of managers (Masso et al. 2020). Also, we estimated some additional regressions by considering the children (at age 0–2 or 0–17) that the woman has. For example, certain work environments might be especially detrimental to women with children (see Bertrand 2018 for a discussion on motherhood penalty in wages and the glass ceiling).

The second major part of our econometric analysis focuses on treatment analysis. We endeavour to discover whether there is also a linkage between innovation at the firm and the wages of men and women that is likely to reflect the (potential causal) effect of individuals taking up a job at an innovative firm, in addition to the (non-random) selection of individuals into the firm. The advantage of our matched employer-employee data is that we are able to track over time both the firms (e.g. how their innovativeness status changes from one year to the other) and employees: how they change their employer or move between different labour market states from year to year. As the main focus of interest in this part, we investigate the treatment effect at the employee level: whether an employee moving (changing the employer) over a year (from January to January, for either voluntary reasons like quitting the prior job or involuntary reasons like firings) from non-innovative to innovative company has any effect on the employee's wage, and whether that effect differs for males and females. If such a difference can be observed, we consider that as evidence of innovation being associated with or possibly even causing a greater gender pay gap. The control group in the case of the employee-level treatment analysis includes only employees that were working in a non-innovative company (non-innovative in terms of the four aforementioned core innovation variables) for years *t-1, t, t+1, t+2* (*t* being the year of treatment).

The list of control variables included in the estimation of the propensity score in the probit model for individuals changing their place of employment includes mostly a similar set of variables as in the Mincerian wage regressions (but all measured at the pre-treatment period, i.e. at *t-1*), but also two additional firm-level controls – company liquidity ratio and capital-labour ratio. The control variables include also the lagged values of the outcome variables, log real wages and log real wages squared. As the matching algorithm, we used the nearest neighbour matching with two neighbours. After the estimation of the propensity score, we calculated the average treatment effect on the treated (ATT) on employee wages over the post-treatment periods. Formally, the ATT will be calculated as

$$ATT_{PSM} = \overline{\Delta^s \pi_{t+s}^{treated}} - \overline{\Delta^s \pi_{t+s}^{control}}, \tag{2}$$

where the first term on the right-hand side is the mean growth of the wage as the outcome variable (denoted here as π), treated individuals (those moving from a non-innovative company to an innovative company), and the second term is a weighted mean of the growth of the outcome variable (wage) for the counterfactuals over the same period. The symbol *s* denotes the time over which the change is calculated; for example, for *s=2*, $\Delta\pi_{t+2} = \pi_{t+2} - \pi_t$. We have hereby considered the growth in the outcome variables relative to the pre-treatment (time *t=1*) values at time *t+1* and *t+2*.

5. RESULTS

The key results from estimating the Mincerian wage regressions with firm-level fixed effects are shown in Table 1, based on employer-employee data from 2006–2018. The regression models in Columns 1–4 focus each on the effect of a different innovation indicator: i) technological innovation, ii) non-technological innovation, iii) continuous R&D at the firm and iv) collaboration in innovation activities with external partners. Each model is estimated based on data from the corresponding treatment group and the non-innovating firms.

The dummy variable for women in our regressions has a plausible size given the aggregate statistics for Estonia and prior studies using related datasets (e.g. Masso et al. 2020). The conditional gender wage gap varies between 29 –31 per cent of men's wages in Table 1, depending on the specification. Due to the log transformation of the dependent variable in the wage equation, this effect of a dummy variable is calculated using the standard exponential transformation: *exp(coefficient)-1.*

The estimated conditional within-firm 'effect' of innovation on men's wages is given by the coefficient of the variable for innovation in each column. The corresponding innovation premium in women's wages is calculated as the combination of this coefficient and the coefficient of the interaction term between the dummy variable indicating women and the innovation indicator at firm level. We observe that men gain about 3.6 per cent in wages from working in a firm that has technological innovation, compared to working in a firm with no innovation (neither technological nor non-technological). The men's wage premium from organisational innovation introduced at the firm is, after taking into account other covariates, smaller. This effect amounts to an increase in wages of 2.4 per cent. These numbers are not particularly high and may partly reflect the fact that various other aspects of sector or firm heterogeneity have been taken into account in these regressions (incl. firm size, ownership and exporting, share of managerial employees at the firm, share of women at the firm), as well as individual-level characteristics (education, age, etc.). We note that these estimates are close in terms of the economic size of the effects to some other papers on the effects of innovation on wages, such as the recent Cirera and Martins-Neto (2020) study on innovation and wages in Brazil. Further, we observe that men gain a 2.6 per cent wage increase if the firm that they are working in is engaging in R&D (compared to working at a firm that engages neither in R&D nor innovation cooperation). Men gain 3.3 per cent in pay if their employer is engaging in innovation-related collaboration with other organisations. A large share of this is collaboration with clients and suppliers of the firm.

Our review of the various channels of the effects of innovation on the gender pay gap suggested that there are several reasons why innovation in firms may be associated with a higher gender wage gap. This regularity is confirmed in Table 1 and in the rest of our analysis. Indeed, this is a highly robust result. Innovating firms in Estonia have a larger gender wage gap, even if we take into account the various other standard drivers of wages and the gender pay gap. While men gained 3.6 per cent from technological innovation and 2.4 in the case of non-technological innovation, the corresponding conditional wage premiums for these core types of innovation are close to zero in the case of women (on average). In fact, innovation is correlated with a tiny fall in women's wages, and in the case of both types of innovation outputs, this amounts to a fall of 0.5 per cent. A similar lack of any substantial average positive effects on all women's wages is observed in the case of R&D and collaboration in innovation (see Table 1).

The average gross monthly salary in Estonia in 2018 was 1,310 EUR. For an individual earning this salary, the effect of technological innovation at the firm if this person is male is an additional 47.2 EUR. The corresponding effect on a woman earning this same monthly salary is almost zero: a fall in wages of 6.6 EUR. We note that these average estimated effects on the gender pay gap in general are significantly smaller than the effects of one other key aspect of firm heterogeneity – foreign ownership, as studied based on Estonian employer-employee data in Vahter and Masso (2019). The analysis in that paper showed that both men and women gained substantially from the international activities of their employer, but men gained significantly more than women.[10]

[10] There the gain for men from working at a foreign owned firm was an increase in monthly wages by 171 EUR and for women by 62 EUR (in year 2016).

