NBER WORKING PAPER SERIES

A YEAR OLDER, A YEAR WISER (AND FARTHER FROM FRONTIER): INVENTION RENTS AND HUMAN CAPITAL DEPRECIATION

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Working Paper 29863
http://www.nber.org/papers/w29863

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
March 2022

We would like to thank Atte Pudas for excellent research assistance, and the ERC (grant agreement No. 786587), NSF CAREER Grant (NSF grant No: 1654719), and the Yrjö Jahnsson foundation (grant number 20207329) for financial support. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

At least one co-author has disclosed additional relationships of potential relevance for this research. Further information is available online at http://www.nber.org/papers/w29863.ack

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NBER Working Paper No. 29863
March 2022
JEL No. I24,J24,O31

ABSTRACT

We look at how the arrival of an invention affects wage returns and probability of moving out of employment for white- and blue-collar coworkers of the inventor. First results suggest that older workers are hurt by the arrival of an invention. This negative effect disappears when we control for education and, in particular, for time that since obtaining the last formal degree, i.e., distance to human capital frontier. If anything, this effect is slightly higher for non-STEM than STEM-educated co-workers. This result suggests that retraining programs could be helpful in making the process of creative destruction and economic growth more inclusive.

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Abstract

We look at how the arrival of an invention affects wage returns and probability of moving out of employment for white- and blue-collar coworkers of the inventor. First results suggest that older workers are hurt by the arrival of an invention. This negative effect disappears when we control for education and, in particular, for time that since obtaining the last formal degree, i.e., *distance to human capital frontier*. If anything, this effect is slightly higher for non-STEM than STEM-educated co-workers. This result suggests that retraining programs could be helpful in making the process of creative destruction and economic growth more inclusive.

JEL codes: O31, I24, J24

1 Introduction

This paper is a first attempt to look at how human capital affects the division of invention rents within a firm. More specifically, we look at how the arrival of an invention affects the (wage) rents and the probability of leaving employment

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for white-collar and blue-collar workers within the inventing firm. We utilize three measures of human capital: age, capturing experience; level of education, capturing the acquired formal human capital; and finally, in order to capture the distance to the human capital frontier (DTHCF), the time that has passed since obtaining the last formal degree.

The underlying event we are interested in is the invention and the associated intellectual property rights that come with a patent and in particular, the possibilities to re-orient the activities of the firm one way or the other as a consequence. For example, patents on process inventions may lead to a reorganized production process with lower marginal costs, while patents on product inventions may present the opportunity to switch production to products with a higher markup. Coworkers may earn rents due to them being crucial in developing an invention into an innovation that can be commercialized, or they may suffer due to their skills becoming obsolete.

Identifying rents from invention has preoccupied economists for several decades, but the literature has been revived by the availability of new individual-level datasets. While most existing studies have focused on rents among inventors, our focus in this paper is instead on the rents to non-inventing coworkers within the same firm, and on how such rents vary with the level of education and time since education for white- and blue-collar coworkers within the same firm.[1]

To analyze the returns to invention for coworkers or stakeholders of an inventor within the same firm, we merge individual income data, firm-level data, and patenting data in Finland over the period of 1988-2012 and employ a conditional difference-in-difference approach. This approach means that we match[2] each treated individual with a control individual using the following variables: (i) having at least an MSc (white-collar workers) or BSc (blue-collar workers); (ii) having a STEM education; (iii) time since last degree; (iv) working in manufacturing; (v) living in the South-West of Finland; (vi) age (4 groups); and (vii) and quintiles of the annual firm size distribution. We execute the matching separately for each treated group (blue-collar and subgroups[3] of white-collar coworkers), and we limit the potential control group to individuals who have never been cowork-

[1]Recent work on within-firm rents include Aghion et al. (2018) and Kline et al. (2019). The former uses Finnish and the latter US data to assess how invention rents are shared within the firm among several types of employees and stakeholders. We come back to these papers below.

[2]The conditional difference-in-difference approach was introduced by Heckman et al. (1998). Our implementation builds on Jaravel et al. (2018).

[3]These subgroups are senior white-collar workers, senior white-collar managers, junior white-collar workers and junior white-collar managers.

ers of an inventor and who work in the private sector in the year of treatment.

Our main finding is that human capital indeed affects invention returns within a firm, but in a specific way. Our prior view was that age can have two counteracting effects on invention rents. On the one hand, age brings experience, which should interact positively with invention. On the other hand, older workers have older degrees, and the skills and knowledge embedded in older degrees are less likely to be useful when implementing a recent invention. When conditioning the wage returns from invention on age only, we find that the latter effect dominates: young white-collar workers get positive post-invention rents (5.1%) and young blue-collar workers are unaffected. In contrast senior workers, defined as those above (the mean and median of) 40 years of age, get either no rents on invention (white-collar) or are affected negatively (blue-collar).[4]

To see more precisely whether this negative effect of age on invention returns reflects human capital depreciation or obsolescence, we introduce education and time since education as additional explanatory variables in our regressions. When we use this specification, the above negative age effect either disappears or is reversed; moreover, post-invention rents are negatively affected by the time since last degree for both white- and blue-collar workers, with the decrease being circa 0.5 percentage points per year for each year since completing the last education. This new result confirms that a specification that only includes age as a human capital variable fuses the counteracting effects of experience and human capital depreciation on invention rents. The initial but illusory negative effect of seniority thus likely reflects them being further from the human capital frontier and, possibly, the lower average educational level of older workers.

Finally, we find that while the direct effect of invention on the probability of a coworker moving out of employment (non-employment henceforth)[5] varies somewhat with human capital, two consistent patterns emerge. First, once the returns are allowed to vary with age, education, and the time since education, the likelihood of coworker non-employment typically decreases due to within-firm invention. For example, the non-employment probability is 5 percentage points lower for young blue- and white-collar workers with a recent low education diploma. Second, the probability of coworker non-employment increases steadily with the time since education, with the increase being 0.2-0.5 percentage points per year

[4] Acemoglu et al. (2014) also look at the effect of age on innovation, and find that firms managed by younger managers are more likely to make disruptive innovations.

[5] We study the transition to non-employment instead of unemployment as the data reveal that there are multiple non-employment outcomes that individuals transfer to. The different outcomes besides employment mirror disattachment from the labor market and include unemployment, student, military service, retirement and unknown.

for each year since obtaining the latest degree. This increase in the probability of coworker non-employment can be observed both for white- and blue- collar workers and pre- and post-invention.

Our paper relates to several strands of literature. The first is the literature on innovation spillovers (among many others, see Jaffe et al., 1993; Azoulay et al., 2010; Waldinger, 2011; Borjas and Doran, 2012; Bloom et al., 2013; Akcigit et al., 2016; Jaravel et al., 2018; and the survey by Aghion and Jaravel, 2015). We contribute to this literature by looking at innovation spillovers in the form of rents to non-innovating individuals within the same firm, and how these depend on education and the time since education.

Second, there are recent papers using individual administrative data, firm-level data, and patenting data to look at the social origins of inventors and on the returns to invention (e.g., see Toivanen and Väänänen, 2012; Aghion et al., 2017, 2018; Bell et al., 2019; Akcigit et al., 2017, 2020; and Kline et al., 2019). Toivanen and Väänänen (2012) use Finnish patent and income data to study the return to inventors of US patents. They find strong and long-lasting impacts, especially for the inventors of highly cited patents. Bell et al. (2019) merge US individual fiscal data, test score information, and US individual patenting data over the recent period to look at the lifecycle of inventors and the returns to invention. Aghion et al. (2017) merge administrative data, patenting data, and military data from Finland to look at how the probability of becoming an inventor depends upon parental income, parental education, and the individual's IQ. Akcigit et al. (2017) merge historical patent and individual census records to study, among other things, inventor compensations.

Most closely related to our paper are Kline et al. (2019) and Aghion et al. (2018), which use individual administrative data merged with patent data, respectively, in the US and in Finland to look at the individual returns from invention to the inventors and to their coworkers.[6] Both papers find significant returns to invention, most of which accrue to other employees or stakeholders within the inventor's firm.[7] Using identification similar to that of Aghion et al. (2018), we contribute

[6] Van Reenen (1996) is an early important study of rent-sharing from invention.

[7] Identification in Kline et al. (2019) is based on comparing workers in firms whose initial patent applications were granted to those in firms whose initial patent application was rejected (in the latter group, the modal patent is eventually rejected). Their comparison is thus between workers in firms which are granted intellectual property to workers in firms which most likely are not. They find that workers capture about 30 cents of every dollar of patent-induced operating surplus. Aghion et al. (2018) base their identification on a conditional differences-in-differences approach and compare coworkers of inventors to otherwise similar control individuals who have never worked in a firm that receives a patent. They thus compare coworkers of inventors to observationally identical coworkers of non-inventors. Aghion et al. (2018) find that inventors get only 8% of the total wage gains; second,

to this literature by analyzing how education and the time since diploma (as our measure of DTHCF) affect the returns to invention for white-collar and blue-collar workers within the same inventing firm.[8] Placing emphasis on how invention rents vary conditional on age, level of education and time since education we complement the work of Aghion et al. (2019) whose focus is on the innovation premium to soft skills (for which we control through individual fixed effects).

Third, our work relates to the labor literature on employment and human capital accumulation and depreciation (e.g., see Ben-Porath, 1967; and more recently Heckman et al., 2003, Blundell et al., 2016, Deming and Noray, 2020).[9] Of particular relevance to us is the literature on the Race Between Education and Technology (RBET): In an important recent paper Deming and Noray (2020) find that the earnings premium for STEM (and business) graduates declines more rapidly than that for other types of education. We contribute to this literature by bringing invention into the picture, and by analyzing how education and the time since education affect the returns to invention for white- and blue-collar workers within the innovating firm.

The remaining part of the paper is organized as follows. Section 2 presents the data. Section 3 presents the methodology and the regressions equations. Section 4 presents our results and Section 5 concludes.

2 Data

The data come from two main sources. First, we use the *Finnish longitudinal employer-employee data* (FLEED), which we exploit over the period 1988-2012. FLEED is an annual panel dataset. It is constructed on the basis of administrative registers for individuals, firms, and establishments, all maintained by Statistics Finland. This dataset provides information on individuals' labor market status, salaries, and other sources of income extracted from tax and other administrative regis-

entrepreneurs get over 45% of the total gains; and finally, blue-collar workers get about a quarter of the gains.

[8]The identification assumption in our conditional difference-in-differences approach is that had the coworkers of an inventor not worked with the inventor at the time of patenting their wages/employment would have developed as they did in the control group.

[9]Heckman et al. (2003) explore the effect of the EITC employment tax credit on the incentives to work and thereby accumulate human capital in the firm (through learning-by-doing or through on-the-job training); Blundell et al. (2016) estimate a dynamic model of employment and human capital accumulation for women in the UK, and find significant returns to being fully employed - and thereby increasing experience - for educated women who completed a three-year university degree, but not for women with only secondary education; and Deming (2017) provides evidence that the share of jobs requiring social skills has been increasing and that that the returns to social skills have increased.

ters. FLEED also includes information on other individual characteristics, and on employer and plant characteristics. This information allows us to identify an inventor's coworkers and to analyze how invention differentially affects different types of coworkers' wages. Second, we use the *European Patent Office* data which provide information on inventos.[10] We collected patent information on all patents with at least one inventor who registers Finland as his or her place of residence, and we use data on all patents with a Finnish inventor up to and including 2012. The matching of the two data sets follows the procedures in Aghion et al. (2018) and is also briefly described in Online Appendix A.1.

