# Who Becomes an Inventor in Italy? The Role of Firms in Talent Discovery

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**Abstract**

This paper investigates the role of firms in discovering new inventors who apply for a patent for the first time. Using employer-employee data from the Italian Social Security Institute matched with patent applications from 1987 to 2009, we identify more than one hundred thousand *potential* inventors, who either apply for a patent during the sample period or are predicted to ever invent based on observable characteristics. We find substantial heterogeneity in the discovery of new inventors between firms. Younger potential inventors are less likely to apply for their first patents at a lower-wage firm. The gap between low-wage and high-wage firms in patenting disappears, however, among experienced inventors who have previous patent applications. Furthermore, there is on average a 5 to 9 log-point increase in the annual wage when a young worker files her first patent application. We interpret the empirical findings through a model in which heterogeneous firms invest in talent discovery and use wage incentives to elicit effort from workers. When a firm's investment and a worker's effort are substitutable in innovation production, the model explains why lower-wage firms set a higher return to patenting despite limited turnover of inventors.

**Keywords:** Inventors, Employer Learning, Young Workers.

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## 1 Introduction

Younger workers in Italy have been experiencing a decline in economic opportunities relative to older cohorts in the past decades. Labor market reforms aimed at increasing flexibility have been shown to reduce well-paid and stable jobs available to younger workers (Daruich, Di Addario, and Saggio 2023), and the older workers who delay retirement because of pension reforms have negative spillovers on their younger counterparts (Bianchi, Bovini, Li, Paradisi, and Powell 2023; Goldin, Koutroumpis, Lafond, and Winkler 2024). Despite a growing body of literature that studies the widening inequality between younger and older cohorts in Italy, little is known about the role of firms in training and discovering higher-ability individuals. When employers invest less in talent discovery, uncertainty about the true ability of a worker increases, hurting especially the career mobility of younger workers (Pallais 2014) and reducing aggregate productivity growth (Terviö 2009; Cetrulo, Cirillo, and Guarascio 2019).

Analyzing the role of firms in talent discovery is often difficult when researchers have little information on the ability or productivity of an individual. This paper overcomes this challenge by focusing on Italy's labor market for potential inventors, for whom we observe patent applications produced on the job, wages, and other job characteristics from administrative data. We investigate the differences between lower-wage and higher-wage firms in (1) discovering new inventors (i.e., the employees applying for a patent for the first time), and (2) wage returns to patent applications. We interpret the findings with a stylized model of employer learning plus incentive contract, taking into account the dynamic incentives of firms and workers.

In Italy young inventors are highly concentrated in a few firms: about 90% of the successful inventors younger than 35 are employed by less than 5% of the firms with at least one inventor (Figure 1). In contrast, the distribution of the younger workers who have not yet applied for a patent but will eventually do so (possibly at another employer) is relatively more balanced across firms. These patterns suggest that in Italy a large fraction of firms within the mobility network of inventors do not encourage or support younger employees to innovate, under-investing in discovering new inventors. This is an important drawback since a faster rate of discovering the ability of workers can reduce the misallocation of labor and therefore improve productive efficiency (Wu 2025).

Using the employer-employee Italian Social Security Institute (INPS) data matched to European patent applications by Depalo and Di Addario (2014), we identify roughly 112,000 *potential* inventors who are either estimated to have a high probability of ever inventing based on observable characteristics or contribute to at least one patent application assigned to their employers during the sample period (1987-2009). Relative to an average worker in the INPS data, potential inventors earn, on average, 20 log-point higher wages, are more likely to work in white-collar jobs, and are less likely to have a temporary contract.

We focus on the innovative firms (that is, those that have hired at least one inventor in our sample period) and classify them based on the quartile of mean coworker wages.[1] We estimate the differences between quartiles of firms in the probability that a worker files her first patent application at her current employer. We compute this probability separately by age, comparing workers who are younger than 35 to those who are older. Younger potential inventors who have not applied for patents are 19% less likely to become inventors while employed in lower-wage firms (quartile 1) than in higher-wage firms (quartile 4). Older potential inventors are also less likely to invent at lower-wage firms, but the gap in filing a person's first patent application between quartile 1 and 4 firms shrinks to 7% - 10%. Thus, on average, higher-wage firms are more able to scout for new inventors, especially when they are young.

[1]The firms are connected by the job movements of the inventors, who are defined as the workers with at least one patent application during the years 1987-2009. Note that inventors do not necessarily submit a patent in each of the firms in which they work in our observational period.

The gap in the probability of submitting a patent between lower- and higher-wage firms, however, regards only potential inventors without an invention yet: after workers apply for a patent, the gap disappears for both younger and older workers. If anything, experienced inventors appear more likely to apply for patents again at lower-wage quartiles relative to quartile 4. This contrast suggests that lower-wage firms on average also engage in patenting, but they are more likely to rely on experienced inventors rather than potential inventors. These findings can be explained by employer learning. Firms may be reluctant to assign innovation tasks to employees whose ability is not yet known, especially if they are young; on the contrary, they may be more willing to offer the opportunity to patent to experienced inventors, who have already shown their ability with prior patent applications. In this labor market, the main difference between lower- and higher-wage firms is not in the chances of patenting they offer, but rather in the ability to discover new inventors, a gap that disproportionately affects younger workers.

By considering patent applications as positive signals on a worker's research ability, employer learning models predict a wage increase when workers become inventors, that is, when they submit their first patent application (e.g., Altonji and Pierret 2001; Farber and Gibbons 1996; Lange 2007; Kahn 2013; Schönberg 2007). We provide regression estimates of the wage returns to a person's first patent application, as a direct test of this prediction in the labor market of potential inventors. Conditioning on person fixed effects and controlling for industry and geographic regions, younger potential inventors earn a 4.7 log-point significantly higher wage when they file their first patent application in quartile 4. This pattern is consistent with the findings that wages start to rise *before* patents are granted (Depalo and Di Addario 2014; Bell, Chetty, Jaravel, Petkova, and Van Reenen 2019a). Yet, existing studies on inventors' wage growth have rarely looked at the differences between firms. We find that the wage return to a younger person's first patent application is 3.9 log-point higher at lower-wage firms (quartile 1) than at higher-wage firms (quartile 4). Older workers who file their first patent application also receive a wage increase in the same year, but the relative gap in wage return between quartile 1 and quartile 4 is smaller.

In contrast with new inventors, we do not find a significant wage premium after a new patent application for experienced inventors who have already contributed to patent applications before. These findings suggest that firms reward workers only at their first patent application, which provides a greater information shock to employers than the subsequent patent applications filed by experienced inventors. Such rewards are more aligned with employer learning than with rent sharing that has been documented in other studies (e.g., Kline, Petkova, Williams, and Zidar 2019; Toivanen and Väänänen 2012).

Why is the wage return to a person's first patent application higher at lower-wage firms in quartile 1? One explanation is that patent applications move upward the posterior beliefs about the workers in lower-wage firms to a greater extent than they do for the employees selected into higher-wage firms. Indeed, wage increases upon a patent application partly reflect employers' beliefs updates. Since the labor market's prior belief on lower-wage firm workers is lower than higher-wage firm employees, the belief update after the first patent must be stronger for quartile 1 than for quartile 4. An alternative explanation is that low-wage firms face a higher turnover of new inventors and have to set a higher wage return to counter poaching from competitors. On average, young potential inventors in quartile 1 are indeed more likely to move between firms. When we test this hypothesis, however, this result is not confirmed: new inventors' inter-firm mobility is not significantly higher in lower-wage than in higher-wage firms. Since we do not find an increase in new inventors' poaching, public learning about worker ability by outside employers alone cannot fully explain why low-wage firms set a higher return to the first patent. We show in the model below that considering employer learning and incentive contracts simultaneously can better explain the disparity in wage returns.

We formulate a two-sided dynamic model of talent discovery: firms post wages and invest in employees' research, workers choose effort accordingly, and firm-worker pairs jointly produce an innovation. Information on worker ability is imperfect but symmetric between all players, and an innovation output will fully reveal an employee as a high-ability inventor. In equilibrium, the more productive firms would set a higher base wage and invest more in a worker's research than their less productive counterparts. This equilibrium result is consistent with the empirical finding that workers are less likely to become inventors at lower-wage firms. A worker's effort on innovation is not contractible; each person chooses an effort that maximizes her expected earnings today plus her option value on the labor market next period, which is higher if she is recognized as an inventor. When there are fewer opportunities to move between firms for new inventors, the increase in option value is lower, and firms would have to set a larger bonus for innovation to elicit effort from workers. The model provides an explanation for the significantly positive wage increase around a worker's first patent application, despite limited mobility between firms. Depalo and Di Addario (2014) show that the average increase in wages around an application is in fact higher than the increase around a patent grant, which is likely to benefit managers more than the inventors themselves (Kline et al. 2019).

Our model shows the conditions under which lower-wage firms set higher wage returns to patent applications despite limited job mobility among inventors. An important necessary condition is that a worker's effort on innovation and her employer's R&D investment are substitutes rather than complements in the innovation production function. By setting a higher wage incentive contingent on innovation output, less productive firms can elicit more effort from workers and compensate for the lower investment they make. Admittedly, with neither measures of a firm's R&D investment nor information on the effort of a worker, we are unable to estimate if they are indeed substitutes.[2] This mechanism does not rule out other explanations. Still, it helps understand the relatively higher wage returns to a worker's first patent application at lower-wage firms, even when they are less likely to change employer in the short term than workers who are not inventing.

### 1.1 Related Literature

This paper contributes to several strands of literature. First, we contribute to the growing literature on the dynamics of inventors' careers. Recent studies in the labor market for inventors rely on linking data on patents to administrative employer-employee data that provides wages and employment information (e.g. Bell, Chetty, Jaravel, Petkova, and Van Reenen 2019b and Akcigit and Goldschlag 2023 in the U.S.; Akcigit, Baslandze, and Lotti 2023 in Italy; Aghion, Akcigit, Hyytinen, and Toivanen 2018 in Finland). Building on the PATSTAT-INPS data in Depalo and Di Addario (2014), we find significant wage returns to first-time inventors that are consistent with estimates in other advanced economies (Aghion et al. 2018; Bell et al. 2019a). We contribute to the return-to-invention literature by documenting the gap in wage returns between low-wage and high-wage firms, for workers who are applying for patents for the first time. We provide a dynamic model to explain our findings through employer learning and incentive contract, both of which are emphasized in Toivanen and Väänänen 2012. Previous studies have emphasized the role of childhood exposure to innovation and socioeconomic background in the likelihood of becoming an inventor (Bell et al. 2019b; Aghion, Akcigit, Hyytinen, and Toivanen 2023). Our analysis of the heterogeneity between firms suggests that exposure to firms that engage younger workers in patenting activity is another important channel through which high-ability researchers and

[2] To obtain a measure of R&D investment, we matched our data to the firms interviewed in INVIND, which is a survey run by the Bank of Italy every year. We matched just about 7 percent of the firms, but the R&D investment variable is often missing (in 90% of the firm-by-year observations). Nevertheless, we summarize the investment variables in Appendix Table B2.

inventors could be recognized by the labor market.

Second, our empirical assessment of the discovery of new inventors is related to the growing literature on the career challenges younger workers face in Italy. A series of reforms aimed at increasing the flexibility of the labor market led to a high share of temporary contracts and wage depression that hurt younger workers disproportionately (Daruich et al. 2023). The aging population and delayed retirement further reduce the opportunities available to younger workers (Bianchi and Paradisi 2023; Bianchi et al. 2023). We contribute to this literature by showing that there is a substantial gap in the discovery of new inventors between lower-wage and higher-wage firms, and the gap for workers younger than 35 is almost four times as large as the gap for older workers. Slow discovery of younger inventors can be particularly costly, given that workers often face human capital depreciation (Aghion et al. 2022) and that innovation productivity peaks in an inventor's early 40s (Kaltenberg, Jaffe, and Lachman 2023).

Third, our model of talent discovery contributes to the employer learning literature as a new framework that considers the dynamic incentives of firms and workers simultaneously. The tradeoff between employer learning and retention, as in Acemoglu and Pischke (1998), continues to matter when firms make R&D investments. The introduction of worker effort also lets us consider the optimal incentive contract as in Holmstrom and Milgrom (1991), and makes it possible to make sense of the higher wage return to patenting at lower-wage firms.

The remainder of this paper is structured as follows. Section 2 describes the matched INPS-PATSTAT data and the selection of potential inventors. Section 3 presents our empirical findings on the heterogeneity in talent discovery and wage returns to patent applications between firms. Section 4 presents a two-period model of talent discovery that reconciles our main empirical findings. Section 5 discusses a policy implication and concludes.