Table 1. Innovation and gender wage gap in Estonia, in manufacturing and services sector. OLS with firm fixed effects, with different innovation indicators

Dep. var: log of wage	Technological innovation (dummy)	Non-technological innovation (dummy)	Continuous R&D (dummy)	Innovation cooperation (dummy)
Female (dummy)	**-0.256**	**-0.267**	**-0.273**	**-0.265**
	(0.002)*	**(0.001)***	**(0.001)***	**(0.001)***
Innovation var. (CIS)	**0.036**	**0.024**	**0.026**	**0.033**
	(0.001)*	**(0.001)***	**(0.001)***	**(0.001)***
Female × Innovation var. (CIS)	**-0.041**	**-0.031**	**-0.034**	**-0.037**
	(0.002)*	**(0.002)***	**(0.002)***	**(0.002)***
Individual's age	0.040	0.040	0.040	0.040
	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Individual's age squared	-0.000	-0.000	-0.000	-0.000
	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Firm size	0.102	0.104	0.105	0.105
	(0.002)***	(0.002)***	(0.002)***	(0.002)***
Firm size squared	-0.008	-0.008	-0.008	-0.008
	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Firm age	0.018	0.019	0.020	0.019
	(0.004)***	(0.004)***	(0.004)***	(0.004)***
Firm age squared	-0.005	-0.005	-0.006	-0.005
	(0.001)***	(0.001)***	(0.001)***	(0.001)***
Share of managers at firm (0…1)	1.158	1.160	1.162	1.157
	(0.003)***	(0.003)***	(0.003)***	(0.003)***
Share of women among employees (0…1)	0.053	0.056	0.058	0.054
	(0.003)***	(0.003)***	(0.003)***	(0.003)***
Tertiary education	0.373	0.373	0.373	0.372
	(0.002)***	(0.002)***	(0.002)***	(0.002)***
Secondary education	0.082	0.082	0.082	0.082
	(0.001)***	(0.001)***	(0.001)***	(0.001)***
Number of observations	957,281	957,281	957,281	957,281
R-squared adjusted	0.476	0.476	0.476	0.476
Firm fixed effects, FDI and trade orientation dummies, year dummies	Yes	Yes	Yes	Yes

Notes: robust standard errors in parentheses. *Significant at 10%; **significant at 5%; ***significant at 1%. Period: 2006–2018. Dependent variable: log of wage at employee level. 'Innovation variable' denotes in each column a different innovation indicator.

One potential explanation of the effects on the gender wage gap could be more temporal flexibility and 24/7 availability requirements at more innovative and rapidly growing firms (e.g. Ben Yahmed 2013), with more rewards for these (skilled) individuals who can offer this flexibility. This could possibly be expected to be reflected in a higher motherhood penalty for women in innovative firms. However, no such regularity is observed in our data.[11] Whereas in Estonia, there is a significant wage penalty for women with children (e.g. see Masso et al. 2020), this does not appear to vary on the basis of the innovation status of the firm.

[11]These additional not significant results are omitted to limit the length of the paper and are available upon request.

In another estimated version of Equation 1, as shown in Annex 2, we also control in our regression analysis for the core occupation groups from managers to elementary occupation groups at ISCO 1-digit level. The key results that we have outlined above still hold. As expected, there is a clear ranking in terms of wages by occupation group (Annex 2), with our specifications showing a consistently large wage premium paid to managers (with a coefficient of 0.695 for the managers' occupation dummy). We further note that our core results on the gender wage gap in innovative and non-innovative firms are robust to the inclusion of the firm's log of lagged labour productivity as a control in the wage equation. The inclusion of this control variable considers the possibility that the innovation isexpected to be associated with higher firm-level productivity, and gender wage differences can be due to men and women being segregated according to the productivity level of companies (Masso et al. 2020). However, taking into account the productivity differences of firms only has only a minor effect on our key results.

The estimated contribution of other factors of wages are mostly as expected (see Table 1 and Annex 2). The age and higher education of individuals and firm size are positively correlated with wages. A higher share of managers in the firm are associated with higher wages in the firm. The share of women in the firm has a small positive coefficient in our particular sample, once the other covariates have been taken into account, but the magnitude of this effect is small. We note that the coefficient of this particular variable varies depending on the specification. Therefore, one should be rather cautious about drawing conclusions about the effects of a more equal gender structure in firms from these correlations. We also take into account in our models the fact of whether the firm is foreign owned or an exporter. Both of these indicators of firm-level internationalisation are important drivers of wages (Annex 2). This association can indicate the selection of high wage individuals to work at international firms or the selection of firms with overall high wage levels and high productivity to exporting (Melitz 2003) and to receiving FDI (Arnold and Javorcik 2009). Or alternatively, this premium can indicate the within-firm causal effects of internationalisation on wages. Javorcik (2015) provides a discussion on this.

Table 2 compares the core findings based on employees in all occupations in Table 1 to the innovation premium and gender wage gap among managers (ISCO group 1). A further summary on how the estimated effects vary across the core occupation groups at an ISCO 1-digit level is shown in Figure 2. The wage gain for male managers from having a job at an innovative firm that engages in R&D or innovation-related collaboration is between 5–5.5 per cent (see Table 2). The effect on wages for male managers in the case of effects of R&D and innovation-related collaboration is higher than the effect of these innovation activities on wages on average at firms. Interestingly, no such positive effect of R&D and collaboration is observed, on average, for women managers. Note that this average effect covers all employees: both the incumbent employees and recently hired employees. The effects within the broad category of all female managers could of course vary.

Table 2. Innovation and gender wage gap in Estonia, all employees and managers (dependent variable is log of wages)

Variable	**Non-technological innovation**	**Technological innovation**	**R&D**	**Innovation-related collaboration**
		All employees (from Table 1)		
Female (dummy)	-0.267	-0.256	-0.273	-0.265
	(0.001)***	(0.002)***	(0.001)***	(0.001)***
Innovation var. (CIS)	0.024	0.036	0.026	0.033
	(0.001)***	(0.001)***	(0.001)***	(0.001)***
Female × Innovation var. (CIS)	-0.031	-0.041	-0.034	-0.037
	(0.002)***	(0.002)***	(0.002)***	(0.002)***
		Managers		
Female (dummy)	-0.219	-0.211	-0.236	-0.228
	(0.016)***	(0.017)***	(0.014)***	(0.015)***
Innovation var. (CIS)	0.03	0.033	0.055	0.052
	(0.013)**	(0.014)**	(0.017)***	(0.014)***
Female × Innovation var. (CIS)	-0.063	-0.067	-0.05	-0.051
	(0.022)***	(0.022)***	(0.025)**	(0.022)**

Notes: robust standard errors in parentheses. *Significant at 10%; **significant at 5%; ***significant at 1%. Period: 2006–2018. Dependent variable: log of wage at employee level. Control variables are the same as in Table 1.