We limit our estimation sample to years 1994 – 2010 to allow for a period prior to invention in the early part of the data sample and to ensure sufficient coverage of patent applications in the late parts of the data. We focus on all Finnish inventions patented during this sample period. In order to ensure that we have workers in their (late) 50s in our sample, we depart from Aghion et al. (2018) and do not match on IQ, as this variable is only available from birth cohort 1961 onwards. Instead, we add the time since last education to the matching vector. To ensure sufficient labor market participation (individuals enter FLEED at age 15), we require positive wage income in preceding four years of included observations. We restrict attention to private sector employees because we can only identify coworkers in the private sector. Finally, we focus on white-collar and blue-collar workers.[11] The job status of an individual is identified through the socioeconomic status code contained in the FLEED.[12]

We obtain also our dependent variables from FLEED. Our main dependent variable is the deflated (log) taxable annual wage income of individual i in calendar year c.[13] To construct our second dependent variable we utilize the principal occupation of an individual. We display the distribution of different occupations (employed, unemployed, student, military service, retirement, unknown) for the non-employment (white- and blue-collar) estimation samples in Online Appendix B Table A3. We code our second dependent variable to take value zero if at the

[10]We thank the research project "Radical and Incremental Innovation in Industrial Renewal" by the VTT Research Centre (Hannes Toivanen, Olof Ejermo and Olavi Lehtoranta) for granting us access to the patent-inventor data they compiled.

[11]Aghion et al. (2018) studies also the rents accruing to entrepreneurs and inventors themselves.

[12]Before matching the merged data contain 32M observations on over 2.5M individuals who work in some 600K firms. The annual number of observations varies between 1.8 and 2.0M. 15 083 individuals invent at least once. After matching, our estimation samples contain some 160K white- and some 130K blue-collar workers and 1.4 - 1.9 million individual-year observations. See Tables A1 and A2 in the Online Appendix for more details.

[13]Previous research using Finnish data shows that adding capital income makes no difference to the results (Toivanen and Väänänen, 2012, Aghion et al., 2018). As an unreported robustness test, we have verified that this is the case also with our data.

end of the year an individual is employed and value one otherwise, corresponding to a generic non-employment status.

Our data display the same rising wage pattern as a function of age as documented in the labor literature. Our interest is in how the return to invention for white-collar and blue-collar workers varies with age, education and time since education (i.e., DTHCF). A strength of our data is that there is time variation in the number of years since last degree conditional on the age of an individual, allowing us to separately identify the age effect from the time since last degree effect (see Online Appendix, Figures A1 and A2, which demonstrate this graphically). The reason for this time variation is that individuals enter and complete their education at different ages, with some of a given age cohort studying longer or later in life for the same degree, and some obtaining new degrees.

We provide more information on the institutional setting in Finland in Online Appendix B, but note here that, as in many other European countries, there is a specific law in Finland that governs invention made by employees. While the act says that an employer may acquire the right to ownership of an employee invention, it does not determine the amount firms have to pay if they exercise the right. Rather, the amount of compensation is largely determined by the market forces. Neither does the act take any stance on how, if at all, the coworkers of the employee(s) who made the invention ought to be treated or compensated.

3 Regression equations

The left-hand side (LHS) variables y_{itca} in our regressions are: (1) the wage returns, measured in logs, and (2) a dummy for non-employed. We estimate the following equation:

$$\begin{aligned} y_{itca\tau} &= \alpha_i + \delta_{pre\tau} treated_i \times pre_t + \delta_{post\tau} treated_i \times post_t \\ &+ \sum_{\tau=-4,..,10} \alpha_\tau 1[t=\tau] + \sum_{c=1995,..,2012} \alpha_{year} 1[c = calendar\_year] \\ &+ \sum_{age=\min(age)+2,...,\max(age)} \alpha_{age} 1[a = age] + \varepsilon_{itca\tau}, \end{aligned} \tag{1}$$

where subscript i denotes individual; subscript t denotes treatment time ($t = -5, ..., 10$), c denotes calendar year ($c = 1995, ..., 2012$), and a denotes age in years ($a = \min(age) + 2, ..., \max(age)$). The variables pre_t and $post_t$ are dummy variables taking values one in the treatment years $t = -4, ..., -1$ and $t = 0, ..., 10$

respectively, and zero otherwise.[14]

Our specification includes individual fixed effects α_i, treatment time fixed effects α_τ, with $t = 0$ denoting the year of patent application (baseline is $t = -5$), calendar year fixed effects α_{year} (baseline year 1994); and age fixed effects α_{age} (baseline is $a \leq \min(age) + 1$ which may vary across estimation samples). The variable $treated_i$ is an indicator variable capturing an individual i belonging to the treatment group (coworker of type k = white-collar worker, blue-collar worker), i.e, individual i working in the same firm as an inventor in the year of patent application (without ever inventing herself).[15] In addition to the aforementioned variables, we include a dummy variable for a missing time since last diploma; this is necessary as Statistics Finland does not record the year of last diploma for those individuals with only compulsory education.[16] To ensure that these observations do not bias the other coefficients (especially that of DTHCF), we interact this dummy with both the $treated_i$ dummy and its interactions with the pre_t and $post_t$ dummies. We further include the number of employees in the firm where individual i works in year t.[17] We cluster standard errors at the level of the employer in the treatment year (i.e., all individuals working in the same firm at the time of treatment form a cluster). We run the estimations separately for the white- and blue-collar workers.

Equation (1) describes our base specification. We amend it by introducing the following variables and their interactions with the pre_t, $post_t$, and $treated_i$ dummies as well as the interactions between the first two and $treated_i$: $senior_{it}$ taking value one for individuals over 40 years of age (40 being very close to the median in our estimation samples); $high\_educ_{it}$, taking value one if an individual has a higher education (defined as at least MSc for white-collar and at least college education for blue-collar workers); and $DTHCF_{it}$, Distance to Human Capital Frontier, defined as the years since the last diploma, capturing how the human capital acquired through formal education depreciates.

Equation (1) also allows for pre-invention effects. The usual diagnosis of such

[14] Aghion et al. (2018) found that both the pre- and post-invention returns to white- and blue-collar workers varied little and much less than those or inventors and entrepreneurs. Based on this evidence, we do not consider time-varying coefficients in this paper and concentrate on the variation in the treatment effect in other dimensions.

[15] In line with Aghion et al. (2018), but in contrast to Toivanen and Väänänen (2012) and Kline et al. (2019), we do not condition on the quality or type of the patent. Our results are therefore average treatment effects over different types of patents of varying quality.

[16] Circa 90% of the observations for which this dummy takes value 1 are for individuals with only compulsory education.

[17] For the non-employment analysis, we substitute the number of the employees of the latest employer for those individual-year observations where the individual is not employed.

effects would be that the conditional parallel trends assumption - on which the conditional difference-in-differences approach relies - fails. The pre-invention effects are however also consistent with economic theory and, specifically, with anticipation effects of forward-looking firms. In our case, firms can anticipate the invention, and may therefore have reason to e.g., increase wages of some workers before the patent application so as to not lose them. As Anup and Reif (2015) discuss, one should not automatically attribute pre-trends to endogeneity, as not allowing for anticipation effects can also lead to underestimation of the (total) treatment effect of interest.[18]

As mentioned, we employ a conditional difference-in-difference approach whereby we first match each treated individual with a control individual.[19] The matching is done without replacement on an annual basis, starting from 1994. To prevent contamination of the control group, we limit the potential control group to individuals who never invent and have never been coworkers of an inventor and who work in the private sector in the year of treatment. We use the following variables for matching: (i) having at least an MSc (white-collar) or college degree (blue-collar); (ii) having a STEM education; (iii) DTHCF (<5, 5–10, 11–15, 16–20, >20); (iv) working in manufacturing; (v) living in the South-West of Finland; (vi) age (<30, 31–40, 41–50, >50); and (vii) quintiles of the annual firm size distribution. We execute the matching separately for blue- and white-collar workers. For white-collar workers, we perform the matching separately within the following subcategories: (i) senior managers, (ii) senior workers, (iii) junior managers, and (iv) junior workers.[20]

Our base group of treated are thus young workers without a high education (but more than compulsory education) who have just received their latest diploma.

4 Regression results

4.1 Returns

In Table 1, we report results from the simplest specification with only a treatment dummy, and from a specification that conditions the returns to age (the $senior_{it}$ dummy). Looking at columns (1) and (3), it seems that white-collar workers

[18]The timing structure of our econometric model implies that we cannot test for common pre-trends as we have only one period $t = -5$ outside our two (= pre and post) treatment periods.

[19]We implement one-to-one matching using the coarsened exact matching of Iacus et al. (2012).

[20]In this matching, "senior" and "junior" refer to socioeconomic status, not biological age.

gain 2.5% while blue-collar workers' wages are unaffected after the invention.[21] However, once we condition on age, in columns (2) and (4), we find that the positive returns to invention are actually of the order of 5% for younger white-collar employees, but senior white-collar workers get zero returns. Younger blue-collar workers obtain no return, but the wages of seniors actually decrease by 2%. These results thus suggest that in contrast to the general finding of wages rising as a function of age or seniority (e.g. Blundell et al., 2016), the returns to invention are plagued by an age-related penalty.

TABLE 1 HERE

Table 2 shows the results from richer specifications. The specifications in columns (1) and (3) are otherwise comparable to those in columns (2) and (4) of Table 1, but with DTHCF added. According to these specifications, both young white- and blue-collar workers earn substantial invention-premia and seniors earn higher, not lower returns to invention, with the positive age premium being 2%. The introduction of DTHCF thus turns around the estimated impact of seniority reported in Table 1 which suggested zero or negative invention returns to seniors.

TABLE 2 HERE

In columns (2) and (4), we include both the seniority dummy and the high education dummy along DTHCF. We find strong returns to invention for the workers in our base group (young, without higher education, with zero DTHCF) of 5 - 10%. The effect of age is essentially zero for both white- and blue-collar coworkers. This is a consequence of controlling for education and in particular DTHCF, suggesting that the estimated negative effect of seniority in Table 1 actually reflects the lower educational level of older workers and especially the depreciated human capital of those further from the human capital frontier.

A higher level of education (MSc for white- BSc for blue-collar workers) brings additional returns of the order of four percentage points for white- and seven percentage points for blue-collar workers. We thus find a substantial education premium regarding returns to invention for coworkers.

