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

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Abstract—We look at how the arrival of an invention affects wage returns and the probability of moving out of employment for white- and blue-collar co-workers 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 the time since obtaining the last formal degree, that is, *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.

I. 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 for white-collar and blue-collar workers within the inventing firm. We utilize three measures of human capital: (i) age, capturing experience; (ii) level of education, capturing the acquired formal human capital; and finally, in order to capture the distance to the human capital frontier (DTHCF); and (iii) 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 possibility of reorienting 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. Co-workers may earn rents if they play a crucial role 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 data sets. While most existing studies have focused on rents among inventors, our focus in this paper is instead on the rents to noninventing co-workers within the same firm, and on how such rents vary with the level of education and time since obtaining the most recent degree for white- and blue-collar co-workers within the same firm.[1]

To analyze the returns to invention for co-workers 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 we 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 science, technology, engineering, and math (STEM) education; (iii) time since last degree; (iv) working in manufacturing; (v) living in the South-West of Finland; (vi) age (four groups); and (vii) quintiles of the annual firm size distribution. We execute the matching separately for each treated group (blue-collar and subgroups[3] of white-collar co-workers), and we limit the potential control group to individuals who have never been co-workers 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 postinvention 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, postinvention

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[1]Recent work on within-firm rents include Aghion et al. (2018) and Kline et al. (2019). The former uses Finnish and the latter U.S. 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.

[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.

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rents are negatively affected by the time since the last degree was obtained for both white- and blue-collar workers, with the decrease being ∼0.5 percentage points per year for each year since completing the last level of 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 co-worker moving out of employment (nonemployment 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 the most recent education, the likelihood of co-worker nonemployment typically decreases due to within-firm invention. For example, the nonemployment probability is five percentage points lower for young blue- and white-collar workers with a recent low education diploma. Second, the probability of co-worker nonemployment increases steadily with the time since education, with the increase being 0.2–0.5 percentage points per year for each year since obtaining the latest degree. This increase in the probability of co-worker nonemployment can be observed both for white- and blue-collar workers and pre- and postinvention.

Our paper relates to several strands of the literature. The first is the literature on innovation spillovers (among many others, see Jaffe et al., 1993; Azoulay et al., 2010; Waldinger, 2011; Borjas & Doran, 2012; Bloom et al., 2013; Akcigit et al., 2016; Jaravel et al., 2018; and the survey by Aghion & Jaravel, 2015). We contribute to this literature by looking at innovation spillovers in the form of rents to noninnovating 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 (see, e.g., Toivanen & 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 U.S. patents. They find strong and long-lasting impacts, especially for the inventors of highly cited patents. Bell et al. (2019) merge U.S. individual fiscal data, test score information, and U.S. individual patenting data over the recent period to look at the life cycle 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), who use individual administrative data merged with patent data, respectively, in the United States and in Finland, to look at the individual returns from invention to the inventors and to their co-workers.[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 to this literature by analyzing how education and the time since the last 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 (see, e.g., Ben-Porath, 1967; and more recently Heckman et al., 2003; Blundell et al., 2016; Deming & 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.

[5]We study the transition to nonemployment instead of unemployment as the data reveal that there are multiple nonemployment 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.

[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 inventing 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 co-workers of inventors to otherwise similar control individuals who have never worked in a firm that receives a patent. They thus compare co-workers of inventors to observationally identical co-workers of noninventors. Aghion et al. (2018) find that inventors get only 8% of the total wage gains; second, 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 co-workers 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 they 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.

The remaining part of the paper is organized as follows. Section II presents the data. Section III presents the methodology and the regressions equations. Section IV presents our results, and section V concludes.