Men who are managers indeed gain to some extent more from innovation than women. However, it has to be acknowledged that the magnitudes of the effects and differences between effects by gender are not very large. Figure 2 shows in more detail the heterogeneity of the estimated contribution of innovation to gender pay gap, with the largest increase in the gender wage gap associated with innovation in the case of managers and plant and machine operators. These effects include possibly also the selection effects[12] and, of course, do not necessarily reflect only the causality running from innovation to wages.

[12] The significant selection of high-wage employees in general to innovative firms already before innovation has been shown in Cirera and Martins-Neto (2020).

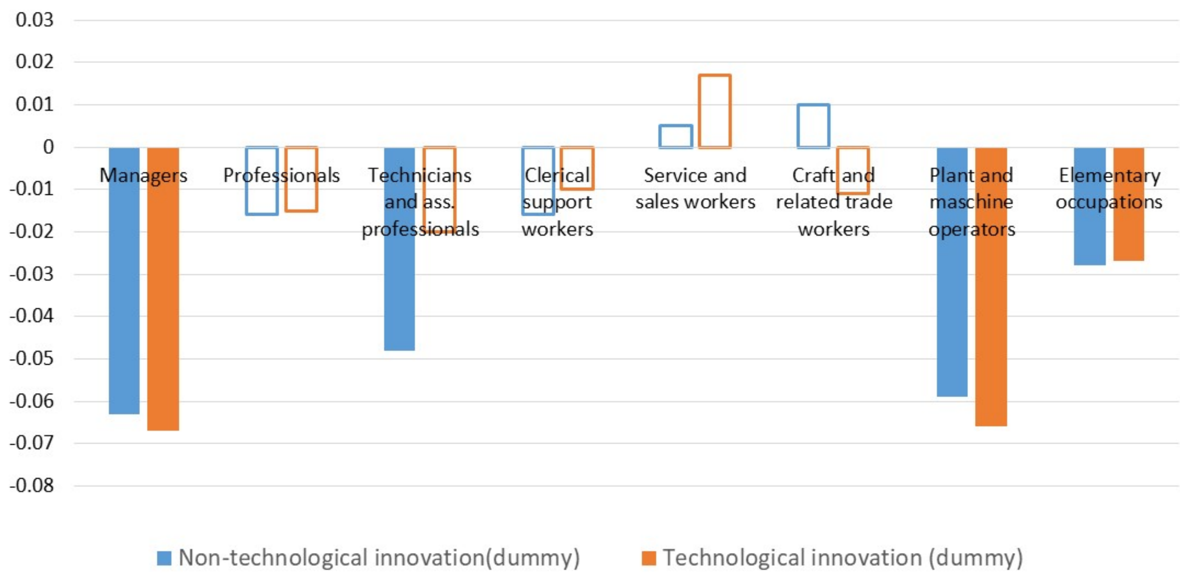


Figure 2. The estimated effect of technological and non-technological innovation on the gender wage gap by occupation group, from the Mincerian wage regressions as specified in Equation 1 (The blank bars indicate statistically insignificant estimates)
Notes: period 2006–2018, manufacturing and services sector firms and employees.

In the next step, we apply propensity score matching (PSM) to investigate how the mobility of men and women from non-innovative firms to work in innovative firms shapes their wages and the gender wage gap in firms. The previously shown Mincerian wage regressions provided evidence that should be interpreted strictly as partial correlations between innovation indicators and wages. One aspect that may affect the interpretation of the findings is that more capable individuals with higher skills and higher previous wages could be more likely to take up a job at an innovative firm. There may be significant selection process(es) going on, including self-selection, determining who is going to apply to an innovative firm and eventually also who gets hired at the innovative firms. We endeavour to take the selection to working at an innovative firm into account by applying the PSM approach and estimating the ATT effects of moving to work at an innovative firm. We distinguish in this section between four core innovation output types and two types of innovation inputs. This means that the different treatments are movement to work in a firm with a certain type of innovation, such as product, process, organizational and marketing innovation, or movement to firms that have R&D or external collaboration in innovation.

For each treated individual that moves from a non-innovating firm to an innovator with a specific type of innovation, we construct a proxy for the counterfactual of the observed movement based on data on employees that did not change their workplace and stayed in the same firm, and more importantly, stayed in the same non-innovative firm. For example, that way the proxy of the counterfactual for moving to a firm with product innovation does not include individuals moving to firms with organizational or marketing innovation. Otherwise, we would not identify the effects of a certain innovation because the control group might be affected by other core types of innovation. Similarly, in the case of the two innovation input variables, the control group includes the companies without either of the two studied innovation input variables (innovation cooperation and R&D).

We apply different probit models in Annex 3 to estimate the propensity of the individual to move to work in a firm with the particular type of innovation activity. We note that we estimate the propensity score separately for men and women, so that in the next steps of the PSM, men are matched only with men and women only with women. The controls used in this analysis include a number of firm and individual-level characteristics; the size of the firm (that hires the individual), size squared, firm age, age squared, location in northern Estonia (the capital region), log of value added per employee, liquidity ratio, log of capital-labour ratio, share of managers at the firm as well as prior real wages, education age of the individual, age of the individual square, and the dummy variable indicating a woman. These controls are always taken from one year before the individual moves to a new job in an innovative firm. These predictors are highly significant in the probit model (see Annex 3).