To visualize the results, Figure 1 provides bar charts for the main variables of interests of the white-collar workers in Panel A and blue-collar workers in Panel B. Juniors and seniors are represented in different shades of red and blue, respectively. In Panel A, the upper-left figure plots the impact of invention on juniors

[21] These estimates that do not allow for treatment effect heterogeneity are in line with but not identical to those reported by Aghion et al. (2018). The differences are explained by the current estimation sample including also older workers.

and seniors with average level of higher education (0.22 and 0.23, respectively) and average level of DTHCF (8.1 and 20.8 years, respectively). The results show a very visible positive impact of invention on the average junior and almost no effect on the average senior coworker. Next, in order to tease out the effect of education, the upper-right figure shows the effect for juniors with low education (no MSc; labelled JLD in the figure, for ***J***unior ***L***ow education, ***D***THCF 8.73), seniors with lower education (SLD), juniors with high education (JHD), and seniors with high education (SHD), each person with their respective average DTHCF. The results show that while higher education has a significant positive impact for both juniors and seniors, within each education level, seniors experience a much smaller, even negative gain from inventionn. This is due to their formal education being farther from the frontier. Finally, the lower figure in Panel A evaluates the returns to invention for different age, education, and DTHCF levels. The first two bars (JLD(0), SLD(0)) imply that low-educated juniors and seniors would earn the same invention rents, were their DTHCF completely eliminated. Similarly, among high-educated juniors and seniors (bars 3 and 4, JHD(0) and SHD(0)), we see a very similar pattern, but higher rents. The picture flips completely when we evaluate the impact on seniors and juniors at their respective DTHCF levels (same as in the upper-right panel). Panel B shows that the results for blue-collar workers follow mostly a very similar patterns with returns being across the board smaller than for white-collar workers. The one pronounced difference between white- and blue-collar workers is that at average DTHCF (upper-left figure), low-educated blue-collar workers earn either a zero (juniors) or a negative (seniors) invention rents.

FIGURE 1 HERE

What comes across very strong over all specifications is that post-invention returns are negatively affected by the distance to the human capital frontier, with the decrease being of circa 0.5 percentage points per year for each year since education. The point estimate of the distance to the human capital frontier is remarkably stable across specifications.

Moving to pre-invention returns, we point out that - as discussed above - such returns cannot be ruled out, because the innovating firm may benefit from the invention and foresee the benefits, already before obtaining the patent. The firm may therefore feel compelled to reorganize and possibly adjust wages prior beforehand. As Table 2 shows, we find that white-collar workers get a pre-invention increase in their wages which is around 4% per annum. The evidence for blue-collar workers is weaker. The pre-invention returns are the same for young and old. Highly educated white-collar workers get an additional one percentage point pre-return. Pre-invention returns are also negatively affected by time since last degree for both white- and blue-collar workers.

The results are robust to excluding the three largest employers of inventors from the estimation sample, and remain qualitatively similar when we exclude all but those observations where the employer is the same as at time of invention (see Online Appendix, Tables C1-C6). Regarding the latter, we find somewhat lower returns for our base group of treated individuals. This result suggests that the labor market is a source of invention-related returns to coworkers. We then exclude all other treated individuals but those for whom the treatment is the first (observed) patent of their employer (see Online Appendix, Tables D1-D4). Results are in again qualitatively mostly the same as our main results: we find that the effect of DTHCF is, in absolute value, smaller for white- and larger for blue-collar workers than in our main results. The notable difference is that the impact of education on the invention rents changes: we find no extra returns for highly educated white-collar workers, but do find them for highly educated blue-collar workers. As our third robustness test, we estimate the model separately for those individual-year observations where the individual has or does not have a STEM education. (see Online Appendix, Tables E1-E4). This robustness test is motivated by the interesting results of Deming and Noray (2020) that STEM jobs have the fastest rate of skill change across occupations and faster depreciation of the college premium, suggesting that the DTHCF coefficients should be higher in absolute value for STEM educated individuals than for others. In the simplest specification (equivalent to Table 1) we find positive returns to non-senior white-collar worker for non-STEM educated workers, but no returns to either type of senior workers. With the richer specifications we find positive returns to the base-group of both STEM- and non-STEM-educated workers. However, the returns are higher for the non-STEM workers regarding white- as well as blue-collar workers. STEM-educated senior workers obtain higher rents whereas non-STEM-educated senior workers do not. What we do find across the board is that DTHCF obtains a negative and statistically significant coefficient. The absolute size of the effect varies between -0.6 (STEM-educated white-collar workers) and -0.8 percentage points (non-STEM educated white- and blue-collar workers), i.e., the depreciation is of the same size quantitatively, and if anything, slightly faster for non-STEM than STEM-educated workers. In our fourth robustness test we exclude all individuals who eventually (within our data) obtain a PhD, the idea being that while having an MSc they are accumulating human capital instead of having their human capital depreciate (see Online Appendix, Tables F1-F4). This robustness test produces results that are very close to those obtained with our main sample. In unreported regressions, we also considered richer specifications which included progressively more interactions with DTHCF, and richer specifications of both age and DTHCF. What becomes especially clear across all these robustness tests is that post-invention returns are negatively affected by distance to human capital frontier (at circa -0.5 percentage points per year).

4.2 Non-employment

Table 3 presents our results on the effect of invention on the probability of coworkers of the inventor becoming non-employed. These simpler specifications (columns (1) and (2) for white-collar workers, (3) and (4) for blue-collar workers), correspond to those reported in Table 1. They seem to suggest that the probability of coworker non-employment is either unaffected (white-collar workers), or increases (blue-collar workers), as a result of invention. The effect appears to be the same for senior workers with the exception that the impact seems smaller before the invention for senior blue-collar workers. However, these results mask a great deal of heterogeneity. Table 4 reports the results from specifications that correspond to those of Table 2 and thus allow the returns to vary with age, education, and DTHCF.

TABLE 3 HERE

Results in Table 4 suggest two consistent patterns. First, the likelihood of coworker non-employment typically decreases due to within-firm invention: for example, the non-employment probability is 5-6 percentage points lower for young blue- and white-collar workers with a recent low education diploma (columns (2) and (4)). The probability of non-employment decreases for both younger and older workers: although the coefficients for the interactions with the senior-dummy are positive also in the fuller specifications in columns (2) and (4), neither is significant at the 5% level (that for blue-collar workers is significant at 10% level though). The probability of non-employment decreases also for highly educated workers, though less so: the coefficient of the high education - interaction is positive and significant for both white- and blue-collar workers.

TABLE 4 HERE

Second, the probability of coworker non-employment increases steadily with the time since education. As Table 4 shows, the increase is 0.2-0.5 percentage points per year for each year since obtaining the latest degree. This increase in the probability of coworker non-employment can be observed both for white- and blue-collar workers and pre- and post-invention.

We subjected these results to the same robustness tests as the wage results. Excluding the three largest employers of inventors we obtain very similar results to those reported in the main text. When we exclude all other treated individuals but those for whom the treatment is the first invention of the firm, we find somewhat smaller DTHCF coefficients. The post-treatment effects are otherwise qualitatively similar to those in the main text, but the effect of education on the treatment effect vanishes. Regarding the pre-treatment effects, instead of finding a negative effect for base group of white-collar workers, we find a positive one. The impact of seniority and high education on the pre-treatment effect disappear for both groups. When we only include STEM- or non-STEM educated workers, the results are in line with those obtained with our main estimation sample and our wage results, with somewhat smaller DTHCF coefficients for STEM-educated and somewhat larger DTHCF coefficients for the non-STEM educated. Excluding the (eventual) PhDs from our sample leads to no discernible change in the results.

5 Conclusion

In this paper we looked at the effect of coworker invention on the wage returns and non-employment probability of white-collar and blue-collar workers. We merged individual income data, firm-level data, and patenting data in Finland over the period of 1988-2012, and we employed a conditional difference-indifference approach. We are particularly interested in how the invention rents of coworkers depend on their education-based human capital, measured both through the level of education, and in the spirit of much of the literature on Schumpeterian endogenous growth, distance to the (education) frontier which we measure by the time lapsed since the last degree.

Our main findings were: first, invention results in substantial rents for white- and blue-collar workers, and second, the level of education positively affects the returns to invention for both types of workers. Third, biological age appears to negatively affect the returns to invention for both types of workers, but this negative effect is entirely due to the fact that the distance to the human capital frontier is higher for older workers. Fourth, the direct effect of invention is to lower the probability of non-employment, but this effect goes down with the time since education. Fifth, we find that the invention rents differ between those with and without a STEM-education: non-STEM educated get a higher base return;

STEM-educated seniors get an extra return but non-STEM educated seniors do not; the higher education premium is similar to both groups; and if anything, the effect of DTHCF is larger in for the non-STEM than the STEM-educated. As far as we are aware, these results are new to the literature; this applies in particular to our analysis of how the distance to the human capital frontier affects coworker returns to invention.

Overall, our findings vindicate the Schumpeterian view whereby invention is associated with creative destruction and knowledge obsolescence. Our analysis suggests that bringing the workforce closer to human capital frontier, for instance by utilizing worker retraining programs, provides an important policy tool to allow more workers to benefit from invention and make the economic growth process more inclusive. The fact that we find similar results for the overall sample and the subsample of STEM-educated suggests that what is important is to bring individuals (back) to the human capital frontier, not the type of education as such. The costs of such retraining should be borne at least to some extent by the workers as we find that part of the rents they accumulate come through the labor market and change of jobs.

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Figure and Tables

Table 1: Wage returns to invention, conditioning on age

	white-collar (1)	white-collar (2)	blue-collar (3)	blue-collar (4)
post	0.0246***	0.0507***	0.000981	0.00913
	(0.00324)	(0.00490)	(0.00395)	(0.00563)
post x senior		-0.0513***		-0.0212***
		(0.00625)		(0.00751)
pre	0.0120***	0.0218***	-0.0175***	-0.0204***
	(0.00271)	(0.00406)	(0.00353)	(0.00505)
pre x senior		-0.0237***		0.00634
		(0.00517)		(0.00664)
Observations	1,885,513	1,885,513	1,396,204	1,396,204
R-squared	0.266	0.267	0.203	0.203
Number of individuals	159,429	159,429	132,787	132,787

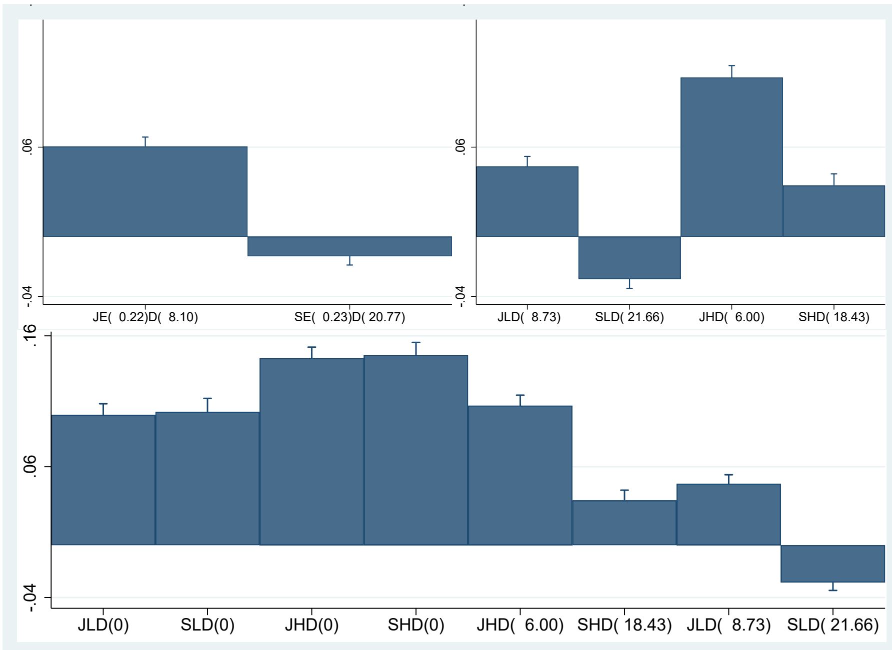
Notes: Standard errors, clustered at the employer level (at $\tau = 0$) level in parentheses. All specifications include individual fixed effects, treatment and calendar year dummies, age fixed effects, dummies for the relevant interaction variables (senior, educ, DTHCF), a dummy for missing DTHCF (for those with compulsory education only) and its interactions, the number of employees in the firm, and a dummy for missing number of employees.