II. 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 data set. It is constructed on the basis of administrative registers for individuals, firms, and establishments, all maintained by Statistics Finland. This data set provides information on individuals' labor market status, salaries, and other sources of income extracted from tax and other administrative registers. FLEED also includes information on other individual characteristics, and on employer and plant characteristics. This information allows us to identify an inventor's co-workers and to analyze how invention affects different types of co-workers' wages differently. Second, we use the *European Patent Office* data which provide information on inventors.[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 the 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. 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 the preceding four years of included observations. We restrict attention to private sector employees because we can only identify co-workers 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 nonemployment (white- and blue-collar) estimation samples in online appendix B table A3. We code our second dependent variable to take value 0 if at the end of the year an individual is employed, and value 1 otherwise, corresponding to a generic nonemployment 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 the last degree conditional on the age of an individual, allowing us to separately identify the age effect from the time since the 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 co-workers of the employee(s) who made the invention ought to be treated or compensated.

III. 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 nonemployed. We estimate the following equation:

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

[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) study 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 & Väänänen, 2012; Aghion et al., 2018). As an unreported robustness test, we have verified that this is the case also with our data.

where subscript i denotes individual, subscript t denotes treatment time ($t = -5, \ldots, 10$), c denotes calendar year ($c = 1995, \ldots, 2012$), and a denotes age in years [$a = \min(age) + 2, \ldots, \max(age)$]. The variables pre_t and $post_t$ are dummy variables taking a value of 1 in the treatment years, $t = -4, \ldots, -1$ and $t = 0, \ldots, 10$, respectively, and 0 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 (co-worker 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 the 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 1 for individuals over 40 years of age (40 being very close to the median in our estimation samples); $high\_educ_{it}$, taking value 1 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 preinvention effects. The usual diagnosis of such effects would be that the conditional parallel trends assumption—on which the conditional difference-in-differences approach relies—fails. The preinvention 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, for example, increase wages of some workers before the patent application so as not to lose them. As Anup and Reif (2015) discuss, one should not automatically attribute pretrends to endogeneity, as not allowing for anticipation effects can also lead to an 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 co-workers 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 M.Sc. (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 are thus young workers without a high education (but more than compulsory education) who have just received their latest diploma.

IV. Regression Results

A. *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 gain 2.5% while blue-collar workers' wages are unaffected after the invention.[21] However, once we condition on age, in

[14] Aghion et al. (2018) found that both the pre- and postinvention returns to white- and blue-collar workers varied little and much less than those of inventors and entrepreneurs. Based on this evidence, we do not consider time-varying coefficients in this paper, and we 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] Approximately 90% of the observations for which this dummy takes value 1 are for individuals with only compulsory education.

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

[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.

[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.

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 × 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 × 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

Standard errors, clustered at the employer level (at $\tau = 0$) 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. Statistically significant at ***1%, **5%, and *10%.

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 × senior	0.0178***	0.00232	0.0209***	−0.00734
	(0.00585)	(0.00592)	(0.00678)	(0.00678)
post × educ		0.0432***		0.0713***
		(0.00571)		(0.0114)
post × 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 × senior	0.00791	0.00373	−0.00265	−0.00887
	(0.00501)	(0.00512)	(0.00600)	(0.00602)
pre × educ		0.0101**		−0.00431
		(0.00487)		(0.00996)
pre × 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

Standard errors, clustered at the employer level (at $\tau = 0$) 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. Statistically significant at ***1%, **5%, and *10%.

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 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.