## 2 Data

We build a panel data on the employment and innovation history of more than 100,000 potential inventors in Italy, using the database in Depalo and Di Addario (2014) that matched the employer-employee data from the Italian Social Security Institute (INPS) with the Worldwide Patent Statistical Database (PATSTAT). The original database in Depalo and Di Addario (2014) contains the employment and patent records for about sixteen thousand Italian inventors and the employment history of their coworkers across employers from 1987 to 2009.

In this section, we first summarize the matching between PATSTAT and INPS originally done by the team Depalo and Di Addario (2014), and then we discuss the methodology used to identify potential inventors, who are the workers who either file a patent application during the sample period or are predicted to do so based on observable characteristics. Throughout the empirical analysis, we focus on the panel of potential inventors to study the role of firms in discovering new inventors.

### 2.1 INPS-PATSTAT Matched Database

PATSTAT contains the universe of patent applications ever submitted to the European Patent Office (EPO). It provides detailed information both on the inventors listed in the applications, and on the assignees, or owners of the patent, which are typically the inventors' employers. Depalo and Di Addario (2014) selected all the patent applications submitted by any firm located in Italy, as recorded in PATSTAT 2009.[3] Between 1987 and 2009, EPO received more than 50,000 patent applications from the private sector, submitted, overall, by 36,000 inventors from $16,000$ firms.

After cleaning the names of inventors and firms applying for patents, Depalo and Di Addario (2014) asked INPS to match the firms with employers (by

[3]This restriction excludes patent applications by individuals, universities, or public entities that could not be matched with INPS data, which only covers the private sector in Italy.

name and location) in their administrative data, and to match the inventors with individual employees (by name and municipality of residence). INPS returned a de-identified database of about $16,000$ matched inventors (as well as 4.5 million coworkers employed in the same company) and all the firms in which these inventors have transited in our observational period, even before or after submitting a patent. We refer to Depalo et al. (2023) for further details on the matching process.

The matched INPS-PATSTAT database contains information on a worker's annual wage at her employer in the private sector, type of contract (permanent or temporary), occupation group (blue or white collar), and basic demographic information such as gender or year of birth. INPS also provided information at the establishment level, such as size, sector, location, and dates of business opening and closure. The matching between patent applications and employment records also allows us to build a measure of worker's on-the-job innovation outputs, and identify the employer at which a worker files her first patent application ever, if it occurs during the sample period.

### 2.2 Selection of Workers with Inventor Potential

In this paper, a person is defined as a "matched inventor" if she is acknowledged on a patent application submitted by her employer at the time of initial filing. Among the 4.5 million coworkers of the matched inventors, the vast majority are unlikely to ever become an inventor. For example, an inventor with patents at the largest automobile company in Italy would have thousands of coworkers who work in factories rather than in R&D departments. Unfortunately, we do not have access to a person's educational background or detailed occupation codes in the INPS sample. Instead, we rely on observable information such as broad occupation groups (white collar/blue collar), type of contract (permanent/temporary/seasonal), and demographic characteristics to predict how likely a worker is to ever file a patent application.

To do so, we first restrict to workers who entered the INPS sample between age 14 and 55, were employed in the private sector for at least five years between 1987 and 2009, and spent more years in white-collar than in blue-collar occupations.[4] This initial selection restricts the sample to 1.5 million workers. We then fit a Poisson model of ever-inventing on observable demographic and employment characteristics, specified as follows:

$$E[Inv_i|x_i, z_{it}, j(i,t), t] = exp\left(x_i'\lambda + z_{it}'\gamma + \psi_{j(i,t)} + \theta_t\right) \tag{2.1}$$

where $Inv_i = 1$ if worker $i$ is a "matched inventor", i.e. she has at least one patent application and she is matched to INPS employment records between 1987 and 2009. The individual-level controls, $x_i$, include a dummy for whether the person is female, the age at which she first enters the INPS data and its interaction with whether her employment records are left-truncated in 1987 (due to data constraint). The time-varying controls at person-year level, $z_{it}$, include a cubic polynomial of age, a cubic polynomial of tenure at the worker's current employer $j(i,t)$, characteristics of her current job (white versus blue collar, permanent versus temporary contracts) and their interactions with her age. Finally, to take into account the heterogeneity in patenting across firms and over time, we control for firm fixed effects $\{\psi_{j(i,t)}\}$ and calendar year fixed effects $\{\theta_t\}$.

The first column of Table B1 reports the results obtained after controlling for industry and region, while the second specification controls for firm-fixed effects. Results indicate that younger workers have a higher chance of ever inventing (consistent with the findings of Figure 2): for instance, 30-year-old employees are 30 percent more likely to patent than those who are 35, while individuals aged 40 are

[4]The restriction on the minimum age a person enters the INPS sample removes the outliers who were employed by a private sector employer at a young age, and also workers older than 55 for whom we can only observe employment closer to retirement. The restriction that we observe a person for at least five years (not necessarily consecutively) ensures the panel is long enough and allows us to keep track of wage changes and job movements for at least some years. Finally, the third restriction is motivated by the finding that most inventors have a white-collar job status (Table 1's column 1); note, however, that our restriction does not exclude the possibility that potential inventors work in blue-collar jobs in some years.

20 percent less likely (column 1). Moreover, women's probability of ever inventing is on average 30% that of their male co-workers. When comparing the within-firm job characteristics, we find that the employees with longer tenure are more likely to apply for a patent, white-collar workers are 3 times as likely than the base group (with missing occupation), while blue-collar individuals have about half a chance (column 2). Workers on permanent contracts are significantly more likely to invent (column 1), but this relationship is driven by the heterogeneity between firms.[5]

To select the potential inventors, we rank the 1.5 million workers in the estimation sample by the predicted probability of ever-inventing from model (2.1). As shown in Figure 3, the distribution of the estimated probabilities among the matched inventors (i.e. those with at least one patent application matched to the INPS data) is skewed more to the right than the distribution among all workers. We classify a worker as a potential inventor if any one of the following conditions holds:

1. $max\{\hat{p}_{it} : age_{it} <= 35\} \geq 0.05$: the maximum estimate of an employee's propensity to invent when they are less than 35 years old exceeds the median estimate among the matched inventors younger than 35;[6]
2. $max\{\hat{p}_{it} : age_{it} > 35\} \geq 0.06$: the maximum estimate of an employee's propensity to invent when they are older than 35 exceeds the median estimate among the matched inventors older than 35;
3. any matched inventor.

This selection rule results in a total of about 112,000 potential inventors, including about 97,000 workers who do not have a matched patent during the 1987-2009 period but are estimated to ever invent with a relatively high probability. In comparison with the full estimation sample of 1.5 million workers, the vast majority of

[5]Conditional on firm fixed effects (column 2), permanent contract has a positive but much smaller predictive power of future invention.

[6]The age 35 threshold is selected based on Figure 2, which shows that the probability of a worker becoming an inventor increases faster in the early career, peaks at around age 32, and begins to flatten after age 35.

potential inventors are male (Table 1). They also are younger (-2 years on average), more mobile across firms, more likely to be white-collar than blue-collar workers, and more likely to have a permanent contract. On average there is a 22 log-point wage gap between potential inventors and workers in the estimation sample; this gap increases with age: it is about 14 log points at age 30, and raises to over 30 log points at age 45 and above. Table 1 also compares potential inventors with the matched inventors. While on average matched inventors earn 22 log points higher wages than potential inventors, the wage gap at age 30 is relatively small, which suggests that model (2.1)'s selection allows us to compare workers who are similar early in their careers.

To examine the age profile for becoming an inventor (Figure 2), we fit a logistic regression of filing the first patent application on age dummies, gender, and calendar year fixed effects. The rate at which a potential inventor files her first patent is steeply increasing with age up to age 32, when it reaches the peak, and slowly declines afterward, stabilizing at a 4 log-points higher level than that at age 25. Throughout this paper, we estimate separate models for workers younger / older than 35, given the age profile shown above.

Finally, we perform across-firm heterogeneity analysis in their ability to identify talent from the pool of potential inventors, obtained after excluding the workers who are considerably different from the matched inventors and may thus specialize in tasks unrelated to R&D.

## 3 Empirical Findings

We analyze the heterogeneity between firms in talent discovery. First, we study the differential rates at which potential inventors apply for patents at lower-wage versus higher-wage firms. We find a significant gap between lower- and higher-wage firms in the probability that workers file their first-ever patent application. The gap disappears, however, after the initial patent application. Second, we estimate the wage return to a new patent application at different tiers of firms, and we find that the return is on average higher at lower-wage firms.

We interpret the empirical findings from the employer learning perspective, considering patent applications as positive signals of an employee's innovation ability. However, given the low between-firm mobility among inventors, employer learning theory alone cannot explain the higher wage return to patenting at lower-wage firms. We discuss this empirical puzzle and address it formally in Section 4.

### 3.1 Becoming an Inventor at Low-Wage versus High-Wage Firms

We begin by estimating the probability that an individual will file her first patent application as an employee.[7] For workers with no prior patenting experience, the first patent application submitted at their current employers will also be their first patent application ever. After a person's first-ever patent application, we refer to her as an experienced inventor.

We analyze the differences in becoming an inventor in lower-wage versus higher-wage firms. Coworker wages are used as a proxy for firm productivity, which we cannot directly measure in the data.[8] This ranking choice is consistent with the micro-foundation for the AKM models, in which more productive firms set a higher wage premium in an imperfectly competitive labor market (Abowd, Kramarz, and Margolis 1999; Card, Cardoso, Heining, and Kline 2018; Kline 2024). Denote by $j(i,t)$ the primary employer of worker $i$ in year $t$, and by $Q(i,t)$ the

[7]This paper considers only the patent applications submitted by firms, not by individuals. Patent applications report the names of each inventor who contributed to the invention. Note that State-owned enterprises, which undertook a large amount of R&D between 1950 and 1994, are not included in our data (Antonelli, Barbiellini Amidei, and Fassio 2014).

[8]To provide some evidence that the mean firm wage is positively correlated with its revenue and investment, we matched our INPS firms to the companies interviewed in the INVIND Survey, which reports some information on investment in machinery, material and immaterial goods, housing, and R&D. Unfortunately, we could match only 7 percent of our firms (by fiscal code or firm name), but results, shown in Appendix Table B2, display the expected sign: the matched firms in quartile 1 have lower revenue and lower investment than those in the other quartiles of the wage distribution.

quartile of coworker wages to which her employer belongs.[9] On average potential inventors at the bottom quartile are less likely to submit patent applications than workers at higher-wage quartiles (Table 2). The gap between low- and high-wage firms is larger for younger than for older workers (Figure 4).

We estimate a Poisson regression of a person becoming an inventor at their current employer as follows:

$$E[y_{it}|j(i,t), x_{it}] = exp\left(\beta_0 + \sum_{q<4} \underbrace{\beta_q \times 1[Q(i,t) = q]}_{\text{if leave-out mean in quartile } q} + \underbrace{x'_{it}\Gamma}_{\text{controls}} + \underbrace{\phi_{G(j(i,t))} + \theta_t}_{\text{fixed effects}}\right) \tag{3.1}$$

where $y_{it}$ is an indicator for worker $i$ filing her first patent application at employer $j(i,t)$. The coefficient of interest $\beta_q$ represents a proportional increase in the mean outcome when a worker is employed by a firm in quartile $q$, relative to the mean in quartile 4 that pays the highest wages. The covariates $x_{it}$ include sex, a cubic polynomial in age (normalized at age 35), indicators for white/blue collar and permanent/temporary contract, and their interactions with age. We also control for the calendar year to absorb any common trend, 2-digit industry fixed effects to account for time-invariant heterogeneity in patenting across industries, and geographic region fixed-effects to absorb unobserved heterogeneity across regions. For each person $i$, the estimation sample includes all years she is employed (i.e., she is present in the INPS data) until $y_{it}$ changes from 0 to 1 at employer $j(i,t)$.[10]

We fit separate models for the workers younger than thirty-five and for those

[9]Following Card et al. (2018)'s definition, for each person-year, we compute the mean coworker wage at her employer and rank the leave-out coworker wage into quartiles. Note that the same firm could belong to different quartiles for high- and low-wage employees. We also provide regression estimates after ranking firms by the mean wage each year; in this case, $Q(i,t)$ assumes the same value for all coworkers (see Appendix Table B3, mirroring Table 3).

[10]That is, $y_{it}$ changes from 0 to 1 in the year worker $i$ files her first patent application at employer $j(i,t)$. For potential or matched inventors who have not applied for a patent before, this will indicate their first patent application ever. For experienced inventors who have applied for patents elsewhere, $y_{it} = 1$ indicates their first application at the current employer.

who are older; the age cutoff was selected based on the age profile of becoming inventors shown in Figure 2. For each age group, we further distinguish between the workers who had and those who had not a prior patent application elsewhere.