Table 2: Wage returns to invention, conditioning on age and education

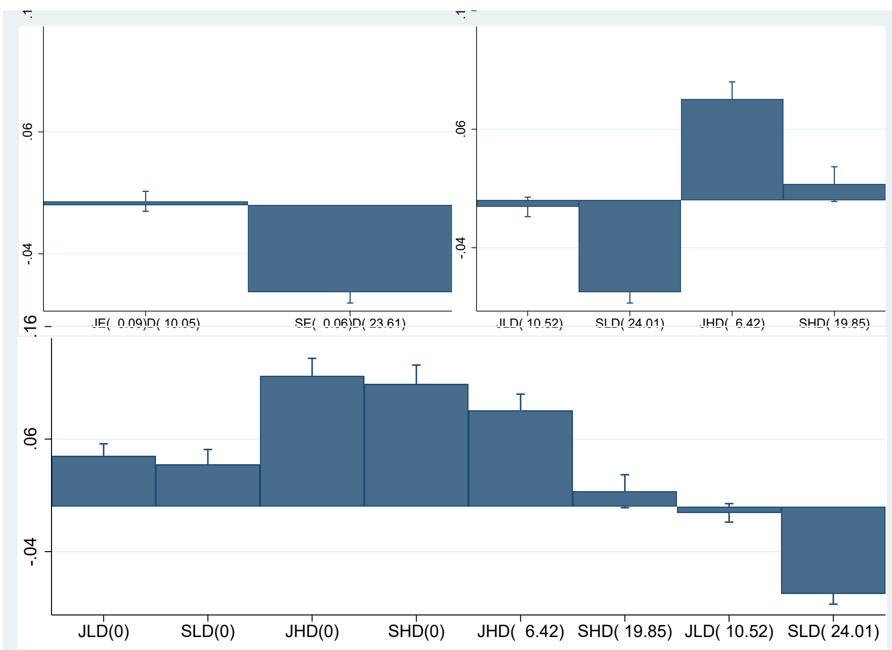
	white-collar (1)	**white-collar** (2)	**blue-collar** (3)	**blue-collar** (4)
post	0.114***	0.0996***	0.0897***	0.0448***
	(0.00582)	(0.00609)	(0.00840)	(0.00847)
post x senior	0.0178***	0.00232	0.0209***	-0.00734
	(0.00585)	(0.00592)	(0.00678)	(0.00678)
post x educ		0.0432***		0.0713***
		(0.00571)		(0.0114)
post x DTHCF	-0.00669***	-0.00602***	-0.00591***	-0.00479***
	(0.000365)	(0.000375)	(0.000487)	(0.000490)
pre	0.0440***	0.0429***	-0.0127*	-0.00946
	(0.00473)	(0.00508)	(0.00763)	(0.00780)
pre x senior	0.00791	0.00373	-0.00265	-0.00887
	(0.00501)	(0.00512)	(0.00600)	(0.00602)
pre x educ		0.0101**		-0.00431
		(0.00487)		(0.00996)
pre x DTHCF	-0.00284***	-0.00273***	-0.000520	-0.000917**
	(0.000323)	(0.000333)	(0.000449)	(0.000452)
Observations	1,885,513	1,885,513	1,396,204	1,396,204
R-squared	0.270	0.280	0.205	0.221
Number of individuals	159,429	159,429	132,787	132,787

Notes: Standard errors, clustered at the employer level (at $\tau = 0$) level in parentheses. All specifications include individual fixed effects, treatment and calendar year dummies, age fixed effects, dummies for the relevant interaction variables (senior, educ, DTHCF), a dummy for missing DTHCF (for those with compulsory education only) and its interactions, the number of employees in the firm, and a dummy for missing number of employees.

Figure 1: Return to Invention by Age, Education and DTHCF
Panel A: White Collar



Panel B: Blue collar



J: junior, S: senior, L: low education, H: high education, D: DTHCF. The numbers in parentheses are the average level of higher education (if < 1) and average DTHCF.

Table 3: Effect of invention on probability of non-employment, conditioning on age

	white-collar (1)	**white-collar** (2)	**blue-collar** (3)	**blue-collar** (4)
post	-0.000178	-0.00256	0.0167***	0.0161***
	(0.00153)	(0.00241)	(0.00243)	(0.00338)
post x senior		0.00489*		-0.00137
		(0.00273)		(0.00448)
pre	0.00192	0.00167	0.0155***	0.0187***
	(0.00137)	(0.00207)	(0.00222)	(0.00305)
pre x senior		0.000724		-0.00948**
		(0.00242)		(0.00412)
Observations	1,864,183	1,864,183	1,414,747	1,414,747
R-squared	0.177	0.179	0.148	0.149
Number of individuals	159,385	159,385	132,764	132,764

Notes: Standard errors, clustered at the employer level (at $\tau = 0$) level in parentheses. All specifications include individual fixed effects, treatment and calendar year dummies, age fixed effects, dummies for the relevant interaction variables (senior, educ, DTHCF), a dummy for missing DTHCF (for those with compulsory education only) and its interactions, the number of employees in the firm, and a dummy for missing number of employees.

Table 4: Effect of invention on probability of non-employment, conditioning on age and education

	white-collar (1)	**white-collar** (2)	**blue-collar** (3)	**blue-collar** (4)
post	-0.0335***	-0.0463***	-0.0618***	-0.0558***
	(0.00273)	(0.00285)	(0.00478)	(0.00478)
post x senior	0.00764***	0.00262	0.00225	0.00651*
	(0.00227)	(0.00230)	(0.00378)	(0.00380)
post x educ		0.0346***		0.0228***
		(0.00218)		(0.00643)
post x DTHCF	0.00243***	0.00285***	0.00539***	0.00519***
	(0.000155)	(0.000161)	(0.000274)	(0.000274)
pre	-0.0331***	-0.0425***	-0.0429***	-0.0449***
	(0.00234)	(0.00252)	(0.00441)	(0.00449)
pre x senior	0.0123***	0.00690***	0.00780**	0.00805**
	(0.00213)	(0.00217)	(0.00351)	(0.00353)
pre x educ		0.0310***		0.0277***
		(0.00205)		(0.00594)
pre x DTHCF	0.00266***	0.00299***	0.00440***	0.00445***
	(0.000146)	(0.000153)	(0.000259)	(0.000260)
Observations	1,864,183	1,864,183	1,414,747	1,414,747
R-squared	0.180	0.183	0.150	0.154
Number of individuals	159,385	159,385	132,764	132,764

Notes: Standard errors, clustered at the employer level (at $\tau = 0$) level in parentheses. All specifications include individual fixed effects, treatment and calendar year dummies, age fixed effects, dummies for the relevant interaction variables (senior, educ, DTHCF), a dummy for missing DTHCF (for those with compulsory education only) and its interactions, the number of employees in the firm, and a dummy for missing number of employees.

Online Appendix -- Not intended for publication

P. Aghion, U. Akcigit, A. Hyytinen and O. Toivanen

A Year Older, A Year Wiser (and Farther from Frontier):
Invention Rents and Human Capital Depreciation

Appendix A: Data and descriptive statistics

A.1 Data sources and matching

The data used in this paper cover the period of 1988-2012 and come from Statistics Finland (SF) and European Patent Office (EPO). SF is our source of individuals' characteristics and their employers. These data come from the Finnish Linked Employer-Employee Data (FLEED) for the period of 1988-2012. FLEED is a standard administrative register-based data, collected and maintained by SF. EPO data allow us to identify Finnish inventors. Our EPO data are derived from OECD's REGPAT database, which includes patent applications to the EPO and PCT filings.

The datasets were matched as follows: SF's FLEED contains unique but anonymized individual identifiers, which are based on unique social security numbers that everybody in Finland has. EPO data, in contrast, does not contain linkable individual identifiers. Linking of patent data to individuals was done by a civil servant of SF, using the information on individual name (first and surname), employer name, individual address and/or employer's address (postcode, street name street number), and year of patent application. These were used in different combinations, also varying the year of the match to be before or after the year of application (e.g., matching a patent applied for in 1999 with the street address of the firm from the registry taken in 1998 or 2000). The match rate is 90% when calculated for the patents applied for in the years 1988-2012. The procedure follows that used in Aghion, Akcigit, Hyytinen, and Toivanen (2018).

A.2 Descriptive statistics

Tables A1 and A2 display the descriptive statistics (mean, median and standard deviation) separately for the white- and blue-collar samples. Both tables provide descriptive statistics for the respective estimation samples, as well as for the subsamples of treated and control individuals. For DTHCF, we report the descriptive statistics conditional on DTHCF not missing. As explained in the main text, DTHCF is missing for those individuals with only compulsory education. For them, we set DTHCF to be equal to age – 15, the age at which compulsory education finishes. In the regressions, we include a separate dummy for these individuals, and take a full set of interactions between that dummy and the treatment – variables.

Figures A1 and A2 display DTHCF conditional on individuals' age, separately for white- and blue-collar samples. The lines display the 10th and 90th percentiles and the shadow area (in gray) between the lines illustrates how much there is variation in the DTHCF -measure for a given age group of individuals in the data.

Table A3 tabulates the information on the principal occupation of the individuals in our wage estimation samples for white- and blue-collar workers.