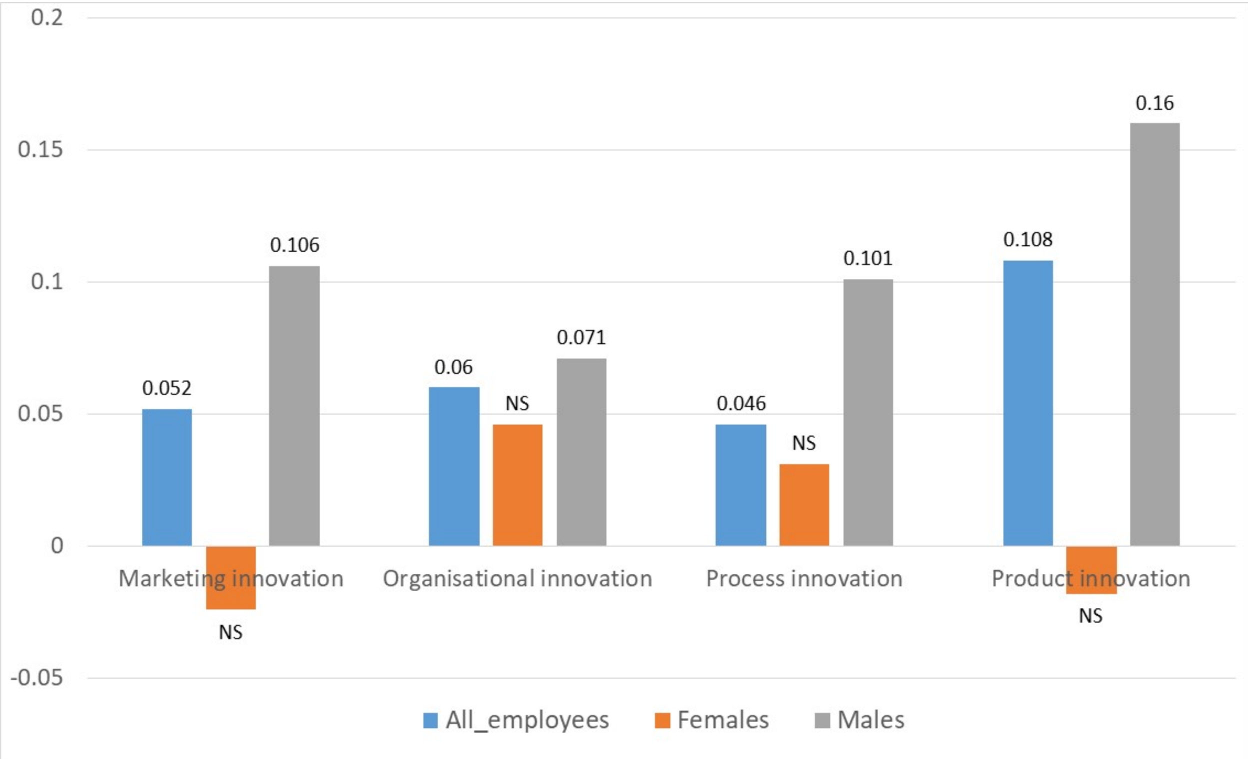


Figure 3. ATT effects at *t+2* due to movement of employees at year *t* to firms with different types of innovation, effects on wages of men and women, NS- not significant.

Notes: period 2006–2018, PSM results: nearest neighbour matching with 2 neighbours. Mobility between jobs: from a non-innovative firm to an innovative firm. The potential pool for control units includes only the firm-employee-year combinations where the firm that have none of the four types of innovation. Note that the matching is based on period *t-1* data. Propensity score matching results in more detail, as well as the probit models used in constructing the propensity scores and balancing property tests are documented in Annex 3.

Our pooled probit models are next used to construct the propensity score of each treatment, both among the treated individuals as well as among the controls. Based on the similarity of the propensity score, we then construct a control group for each treated man or woman. This is now a more suitable control group than the overall group of non-treated individuals. We apply nearest neighbour matching with 2 neighbours chosen for each treated unit.

The results of the balancing test of the covariates from the pre-treatment year (t-1) show that matching has performed reasonably well and the matched group is not statistically significantly different anymore from the treatment group in the case of the core control variables (see Annex 4 as an example of the balancing test in the case of process innovation among men). Annex 4 shows the mean values of the variables and the p-values of the balancing t-tests for different key covariates (from year *t-1*), both before and after matching has been implemented.

Table 3. Average treatment effects on the treated (ATT) estimates: effects of taking up a job at an innovative firm on wages of newly hired individuals

ATT effects of movement to firms with different types of innovation:	Sample	No. of treated	No. of untreated	Log real wage (+1)	Log real wage (+2)
Marketing innovation (dummy)	All employees	3,499	73,231	0.005	0.052*
	Women	1,917	28,224	-0.138***	-0.024
	Men	1,569	44,345	0.088***	0.106***
Organizational innovation (dummy)	All employees	2,427	74,383	0.056***	0.06***
	Women	1,072	28,502	0.02	0.046
	Men	1,326	45,277	0.083***	0.071***
Process innovation (dummy)	All employees	2,711	74,751	0.016	0.046***
	Women	1,160	28,698	-0.034	0.031
	Men	1,535	45,358	0.096***	0.101***
Product innovation (dummy)	All employees	3,693	74,541	0.033	0.108***
	Women	1,931	28,853	-0.078*	-0.018
	Men	1,750	45,512	0.127***	0.16***

Notes: robust standard errors in parentheses. *Significant at 10%; **significant at 5%; ***significant at 1%. Period: 2006–2018. Dependent variable: log of wage at employee level. +1 denotes one year after treatment, +2 denotes the 2nd year after treatment.

Table 4. Average treatment effects on the treated (ATT) estimates: effects of taking up a job at a firm with R&D or innovation collaboration with external partners, effects on wages of newly hired individuals

ATT effects of movement to firms with different types of innovation:	Sample	No. of treated	No. of untreated	Log real wage (+1)	Log real wage (+2)
Continuous R&D (dummy)	All employees	1,867	71,401	0.107***	0.094***
	Females	779	27,152	0.033	0.068*
	Males	1,088	42,163	0.166***	0.146***
Innovation cooperation (dummy)	All employees	2,614	71,599	0.157***	0.172***
	Females	1,057	27,494	0.135***	0.157***
	Males	1,557	42,955	0.166***	0.182***

Notes: robust standard errors in parentheses. *Significant at 10%; **significant at 5%; ***significant at 1%. Period: 2006–2018. Dependent variable: log of wage at employee level. +1 denotes one year after treatment, +2 denotes the 2nd year after treatment.

Next, we calculate the average treatment effects on the treated (ATT) as defined in the Methodology section in Equation 2. The individual outcome variable is the log of wages at the individual level. Figure 3 presents the estimated ATT effects separately for men and women, of a movement to work in an innovative firm. The effect in Figure 3 is measured two years after the treatment. The detailed results, with effects on individual's wages a year after the treatment ($t+1$) due to moving to an innovative firm are shown in Table 3. The ATT results in period $t+2$ strongly qualitatively confirm the prior findings from the simple Mincerian equations. We find that moving to work at an innovative firm has significant large effects especially on a man's wages and no significant effect on a woman's wages by the 2nd year after the move.

The largest effects on newly hired men's wages and on the gender wage gap among the newly hired employees are found in the case of taking up a new job in a firm that has introduced product innovation. This move is associated with a 16 per cent increase in wages for men. Taking up a job in a firm introducing a marketing innovation is associated with close to an 11 per cent wage gain and in a firm with process innovation, a 10 per cent wage gain. The effects of moving to a firm with organizational innovations have a somewhat smaller effect on men's wages compared to other innovation types, although are still significant in economic terms: a 7.1 per cent increase in men's wages.

We may speculate that the difference between the effect on men's wages in the case of technological innovation and organisational innovation could possibly reflect the different productivity effects of these types of innovation. The estimated effects could also include possible complementarities between different types of innovation.