### 3.1.1 Potential Inventors without Patenting Experience

We first analyze the potential inventors who have not applied for any patent. The younger potential inventors are 19% less likely (at the 1% statistical significance level) to file their first patent application when they are employed in a quartile 1 firm than when they work in a quartile 4 company, as shown in the first column of Table 3. The gap between quartiles 2 and 4 is insignificant, while the potential inventors in quartile 3 are 16% more likely to become inventors than those in quartile 4. We find a similar pattern among the younger matched inventors who have not patented by year $t$ but will do so by 2009, the end of our sample period. Column 2 shows that the employees in quartile 1 are 15% less likely to become inventors than similar workers in quartile 4. Moreover, the estimated relationship between firm ranking (quartile) and the rate of becoming an inventor is also monotonic: younger matched inventors in quartile 2 are 12% less likely to become inventors than observably similar workers in quartile 4, and those in quartile 3 are 10% less likely to do so.

We then examine the potential inventors who are older than 35. On average, these workers are less likely to become inventors than employees aged 28-32 (Figure 2). However, we do not find any difference in the probability of filing the initial patent between the older potential inventors employed in quartile 1 companies and those in quartile 4 firms. If anything, the employees of lower-wage firms are more likely to become inventors, although the effect is only significant at the 10 percent level (Table 3's column 4). Restricting the sample to the matched inventors shows a pattern more similar to that of younger workers: the employees in lower quartiles are 7%-10% less likely to become inventors than comparable workers in quartile 4 (column 5). However, the estimated gap between firms is notably smaller than it occurs for younger matched inventors (column 2).

These findings suggest that lower-wage firms provide fewer opportunities to patent for employees without prior experience, especially if they are young. We also show that the contrast between the workers at the bottom and at the top quartiles is stronger in the pharmaceutical industry and in the more traditional manufacturing (Table B4).

#### 3.1.2 Experienced Inventors

Do lower-wage firms assign fewer innovation tasks to everyone or just to potential inventors, whose innovation ability is not yet revealed? To answer this question, we estimate regression 3.1 on the "experienced" inventors, that is, those who have already applied for a patent. In this case, the gap between quartile 1 and quartile 4 in filing the first application at the current employer disappears, both for younger and older workers (respectively, column 3 and 6, Table 3): experienced inventors are as likely to apply for a patent again at lower-wage and higher-wage firms. In contrast, the experienced inventors in quartiles 2 and 3 are more likely to apply for a new patent at their current employers than those in quartile 4, especially if they are young.

The contrast between potential inventors and experienced inventors suggests that lower-wage firms discover new inventors at lower rates than higher-wage firms, but they do not necessarily provide fewer patenting opportunities to employees who have already proved their ability.

To summarize, workers are less likely to apply for their first patent ever and thus become inventors at firms that pay lower wages. Younger workers are particularly affected when they are employed in the bottom quartile of firms (ranked by coworker mean wage), which are presumably also the least productive. Less productive firms may be particularly concerned about allowing good young employees to submit a patent application, because by doing so they would publicly reveal their names (listed on the patent), and may thus risk losing the young inventor to the competitors that pay higher wages; to avoid this risk these firms may therefore assign fewer innovation tasks at the beginning of inventors' career (Wu 2025). This learning concern is often argued to matter more for workers earlier in their career since their ability is more uncertain (e.g., Altonji and Pierret 2001; Farber and Gibbons 1996; Schönberg 2007), which would explain why the gaps between firms are more salient among younger than older workers.

### 3.2 Wage Returns to First Patent Applications

Are workers rewarded for filing new patent applications? To answer this question we use the annual wages of potential inventors in the INPS data. To estimate the wage return to a new patent in each firm quartile, we specify an OLS regression as follows:

$$ln(w_{it}) = \underline{\mu} + \underbrace{\sum_{q<4} \mu_q \times 1[Q(i,t) = q]}_{\text{avg wage difference rel. to quartile 4}} + \underline{\gamma} \times y_{it} + \underbrace{\sum_{q<4} \gamma_q \times y_{it} \times 1[Q(i,t) = q]}_{\text{excess returns to new patent rel. to quartile 4}} \tag{3.2}$$

$$+ \underbrace{x'_{it}\Lambda}_{\text{controls}} + \underbrace{\alpha_i + \phi_{G(j(i,t))} + \theta_t}_{\text{fixed effects}} + e_{it}$$

in which $ln(w_{it})$ is the log annual wage of worker $i$ in year $t$. The coefficient $\underline{\gamma}$ represents the average wage return to a new patent application among workers in the base group, quartile 4. And $\{\gamma_q : q < 4\}$ represent the excess returns to a patent application in other quartiles of employers, relative to the base. The regression includes the same set of time-varying controls, $x_{it}$, as in (3.1). In addition to year, industry, and region-fixed effects, we include person-fixed effects to absorb unobserved individual heterogeneity that matters for wages. Therefore, the excess returns $\{\gamma_q\}$ can be interpreted as within-person wage increases when a person produces a patent application in quartile $q$ relative to the base quartile 4.

As expected, the potential inventors younger than 35 without a previous patent application working in quartile 4 firms earn a 13 log-point higher wage than observationally similar workers employed in quartile 1 companies (column 1, Table 4). In the year of their first patent application, these young potential inventors in quartile 4 earn a further 4.7 log-point significant wage premium. However, the excess return to a new application, denoted by $\gamma_1$ in (3.2), is estimated to be 3.9 log points higher (and statistically significant at the 1% level) in quartile 1 than in quartile 4.[11] Applying for the first patent provides a higher return (2.2 log-points) to the employees in quartile 1 than to those in quartile 4 also when we restrict to the sample of matched inventors.

Potential inventors in quartiles 2 and 3 on average experience a similar wage return to their first patent applications ever as those in quartile 4. The average returns for the matched inventors in quartiles 2 and 3 are positive but smaller than in quartile 4. We find a smaller wage gap between matched inventors across quartiles even before they become inventors, which suggests that firms may have additional information about future inventors, so as to set a higher wage even before they start patenting.

Wage returns to initial patent applications are smaller for potential inventors who are older than 35, as shown in column 4 of Table 4. When an older potential inventor files her first patent application at a firm in quartile 4, she earns a 3.1 log-point significant increase in wage, which is about 1.6 log-points lower than the estimate for younger potential inventors. The excess return to the first patent application in quartile 1 is 2.1 log points, which is 55% of the excess return $\hat{\gamma}_1$ among younger potential inventors (column 1).

Experienced inventors who have applied for patents at former employers, do

[11] The differences in wage returns to a worker's first patent application between firm quartiles are about 3-5 times larger if we ignore individual heterogeneity (dropping person fixed-effects from 3.2), as shown in Appendix Table B5.

not receive a wage increase when they file the first patent applications at their current firm. In quartile 4, we find a noisily estimated 1.5 log-point increase when an experienced inventor begins patenting again (columns 3 and 6). There are no excess returns to patenting at lower-wage quartiles either.

These findings confirm that firms reward workers for their first patent applications, in spite of the fact that it takes a few more years to know if the patent will be granted successfully. The wage returns among younger potential inventors are significantly higher in the bottom quartile, which pays the lowest wages on average. The estimated wage returns are similar when we rank firms by the one-year lagged mean wage rather than the leave-out coworker wage in the current year. Using lagged wages to rank firms can mitigate concerns about common firm shocks in the same year that affect both the quartile of coworker wage $Q(i,t)$ and the outcome variable $ln(w_{it})$. We show in Appendix Table B6 that younger potential inventors in (lagged) quartile 4 receive a 3.6 log-point wage increase upon their first patent applications, and 4.2 log-point higher return if they are in quartile 1. Older potential inventors receive very similar wage returns as estimated in Table 4 when we rank firms by leave-out coworker wages in the same calendar year.

### 3.2.1 Interpreting the Wage Returns to Patenting via Employer Learning

Employer learning provides an explanation for why first-time inventors receive a higher wage increase than experienced inventors when they apply for patents, and why younger workers experience a stronger wage increase than older counterparts. A patent application sends a positive signal about a worker's research or innovation ability. As employers revise upward the belief about a potential inventor's ability, employer learning models suggest that wage bids would rise.[12]

[12] In a perfectly competitive labor market, wages would increase to fully match the marginal revenue product of labor expected from a worker (Altonji and Pierret 2001; Farber and Gibbons 1996; Lange 2007; Kahn 2013; Schönberg 2007). In an imperfectly competitive labor market, wages that are marked down from the marginal revenue product would also increase when there is public and positive information about talent (Wu 2025).

In contrast with potential inventors, there is less room for upward belief updating about the ability of experienced inventors who have already showcased their ability in earlier patent applications. A similar argument can be made for older workers who have been observed in the labor market for a longer period of time. The marginal impact of a patent application on employers' belief about worker ability is smaller for experienced and older workers, and therefore makes sense of a smaller wage increase in columns 3-6 of Table 4.

#### 3.2.2 Why is there a higher wage return to patenting at lower-wage firms?

Can the employer learning mechanism explain the higher wage return to a patent application at lower-wage firms? The answer depends on the initial selection of workers into lower-wage versus higher-wage firms and the subsequent sorting of workers between firms.

First, the labor market could hold a lower prior on the workers who are initially employed by lower-wage firms. Employees whose coworker wages are placed in quartile 1 earn 48 log-point lower wages on average than the workers in quartile 4 (Table 2). Conditional on observable individual and firm characteristics, there remains a 23 log-point wage gap between the employees in quartile 1 and similar workers in quartile 4 (Appendix Table B5). The average wage gaps reflect differences in the market perception about the ability of workers in lower-wage versus higher-wage firms. When the prior belief is lower for a potential inventor in quartile 1, a patent application, as a signal on research ability, generates a stronger increase of the posterior employer belief relative to the prior and therefore a higher wage return in quartile 1 (columns 1-2 of Table 4).

Second, lower-wage firms may have to set a higher wage return to patent applications when they face a higher turnover. We find some mixed evidence that supports this hypothesis. 16% of the younger potential inventors in quartile 1 move to a new firm the following year, versus 10%-14% in higher-wage quartiles (Figure

5a). By setting a higher wage return to patent applications, firms in quartile 1 may counter the risk of turnover and increase the probability of retaining an inventor. To test this idea, we estimate a Poisson regression of job mobility between firms in 1-3 years on whether a worker files a patent application this year, interacted with firm quartiles:

$$ln\,(\,E[\text{Move}_{it}|j(i,t),x_{it}]\,) = m_0 + \underbrace{\sum_{q<4} m_q \times 1[Q(i,t)=q]}_{\text{avg mobility rel. to quartile 4}} + \underbrace{\eta_0 \times y_{it}}_{\triangle\text{mobility in quartile 4}} \tag{3.3}$$
$$+ \sum_{q<4} \underbrace{\eta_q \times y_{it} \times 1[Q(i,t)=q]}_{\text{excess mobility response rel. to quartile 4}} + \underbrace{x_{it}\,\Psi}_{\text{controls}} + \underbrace{\phi_{G(j(i,t))} + \theta_t}_{\text{fixed effects}}$$

Denote by $\text{Move}_{it} := 1[j(i,t+1) \neq j(i,t)]$ any job movement between firms in the next year. Column 1 of Table 5 shows that on average younger potential inventors who file their first patent application are 74% significantly less likely to move to a new firm than otherwise similar workers.[13] Importantly, we do not see a significant increase in turnover among new inventors in quartile 1 relative to quartile 4. It is thus possible that the higher wage return to a patent application in quartile 1 results in an equal turnover of first-time inventors in equilibrium.

We also examine how mobility changes with patent applications in a longer time horizon. With $\text{Move}_{it} := 1[j(i,t+3) \neq j(i,t)]$, we find no increase in job mobility in 3 years (Appendix Table B7). Experienced inventors are consistently less likely to move than the potential or matched inventors who have not applied for a patent in 3-7 years (Figure 5, c versus a and b). Furthermore, there is no evidence that filing a patent application helps a worker move up the job ladder, except for the potential inventors in quartile 2, who are more than twice as likely to move to a higher-wage quartile of employers relative to workers who are already in the highest quartile.[14]

[13] See the Poisson coefficient on $y_{it}$ in column 1. $exp(-1.35) \approx 0.26$.

[14] For the employees in quartile 4, in Table 6 we define a between-firm movement within quartile 4 as an upward move.

In summary, we find that younger potential inventors are 19% less likely to file their first patent application at a lower-wage employer in quartile 1 than similar workers in quartile 4. The gap between low-wage and high-wage firms in patent applications disappears, however, among experienced inventors who have already applied for patents before. Further, there is a significant 5-9 log-point increase in a person's annual wage when she files her first patent application, and the average wage return is highest at firms in quartile 1.