Table A1: *Mean, median and standard deviations: White collar sample*

Descriptive statistics - whitecollar

	lnwage	UE_d	age	BSc	MSc	DTHCF
Lnwage estimation sample						
Estimation sample						
	lnwage	UE_d	age	BSc	MSc	DTHCF
mean	10.53	0.00	40.45	0.64	0.23	13.19
sd	0.64	0.00	9.73	0.48	0.42	9.12
p50	10.61	0	40	1	0	12
N	2 905 759	2 788 499	2 905 759	2 905 759	2 905 759	2 588 963
Control group						
	lnwage	UE_d	age	BSc	MSc	DTHCF
mean	10.51	0.00	40.44	0.63	0.22	13.48
sd	0.65	0.00	9.76	0.48	0.42	9.16
p50	10.60	0	40	1	0	12
N	1 421 257	1 361 997	1 421 257	1 421 257	1 421 257	1 266 292
Treatment group						
	lnwage	UE_d	age	BSc	MSc	DTHCF
mean	10.55	0.00	40.46	0.66	0.24	12.92
sd	0.63	0.00	9.70	0.47	0.43	9.07
p50	10.63	0	40	1	0	11
N	1 484 502	1 426 502	1 484 502	1 484 502	1 484 502	1 322 671
Unemployment estimation sample						
Estimation sample						
	lnwage	UE_d	age	BSc	MSc	DTHCF
mean	10.50	0.03	40.21	0.64	0.23	13.04
sd	0.73	0.17	9.87	0.48	0.42	9.12
p50	10.61	0	40	1	0	11
N	2 849 605	2 875 851	2 875 851	2 875 851	2 875 851	2 554 439
Control group						
	lnwage	UE_d	age	BSc	MSc	DTHCF
mean	10.48	0.03	40.21	0.62	0.22	13.33
sd	0.73	0.17	9.90	0.49	0.41	9.16
p50	10.59	0	40	1	0	12
N	1 392 486	1 405 137	1 405 137	1 405 137	1 405 137	1 248 088
Treatment group						
	lnwage	UE_d	age	BSc	MSc	DTHCF
mean	10.51	0.03	40.20	0.65	0.24	12.76
sd	0.72	0.17	9.85	0.48	0.43	9.07
p50	10.62	0	40	1	0	11
N	1 457 119	1 470 714	1 470 714	1 470 714	1 470 714	1 306 351

Table A2: *Mean, median and standard deviations: Blue collar sample*

Descriptive statistics - bluecollar

Lnwage estimation sample

Estimation sample	lnwage	UE_d	age	BSc	MSc	DTHCF
mean	10.26	0.00	39.67	0.08	0.01	14.77
sd	0.57	0.00	10.35	0.27	0.10	9.62
p50	10.36	0	40	0	0	14
N	2,190,592	2,115,702	2,190,592	2,190,592	2,190,592	1,438,356
Control group	**lnwage**	**UE_d**	**age**	**BSc**	**MSc**	**DTHCF**
mean	10.21	0.00	39.56	0.07	0.01	14.88
sd	0.59	0.00	10.39	0.25	0.09	9.54
p50	10.32	0	40	0	0	14
N	1,075,177	1,030,487	1,075,177	1,075,177	1,075,177	702,859
Treatment group	**lnwage**	**UE_d**	**age**	**BSc**	**MSc**	**DTHCF**
mean	10.31	0.00	39.77	0.09	0.01	14.67
sd	0.55	0.00	10.31	0.28	0.12	9.69
p50	10.40	0	40	0	0	14
N	1,115,415	1,085,215	1,115,415	1,115,415	1,115,415	735,497

Unemployment estimation sample

Estimation sample	lnwage	UE_d	age	BSc	MSc	DTHCF
mean	10.22	0.04	39.45	0.08	0.01	14.55
sd	0.66	0.20	10.47	0.27	0.10	9.62
p50	10.35	0	40	0	0	14
N	2,178,294	2,209,644	2,209,644	2,209,644	2,209,644	1,444,847
Control group	**lnwage**	**UE_d**	**age**	**BSc**	**MSc**	**DTHCF**
mean	10.17	0.05	39.34	0.07	0.01	14.67
sd	0.67	0.21	10.49	0.25	0.09	9.54
p50	10.31	0	39	0	0	14
N	1,065,282	1,081,104	1,081,104	1,081,104	1,081,104	704,622
Treatment group	**lnwage**	**UE_d**	**age**	**BSc**	**MSc**	**DTHCF**
mean	10.27	0.04	39.55	0.09	0.01	14.43
sd	0.64	0.19	10.46	0.28	0.12	9.70
p50	10.39	0	40	0	0	13
N	1,113,012	1,128,540	1,128,540	1,128,540	1,128,540	740,225

Descriptive statistics - bluecollar

Lnwage estimation sample

Estimation sample	lnwage	UE_d	age	BSc	MSc	DTHCF
mean	10.26	0.00	39.67	0.08	0.01	14.77
sd	0.57	0.00	10.35	0.27	0.10	9.62
p50	10.36	0	40	0	0	14
N	2,190,592	2,115,702	2,190,592	2,190,592	2,190,592	1,438,356

Control group

	lnwage	UE_d	age	BSc	MSc	DTHCF
mean	10.21	0.00	39.56	0.07	0.01	14.88
sd	0.59	0.00	10.39	0.25	0.09	9.54
p50	10.32	0	40	0	0	14
N	1,075,177	1,030,487	1,075,177	1,075,177	1,075,177	702,859
Treatment group						
	lnwage	UE_d	age	BSc	MSc	DTHCF
mean	10.31	0.00	39.77	0.09	0.01	14.67
sd	0.55	0.00	10.31	0.28	0.12	9.69
p50	10.40	0	40	0	0	14
N	1,115,415	1,085,215	1,115,415	1,115,415	1,115,415	735,497
Unemployment estimation sample						
Estimation sample						
	lnwage	UE_d	age	BSc	MSc	DTHCF
mean	10.22	0.04	39.45	0.08	0.01	14.55
sd	0.66	0.20	10.47	0.27	0.10	9.62
p50	10.35	0	40	0	0	14
N	2,178,294	2,209,644	2,209,644	2,209,644	2,209,644	1,444,847
Control group						
	lnwage	UE_d	age	BSc	MSc	DTHCF
mean	10.17	0.05	39.34	0.07	0.01	14.67
sd	0.67	0.21	10.49	0.25	0.09	9.54
p50	10.31	0	39	0	0	14
N	1,065,282	1,081,104	1,081,104	1,081,104	1,081,104	704,622
Treatment group						
	lnwage	UE_d	age	BSc	MSc	DTHCF
mean	10.27	0.04	39.55	0.09	0.01	14.43
sd	0.64	0.19	10.46	0.28	0.12	9.70
p50	10.39	0	40	0	0	13
N	1,113,012	1,128,540	1,128,540	1,128,540	1,128,540	740,225

Principal occupation	White-collar sample	Blue-collar sample
Employed	98.08	96.89
Unemployed	0.61	1.73
Student	0.92	0.77
Retirement	0.11	0.18
Military service	0.11	0.23
Unknown	0.17	0.19

Table A.3: *Principal occupation, percentage shares*

Figure A1: *DTHCF conditional on age: White-collar sample*

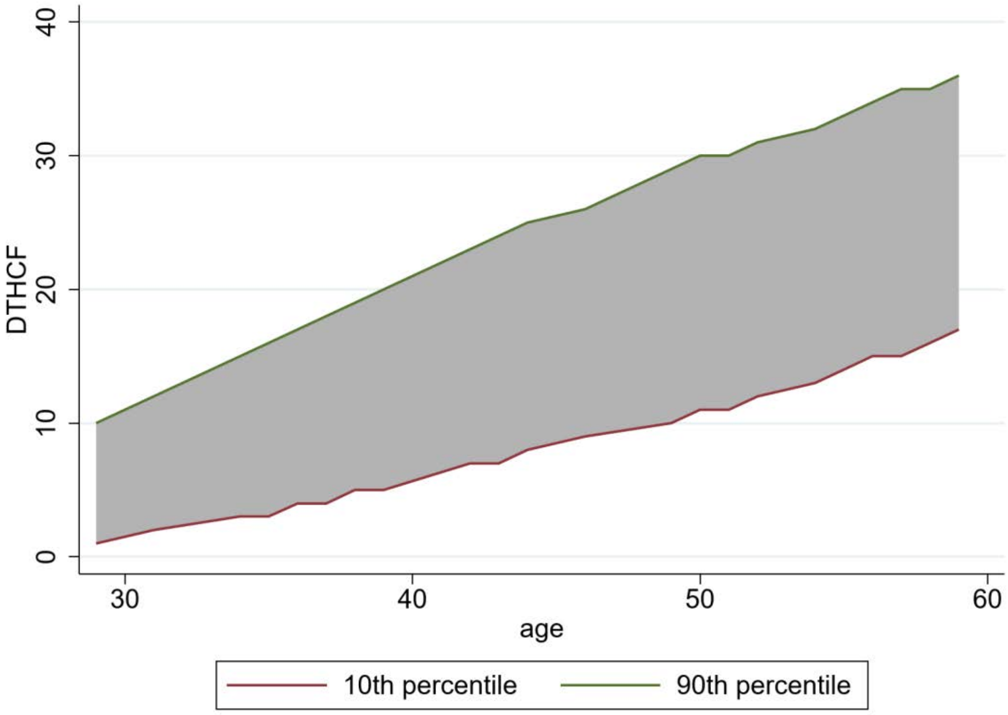
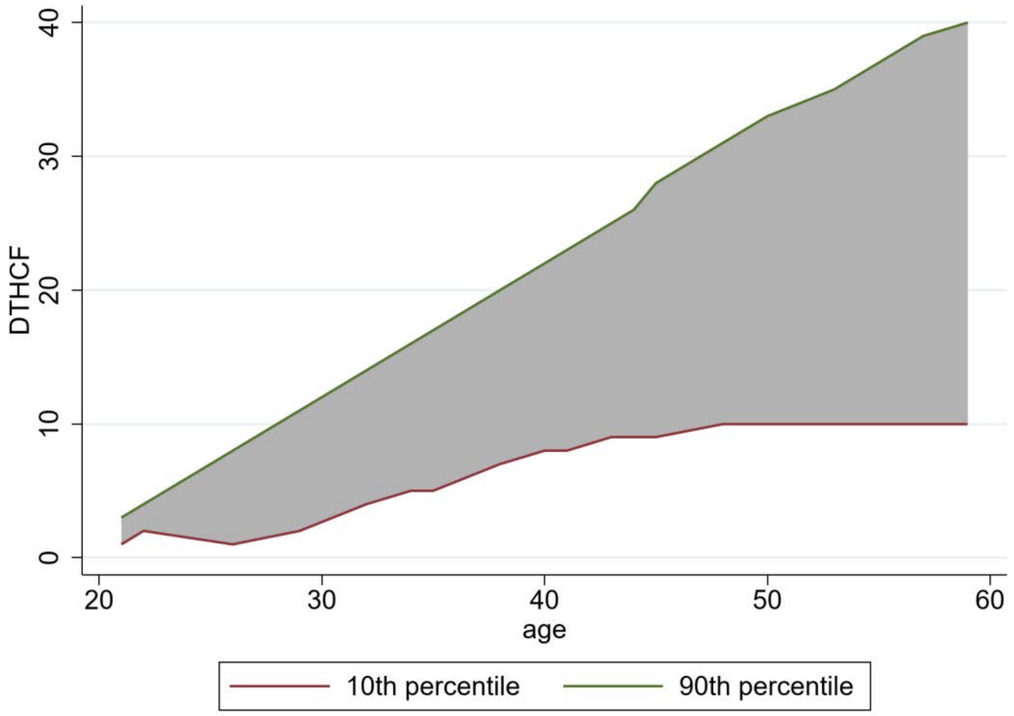


Figure A2: *DTHCF conditional on age: Blue-collar sample*



Appendix B: Institutional environment

B.1 Overall economic environment in 1988-2012

Finland has been a member of EU since 1995 and has a population of 5.5 million. It has been a member of the euro area since its introduction in 1999/2002.

During our observation period from 1988 to 2012, Finland's gross domestic product (GDP) grew on average 2.1% per year. The average masks a lot of variation (std = 3.6%), because the economy experienced boom periods in the late 1980s and late 1990s and two major economic slumps, one in the early 1990s and another in 2008/2009. In 1988/1989, unemployment rate was low, at around 3.1%. Unemployment peaked in the economic crisis of the early 1990s at around 16% (1993-1994), but decreased then to 7.7% by 2012.