We observe a similar association between moving to an innovative firm and an increase in the gender wage gap among newly hired employees in the case of indicators such as firm's (continuous) R&D and innovation cooperation with partners from outside the firm (see Table 4). Men gain about 14.6 per cent in wages by the 2nd year after moving to a firm with continuous R&D investments (see Table 4). By comparison, when moving to a firm with technological or non-technological innovation, women do gain but only by a 6.8 per cent increase in wages. An important result is that among the indicators that we have covered, innovation cooperation shows the strongest effect on women's wages: an increase of 15.7 per cent in wages due to moving to a more 'open' innovator, compared to the matched individuals working at firms without either its own R&D or collaboration in innovation. Still, even in this case the gains fall short of the gains for men, although the gap is not as large as in the case of the R&D or innovation output indicators covered. An important conclusion is that there is a tendency for firms to reward newly hired women especially in more collaborative contexts, where interactions and knowledge sourcing from external sources are an important ingredient in an innovation strategy.

6. AN EXTENSION: THE CORRELATION BETWEEN IT INDICATORS AND THE GENDER WAGE GAP

We complement the analysis of the effects of innovation in the earlier sections of the paper with a brief investigation into the link between some measures of IT adoption in firms and the gender wage gap. The first two measures are about the basic usage of IT in the workplace of the individual: two dummy variables denoting correspondingly that at least 50% of the employees at the firm use PCs or PCs with internet access in their work. The third variable is the share of employees at the firm using mobile devices for work purposes. As in the case of innovation indicators, we introduce these variables separately in the wage equation and in the interaction with the dummy variable for women. We use IT variables from the Information Technology in Enterprises survey for 2015–2019 covering approximately 3,000 companies annually. This dataset is then merged with the rest of the datasets used in the earlier sections of the paper.

Table 5. The correlation between IT usage in the firm and the wages of men and women

	(1)	(2)	(3)
	Share of employees using computers at work >=50% (dummy)	Share of people using computers connected to Internet at work>=50% (dummy)	Share of employees (0,..,1) using mobile devices
Female (dummy)	-0.200	-0.200	-0.203
	(0.002)***	(0.002)***	(0.002)***
IT variable	0.031	0.028	0.046
	(0.002)***	(0.003)***	(0.004)***
Female × IT variable	-0.026	-0.027	-0.036
	(0.003)***	(0.003)***	(0.006)***
R-squared adjusted	0.418	0.417	0.417

Notes: robust standard errors in parentheses. *Significant at 10%; **significant at 5%; ***significant at 1%. Period: 2006–2018. Dependent variable: log of wage at employee level. All models include similar control variables as in Table 1.

We observe that the interaction term is negative, as in our prior analysis of effects of innovation indicators, which suggests that firms that use PCs more or that employ more mobile devices at work tend to have a higher gender wage gap. The size of the associated effect on the gender pay gap – the estimated size of the interaction term parameter – is similar in terms of the order of magnitude observed before in our analysis of innovation using CIS data, approximately 2.5–3.5%. Of course, these numbers here show only partial correlations, not necessarily any causal effects.

7. CONCLUSIONS

We provide evidence here based on matched employer-employee data that technological and non-technological innovation, as well as a firm's own R&D and innovation-related collaboration with external partners are associated, on average, with a higher gender wage gap in firms. Technological innovation in our analysis includes product and process innovation. Non-technological innovation includes organisational and marketing innovation. The contribution of innovation to increasing the gender pay gap is somewhat stronger in the case of certain occupational groups, such as managers and plant and machine operators. Thus, relationship between innovation and gender wage gap is stronger both at the higher and lower end of the wage distribution, potentially indicating the importance of routine-biased technological change.

However, the average effects on all employees (incumbents and new employees) are relatively small in magnitude and hide significant heterogeneity in terms of the effect on newly hired employees compared to others.

Using the propensity score matching approach, we find that men appear to gain more from taking up a new job at an innovative firm than women. The effect of innovation on men's wages and on the gender wage gap is significantly larger among the newly hired employees compared to incumbent employees. Taking up a job at more 'open' innovators (that engage in external collaboration in innovation process) appears to be associated with especially strong gains for the newly hired women, and especially if compared to the gains from R&D. However, these gains fall still short of the gains for men. Further analysis on this topic could look in more detail into how openness at firms translates into the net effects on wages for men and women. In particular, the effects can exhibit non-linearities due to the various costs and benefits of the particular innovation strategy adopted at the firm.

An advantage of our study is the focus on general comparable innovation indicators across firms active in different contexts and sectors and the analysis of the net effects of general core types of innovation. Our findings suggest that the recent evidence that robotization can be associated with a larger gender wage gap (Aksoy et al. 2020) may be reflecting also a more general effect of innovation activities at firms. Of course, it has to be acknowledged that the general indicators that we apply hide many differences in the effects of different types of technologies or organisational practices adopted in the firms.

In terms of implications, our analysis emphasizes the role of firm-level heterogeneity affecting the gender wage gap. The potential policy implications would be those that address the firm-level component of the pay gap, such as monitoring and publicly reporting of pay gap at the firm level and the wider availability of child-care facilities that facilitate the full-time participation of women in the labour market and increase their ability to offer temporal flexibility in the workplace that tends to be highly valued in high-performance firms.

Annex 1. Descriptive statistics of variables used in the regression analysis and propensity score matching.