From the perspective of employer learning, at least part of the wage increase upon workers' first patent applications reflects an upward change in employers' belief about their ability. Nevertheless, we do not see an increase in poaching or upward mobility among workers who become inventors in quartile 1, which would have explained why lower-wage firms set a higher wage return to patent applications. There can be alternative explanations for the wage increase around a patent application. We formally consider incentive-contract theory as an alternative explanation in the next section and specify the conditions under which employer learning plus incentive-contract models could justify the empirical findings above.

## 4 A Model of Talent Discovery

We formulate a dynamic framework where employers invest in learning the innovation ability of workers and use wage incentives to influence their efforts on innovation. Taking into account the dynamic decisions of firms and workers simultaneously, this model helps us reconcile the empirical findings that could not be explained by employer learning alone. In particular, it shows the conditions under which lower-wage firms set higher wage returns to patent applications despite limited job mobility among inventors.

### 4.1 Model Environment

We introduce the model environment that features workers who vary in innovation ability and firms that vary in productivity. We describe the labor market matching process across two periods. To keep it simple, the information about workers is symmetric between all players in each period.

#### 4.1.1 Workers

Workers (indexed by $i$) are endowed with a binary one-dimensional ability $\alpha_i$, which can be high $H$ or low $L$. In the first period, there is public information $I_{i1}$ on the innovation ability of a worker. Workers and all potential employers share a prior belief $\pi_{i1} = Pr(\alpha_i = H|I_{i1})$.

$L$-ability workers cannot produce a patent, while $H$-ability can with probability $h(\tau, e)$ when their employer decides to invest $\tau$ on innovation and workers themselves choose effort $e$. A worker's innovation effort $e$ is not contractible, whereas the investment $\tau$ is set by employers and specified in the contracts.

If a worker applies for a patent at $t = 1$, denoted by $y_{i1} = 1$, she will be publicly known as $H$-ability the next period. Otherwise, the common belief is updated to $\pi_{i2} = Pr(\alpha_i = H|I_{i2}) < 1$, conditional on new information $I_{i2} = I_{i1} \cup \{j(i, 1)\} \cup \{y_{i1} = 0\}$, which includes her $t = 1$ employer $j(i, 1)$ and the fact that there is no innovation output.

#### 4.1.2 Employers

Employers (indexed by $j$) are endowed with publicly known productivity $f_j$. Employers simultaneously post contracts based on public information at the beginning of each period. A contract contains a base wage $\underline{w}_{itj} \in \mathbb{R}^+$, a proportional increase in wage, $\gamma_{itj}$, if $i$ produces a patent application ($y_{i1} = 1$), and an investment in innovation $\tau_{itj} \geq 0$.

The total production at a firm each period is the sum of the outputs across individual employees.[15] The marginal revenue product expected from a worker at $j$, given belief $\pi$ of being $H$-ability, investment $\tau$ and worker effort $e$, can be written as:

$$MP_j(\pi, \tau, e) \coloneqq \underbrace{f_j \times}_{\text{Productivity}} \left( \underbrace{1}_{\text{Routine}} + \underbrace{\theta \times \pi \times h(\tau, e)}_{\text{Expected Innovation}} \right) - \underbrace{\zeta/2 \times \tau^2}_{\text{Innovation Cost}} \tag{4.1}$$

where $\theta > 0$ represents the return to innovation in proportion to a firm's productivity $f_j$, and $e$ is the amount of effort chosen by the worker. There is a convex cost of allocating workers to innovation tasks, determined by parameter $\zeta > 0$.[16]

#### 4.1.3 Labor Market Dynamics

Figure 7 illustrates the model timeline.[17] Every worker is on the labor market at $t = 1$. Each worker observes contracts $\{\underline{w}_{i1j}, \gamma_{i1j}, \tau_{i1j}\}$ posted by potential employers and draws idiosyncratic preferences for employers i.i.d. from a type-I extreme value distribution:

$$F(\{\epsilon_{itj}\}) = exp\left( \sum_j exp(-\epsilon_{itj}) \right) \tag{4.2}$$

Worker $i$ chooses her initial employer $j(i, 1)$ and chooses her effort $e_{i1j}$ that maximizes her expected utility conditional on entering firm $j = j(i, 1)$. Following a dynamic extension of Card et al. (2018), a worker can get back on the market at $t = 2$ with probability $\lambda \in [0, 1]$. Conditional on re-entering the market, a worker redraws her preferences across potential employers from (4.2), independent of her

[15] This model assumes away the joint production by workers. Identifying talent from team output can be difficult and requires more careful analysis in future work.

[16] This cost may include investment in computing power that often grows in a convex way as employees spend more time on innovation. It may also absorb the management costs of moving workers away from routine activities at a firm. For example, a firm may have to establish an in-house research lab, hire new managers, and establish a new performance evaluation system for workers who are increasingly involved in innovation tasks.

[17] Appendix A0 describes the model timeline and information structure of each period in detail.

preferences at $t = 1$. Other workers who are not on the market at $t = 2$ stay put.

### 4.2 Optimization by Workers and Firms

We state the problems of workers and firms in each period. The model is solved backward in Appendix A1, and we discuss the model results below.

#### 4.2.1 Workers' Problem

At the beginning of $t = 2$, given contracts $\{(\underline{w}_{i2j}, \gamma_{i2j}, \tau_{i2j})\}$ from employers, a worker who re-enters the job market chooses her employer $j(i,2)$ as follows:

$$j(i,2) = argmax_j\ \boldsymbol{u_{i2j}} + \epsilon_{i2j} = E_y[b \times ln(w_{i\,2\,j}) \,|\, \pi_{i2},\, \tau_{i2j},\, e_{i2j}] - c(e_{i2j}) + \epsilon_{i\,2\,j} \quad (4.3)$$

$$\text{where } w_{i\,2\,j} = \underline{w}_{i2j} \times \left(1 + y_{i2} \times \gamma_{i2j}\right)$$

$$e_{i2j} = argmax_e\ \underbrace{\pi_{i2}\, h(\tau_{i2j}, e) \times b\, ln(1 + \gamma_{i2j})}_{\text{expected bonus}} - \underbrace{\frac{c}{2}e^2}_{\text{effort cost}}$$

$$= \pi_{i2} \frac{\partial h(\tau, e)}{\partial e} \times \frac{b\, ln(1 + \gamma_{i2j})}{c}$$

The probability of her choosing firm $j$ is:

$$p_{i2j} = \frac{exp(E[b \times ln(w_{i2j})] - c(e_{i2j}))}{\sum_{j'} exp(\boldsymbol{u_{i2j'}})} \quad (4.4)$$

The labor supply of an incumbent worker is thus $p^{(1)}_{i2j} = 1 - \lambda(z_{i1}) \times (1 - p_{i2j})$, and the labor supply of a worker from a different firm is $p^{(0)}_{i2j} = \lambda(z_{i1}) \times p_{i2j}$.

At $t = 1$, every worker is on the market, observes initial contracts $\{(\underline{w}_{ij}, \gamma_{ij}, \tau_{i1j})\}$, and draws her preferences over employers from (4.2). Let $\beta_W \in [0, 1]$ denote the exponential discount factor shared by all workers. When $\beta_W > 0$, workers take into account their option value at $t = 2$ when choosing an employer at $t = 1$. The discrete choice facing a worker with an initial belief $\pi_{i1}$ is summarized as follows:

$$j(i,1) = argmax_j\ \boldsymbol{u_{i1j}} + \epsilon_{i1j} = \underbrace{E_y[b \times ln(w_{i1j})|\ \pi_{i1},\ \tau_{i1j},\ e_{i1j}]}_{\text{expected utility from wage at t=1}} + \beta_W \times \underbrace{E_y[\Omega_j\,(\pi_{i2})\ |\ \pi_{i1},\ \tau_{i1j},\ e_{i1j}]}_{\text{option value at t=2}} - c(e_{i1j})$$

$$\text{where } e_{i1j} = argmax_e\ \underbrace{\pi_{i1}\, h(\tau_{i1j}, e)}_{Pr(y_{i1}=1|...)} \times \underbrace{\left(b\, ln(1+\gamma_{i1j}) + \beta_W \triangle_y \Omega_j\right)}_{\text{increase in expected utility}} - \frac{c}{2}e^2 \tag{4.5}$$

in which the expectation is over $y_{i1}$ - whether a worker produces a patent during $t = 1$. The option value of choosing firm $j$ at $t = 1$, $\Omega_j$, is a function of worker's effort $z$ on job search during $t = 1$ and the next-period public belief $\pi_{i2}$:

$$\Omega_j(\pi_{i2}) = \underbrace{(1-\lambda) \times u_{i2j}(\pi_{i2})}_{\text{not on market, stay at j}} + \underbrace{\lambda \times E[max\{u_{i2j'}(\pi_{i2}) + \epsilon_{i2j'}\}]}_{\text{on market}} \tag{4.6}$$

Define $\triangle_y f := E[f|y = 1] - E[f|y = 0]$, and hence $\triangle_y \Omega_j = \Omega_j(\pi_2(1)) - \Omega_j(\pi_2(0))$ represents the change in a worker's option value at $t = 2$ when she produces a patent application at $t = 1$.[18]

Forward-looking workers conjecture how beliefs about their ability evolve. The option value can also be interpreted as a preference for innovation tasks, where workers with a higher prior $\pi_{i1}$ have a stronger preference for higher $\tau$ that would increase the chance of being experienced as $H$-ability the next period.[19] The labor supply to firm $j$ can be written as:

$$p_{i1j} = \frac{exp\left(E[b \times ln(w_{i1j}) + \beta_W\, \Omega_j(\pi_{i2}]\right)}{\sum_{j'} exp\left(\boldsymbol{u_{i1j'}}\right)} \tag{4.7}$$

### 4.2.2 Employers' Problem

Firms set optimal contracts $\left(\underline{w}_{itj},\ \gamma_{itj},\ \tau_{itj}\right)$ given imperfect but symmetric information about a worker's research ability. At the beginning of $t = 2$, conditional

[18]According to the information structure in Section 4.1.1., $\pi_{i2}(1) = 1$ and $\pi_{i2}(\pi_2(0)) = Pr(\alpha_i = H|\pi_{i1},\ j(i,1)\, y_{i1} = 0) < 1$.

[19]See Appendix A4 of Wu (2025), which allows $\beta_W > 0$ and expresses the option value as a preference for innovation tasks.

on belief $\pi_{i2} = Pr(\alpha_i = H|I_{i2})$, each firm solves:

$$v_{2j}^{(\delta_{ij})}(\pi_{i2}) = max_{(\underline{w},\gamma,\tau)} \quad \underbrace{p_{2j}^{(\delta_{ij})}}_{\text{labor supply}} \times \underbrace{\left(MP_j(\pi_{i2},\, \tau,\, e) - E_y[w_{i2j}|\pi_{i2}, \tau,\, e]\right)}_{\text{expected profits}} \tag{4.8}$$

$$\text{s.t. worker effort } e = \pi_{i2}\frac{\partial h(\tau,e)}{\partial e} \times \frac{b\; ln(1+\gamma)}{c} \text{ solves (4.3)}$$

in which $\delta_{ij} = 1[j(i,1) = j]$ indicate if $i$ is employed by $j$ in the first period, at the beginning of $t = 2$. The labor supply of incumbent workers is different from that of an outside worker:

$$p_{2j}^{(\delta_{ij})} = \begin{cases} 1 - \lambda \times (1 - p_{2j}) & \text{if } \delta_{ij} = 1 \text{, incumbent} \\ \lambda \times p_{2j} & \text{if } \delta_{ij} = 0 \text{, new employee} \end{cases}$$

At $t = 1$, given prior $\pi_{i1}$, firms set contracts that maximize their profits at $t = 1$ and expected returns from an incumbent employee at $t = 2$. Letting $\beta_J \in (0, 1]$ denote the exponential discount factor shared by all employers, each firm solves:

$$v_{1j}(\pi_{i1}) = max_{\underline{w},\gamma,\tau} \quad \underbrace{p_{1j}}_{\text{labor supply}} \times \left( \underbrace{MP_j(\pi_{i1},\tau,e) - E_y[w_{i1j}|\, \pi_{i1}, \tau,\, e]}_{\text{expected profit at } t=1} + \underbrace{\beta_J \times\; E_y[v_{2j}^{(1)}(\pi_{i2}(y))\,|\pi_{i1}, \tau,\, e]}_{\text{continuation value}} \right) \tag{4.9}$$

$$\text{s.t. worker effort } e = \pi_{i1} \times \frac{\partial h(\tau,e)}{\partial e} \times \frac{\left(b\; ln(1+\gamma)\; + \beta_W \triangle_y \Omega_j\right)}{c} \text{ solves (4.5)}$$

Firms are in Bertrand competition with each other, where the strategic variables are base wage $\underline{w}$, return to patent $\gamma$, and investment $\tau$ on innovation. In equilibrium, workers on the market take the contracts from firms as given and choose their employer and effort in innovation $e$ optimally. Firms take into account the efforts of employees when deciding on an investment. The equilibrium concept is subgame perfect Nash as in Wu (2025). We complete the backward induction in Appendix A1.