At the beginning of our observation period, the employment rate among the population aged 15-74 was 67.3%. The employment rate has fluctuated somewhat, and decreased to 60.9% by 2012, mostly due to the aging of the population. Commerce, hotel and restaurant services, education, social services and health services and transport employ the greatest number of people, with the public sector (municipalities, government) being a major employer in many of these sectors.

In 1988, 51% of population aged 15 or over had basic education, but the share dropped to 31% by 2012. The share of population having higher level tertiary (ISCED 7) or doctorate level (ISCED 8) education increased from 7% (1988) to nearly 18% (2012) over our observation period. Research and development expenditures also increased steadily during our observation period, reaching their peak in 2011 when the total R&D expenditure by business sector and public sector amounted to 3.8% of the GDP. Based on its Global Competitiveness Index, World Economic Forum has quite consistently ranked Finland to be one of the ten most competitive countries in the world.

B.2 Wage setting

The Finnish labor market is characterized by widespread organization of employees (unionization) and employers, as well as by centralized wage-setting (bargaining and co-operation), which have resulted in various types of collective wage and labor agreements. A special feature of the Finnish labor market is national income policy settlements, which cover issues related to wage setting and salaries, taxation, pensions, and unemployment benefits, which are agreements between the government and the central confederations of employees and employers (the tripartite system). About three out of four Finnish employees are members of a trade union, and also those with higher education belong often to unions. In 2007, the system of centralized agreements largely ended when the private sector employers' association called for industry level negotiations. In 2011 there was a partial and temporary return to signing a national framework agreement, which was triggered by perceptions of deterioration of national price-cost competitiveness.

Despite these centralized features, wage setting is a mixture of collective and individual mechanisms. As Uusitalo and Vartiainen (2009) have emphasized, a key feature of the centralized agreements is that they coordinate the overall rate of wage increases. This does not prevent a firm from increasing its workers' wages by more than the coordinated overall increase. The collective agreements also restrict local bargaining by instituting agreed minimum wages for certain occupations and job levels. If a firm wants to employ somebody, the bargaining of his/her initial salary is subject to the minimum tariffs. However, as Uusitalo and Vartiainen (2009) stress, for most employees in the manufacturing sector, the minimum wages rarely bind. These features of the Finnish labor market mean that relative wages have largely been set by market forces and that wage bargaining is to a significant extent local. Moreover, various firm-specific arrangements and performance-related pay components became more widespread in the 1990s.

B.3 Remuneration of inventors and ownership of employee inventions

A specific law governs innovations made by employees ("Act on the Right in Employee Inventions", originally given in 1967, augmented in 2000). The provisions of the act apply to inventions (potentially) patentable in Finland.

The employee inventions act says, in particular, that i) an employer may acquire the right in the invention (made by its employee) if the use of the invention falls within the field of activity of the employer's enterprise; that ii) an employee who makes an invention has to notify the employer of it without delay, and that the employer has to notify the employee, if the employer wishes to acquire the right in the invention; and, finally, that iii) if the employer acquires the right in the invention, the employee is entitled to a reasonable compensation from the employer.

When determining the amount of the compensation, particular attention is to be paid to the value of the invention, the scope of the right which the employer acquires, as well as to the terms and conditions of the employment contract of the employee and the contribution which other circumstances connected with the employment had to the conception of the invention.

In sum, the act assigns the right to ownership of an employee invention, but it does *not* directly determine the amount firms have to pay if they exercise the right. Rather, the determination of the amount of compensation is largely left to the market forces. In particular, the act does not take any stance on how, if at all, the coworkers of the employee(s) who made the invention ought to be treated or compensated.

The Finnish act is by no means unique in an international comparison: for example, the Swedish "Act on the Right to Employee's Inventions" (introduced in 1949) shares many features with the corresponding Finnish act. Moreover, the German "Employee Invention Act" is in many ways similar: e.g. it states that when the employer claims the rights to an employee-made invention, the employer owes the employee an "adequate" remuneration. Things are a bit more complex in the UK, but when an employer owns his employee's invention, it is possible for the employee to claim compensation if his invention or the patent is of outstanding benefit to his employer and it is just to award such compensation.

Appendix C: Are the results robust to excluding the largest employers of inventors from the estimation sample or using only those observations where the employer is the same as at the time of the (counterfactual) invention?

C.1 Are the results robust to excluding the largest employers of inventors from the estimation sample?

In Tables C1 – C4 we reproduce the estimations reported in Tables 1-4, but so that the individuals working for the three largest employers of inventors are excluded. The aim of this robustness check is to investigate whether some of the largest technology-oriented firms are driving our findings. This turns out not to be the case.

Table C1. Wage returns to invention, conditioning on age. Excluding top-3 employers of inventors

	whitecollar	whitecollar	bluecollar	bluecollar
post	0.0245***	0.0508***	0.000926	0.00902
	(0.00521)	(0.00745)	(0.00723)	(0.00879)
post x senior		-0.0515***		-0.0211***
		(0.00800)		(0.00961)
pre	0.0121***	0.0220***	-0.0174***	-0.0203***
	(0.00354)	(0.00497)	(0.00517)	(0.00652)
pre x senior		-0.0238***		0.00621
		(0.00581)		(0.00761)
Observations	1,884,160	1,884,160	1,395,940	1,395,940
R-squared	0.267	0.267	0.203	0.203
Number of individuals	159,300	159,300	132,763	132,763

Standard errors, clustered at the employer level (at τ=0) level in parentheses. All specifications include individual fixed effects, treatment and calendar year dummies, age fixed effects, dummies for the relevant interaction variables (senior, educ, DTHCF), a dummy for missing DTHCF (for those with compulsory education only) and its interactions, the number of employees in the firm, and a dummy for missing number of employees.

Table C2. Wage returns to invention, conditioning on age and education. Excluding top-3 employers of inventors

	whitecollar	whitecollar	bluecollar	bluecollar
	(1)	(2)	(3)	(4)
post	0.114***	0.0999***	0.0896***	0.0449***
	(0.00863)	(0.00850)	(0.0113)	(0.0110)
post x senior	0.0173***	0.00190	0.0208***	-0.00735
	(0.00683)	(0.00673)	(0.00747)	(0.00754)
post x educ		0.0430***		0.0713***
		(0.00740)		(0.0131)
post x DTHCF	-0.00669***	-0.00602***	-0.00591***	-0.00479***
	(0.000433)	(0.000438)	(0.000555)	(0.000542)
pre	0.0441***	0.0429***	-0.0124	-0.00920
	(0.00558)	(0.00594)	(0.00863)	(0.00873)
pre x senior	0.00777	0.00355	-0.00266	-0.00886
	(0.00557)	(0.00559)	(0.00640)	(0.00645)
pre x educ		0.0104**		-0.00440
		(0.00541)		(0.0109)
pre x DTHCF	-0.00284***	-0.00273***	-0.000536	-0.000929*
	(0.000342)	(0.000353)	(0.000555)	(0.000477)
Observations	1,884,160	1,884,160	1,395,940	1,395,940
R-squared	0.271	0.280	0.204	0.221
Number of individuals	159,300	159,300	132,763	132,763

Standard errors, clustered at the employer level (at τ=0) level in parentheses. All specifications include individual fixed effects, treatment and calendar year dummies, age fixed effects, dummies for the relevant interaction variables (senior, educ, DTHCF), a dummy for missing DTHCF (for those with compulsory education only) and its interactions, the number of employees in the firm, and a dummy for missing number of employees.

Table C3. Effect of invention on probability of unemployment. Excluding top-3 employers of inventors

	whitecollar	whitecollar	bluecollar	bluecollar
post	-0.000157	-0.00250	0.0167**	0.0161*
	(0.00334)	(0.00537)	(0.00738)	(0.00926)
post x senior		0.00483		-0.00140
		(0.00553)		(0.00800)
pre	0.00188	0.00160	0.0155***	0.0186***
	(0.00267)	(0.00390)	(0.00561)	(0.00672)
pre x senior		0.000788		-0.00943**
		(0.00420)		(0.00598)
Observations	1,862,793	1,862,793	1,414,470	1,414,470
R-squared	0.177	0.179	0.148	0.149
Number of individuals	159,256	159,256	132,740	132,740

Standard errors, clustered at the employer level (at τ=0) level in parentheses. All specifications include individual fixed effects, treatment and calendar year dummies, age fixed effects, dummies for the relevant interaction variables (senior, educ, DTHCF), a dummy for missing DTHCF (for those with compulsory education only) and its interactions, the number of employees in the firm, and a dummy for missing number of employees.

Table C4. Effect of invention on probability of unemployment, conditioning on age and education. Excluding top-3 employers of inventors

	whitecollar (1)	whitecollar (2)	bluecollar (3)	bluecollar (4)
post	-0.0333***	-0.0461***	-0.0617***	-0.0558***
	(0.00618)	(0.00649)	(0.0107)	(0.0107)
post x senior	0.00758***	0.00256	0.00224	0.00649
	(0.00334)	(0.00324)	(0.00559)	(0.00556)
post x educ		0.0346***		0.0228***
		(0.00332)		(0.00708)
post x DTCHF	0.00242***	0.00284***	0.00539***	0.00518***
	(0.000245)	(0.000268)	(0.000424)	(0.000422)
pre	-0.0332***	-0.0425***	-0.0430***	-0.0449***
	(0.00461)	(0.00502)	(0.00796)	(0.00809)
pre x senior	0.0124***	0.00692***	0.00780*	0.00805**
	(0.00292)	(0.00286)	(0.00460)	(0.00460)
pre x educ		0.0311***		0.0276***
		(0.00299)		(0.00632)
pre x DTHCF	0.00266***	0.00299***	0.00440***	0.00445***
	(0.000222)	(0.000239)	(0.000349)	(0.000352)
Observations	1,862,793	1,862,793	1,414,470	1,414,470
R-squared	0.180	0.183	0.150	0.154
Number of individuals	159,256	159,256	132,740	132,740

Standard errors, clustered at the employer level (at τ=0) level in parentheses. All specifications include individual fixed effects, treatment and calendar year dummies, age fixed effects, dummies for the relevant interaction variables (senior, educ, DTHCF), a dummy for missing DTHCF (for those with compulsory education only) and its interactions, the number of employees in the firm, and a dummy for missing number of employees.

C.2 Are the results robust to only including observations where the employer is the same as at the time of invention?

In Table C5 – C6 we reproduce the estimations reported in Tables 1-2, but so that the estimation sample only includes observations where the employer is the same as at the time of invention. The aim of this robustness check is to investigate whether those exiting employment or switching to new jobs are driving our (wage) return estimates. We obtain smaller returns to invention throughout. The returns to invention for our base group are of the order of 2 – 4 per cent instead of 4 - 10 per cent; the depreciation of returns through DTHCF is now 0.3 - 0.4 percentage points per year rather than 0.5 as in the main results.