Variable name	Mean. tot. sample	St. dev. tot. sample	Mean. females	St. dev. females	Mean. males	St. dev. males	Count. tot. sample
Log real wage	6.143	0.569	5.982	0.534	6.268	0.564	1413183
Firm average wage	553.772	219.159	525.422	216.865	575.742	218.404	1413183
Firm average wage of females	485.224	198.107	464.017	189.121	501.945	203.361	1399536
Firm average wage of males	630.202	262.926	639.155	281.688	623.326	247.330	1407763
Female (dummy)	0.437	0.496	1.000	0.000	0.000	0.000	1413183
0-17 year old kids in household (dummy)	0.281	0.449	0.269	0.443	0.291	0.454	94988
0-2 year old kids in household (dummy)	0.082	0.275	0.046	0.209	0.112	0.315	94988
Individual's age	42.882	12.445	43.360	11.743	42.512	12.951	1413183
Individual's age squared	1993.784	1102.232	2017.988	1032.846	1975.027	1152.783	1413183
Tertiary education	0.264	0.441	0.298	0.457	0.237	0.425	1282899
Secondary education	0.621	0.485	0.618	0.486	0.624	0.484	1282899
Primary education	0.114	0.318	0.084	0.277	0.139	0.346	1282899
Managers	0.094	0.292	0.073	0.261	0.110	0.313	147587
Professionals	0.110	0.313	0.127	0.333	0.097	0.296	147587
Technicians and ass. professionals	0.180	0.384	0.201	0.401	0.164	0.370	147587
Clerical support workers	0.106	0.308	0.163	0.369	0.061	0.240	147587
Service and sales workers	0.024	0.152	0.037	0.189	0.013	0.114	147587
Skilled agricultural workers	0.001	0.028	0.001	0.028	0.001	0.028	147587
Craft and related trade workers	0.177	0.382	0.086	0.280	0.248	0.432	147587
Plant and machine operators	0.238	0.426	0.226	0.418	0.246	0.431	147587
Elementary occupations	0.067	0.250	0.084	0.277	0.054	0.226	147587
Firm size	5.076	1.413	5.175	1.401	5.003	1.418	1184811
Firm size squared	27.762	14.945	28.745	14.970	27.039	14.885	1184811
Firm age	2.673	0.549	2.681	0.551	2.667	0.548	1411592
Firm age squared	7.448	2.469	7.493	2.456	7.413	2.479	1411592
Share of managers at firm	0.253	0.178	0.230	0.164	0.270	0.187	1413183
Share of female among employees	0.445	0.262	0.601	0.230	0.324	0.218	1413183
Foreign firm (dummy)	0.378	0.485	0.451	0.498	0.322	0.467	1406858
All exporters (goods and services)	0.829	0.376	0.842	0.365	0.820	0.385	1413183
Log LPV	10.404	0.795	10.262	0.806	10.501	0.772	828014
Log firm average wage	6.186	0.436	6.120	0.454	6.237	0.414	1345357
Log average wage of females	6.026	0.434	5.983	0.431	6.060	0.434	1335936
Log average wage of males	6.329	0.454	6.333	0.488	6.326	0.425	1341557
Firm gender pay gap	-0.203	0.212	-0.241	0.186	-0.173	0.227	1394116
Liquidity ratio	0.107	0.157	0.112	0.167	0.103	0.150	1257433
Log capital-labour ratio	9.776	1.692	9.485	1.692	9.987	1.659	1155836
Northern Estonia	0.318	0.466	0.349	0.477	0.294	0.455	1413176
Central Estonia	0.065	0.247	0.072	0.258	0.060	0.238	1413176
North-Eastern Estonia	0.107	0.309	0.073	0.260	0.134	0.340	1413176
Western Estonia	0.075	0.263	0.084	0.278	0.067	0.250	1413176
Product innovation (dummy)	0.432	0.495	0.495	0.500	0.383	0.486	1413183
Process innovation (dummy)	0.569	0.495	0.602	0.489	0.543	0.498	1413183
Organizational innovation (dummy)	0.424	0.494	0.455	0.498	0.399	0.490	1413183
Marketing innovation (dummy)	0.370	0.483	0.420	0.493	0.332	0.471	1413183
Marketing or organizational innovation (dummy)	0.529	0.499	0.568	0.495	0.499	0.500	1413183
Technological innovation (dummy)	0.665	0.472	0.701	0.458	0.637	0.481	1413183

Variable name	Mean. tot. sample	St. dev. tot. sample	Mean. females	St. dev. females	Mean. males	St. dev. males	Count. tot. sample
Continuous R&D (dummy)	0.283	0.450	0.321	0.467	0.254	0.435	1413183
Innovation cooperation (dummy). ext. over years	0.460	0.498	0.485	0.500	0.441	0.497	1413183
Share of employees using computers >=50% (dummy)	0.542	0.498	0.592	0.491	0.504	0.500	122618
Share of employees using computers connected to Internet >=50% (dummy)	0.497	0.500	0.547	0.498	0.458	0.498	122618
Share of employees using mobile devices	0.272	0.337	0.283	0.374	0.263	0.307	122618

Notes: merged employer-employee dataset. Manufacturing and services sector. Period: 2006-2018

Annex 2. Wage regressions with occupation dummies (at ISCO 1-digit level).

Innovation variables	Technological innovation (dummy)	Marketing or organizational innovation (dummy)	Continuous R&D (dummy)	Innovation cooperation (dummy)
Female (dummy)	**-0.243**	**-0.241**	**-0.241**	**-0.244**
	(0.004)*	**(0.004)***	**(0.003)***	**(0.004)***
Innovation var. (CIS)	**0.022**	**0.013**	**0.024**	**0.039**
	(0.004)*	**(0.004)***	**(0.005)***	**(0.004)***
Female × Innovation var. (CIS)	**-0.033**	**-0.030**	**-0.065**	**-0.034**
	(0.005)*	**(0.005)***	**(0.006)***	**(0.005)***
Individual's age	0.039	0.039	0.039	0.039
	(0.001)***	(0.001)***	(0.001)***	(0.001)***
Individual's age squared	-0.000	-0.000	-0.000	-0.000
	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Firm size	0.148	0.146	0.147	0.147
	(0.006)***	(0.006)***	(0.006)***	(0.006)***
Firm size squared	-0.011	-0.011	-0.011	-0.011
	(0.001)***	(0.001)***	(0.001)***	(0.001)***
Firm age	0.105	0.109	0.105	0.109
	(0.017)***	(0.017)***	(0.017)***	(0.017)***
Firm age squared	-0.025	-0.026	-0.025	-0.026
	(0.004)***	(0.004)***	(0.004)***	(0.004)***
Share of managers at firm	1.119	1.120	1.121	1.113
	(0.008)***	(0.008)***	(0.008)***	(0.008)***
Share of female among employees	0.061	0.061	0.057	0.061
	(0.008)***	(0.008)***	(0.008)***	(0.008)***
Foreign firm (dummy)	0.030	0.031	0.031	0.030
	(0.003)***	(0.003)***	(0.003)***	(0.003)***
All exporters (goods and services)	0.033	0.033	0.034	0.031
	(0.004)***	(0.004)***	(0.004)***	(0.004)***
Tertiary education	0.147	0.147	0.146	0.146
	(0.005)***	(0.005)***	(0.005)***	(0.005)***
Secondary education	0.031	0.031	0.030	0.030
	(0.004)***	(0.004)***	(0.004)***	(0.004)***
Managers	0.695	0.695	0.694	0.694
	(0.021)***	(0.021)***	(0.021)***	(0.021)***
Professionals	0.455	0.455	0.454	0.454
	(0.021)***	(0.021)***	(0.021)***	(0.021)***
Technicians and ass. professionals	0.370	0.370	0.369	0.370
	(0.021)***	(0.021)***	(0.021)***	(0.021)***
Clerical support workers	0.204	0.203	0.202	0.203
	(0.021)***	(0.021)***	(0.021)***	(0.021)***
Service and sales workers	0.152	0.151	0.150	0.150
	(0.022)***	(0.022)***	(0.022)***	(0.022)***
Skilled agricultural workers	0.101	0.102	0.101	0.097
	(0.044)**	(0.044)**	(0.044)**	(0.044)**
Craft and related trade workers	0.173	0.172	0.171	0.172
	(0.020)***	(0.020)***	(0.020)***	(0.020)***
Plant and machine operators	0.140	0.140	0.139	0.139

Innovation variables	Technological innovation (dummy)	Marketing or organizational innovation (dummy)	Continuous R&D (dummy)	Innovation cooperation (dummy)
	(0.020)***	(0.020)***	(0.020)***	(0.020)***
Elementary occupations	0.011	0.011	0.010	0.011
	(0.021)	(0.021)	(0.021)	(0.021)
Region dummies	Yes	Yes	Yes	Yes
Number of observations	100,221	100,221	100,221	100,221
R-squared adjusted	0.543	0.543	0.543	0.543

Notes: robust standard errors in parentheses. *Significant at 10%; **significant at 5%; ***significant at 1%. Period: 2006–2018. Dependent variable: log of real wage.