### 4.3 Equilibrium Results and Links to Empirical Findings

We derive three equilibrium results from the model and discuss the assumptions under which they can explain the empirical findings in Section 3. The proof of each proposition can be found at Appendix A2.

**Proposition 1 (Positive Relationship between Firm Productivity and Base Wages)** *Assume the labor supply is not perfectly elastic with respect to wages at both periods, $b < \infty$. We have the base wages set by firms at both periods to be strictly increasing in firm productivity $f_j$*

Proposition 1 suggests we can preserve the ranking of firm productivity by using the mean wage at a firm, which is an underlying assumption in our empirical analysis. We do not have a direct measure of firm productivity from the INPS data, but we match 7% of the firms in our sample to INVIND by fiscal code or firm name. Appendix Table B2 shows that lower-wage firms have lower revenue and invest less on average than higher-wage ones, providing some evidence for Proposition 1.

**Proposition 2 (Heterogeneity in Firm Investment on Innovation)** *Assume at any level of worker effort, the patent production function is increasing in a firm's investment on innovation: $\forall e \in \mathbb{R}^+ : \frac{dh}{d\tau} = \frac{\partial h}{\partial \tau} + \frac{\partial h}{\partial e} \times \frac{\partial e}{\partial \tau} > 0$. Given any belief about a worker's innovation ability $\pi \in (0, 1]$, we have each firm's investment, $\tau_{tj}$, to be increasing in firm productivity $f_j$ at both periods.*

In equilibrium, the more productive a firm is (higher $f_j$), the more investment it would make on innovation.[20] At $t = 2$, firms no longer have a dynamic concern regarding worker turnover in the future. From the solution to the firm's problem

[20]Among the firms that are matched to INVIND, we find lower-wage firms in quartile 1 invest less in R&D, material/immaterial, machinery or housing than higher-wage firms (Appendix Table B2). R&D investment if often missing in INVIND, and firms that are matched to INVIND tend to larger on average (rel. to Table 2). That being said, the lower investment in quartile 1 on machinery/housing/material/immaterial also matter for a firm's innovation environment, supporting the model prediction that less productive firms invest less in innovation.

(4.8, 7.5), we have $\tau_{2j}$ increasing in $f_j$. At $t = 1$, forward-looking firms consider how investment in innovation today affects the information revelation in the next period. Firms that anticipate higher turnover of publicly experienced $H$-ability workers would set fewer innovation tasks initially.[21] In the Italian market for potential inventors, we do not find evidence that successful inventors at lower-ranked firms move elsewhere faster (see Figure 5 or Table 5). Therefore, the dynamic trade-off that would have widened the gap in $\tau_{1j}$ between low- and high- productivity firms may not be as important as in the U.S. labor market.

Despite the limited mobility, the positive relationship between firm productivity and its investment in innovation in Proposition 2 can explain why potential inventors are significantly less likely to file their first patent application at firms that pay lower wages (Table 3).

**Proposition 3 (Heterogeneity in Returns to Innovation)** *Assume the patent production by H-ability workers as a function of the investment chosen by a firm and the effort chosen by the worker, $h(\tau, e)$, satisfies $h_1 > 0$, $h_2 > 0$, \$$\forall e \in \mathbb{R}^+ : \frac{\partial h}{\partial \tau} + \frac{\partial h}{\partial e} \times \frac{\partial e}{\partial \tau} > 0$, and $h_{12} < 0$ ($\tau$, $e$ are substitutes). We have:*

*(a) The wage return to a new patent application at $t = 1$, $\gamma_{1j}$, decreases in $\lambda$ at firms where $\frac{\partial \triangle_y v_{2j}^{(1)}}{\partial \lambda} < 0$.*

*(b) $\gamma_{1j}$ decreases in firm productivity $f_j$ if $\frac{dh_2}{d\tau} = h_{12} + h_{22}\frac{\partial e}{\partial \tau} \ll 0$. More precisely,*

$$\frac{\partial \gamma_{1j}}{\partial f_j} < 0 \text{ iff } \frac{\partial \ln \left( \frac{\mathbf{f_j}\theta + \beta_\mathbf{J} \triangle_\mathbf{y} \mathbf{v_{2j}^{(1)}}}{\underline{\mathbf{w}}} \right)}{\partial \mathbf{f_j}} < \frac{-2 \left( h_{12} + h_{22} \frac{\partial e}{\partial \tau} \right) \frac{(h - \pi h^2)}{h_2} + \left( (1 - 2\pi h) \left( h_1 + h_2 \frac{\partial e}{\partial \tau} \right) \right)}{h - \pi h^2 + \frac{\pi b}{c} (h_2)^2} \times \frac{\partial \tau}{\partial f_j} \tag{4.10}$$

*(c) The wage return to a patent application for incumbent workers at $t = 2$, $\gamma_{2j}^{(1)}$, decreases in market entry rate $\lambda$, whereas the wage return for new employees does not vary with $\lambda$.*

[21] The tradeoff between employer learning and retention is discussed and empirically tested in the U.S. labor market for computer scientists in Wu (2025).

(d) *The wage return to a patent application at $t = 2$, $\gamma_{2j}$, decreases in firm productivity $f_j$ for both the incumbent and new employees iff*

$$\frac{\partial}{\partial f_j} ln(f_j/\underline{w}) < \frac{\partial}{\partial f_j} ln\left(\frac{h - \pi h^2 + \frac{\pi b}{c}(h_2)^2}{(h_2)^2}\right) \tag{4.11}$$

At $t = 1$, the optimal effort a forward-looking worker chooses is increasing in both the wage return $\gamma_{1j}$ and the change in option value the next period, $\triangle_y \Omega_j$ (see equation 4.5). Workers who believe they might be $H$-ability are motivated by the higher wages they can receive at $t = 2$ if there is a successful patent application at $t = 1$, and therefore put in more effort. That is, in a labor market with less frictions or a higher market entry rate ($\lambda$), employers would not need to set a high reward for patent application to elicit efforts. On the other hand, in a labor market with limited job mobility (lower $\lambda$), a higher wage incentive is necessary for eliciting the same level of effort from workers. In equilibrium, the bonus $\gamma_{1j}$ set by firms at $t = 1$ is decreasing in $\lambda$ (Proposition 3(a)). We have not exploited any variation in $\lambda$ within the Italian labor market to test this result, but it provides an explanation for the significantly positive wage increase when a worker produces a patent application despite limited mobility between firms.

Proposition 3(b) shows the condition under which the wage return to a patent application is higher at less-productive/lower-wage firms, a key result we have highlighted in Table 4. Under the assumption that $h_{12} < 0$, a firm's innovation investment $\tau$ and an employee's own effort $e$ are substitutes. More productive firms set a higher $\tau$ (Proposition 2), conditional on which the marginal return to worker effort becomes lower. When $h_{12}$ is sufficiently negative that (7.12) holds, we have the wage return $\gamma_{1j}$ to be decreasing in firm productivity, which explains the higher wage increases at lower-wage firms, especially in quartile 1 (Table 4). In other words, setting a higher wage incentive $\gamma$ can increase effort from workers and compensate for the lower firms' investment in innovation. If instead, $h_{12} > 0$, firm investment $\tau$ and worker effort $e$ are complements, we are more likely to see $\gamma$ increasing in $f_j$, which contradicts our empirical results (Section 3.2).

Proposition 3(c) shows the relationship between the reward for a patent application and $\lambda$ at $t = 2$, the last period in this model at which firms and workers make static decisions (4.3, 4.8). When $\lambda$ is higher, a larger fraction of incumbent employees are expected to get on the market, and their employers have to set higher wages. The cost of rewarding incumbent workers for patent applications would increase, and in equilibrium, the proportional bonus $\gamma_{2j}^{(1)}$, decreases as $\lambda \uparrow$. The market entry rate $\lambda$ does not enter the elasticity of labor supply from new workers, and as a result, affects neither the base wage nor $\gamma_{2j}^{(0)}$ for new employees.

Similar to what we have shown in 3(b), whether $(\tau, e)$ are complementary matters for the relationship between the wage return $\tau_{2j}$ and firm productivity $f_j$. If the marginal return to worker effort is decreasing in a firm's investment on innovation, $\frac{dh_2}{d\tau} \ll 0$, we will have $\frac{\partial \gamma_{2j}}{\partial f_j} < 0$ for both incumbent and new employees.

In summary, this 2-period model with dynamic decisions by firms and workers helps reconcile the key empirical findings in Section 3:

1. Younger workers are less likely to become inventors at lower-wage firms.

2. Wage returns to a new patent application are higher at lower-wage firms.

3. There are no significant differences between firms in mobility responses to a patent application.

# 5 Conclusion

This paper focuses on the labor market for potential inventors in Italy to study the heterogeneity in talent discovery across firms. The lack of firms' investment in employees, either in the form of training or taking risks to learn about a worker's ability, can widen the wage gap between younger and older workers and further slow down productivity growth. Italy is a particularly important country for studying this issue, firstly because the aging workforce and labor market reforms hurt the career prospect of younger workers, and secondly, because the overall labor productivity has been sluggish since the 1990s, lagging behind other advanced economies (Goldin et al. 2024). For policymakers, it is also meaningful to understand the role of firms in the discovery of new inventors, in order to design R&D subsidies that can incentivize employers to increase investment in younger employees (who are possibly more inclined to innovate) and reduce the gap between younger and older workers in innovation.

We find that younger potential inventors are 42% less likely to file their first patent application at a firm in quartile 1 than similar workers in quartile 4, where wages are higher. The gap between low-wage and high-wage firms in patent applications disappears, however, among experienced inventors who have already applied for patents before. Further, there is a significant 3-4 log point increase in a person's annual wage when she files her first patent application, and the wage returns are significantly higher at firms that pay lower wages.

We build a dynamic framework of employer learning and incentive contract to reconcile these empirical findings. When firm investment and worker effort are substitutable with one another in innovation production, the wage return to a new patent application can decrease in firm productivity, even if worker turnover remains low and similar across firms. Less productive firms under-invest in research but elicit effort from workers with a higher bonus contingent on any successful innovation. This model contributes to the employer learning literature by taking into account the dynamic incentives of firms and workers simultaneously.

Our findings have a potential policy recommendation on the design of R&D policy. A large number of younger workers who are capable of inventing are not given a chance to do so at lower-wage firms. A policy subsidizing the promotion of younger inventors, targeting the number of young employees allowed to participate in the innovation process, could encourage firms to invest more in talent discovery and nurturing.