Table C5. Wage returns to invention, conditioning on age. Observations where employer same as at time of invention

	whitecollar	whitecollar	bluecollar	bluecollar
post	0.00673*	0.0193***	-0.0169***	-0.0218***
post x senior		-0.0226***		0.00662
pre	0.00303	0.00846	-0.0215***	-0.0310***
pre x senior		-0.0107		0.0199**
Observations	1,047,946	1,047,946	826,835	826,835
R-squared	0.203	0.204	0.185	0.185
Number of individuals	159,424	159,424	132,776	132,776

Standard errors, clustered at the employer level (at τ=0) level in parentheses. All specifications include individual fixed effects, treatment and calendar year dummies, age fixed effects, dummies for the relevant interaction variables (senior, educ, DTHCF), a dummy for missing DTHCF (for those with compulsory education only) and its interactions, the number of employees in the firm, and a dummy for missing number of employees.

Table C6. Wage returns to invention, conditioning on age and education. Observations where employer same as at time of invention

	whitecollar (1)	whitecollar (2)	bluecollar (3)	bluecollar (4)
post	0.0605***	0.0419***	0.0414***	0.0194**
post x senior	0.00545	-0.00502	0.0286***	0.0156**
post x educ		0.0552***		0.0649***
post x DTHCF	-0.00345***	-0.00289***	-0.00423***	-0.00376***
pre	0.0212***	0.0155**	-0.00936	-0.0125
pre x senior	0.00553	0.00215	0.0219***	0.0179***
pre x educ		0.0219***		0.0120
pre x DTHCF	-0.00137***	-0.00124***	-0.00137***	-0.00139***
Observations	1,047,946	1,047,946	826,835	826,835
R-squared	0.205	0.209	0.186	0.194
Number of individuals	159,424	159,424	132,776	132,776

Standard errors clustered at the individual level. All specifications include individual fixed effects, treatment and calendar year dummies, age fixed effects, dummies for the relevant interaction variables (senior, educ, DTHCF), a dummy for missing DTHCF (for those with compulsory education only) and its interactions, the number of employees in the firm, and a dummy for missing number of employees.

Appendix D: Are the results robust using only the first inventions of an employee?

Table D1. Wage returns to invention, conditioning on age. Only first invention included

	whitecollar	whitecollar	bluecollar	bluecollar
post	0.0295***	0.0324**	0.0126	0.0144
	(0.0107)	(0.0146)	(0.0139)	(0.0161)
post x senior		-0.0103		-0.0104
		(0.0133)		(0.0179)
pre	0.0226***	0.0371***	0.00746	0.00632
	(0.00460)	(0.00674)	(0.0126)	(0.0149)
pre x senior		-0.0338***		0.000150
		(0.00834)		(0.0162)
Observations	1,127,934	1,127,934	854,582	854,582
R-squared	0.254	0.255	0.189	0.189
Number of individuals	99,204	99,204	81,866	81,866

Standard errors, clustered at the employer level (at τ=0) level in parentheses. All specifications include individual fixed effects, treatment and calendar year dummies, age fixed effects, dummies for the relevant interaction variables (senior, educ, DTHCF), a dummy for missing DTHCF (for those with compulsory education only) and its interactions, the number of employees in the firm, and a dummy for missing number of employees.

Table D2. Wage returns to invention, conditioning on age and education. Only first invention included

	whitecollar (1)	whitecollar (2)	bluecollar (3)	bluecollar (4)
post	0.0680***	0.0748***	0.121***	0.0710**
	(0.0205)	(0.0205)	(0.0282)	(0.0286)
post x senior	0.00365	0.00282	0.0353*	0.0110
	(0.0125)	(0.0125)	(0.0193)	(0.0193)
post x educ		0.000842		0.159***
		(0.0202)		(0.0410)
post x DTHCF	- 0.00379***	- 0.00435***	- 0.00803***	- 0.00617***
	(0.000990)	(0.000985)	(0.00174)	(0.00171)
pre	0.0608***	0.0657***	0.0312	0.0216
	(0.00894)	(0.00976)	(0.0270)	(0.0282)
pre x senior	0.00368	0.00602	0.00705	0.000308
	(0.00975)	(0.0100)	(0.0181)	(0.0180)
pre x educ		-0.0135		0.0765*
		(0.00956)		(0.0390)
pre x DTHCF	- 0.00333***	- 0.00356***	-0.00203	-0.00181
	(0.000601)	(0.000629)	(0.00158)	(0.00159)
Observations	1,127,934	1,127,934	854,582	854,582
R-squared	0.258	0.269	0.190	0.201
Number of individuals	99,204	99,204	81,866	81,866

Standard errors, clustered at the employer level (at τ=0) level in parentheses. All specifications include individual fixed effects, treatment and calendar year dummies, age fixed effects, dummies for the relevant interaction variables (senior, educ, DTHCF), a dummy for missing DTHCF (for those with compulsory education only) and its interactions, the number of employees in the firm, and a dummy for missing number of employees.

Table D3. Effect of invention on probability of unemployment. Only first invention included

	whitecollar	whitecollar	bluecollar	bluecollar
post	0.0254***	0.0209***	0.0119	0.00387
	(0.00589)	(0.00788)	(0.0109)	(0.0142)
post x senior		-0.00408		0.00789
		(0.00697)		(0.0137)
pre	0.0315***	0.0475***	0.00861	0.0142
	(0.00256)	(0.00367)	(0.00912)	(0.0115)
pre x senior		-0.0414***		-0.0194
		(0.00415)		(0.0118)
Observations	1,112,822	1,112,822	868,156	868,156
R-squared	0.154	0.156	0.133	0.134
Number of individuals	99,192	99,192	81,858	81,858

Standard errors, clustered at the employer level (at τ=0) level in parentheses. All specifications include individual fixed effects, treatment and calendar year dummies, age fixed effects, dummies for the relevant interaction variables (senior, educ, DTHCF), a dummy for missing DTHCF (for those with compulsory education only) and its interactions, the number of employees in the firm, and a dummy for missing number of employees.

Table D4. Effect of invention on probability of unemployment. Only first invention included

	whitecollar (1)	whitecollar (2)	bluecollar (3)	bluecollar (4)
post	-0.0143	-0.0292**	-0.0901***	-0.0809***
	(0.0118)	(0.0129)	(0.0222)	(0.0222)
post x senior	0.0110**	0.0110**	0.00913	0.0143
	(0.00544)	(0.00558)	(0.0133)	(0.0131)
post x educ		0.0129*		-0.0195
		(0.00776)		(0.0244)
post x DTCHF	0.00104**	0.00138**	0.00580***	0.00541***
	(0.000512)	(0.000546)	(0.00112)	(0.00111)
pre	0.0246***	0.0199***	-0.0467**	-0.0422**
	(0.00490)	(0.00532)	(0.0187)	(0.0189)
pre x senior	-0.00420	-0.00431	0.00379	0.00639
	(0.00395)	(0.00406)	(0.0125)	(0.0124)
pre x educ		0.00317		-0.0254
		(0.00384)		(0.0230)
pre x DTHCF	0.000463	0.000591*	0.00387***	0.00368***
	(0.000295)	(0.000310)	(0.00104)	(0.00104)
Observations	1,112,822	1,112,822	868,156	868,156
R-squared	0.156	0.160	0.134	0.137
Number of individuals	99,192	99,192	81,858	81,858

Standard errors, clustered at the employer level (at τ=0) level in parentheses. All specifications include individual fixed effects, treatment and calendar year dummies, age fixed effects, dummies for the relevant interaction variables (senior, educ, DTHCF), a dummy for missing DTHCF (for those with compulsory education only) and its interactions, the number of employees in the firm, and a dummy for missing number of employees.

Appendix E: Are the results different for those with and without a STEM education?

Table E1. Wage returns to invention, conditioning on age. STEM and non-STEM educated separately

	STEM-educated		non-STEM-educated		STEM-educated		non-STEM-educated	
	whitecollar	whitecollar	whitecollar	whitecollar	bluecollar	bluecollar	bluecollar	bluecollar
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
post	-0.00112	0.0134*	0.0479***	0.0274***	-0.00831	-0.00669	0.00537	0.0149
	(0.00520)	(0.00691)	(0.00830)	(0.00776)	(0.00721)	(0.00897)	(0.0101)	(0.0125)
post x senior		-0.0251***		-0.0248***		-0.00633		-0.0254*
		(0.00861)		(0.00882)		(0.0112)		(0.0134)
pre	0.00540	0.0157***	0.0181***	0.0778***	-0.0132**	-0.0175**	-0.0169**	-0.0156
	(0.00388)	(0.00544)	(0.00563)	(0.0116)	(0.00555)	(0.00715)	(0.00738)	(0.00979)
pre x senior		-0.0215***		-0.0634***		0.0107		-0.00504
		(0.00696)		(0.0120)		(0.00923)		(0.0112)
Observations	1,009,382	1,009,382	876,131	876,131	790,215	790,215	605,989	605,989
R-squared	0.189	0.189	0.257	0.258	0.191	0.191	0.179	0.179
Number of individuals	87,520	87,520	84,810	84,810	76,393	76,393	65,226	65,226

Standard errors, clustered at the employer level (at τ=0) level in parentheses. All specifications include individual fixed effects, treatment and calendar year dummies, age fixed effects, dummies for the relevant interaction variables (senior, educ, DTHCF), a dummy for missing DTHCF (for those with compulsory education only) and its interactions, the number of employees in the firm, and a dummy for missing number of employees.

Table E2. Wage returns to invention, conditioning on age and education. STEM and non-STEM educated separately

	STEM-educated		non-STEM-educated		STEM-educated		non-STEM-educated	
	whitecollar (1)	whitecollar (2)	whitecollar (3)	whitecollar (4)	bluecollar (5)	bluecollar (6)	bluecollar (7)	bluecollar (8)
post	0.0681***	0.0526***	0.166***	0.154***	0.0645***	0.0523***	0.157***	0.0877***
	(0.00847)	(0.00896)	(0.0143)	(0.0146)	(0.0118)	(0.0120)	(0.0185)	(0.0188)
post x senior	0.0512***	0.0393***	0.00778	-0.0114	0.0709***	0.0592***	0.00169	-0.0285***
	(0.00850)	(0.00864)	(0.0102)	(0.00990)	(0.00991)	(0.00986)	(0.0101)	(0.0102)
post x educ		0.0505***		0.0331***		0.0534***		0.0486**
		(0.00909)		(0.0115)		(0.0160)		(0.0216)
post x DTHCF	-0.00640***	-0.00557***	-0.00901***	-0.00815***	-0.00714***	-0.00667***	-0.00896***	-0.00781***
	(0.000534)	(0.000542)	(0.000704)	(0.000730)	(0.000661)	(0.000663)	(0.00101)	(0.000975)
pre	0.0319***	0.0275***	0.0589***	0.0600***	0.00448	0.00850	-0.00169	-0.0146
	(0.00647)	(0.00691)	(0.00906)	(0.00988)	(0.00973)	(0.0101)	(0.0155)	(0.0159)
pre x senior	0.0196***	0.0156**	-0.00192	-0.00404	0.0229***	0.0235***	-0.0150*	-0.0231***
	(0.00706)	(0.00725)	(0.00817)	(0.00816)	(0.00890)	(0.00900)	(0.00833)	(0.00832)
pre x educ		0.0172**		-0.00292		-0.0257**		0.00825
		(0.00673)		(0.00858)		(0.0130)		(0.0185)
pre x DTHCF	-0.00268***	-0.00242***	-0.00354***	-0.00344***	-0.00202***	-0.00225***	-0.00125	-0.00129
	(0.000447)	(0.000460)	(0.000533)	(0.000556)	(0.000594)	(0.000605)	(0.000919)	(0.000907)
Observations	1,009,382	1,009,382	876,131	876,131	790,215	790,215	605,989	605,989
R-squared	0.190	0.191	0.261	0.270	0.192	0.198	0.181	0.191
Number of individuals	87,520	87,520	84,810	84,810	76,393	76,393	65,226	65,226

Standard errors, clustered at the employer level (at τ=0) level in parentheses. All specifications include individual fixed effects, treatment and calendar year dummies, age fixed effects, dummies for the relevant interaction variables (senior, educ, DTHCF), a dummy for missing DTHCF (for those with compulsory education only) and its interactions, the number of employees in the firm, and a dummy for missing number of employees.