Annex 3. Propensity score estimation in the case of individual level matching. Probit models separately for men and women. Treatment is taking up a job at an innovative firm.

	(1) Product innovation (dummy)	(2) Process innovation (dummy)	(3) Organizational innovation (dummy),	(4) Marketing innovation (dummy)	(5) Product innovation (dummy)	(6) Process innovation (dummy)	(7) Organizational innovation (dummy),	(8) Marketing innovation (dummy)
Sample:	Women	Women	Women	Women	Men	Men	Men	Men
Firm size (-1)	-0.142	0.286	0.299	-0.165	-0.093	0.067	-0.087	0.049
	(0.081)*	(0.091)***	(0.085)***	(0.077)**	(0.068)	(0.072)	(0.067)	(0.075)
Firm size squared (-1)	0.025	-0.057	-0.026	0.022	0.001	-0.042	-0.006	-0.002
	(0.007)***	(0.010)***	(0.008)***	(0.007)***	(0.006)	(0.007)***	(0.006)	(0.006)
Firm age (-1)	-0.570	-2.103	-2.367	-2.467	0.120	-0.445	-0.635	-0.382
	(0.243)**	(0.173)***	(0.175)***	(0.177)***	(0.225)	(0.181)**	(0.188)***	(0.217)*
Firm age squared (-1)	-0.005	0.273	0.363	0.313	-0.161	-0.041	0.031	-0.031
	(0.051)	(0.037)***	(0.039)***	(0.039)***	(0.046)***	(0.039)	(0.041)	(0.044)
Firm size (-1) × Firm age (-1)	0.167	0.173	0.119	0.203	0.175	0.173	0.140	0.147
	(0.026)***	(0.027)***	(0.025)***	(0.023)***	(0.025)***	(0.025)***	(0.024)***	(0.025)***
Northern Estonia (-1)	0.098	0.037	-0.137	0.122	0.089	-0.003	-0.168	0.133
	(0.041)**	(0.043)	(0.047)***	(0.042)***	(0.035)**	(0.035)	(0.037)***	(0.037)***
Log value added per employee (-1)	0.079	-0.005	0.039	0.135	0.084	-0.015	0.026	0.075
	(0.027)***	(0.026)	(0.029)	(0.030)***	(0.024)***	(0.021)	(0.024)	(0.025)***
Liquidity ratio (-1)	-0.405	-0.376	-0.380	-0.670	-0.613	-0.108	-0.269	-0.541
	(0.109)***	(0.101)***	(0.116)***	(0.114)***	(0.103)***	(0.093)	(0.104)***	(0.112)***
Log capital-labour ratio (-1)	-0.003	-0.018	-0.016	-0.006	0.017	0.004	0.012	0.008
	(0.013)	(0.012)	(0.013)	(0.013)	(0.011)	(0.010)	(0.011)	(0.012)
Individual's age (-1)	0.031	-0.014	-0.005	0.024	-0.020	-0.021	-0.030	-0.030
	(0.012)***	(0.012)	(0.013)	(0.012)**	(0.008)**	(0.008)***	(0.008)***	(0.009)***
Individual's age squared (-1)	-0.001	-0.000	-0.000	-0.000	0.000	0.000	0.000	0.000
	(0.000)***	(0.000)	(0.000)	(0.000)***	(0.000)	(0.000)	(0.000)	(0.000)
Share of female among employees	0.612	0.130	0.275	0.689	2.058	1.095	1.213	1.808
	(0.108)***	(0.111)	(0.119)**	(0.116)***	(0.092)***	(0.087)***	(0.095)***	(0.100)***
Tertiary education	0.098	0.096	0.129	0.177	0.177	0.091	0.169	0.225
	(0.065)	(0.066)	(0.071)*	(0.068)***	(0.050)***	(0.049)*	(0.051)***	(0.053)***
Secondary education	0.013	0.024	0.015	0.079	-0.005	0.035	0.024	0.013

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Product innovation (dummy)	Process innovation (dummy)	Organizational innovation (dummy),	Marketing innovation (dummy)	Product innovation (dummy)	Process innovation (dummy)	Organizational innovation (dummy),	Marketing innovation (dummy)
Sample:	Women	Women	Women	Women	Men	Men	Men	Men
	(0.055)	(0.055)	(0.059)	(0.058)	(0.041)	(0.039)	(0.042)	(0.045)
Log real wage (-1)	-0.212	-0.448	-0.462	-0.042	0.012	-0.103	-0.082	-0.159
	(0.152)	(0.138)***	(0.146)***	(0.193)	(0.149)	(0.093)	(0.104)	(0.102)
Log real wage squared (-1)	-0.004	0.022	0.029	-0.010	-0.017	-0.009	-0.009	-0.000
	(0.014)	(0.013)*	(0.014)**	(0.018)	(0.013)	(0.008)	(0.009)	(0.009)
Share of managers at firm (-1)	1.161	1.297	1.305	1.030	1.030	0.958	0.995	1.024
	(0.113)***	(0.107)***	(0.116)***	(0.117)***	(0.085)***	(0.076)***	(0.084)***	(0.092)***
Number of observations	30784	29858	29574	30141	47262	46893	46603	45914
Log-likelihood	-3795.975	-3515.891	-3009.472	-3620.609	-4943.868	-5183.166	-4477.741	-4296.248
Pseudo R-squared	0.474	0.283	0.347	0.493	0.340	0.233	0.257	0.372
Industry and year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: robust standard errors in parentheses. *Significant at 10%; **significant at 5%; ***significant at 1%. Period: 2006–2018. Dependent variable: dummy variable of an individual moving to work at an innovative firm.

Annex 4. Balancing property test: movement to work at a firm with process innovation, sample of men.