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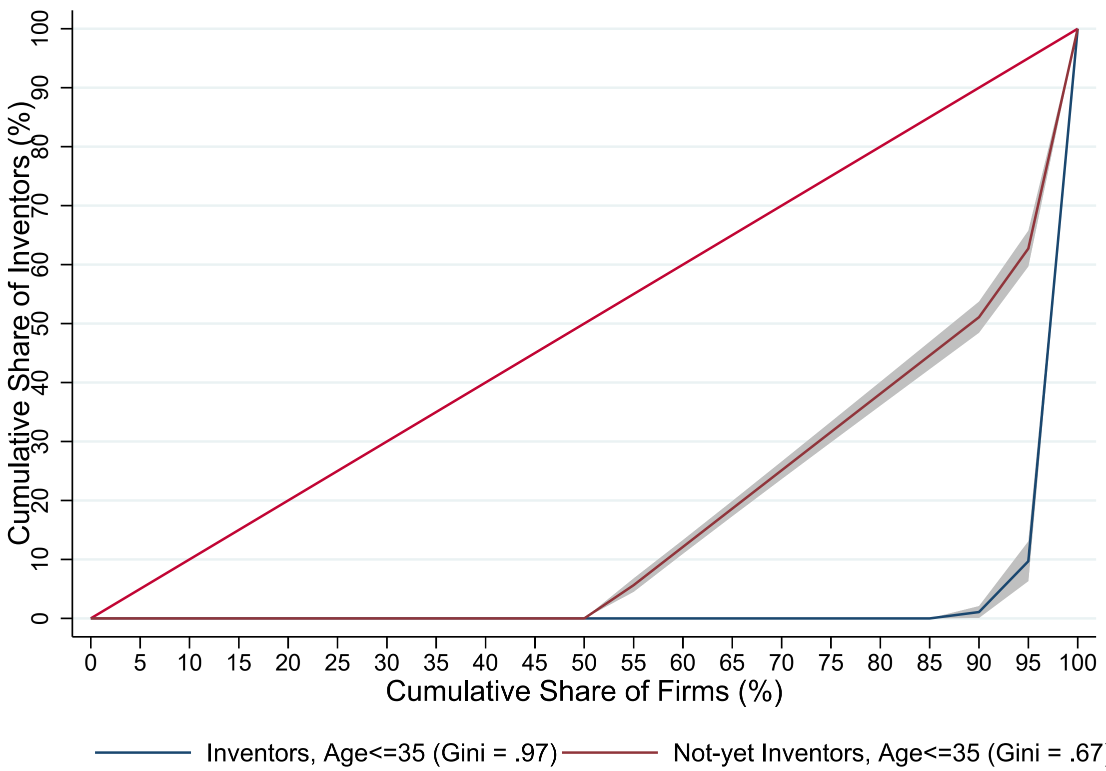
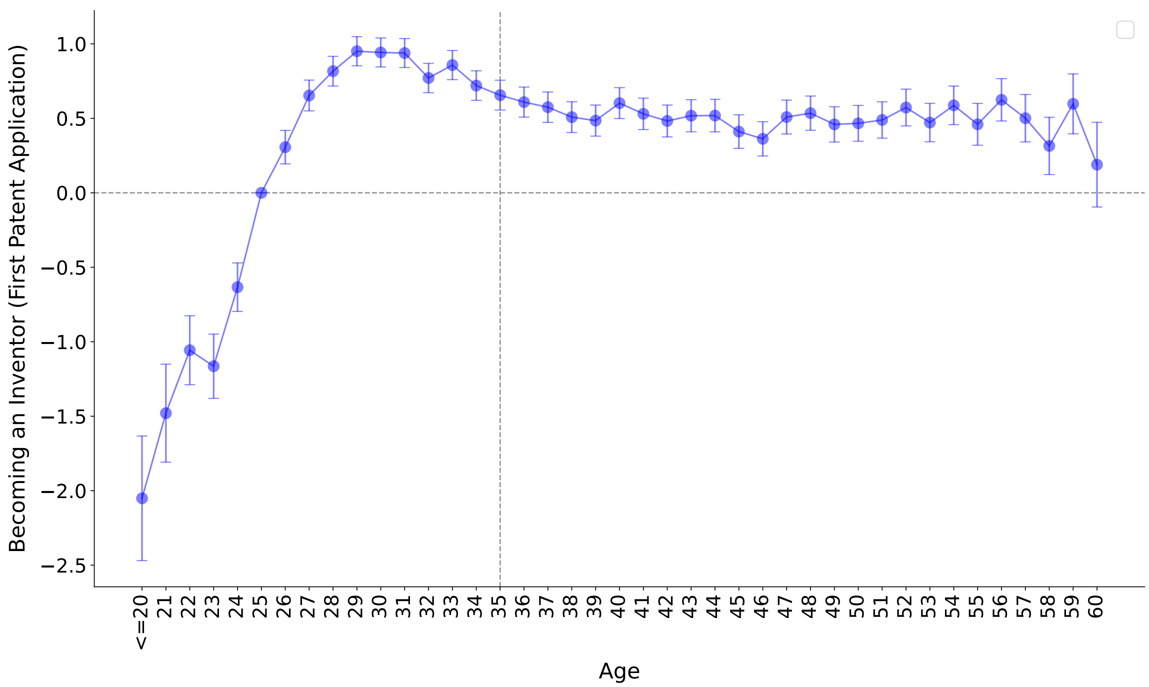
# 6 Figures

Figure 1: Lorenz Curves - Distribution of Younger Inventors Across Firms in Italy




Notes: This figure shows the distribution of younger inventors across firms. For each firm with at least one inventor matched in the INPS data, we compute the number of younger employees who apply for a patent at age $\leq 35$, and the number of younger employees who have not applied for a patent but will do so at another firm in the future (the "not-yet inventors"). We require the patent applications to be assigned to inventors' primary employers in the year of initial filing. Younger inventors are more concentrated than younger workers who will become inventors elsewhere: about 90% of the younger inventors are employed by the 5% of firms (about 550 firms).

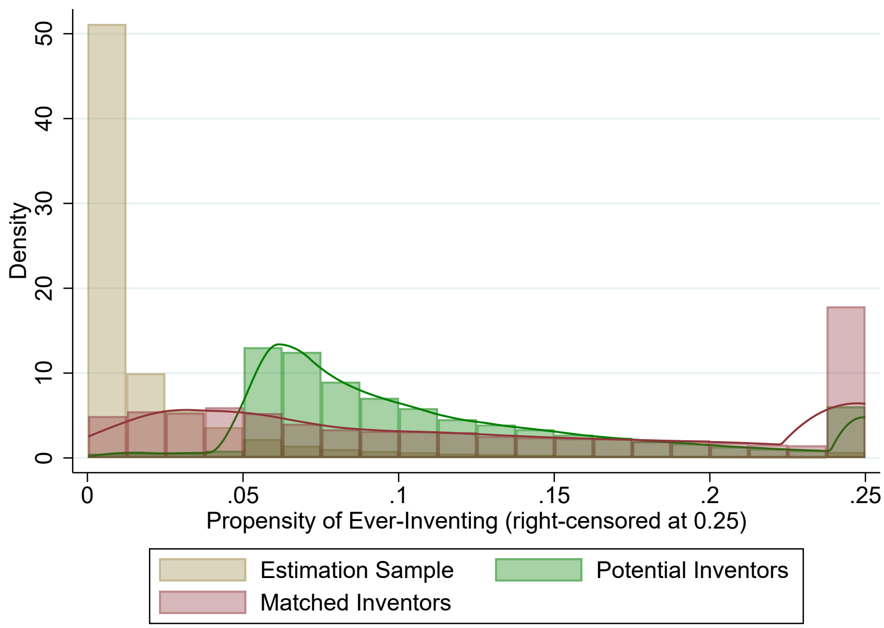
Figure 2: Becoming an Inventor by Age



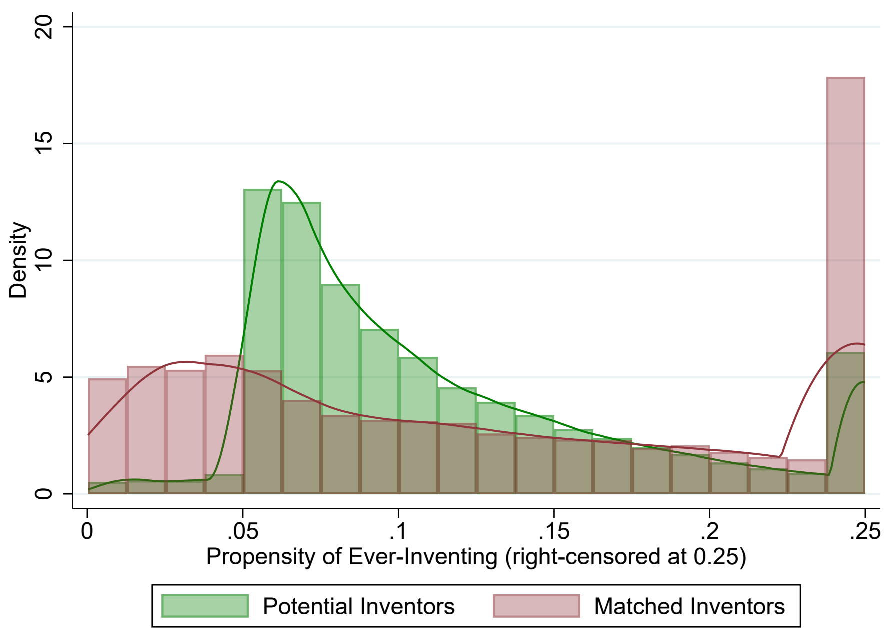

Notes: This figure plots the logit coefficients of becoming an inventor (first patent application) by age, relative to age 25. The estimation sample is at the (person, year) level, comprising the years in which a worker is aged between 18 and 60, has not applied for patents, or just submitted her first application. The logistic regression of becoming an inventor is estimated on a person × year panel that includes all potential inventors (see Section 2.2). We control for age dummies (ages 18-20 are grouped together), calendar year fixed effects, and gender.

Figure 3: Propensity Scores of Ever Inventing

(a) Full Sample




(b) Potential Inventors

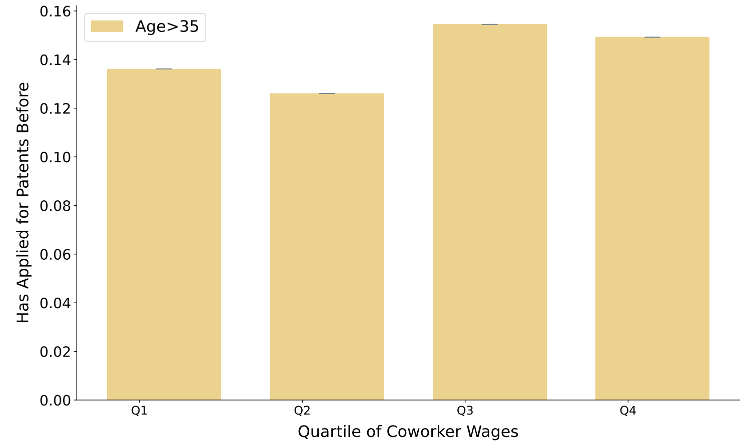



Notes: This figure presents histograms of the estimated probability of a worker ever inventing, as specified in Poisson regression (2.1). For illustration, the p-scores are right-censored at 0.25. The estimation sample includes 1.5 million workers (see the notes under Table 1). Matched inventors are workers with at least one patent application matched to their employment in the INPS data 1987-2009. Potential inventors include all matched inventors and their coworkers whose estimated p-scores are above the median of the p-scores among matched inventors (Section 2.2).

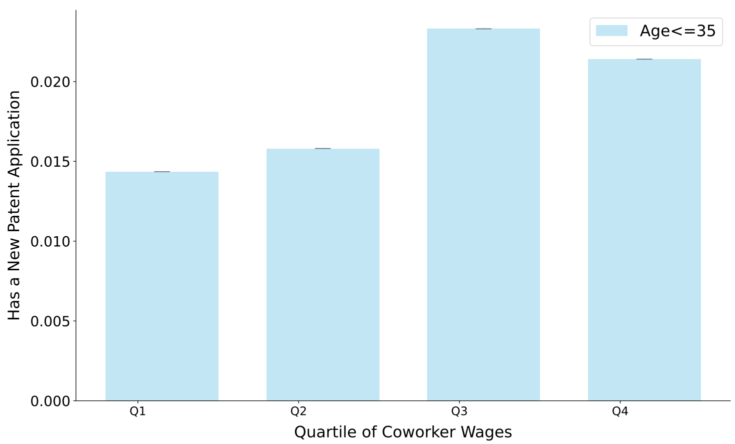
Figure 4: Heterogeneity in Patenting by Age and Coworker Wages