Table E3. Effect of invention on probability of unemployment. STEM and non-STEM educated separately

	STEM-educated		non-STEM-educated		STEM-educated		non-STEM-educated	
	whitecollar	whitecollar	whitecollar	whitecollar	bluecollar	bluecollar	bluecollar	bluecollar
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
post	0.0121***	0.0143***	-0.0149***	-0.0209***	0.0236***	0.0267***	0.0152	0.0146
	(0.00269)	(0.00426)	(0.00504)	(0.00785)	(0.00677)	(0.00831)	(0.00966)	(0.0128)
post x senior		-0.00542		0.0147*		-0.0126		0.000214
		(0.00433)		(0.00806)		(0.00789)		(0.0114)
pre	0.00738***	0.00868***	-0.00580	-0.00791	0.0168***	0.0215***	0.0167**	0.0199**
	(0.00223)	(0.00335)	(0.00406)	(0.00570)	(0.00528)	(0.00648)	(0.00745)	(0.00934)
pre x senior		-0.00342		0.00607		-0.0156**		-0.00789
		(0.00360)		(0.00612)		(0.00670)		(0.00870)
Observations	996,442	996,442	842,888	842,888	797,683	797,683	605,182	605,182
R-squared	0.091	0.092	0.178	0.180	0.117	0.118	0.151	0.152
Number of individuals	87,580	87,580	76,960	76,960	76,440	76,440	61,542	61,542

Standard errors, clustered at the employer level (at τ=0) level in parentheses. All specifications include individual fixed effects, treatment and calendar year dummies, age fixed effects, dummies for the relevant interaction variables (senior, educ, DTHCF), a dummy for missing DTHCF (for those with compulsory education only) and its interactions, the number of employees in the firm, and a dummy for missing number of employees.

Table E4. Effect of invention on probability of unemployment, conditioning on age and education. STEM and non-STEM educated separately

	STEM-educated		non-STEM-educated		STEM-educated		non-STEM-educated	
	whitecollar	whitecollar	whitecollar	whitecollar	bluecollar	bluecollar	bluecollar	bluecollar
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
post	-0.00812*	-0.0143***	-0.0732***	-0.0728***	-0.0420***	-0.0446***	-0.104***	-0.102***
	(0.00487)	(0.00524)	(0.0101)	(0.0101)	(0.0105)	(0.0107)	(0.0173)	(0.0172)
post x senior	0.00283	-0.000386		0.00144	-0.0350***	-0.0361***		0.0140*
	(0.00299)	(0.00298)		(0.00529)	(0.00642)	(0.00662)		(0.00799)
post x educ		0.0184***	0.0418***	0.0414***		0.0310***	0.0332***	0.0321***
		(0.00336)	(0.00546)	(0.00550)		(0.00867)	(0.0118)	(0.0117)
post x DTCHF	0.00115***	0.00140***	0.00421***	0.00413***	0.00518***	0.00531***	0.00849***	0.00809***
	(0.000238)	(0.000250)	(0.000444)	(0.000447)	(0.000507)	(0.000525)	(0.000813)	(0.000791)
pre	-0.0130***	-0.0170***	-0.0592***	-0.0585***	-0.0344***	-0.0384***	-0.0686***	-0.0661***
	(0.00382)	(0.00415)	(0.00780)	(0.00779)	(0.00823)	(0.00848)	(0.0131)	(0.0130)
pre x senior	0.00807***	0.00560**		0.00476	-0.0231***	-0.0258***		0.0185***
	(0.00276)	(0.00278)		(0.00459)	(0.00590)	(0.00607)		(0.00670)
pre x educ		0.0135***	0.0391***	0.0381***		0.0361***	0.0288***	0.0273**
		(0.00298)	(0.00478)	(0.00489)		(0.00758)	(0.0107)	(0.0107)
pre x DTHCF	0.00129***	0.00146***	0.00399***	0.00381***	0.00426***	0.00443***	0.00652***	0.00596***
	(0.000215)	(0.000226)	(0.000362)	(0.000382)	(0.000434)	(0.000447)	(0.000644)	(0.000662)
Observations	996,442	996,442	842,888	842,888	797,683	797,683	605,182	605,182
R-squared	0.093	0.094	0.184	0.184	0.119	0.122	0.155	0.155
Number of individuals	87,580	87,580	76,960	76,960	76,440	76,440	61,542	61,542

Standard errors, clustered at the employer level (at τ=0) level in parentheses. All specifications include individual fixed effects, treatment and calendar year dummies, age fixed effects, dummies for the relevant interaction variables (senior, educ, DTHCF), a dummy for missing DTHCF (for those with compulsory education only) and its interactions, the number of employees in the firm, and a dummy for missing number of employees.

Appendix F: Are the results robust to excluding those who eventually obtain a PhD?

Table F1. Wage returns to invention, conditioning on age. Excluding those who obtain a PhD

	whitecollar	whitecollar	bluecollar	bluecollar
post	0.0211***	0.0474***	0.000553	0.00819
	(0.00520)	(0.00744)	(0.00723)	(0.00878)
post x senior		-0.0508***		-0.0200**
		(0.00807)		(0.00961)
pre	0.0110***	0.0208***	-0.0174***	-0.0204***
	(0.00360)	(0.00505)	(0.00517)	(0.00651)
pre x senior		-0.0233***		0.00666
		(0.00592)		(0.00760)
Observations	1,829,071	1,829,071	1,395,382	1,395,382
R-squared	0.267	0.267	0.202	0.203
Number of individuals	154,607	154,607	132,709	132,709

Standard errors, clustered at the employer level (at τ=0) level in parentheses. All specifications include individual fixed effects, treatment and calendar year dummies, age fixed effects, dummies for the relevant interaction variables (senior, educ, DTHCF), a dummy for missing DTHCF (for those with compulsory education only) and its interactions, the number of employees in the firm, and a dummy for missing number of employees.

Table F2. Wage returns to invention, conditioning on age and education. Excluding those who obtain a PhD

	whitecollar (1)	whitecollar (2)	bluecollar (3)	bluecollar (4)
post	0.111***	0.101***	0.0880***	0.0441***
	(0.00889)	(0.00863)	(0.0113)	(0.0110)
post x senior	0.0170**	0.00342	0.0205***	-0.00743
	(0.00708)	(0.00698)	(0.00745)	(0.00753)
post x educ		0.0348***		0.0714***
		(0.00764)		(0.0131)
post x DTHCF	-0.00642***	-0.00594***	-0.00586***	-0.00476***
	(0.000454)	(0.000453)	(0.000552)	(0.000540)
pre	0.0436***	0.0434***	-0.0125	-0.00944
	(0.00585)	(0.00605)	(0.00860)	(0.00872)
pre x senior	0.00969*	0.00610	-0.00262	-0.00886
	(0.00587)	(0.00586)	(0.00639)	(0.00644)
pre x educ		0.00792		-0.00331
		(0.00578)		(0.0108)
pre x DTHCF	-0.00282***	-0.00277***	-0.000541	-0.000924*
	(0.000365)	(0.000369)	(0.000476)	(0.000475)
Observations	1,829,071	1,829,071	1,395,382	1,395,382
R-squared	0.270	0.280	0.204	0.221
Number of individuals	154,607	154,607	132,709	132,709

Standard errors, clustered at the employer level (at τ=0) level in parentheses. All specifications include individual fixed effects, treatment and calendar year dummies, age fixed effects, dummies for the relevant interaction variables (senior, educ, DTHCF), a dummy for missing DTHCF (for those with compulsory education only) and its interactions, the number of employees in the firm, and a dummy for missing number of employees.

Table F3. Effect of invention on probability of unemployment. Excluding those who obtain a PhD

	whitecollar	whitecollar	bluecollar	bluecollar
post	0.000358	-0.00153	0.0169**	0.0165*
	(0.00331)	(0.00531)	(0.00738)	(0.00926)
post x senior		0.00378		-0.00176
		(0.00549)		(0.00800)
pre	0.00197	0.00200	0.0156***	0.0188***
	(0.00266)	(0.00382)	(0.00562)	(0.00672)
pre x senior		5.72e-05		-0.00967
		(0.00410)		(0.00598)
Observations	1,810,140	1,810,140	1,413,874	1,413,874
R-squared	0.178	0.179	0.148	0.149
Number of individuals	154,566	154,566	132,686	132,686

Standard errors, clustered at the employer level (at τ=0) level in parentheses. All specifications include individual fixed effects, treatment and calendar year dummies, age fixed effects, dummies for the relevant interaction variables (senior, educ, DTHCF), a dummy for missing DTHCF (for those with compulsory education only) and its interactions, the number of employees in the firm, and a dummy for missing number of employees.

Table F4. Effect of invention on probability of unemployment, conditioning of age and education. Excluding those who obtain a PhD

	whitecollar (1)	whitecollar (2)	bluecollar (3)	bluecollar (4)
post	-0.0339***	-0.0451***	-0.0609***	-0.0552***
	(0.00627)	(0.00645)	(0.0107)	(0.0107)
post x senior	0.00362	0.00126	0.00241	0.00660
	(0.00334)	(0.00333)	(0.00559)	(0.00556)
post x educ		0.0331***		0.0226***
		(0.00325)		(0.00707)
post x DTCHF	0.00259***	0.00285***	0.00535***	0.00516***
	(0.000265)	(0.000277)	(0.000424)	(0.000422)
pre	-0.0347***	-0.0420***	-0.0426***	-0.0446***
	(0.00470)	(0.00494)	(0.00797)	(0.00809)
pre x senior	0.00802***	0.00498*	0.00782*	0.00808*
	(0.00287)	(0.00290)	(0.00460)	(0.00460)
pre x educ		0.0287***		0.0273***
		(0.00295)		(0.00631)
pre x DTHCF	0.00288***	0.00306***	0.00438***	0.00444***
	(0.000241)	(0.000248)	(0.000349)	(0.000352)
Observations	1 810 140	1,810,140	1,413,874	1,413,874
R-squared	0.180	0.183	0.150	0.154
Number of individuals	154,566	154,566	132,686	132,686

Standard errors, clustered at the employer level (at τ=0) level in parentheses. All specifications include individual fixed effects, treatment and calendar year dummies, age fixed effects, dummies for the relevant interaction variables (senior, educ, DTHCF), a dummy for missing DTHCF (for those with compulsory education only) and its interactions, the number of employees in the firm, and a dummy for missing number of employees.

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