Variable name	Sample	Mean, treated	Mean, control	Bias	Reduction in bias	t-test	P value of t-test
Firm size (-1)	Unmatched	4.2959	4.0366	21.7		8.03	0.000
	Matched	4.2924	4.093	16.7	23.1	4.69	0.000
Firm size squared (-1)	Unmatched	19.765	17.851	18.1		6.79	0.000
	Matched	19.737	18.193	14.6	19.3	4.09	0.000
Firm age (-1)	Unmatched	2.5916	2.5849	1.2		0.47	0.640
	Matched	2.5921	2.5509	7.6	-514.9	2.12	0.034
Firm age squared (-1)	Unmatched	6.9922	6.9856	0.3		0.1	0.918
	Matched	6.9945	6.8048	7.9	-2818.2	2.17	0.030
Firm size (-1) × Firm age (-1)	Unmatched	11.29	10.412	21.7		8.61	0.000
	Matched	11.283	10.635	16.0	26.2	4.31	0.000
Northern Estonia (-1)	Unmatched	0.28013	0.33438	-11.8		-4.44	0.000
	Matched	0.28	0.28	0.0	100	0	1.000
Log LPV (-1)	Unmatched	10.266	10.251	2.1		0.79	0.428
	Matched	10.268	10.244	3.3	-58.1	0.78	0.433
Liquidity ratio (-1)	Unmatched	0.12526	0.13768	-7.4		-2.92	0.004
	Matched	0.12533	0.11931	3.6	51.6	1.03	0.302
Log capital-labour ratio (-1)	Unmatched	9.3571	9.4563	-6.2		-2.34	0.019
	Matched	9.3589	9.2471	7.0	-12.8	1.8	0.072
Individual's age (-1)	Unmatched	37.969	43.861	-50.0		-18.96	0.000
	Matched	37.976	38.175	-1.7	96.6	-0.48	0.629
Individual's age squared (-1)	Unmatched	1575.5	2067.6	-48.5		-17.7	0.000
	Matched	1576.4	1582.1	-0.6	98.8	-0.17	0.868
Share of female among employees	Unmatched	0.34288	0.25805	39.5		16.44	0.000
	Matched	0.34285	0.34091	0.9	97.7	0.23	0.821
Tertiary education	Unmatched	0.2202	0.19533	6.1		2.41	0.016
	Matched	0.22033	0.22361	-0.8	86.8	-0.22	0.828
Secondary education	Unmatched	0.6443	0.65933	-3.2		-1.22	0.222
	Matched	0.64328	0.64885	-1.2	62.9	-0.32	0.748
Log real wage (-1)	Unmatched	6.0362	6.0955	-9.0		-3.7	0.000
	Matched	6.0387	6.0144	3.7	59	0.93	0.350
Log real wage squared (-1)	Unmatched	36.926	37.532	-7.8		-3.21	0.001
	Matched	36.956	36.715	3.1	60.3	0.83	0.406
Share of managers at firm	Unmatched	0.28221	0.24766	17.5		6.58	0.000
	Matched	0.28279	0.28906	-3.2	81.9	-0.78	0.434

Note: period 2006–2018. LPV- value added per employee. *Significant at 10%; **significant at 5%; ***significant at 1%.

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KOKKUVÕTE

Innovatsioon meeste-naiste palagalõhe ettevõttetasandi tegurina

Ettevõtete uuendustegevuste, sealhulgas uute tehnoloogiate kasutuselevõtmise ning organisatsiooniliste uuenduste mõjusid on teaduskirjanduses laialdaselt uuritud. Vähe on samas teada tehnoloogiliste ja mittetehnoloogiste uuenduste mõjudest soolisele palgalõhele. Ühelt poolt võib näiteks tehnoloogiainvesteeringute tõttu vähenenud füüsilise töö vajadus parandada naiste suhtelist positsiooni tööturul. Teiselt poolt võib naiste suurem tööhõive osakaal ametites, kus on rohkem rutiinsemaid tööülesanded, muuta just naised tööturul haavatavamaks uute tehnoloogiliste muudatuste suhtes, sest rutiinsemate tööülesannetega ametid on tõenäoliselt enam ohustatud tehnoloogilistest muutustest nagu automatiseerimine.

Uuringus kasutame Eesti ettevõtete ja töötajate ühendatud andmeid, sealhulgas ettevõtete innovatsiooniuuringu andmeid ettevõtete tehnoloogiliste ja mittetehnoloogiliste uuendustegevuste kohta koos Maksu- ja Tolliameti andmetega töötajate töötasude kohta. Oma uurimistöös näitame, et keskmiselt on tehnoloogiline (toote- või protsessiinnovatsioon) ning mittetehnoloogiline innovatsioon (organisatsiooniline või turunduslik innovatsioon) ettevõtetes seotud suurema soolise palgalõhega. See tähendab, et kuigi innovatsioonil ettevõtetes on palkadele positiivne mõju, kipub see keskmiselt veidi suurendama soolist palgaerinevust. Sarnased seosed palgalõhega ilmnevad ka ettevõtte teadus- ja arendustegevuse ning innovatsiooniga seotud välise koostöö näitajate puhul. Ettevõtete uuendustegevuste positiivne mõju palkadele on naistel võrreldes meestega umbes 3–5 protsendipunkti võrra väiksem.

Seos innovatsiooni ja soolise palgalõhe vahel on tugevam juhtide ning masinate-seadmete käitajate puhul; st palgajaotuse kõrgemas ja madalamas osas. Uuenduste mõju meeste palkadele ja soolisele palgalõhele on äsja palgatud töötajate seas võrreldes seniste töötajatega oluliselt suurem. Nn tõenäosusliku sobitamisanalüüsi põhjal ilmneb, et mehed võidavad mitteinnovaatilisest ettevõttest innovaatilisse tööle siirdumisest palgalisa näol rohkem võrreldes naistega. Töötajate asumisel tööle nn avatud innovatsiooniga ettevõtetesse ilmneb oluline palgalisa ka naiste puhul, kuid ka antud juhul jääb nende võit palgas meeste omast väiksemaks.

Meie analüüs toob välja ettevõtte tasandi heterogeensuse rolli soolise palgalõhe tegurina. Potentsiaalsed majanduspoliitilised järeldused võivad seega seonduda poliitikameetmetega, mis käsitlevad palgalõhe ettevõttetasandi komponenti, näiteks palgalõhe monitoorimine ja aruandlus ettevõtte tasandil ning laiem lastehoiuteenuste kättesaadavus, mis hõlbustab naiste täistööajaga osalemist tööturul ning suurendab nende võimet pakkuda ajalist paindlikkust töökohal, mida hinnatakse kõrgelt just kõrge tootlikkusega ja edukates ettevõtetes.