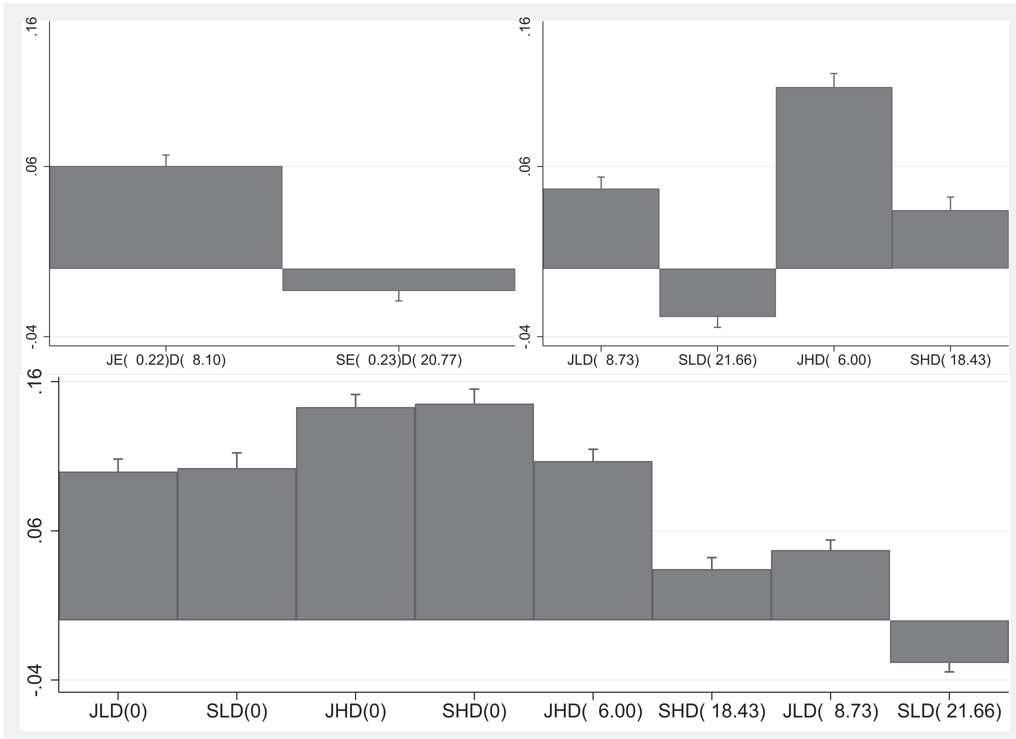
In columns 2 and 4, we include both the seniority dummy and the high education dummy along DTHCF. We find strong returns to invention for the workers in our base group (young, without higher education, with zero DTHCF) of 5–10%. The effect of age is essentially zero for both white- and blue-collar co-workers. 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 co-workers.

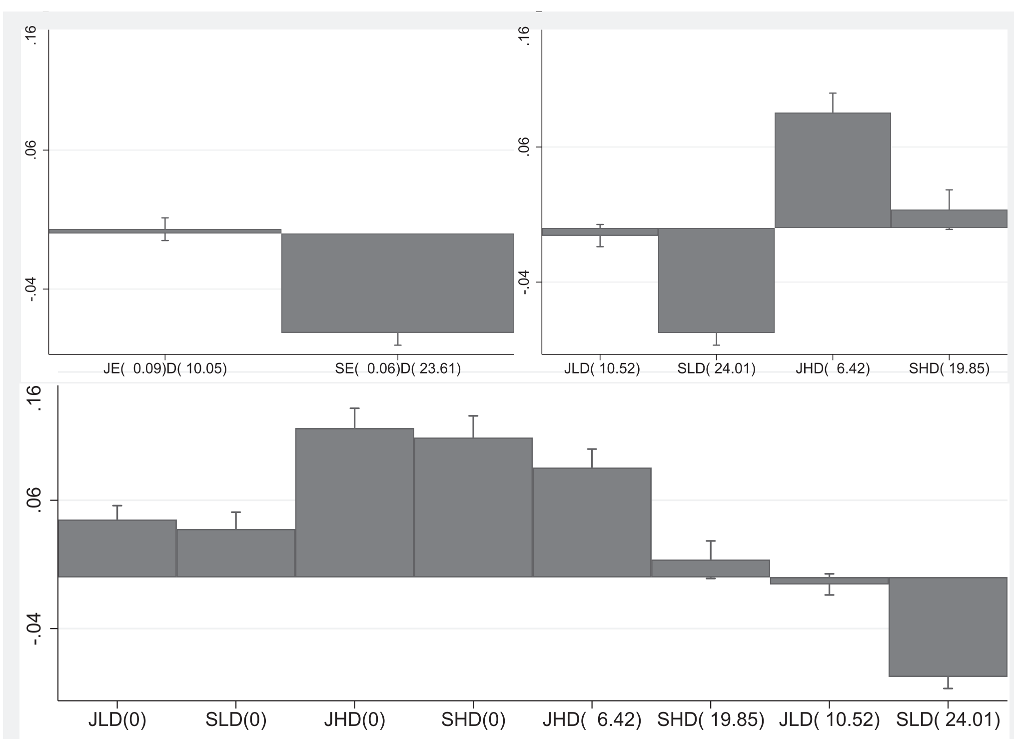
To visualize the results, figure 1 provides bar charts for the main variables of interests of the white-collar workers in panel A and blue-collar workers in panel B. In panel A, the upper-left figure plots the impact of invention on juniors (JE) and seniors (SE) with an average level of higher education (0.22 and 0.23, respectively) and an 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 co-worker. Next, in order to tease out the effect of education, the upper-right figure shows the effect for juniors with low education (no MSc; labeled 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 invention. 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 if their DTHCF were 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 pattern, 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 rent.