(a) % Experienced Inventors, Age ≤ 35

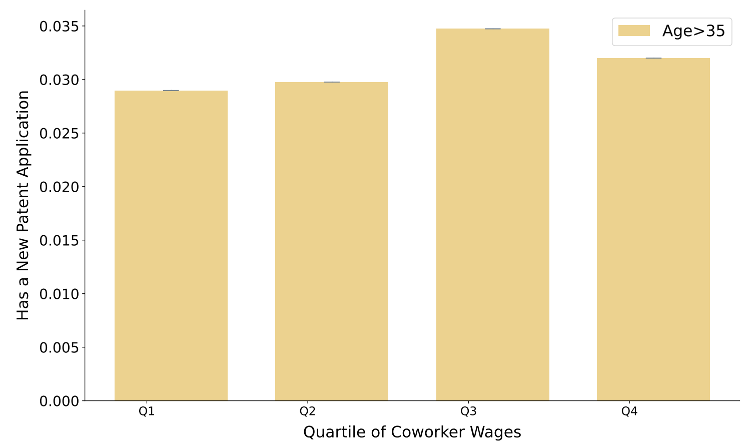

(b) % Experienced Inventors, Age > 35




(c) Patent Application Rate, Age ≤ 35

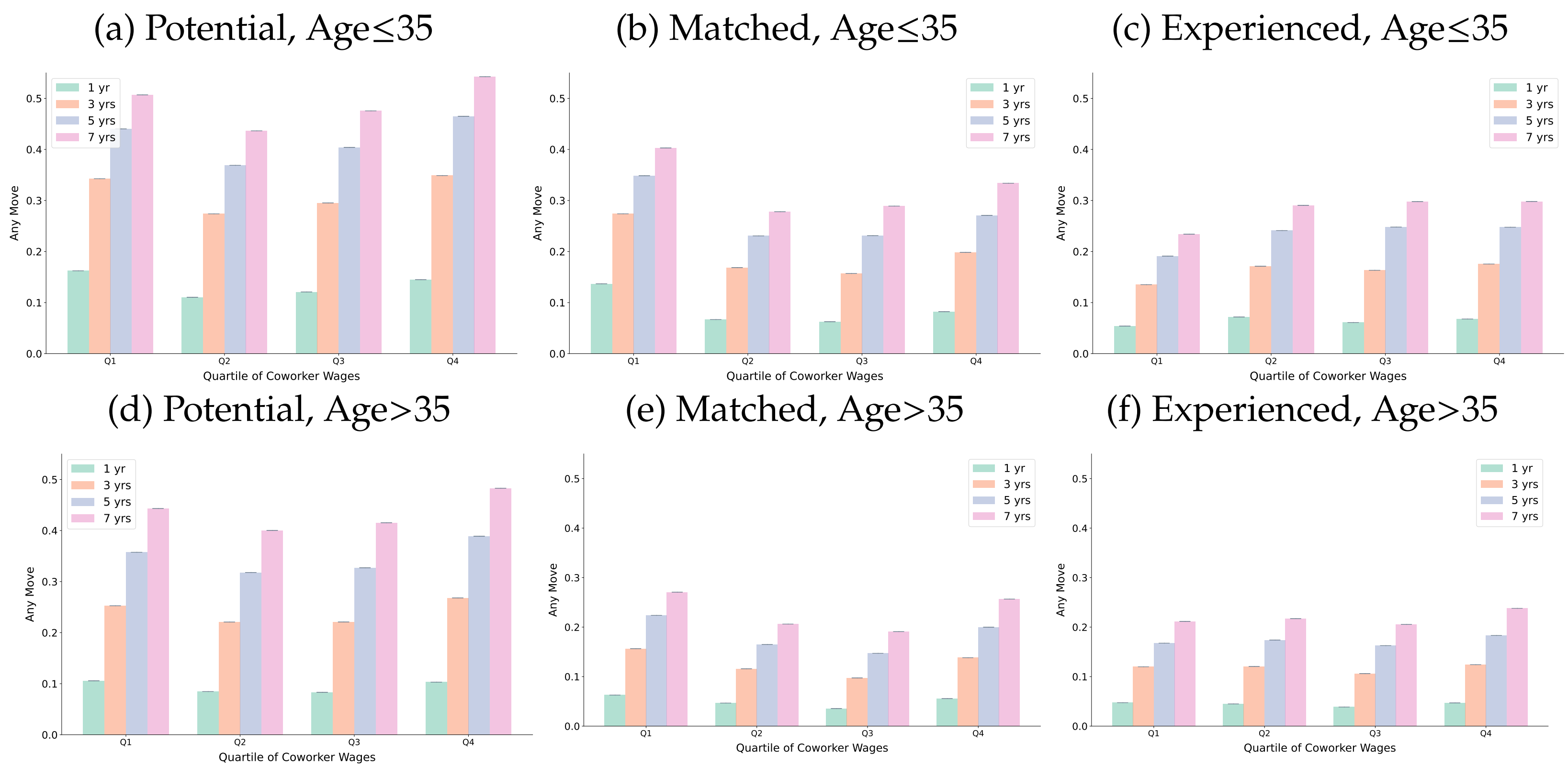



(d) Patent Application Rate, Age > 35



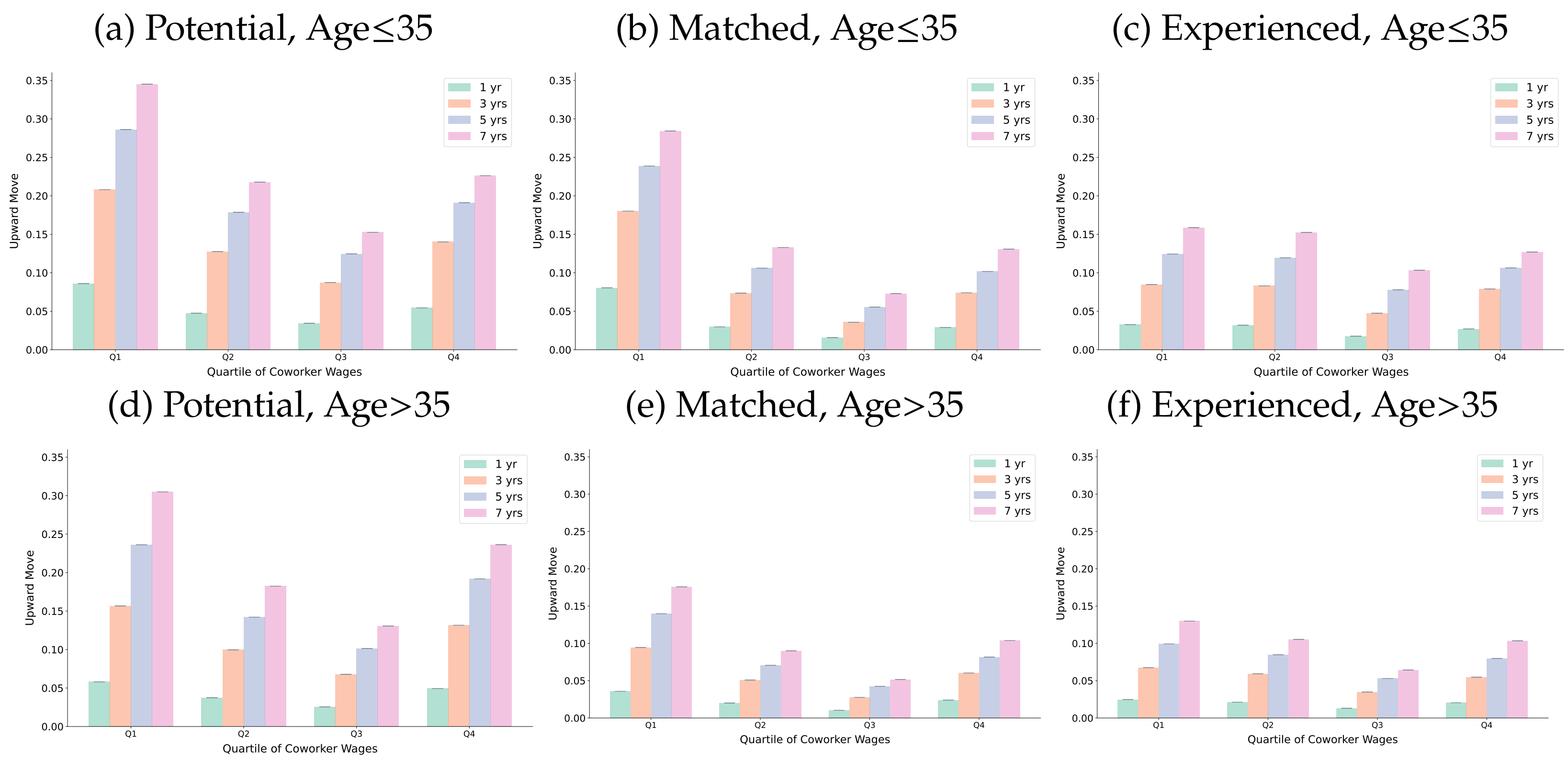

Notes: This figure shows the fraction of employees who have already applied for a patent previously (the "experienced" inventors) in all potential inventors (panels (a) and (b)) and the share of the inventors with a new patent application at $t$ in all potential inventors (panels (c) and (d)), by age group and firm quartile. Firms are ranked by mean coworker wages each year (excluding the focal employee).

Figure 5: Mobility by Firm Quartiles: Any Move between Firms



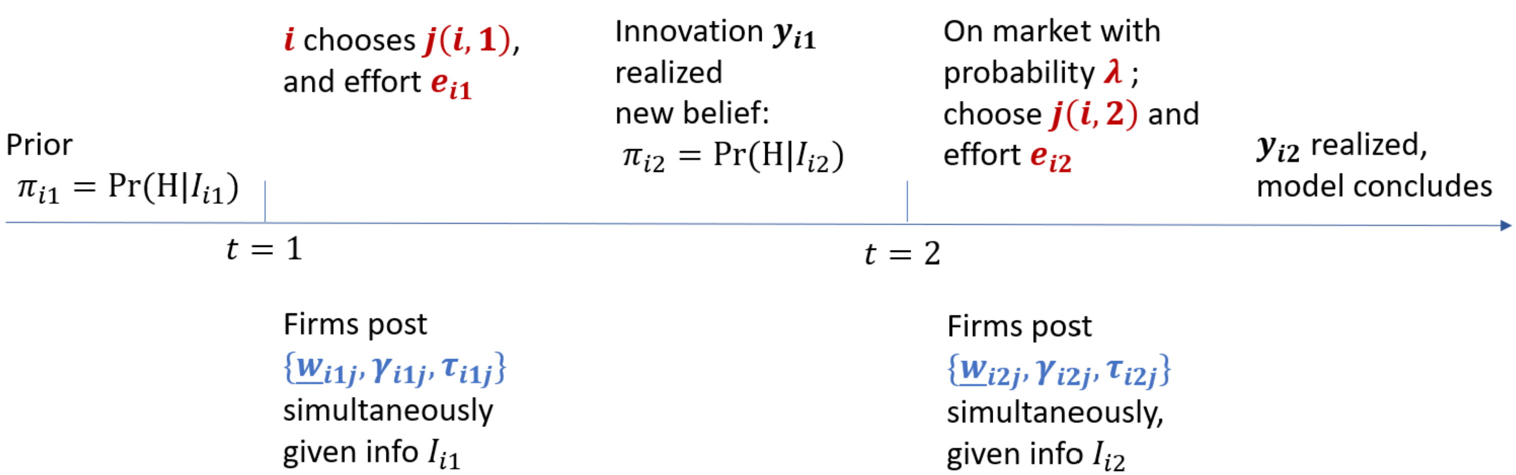

Notes: This figure shows the mean mobility of workers at each firm quartile, ranked by leave-out coworker wages each year. (a)-(c) focus on the fraction of workers younger than 35 at $t$ employed by different firms, $j(i, t+k) \neq j(i, t)$, in $k \in \{1, 3, 5, 7\}$ years, while (d)-(f) shows the same for workers older than 35. Potential inventors are the workers who have not applied for any patent selected as described in Section 2.2. Matched inventors are the employees who have not yet applied for a patent but will eventually do so, and have been matched with their INPS employment records. And finally, experienced inventors are the workers who have already applied for a patent. The three groups are consistent with the definitions of estimation samples in Table 3.

Figure 6: Upward Mobility by Firm Quartiles: Moving to a Higher Quartile




Notes: This figure shows the mean upward mobility of workers at each quartile of firms, ranked by leave-out coworker wages each year. Upward mobility is the movement of a worker into a higher-quartile firm, $j(i.t+k) \neq j(i,t)$ and $Q(i,t+k) > Q(i,t)$, in $k \in \{1,3,5,7\}$ years. For workers starting at the top, a move between firms within quartile 4 is also coded as an upward move. (a)-(c) focus on the fraction of workers younger than 35 at $t$ employed by different firms, $j(i,t+k) \neq j(i,t)$, in $k \in \{1,3,5,7\}$ years, while (d)-(f) shows the same for workers older than 35. Potential inventors are the workers who have not applied for any patent selected as described in Section 2.2. Matched inventors are the employees who have not yet applied for a patent but will eventually do so, and have been matched with their INPS employment records. And finally, experienced inventors are the workers who have already applied for a patent.

Figure 7: Model Timeline




Notes: This figure shows the model timeline. See Section 4 for details.