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.

What comes across very strong over all specifications is that postinvention returns are negatively affected by the distance to the human capital frontier, with the decrease being of ∼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 preinvention 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 beforehand. As table 2 shows, we find that white-collar workers get a preinvention increase in their wages that is around 4% per annum. The evidence for blue-collar workers is weaker. The preinvention returns are the same for young and old. Highly educated white-collar workers get an additional one percentage point prereturn. Preinvention returns are also negatively affected by the time since the most recent 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 they remain qualitatively similar when we exclude all but those observations where the employer is the same as at the 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 co-workers. 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 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 we 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 nonsenior 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), that is, 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 Ph.D., the idea being that while having an M.Sc. 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 postinvention returns are negatively affected by the distance to human capital frontier (at about −0.5 percentage points per year).

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 × 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 × 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

Standard errors, clustered at the employer level (at $\tau = 0$) 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. Statistically significant at ***1%, **5%, and *10%.

B. *Nonemployment*

Table 3 presents our results on the effect of invention on the probability of co-workers of the inventor becoming nonemployed. These simpler specifications (columns 1 and 2 for white-collar workers, columns 3 and 4 for blue-collar workers) correspond to those reported in table 1. They seem to suggest that the probability of co-worker nonemployment 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 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 × senior	0.00764***	0.00262	0.00225	0.00651*
	(0.00227)	(0.00230)	(0.00378)	(0.00380)
post × educ		0.0346***		0.0228***
		(0.00218)		(0.00643)
post × 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 × senior	0.0123***	0.00690***	0.00780**	0.00805**
	(0.00213)	(0.00217)	(0.00351)	(0.00353)
pre × educ		0.0310***		0.0277***
		(0.00205)		(0.00594)
pre × 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

Standard errors, clustered at the employer level (at $\tau = 0$) 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. Statistically significant at ***1%, **5%, and *10%.

Results in table 4 suggest two consistent patterns. First, the likelihood of co-worker nonemployment typically decreases due to within-firm invention: for example, the nonemployment probability is five to six percentage points lower for young blue- and white-collar workers with a recent low education diploma (columns 2 and 4). The probability of nonemployment 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 the 10% level, however). The probability of nonemployment 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.

Second, the probability of co-worker nonemployment 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 co-worker nonemployment can be observed both for white- and blue-collar workers and pre- and postinvention.

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 posttreatment effects are otherwise qualitatively similar to those in the main text, but the effect of education on the treatment effect vanishes. Regarding the pretreatment effects, instead of finding a negative effect for a base group of white-collar workers, we find a positive one. The impact of seniority and high education on the pretreatment effect disappears 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 non-STEM-educated. Excluding the (eventual) Ph.D.'s from our sample leads to no discernible change in the results.

V. Conclusion

In this paper, we looked at the effect of co-worker invention on the wage returns and nonemployment 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 co-workers 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, and distance to the (education) frontier, which we measure by the time lapsed since the most recent degree.

Our main findings were as follows: 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 nonemployment, but this effect decreases 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 in both groups; and if anything, the effect of DTHCF is larger 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 co-worker 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 the 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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