# 7 Tables

Table 1: Sample Overview - Person Level

| | **Full Sample** | | **Potential Inventors** | | **Matched Inventors** | |
|---|---|---|---|---|---|---|
| | mean | sd | mean | sd | mean | sd |
| **Demographics** | | | | | | |
| Female | 0.346 | 0.476 | 0.063 | 0.244 | 0.091 | 0.287 |
| Yr of Birth | 1960 | 11.923 | 1962 | 9.794 | 1958 | 10.836 |
| **INPS Sample (left-censored at 1987)** | | | | | | |
| First Yr in INPS | 1991 | 5.162 | 1991 | 5.083 | 1990 | 4.886 |
| Present in INPS in 1987 | 0.527 | 0.499 | 0.400 | 0.490 | 0.570 | 0.495 |
| **Patent Applications** | | | | | | |
| Any Patent App 1987-2009 | 0.010 | 0.100 | 0.138 | 0.344 | 1.000 | 0.000 |
| Any Patent App Per Year | 0.002 | 0.023 | 0.023 | 0.083 | 0.168 | 0.161 |
| Any Patent App by Age 30 | 0.005 | 0.072 | 0.046 | 0.209 | 0.361 | 0.480 |
| ... by Age 35 | 0.009 | 0.095 | 0.081 | 0.273 | 0.586 | 0.493 |
| ... by Age 40 | 0.011 | 0.103 | 0.109 | 0.312 | 0.685 | 0.464 |
| ... by Age 45 | 0.011 | 0.106 | 0.145 | 0.352 | 0.760 | 0.427 |
| ... by Age 50 | 0.011 | 0.105 | 0.180 | 0.384 | 0.823 | 0.382 |
| **Job Characteristics** | | | | | | |
| Num. Employers (Firms) | 2.089 | 1.337 | 2.726 | 1.492 | 2.150 | 1.414 |
| Blue-Collar | 0.055 | 0.123 | 0.049 | 0.115 | 0.018 | 0.067 |
| White-Collar | 0.935 | 0.145 | 0.949 | 0.118 | 0.980 | 0.070 |
| Permanent Contracts | 0.455 | 0.320 | 0.567 | 0.268 | 0.530 | 0.255 |
| Temporary Contracts | 0.101 | 0.224 | 0.061 | 0.146 | 0.036 | 0.105 |
| Seasonal Contracts | 0.002 | 0.025 | 0.001 | 0.011 | 0.000 | 0.007 |
| Contract Type Missing | 0.454 | 0.339 | 0.384 | 0.284 | 0.443 | 0.275 |
| **Wages** | | | | | | |
| Mean Log Wage | 7.534 | 0.498 | 7.756 | 0.483 | 7.983 | 0.479 |
| Log Wage at Age 30 | 7.376 | 0.442 | 7.515 | 0.337 | 7.585 | 0.294 |
| ... at Age 35 | 7.550 | 0.492 | 7.773 | 0.411 | 7.857 | 0.333 |
| ... at Age 40 | 7.678 | 0.499 | 7.960 | 0.493 | 8.072 | 0.424 |
| ... at Age 45 | 7.776 | 0.491 | 8.088 | 0.552 | 8.240 | 0.486 |
| ... at Age 50 | 7.850 | 0.493 | 8.171 | 0.593 | 8.384 | 0.543 |
| **Observations** | 1,537,000 | | 112,000 | | 15,000 | |

Notes: This table shows the summary statistics at the person level. The full sample includes inventors and their coworkers who 1) are in the INPS sample at age 14-55, 2) have at least five years of employment records in the sample between 1987 and 2009, and 3) worked in white-collar roles for at least 50% of their time in the sample. A worker is defined as a "matched inventor" if she has at least one patent application and at least an employment record in INPS in 1987-2009. We estimate the Poisson regression (2.1) that predicts if a person is a matched inventor on the estimation sample. Potential inventors include all matched inventors and any worker whose estimated propensity score of ever inventing is above the median p-score of the matched inventors (Section 2.2). The means of job characteristics, wages, and patenting rates are computed from the person-year panel.

Table 2: Firm Characteristics by Quartile of Coworker Wages

| | Quartile 1 | | Quartile 2 | | Quartile 3 | | Quartile 4 | |
|---|---|---|---|---|---|---|---|---|
| | mean | sd | mean | sd | mean | sd | mean | sd |
| **Num. Unique Firms** | 12,239 | | 6,862 | | 5,893 | | 7,158 | |
| Log Wage | 7.511 | 0.499 | 7.787 | 0.245 | 7.864 | 0.242 | 7.999 | 0.351 |
| Num. Potential Inventors | 14.668 | 78.561 | 27.684 | 147.763 | 31.249 | 141.079 | 22.856 | 112.887 |
| Age of Employees | 35.202 | 5.836 | 37.522 | 4.511 | 38.122 | 4.377 | 38.995 | 4.746 |
| Age When Applying for a Patent | 42.083 | 7.596 | 42.501 | 6.954 | 42.932 | 6.713 | 43.610 | 6.880 |
| **Patent Applications (per worker-year)** | | | | | | | | |
| Num. Patent Apps | 0.011 | 0.047 | 0.015 | 0.045 | 0.016 | 0.050 | 0.015 | 0.057 |
| Num. Patent Apps, Age<=35 | 0.005 | 0.038 | 0.007 | 0.036 | 0.008 | 0.037 | 0.007 | 0.045 |
| Num. Patent Apps, Age>35 | 0.017 | 0.082 | 0.021 | 0.068 | 0.022 | 0.072 | 0.020 | 0.076 |
| Any Patent App | 0.007 | 0.025 | 0.009 | 0.025 | 0.010 | 0.026 | 0.009 | 0.030 |
| Any Patent App, Age<=35 | 0.004 | 0.023 | 0.005 | 0.021 | 0.005 | 0.021 | 0.005 | 0.026 |
| Any Patent App, Age>35 | 0.011 | 0.038 | 0.013 | 0.037 | 0.013 | 0.038 | 0.012 | 0.039 |
| **Industry (grouped by csc code):** | | | | | | | | |
| Electronics/Telecom | 0.090 | 0.286 | 0.101 | 0.301 | 0.100 | 0.300 | 0.089 | 0.285 |
| Pharmaceutical | 0.032 | 0.175 | 0.049 | 0.216 | 0.057 | 0.232 | 0.059 | 0.236 |
| Automobile | 0.028 | 0.164 | 0.035 | 0.185 | 0.037 | 0.188 | 0.036 | 0.186 |
| Other Manufacturing | 0.471 | 0.499 | 0.530 | 0.499 | 0.518 | 0.500 | 0.491 | 0.500 |
| Services and Others | 0.380 | 0.485 | 0.285 | 0.451 | 0.288 | 0.453 | 0.325 | 0.468 |

Notes: This table summarizes the firm characteristics in each quartile of mean coworker wages. We rank firms by the mean coworker wage leaving out a person's own wage each year, and place them into quartiles (quartile 1 with the lowest wage on average). We keep the unique firms that have ever been in each quartile and summarize the firm-level characteristics above. Our INPS-PatStat sample comprehends all the INPS firms that have employed at least one inventor in the period 1987-2009. The INVIND sample includes firms that can be matched to INVIND by fiscal code or by firm name. See Appendix Table B2 for a summary restricted to firms that are matched to INVIND.

Table 3: First Patent Application at the Current Employer, by Quartile of Firms and Age Group

| | First Patent Application at the Current Employer | | | | | |
|---|---|---|---|---|---|---|
| | Age ≤ 35 | | | Age > 35 | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Quartile of Coworker Mean Wage | | | | | | |
| quartile 1 | -0.2125*** | -0.1627*** | 0.1132 | 0.0751* | -0.1133*** | 0.0245 |
| | (0.0426) | (0.0372) | (0.1570) | (0.0440) | (0.0375) | (0.0625) |
| quartile 2 | -0.0145 | -0.1331*** | 0.3726*** | -0.0242 | -0.1132*** | 0.2294*** |
| | (0.0401) | (0.0363) | (0.1233) | (0.0396) | (0.0348) | (0.0512) |
| quartile 3 | 0.1519*** | -0.1027*** | 0.4162*** | 0.0333 | -0.0707** | 0.2614*** |
| | (0.0390) | (0.0370) | (0.1182) | (0.0382) | (0.0344) | (0.0464) |
| quartile 4 | 0 | 0 | 0 | 0 | 0 | 0 |
| | (.) | (.) | (.) | (.) | (.) | (.) |
| Mean \|quartile 4 | .0091846 | .1205102 | .062799 | .0066348 | .1619296 | .0718585 |
| N | 644238 | 52843 | 5869 | 744670 | 34735 | 33170 |
| Pseudo $R^2$ | .0645567 | .1083685 | .0928058 | .0399737 | .0729711 | .0838201 |

Notes: This table shows the estimated Poisson regression (3.1) of whether a worker files her first patent application at her current employer on the quartile of her employer, ranked by mean coworker wages (excluding her wage) in a year. The estimation sample is at the person × year level, including the years until each worker's first patent application at the current employer. All regressions control for sex, a cubic polynomial in age (relative to age 35), indicators for white/blue collar and permanent/temporary contract interacted with age, and fixed effects of the calendar year, 2-digit industry, and geographic region. Models (1) and (4) are estimated on potential inventors who have not applied for patents before. (2) and (5) are restricted to matched inventors who have not applied for patents yet but will do so during the sample period. (3) and (6) are restricted to experienced inventors, who have already applied for patents at former employers. Significance: * 0.10 ** 0.05 *** 0.010.

Table 4: Wage Returns to New Patent Application, by Quartile of Firms and Age Group

| | Log Annual Wages | | | | | |
|---|---|---|---|---|---|---|
| | Age ≤ 35 | | | Age > 35 | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Quartile of Coworker Mean Wage | | | | | | |
| quartile 1 | -0.1249*** | -0.0847*** | -0.0740*** | -0.1145*** | -0.0743*** | -0.0953*** |
| | (0.0016) | (0.0056) | (0.0142) | (0.0015) | (0.0055) | (0.0065) |
| quartile 2 | -0.0671*** | -0.0281*** | -0.0495*** | -0.0655*** | -0.0381*** | -0.0466*** |
| | (0.0014) | (0.0048) | (0.0127) | (0.0011) | (0.0042) | (0.0052) |
| quartile 3 | -0.0422*** | -0.0133*** | -0.0316*** | -0.0382*** | -0.0182*** | -0.0156*** |
| | (0.0012) | (0.0042) | (0.0099) | (0.0009) | (0.0037) | (0.0042) |
| Any New Patent Application | | | | | | |
| $y_{it}$ | 0.0470*** | 0.0366*** | 0.0151 | 0.0309*** | 0.0086 | 0.0156* |
| | (0.0065) | (0.0068) | (0.0155) | (0.0050) | (0.0053) | (0.0088) |
| Excess Returns (relative to quartile 4) | | | | | | |
| $y_{it}\times$ quartile 1 | 0.0388*** | 0.0219** | -0.0214 | 0.0214*** | 0.0100 | 0.0018 |
| | (0.0087) | (0.0089) | (0.0376) | (0.0080) | (0.0082) | (0.0153) |
| $y_{it}\times$ quartile 2 | 0.0065 | -0.0165* | 0.0019 | 0.0116* | 0.0026 | -0.0102 |
| | (0.0083) | (0.0086) | (0.0255) | (0.0070) | (0.0072) | (0.0129) |
| $y_{it}\times$ quartile 3 | 0.0017 | -0.0150* | -0.0180 | -0.0060 | -0.0123* | -0.0271** |
| | (0.0083) | (0.0086) | (0.0252) | (0.0066) | (0.0068) | (0.0117) |
| Mean \|quartile 4 | 7.678282 | 7.625638 | 7.870129 | 8.230651 | 8.215813 | 8.489231 |
| N | 646123 | 52411 | 5844 | 740741 | 34054 | 32585 |
| Adjusted $R^2$ | .7099518 | .7429179 | .7948655 | .8650494 | .9022971 | .8760036 |

Notes: This table shows the estimated OLS regression (3.2) of log annual wages on whether a worker applies for a new patent and its interactions with the quartile of her current employer, ranked by mean coworker wages (excluding her wage) in a year. The estimation sample is at the person × year level. All models control for person-fixed effects, in addition to the covariates listed under Table 3. Models (1) and (4) are estimated on all potential inventors. (2) and (5) are restricted to matched inventors, and (3) and (6) are restricted to experienced inventors, who have already applied for patents at former employers. Significance: * 0.10 ** 0.05 *** 0.010.

Table 5: Between-firm Job Mobility in a Year, by Quartile of Firms and Age Group

| | Move in 1 Year: $j(i,t+1) \neq j(i,t)$ | | | | | |
|---|---|---|---|---|---|---|
| | Age ≤ 35 | | | Age > 35 | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Quartile of Coworker Mean Wage | | | | | | |
| quartile 1 | -0.0397*** | 0.2106*** | -0.1368 | -0.0680*** | -0.0282 | -0.0386 |
| | (0.0096) | (0.0454) | (0.0885) | (0.0116) | (0.0697) | (0.0475) |
| quartile 2 | -0.1818*** | -0.1719*** | 0.0996 | -0.1710*** | -0.1603** | -0.0210 |
| | (0.0104) | (0.0509) | (0.0802) | (0.0109) | (0.0713) | (0.0454) |
| quartile 3 | -0.0972*** | -0.1608*** | -0.0099 | -0.1571*** | -0.3080*** | -0.0433 |
| | (0.0104) | (0.0521) | (0.0840) | (0.0108) | (0.0740) | (0.0432) |
| quartile 4 | 0 | 0 | 0 | 0 | 0 | 0 |
| | (.) | (.) | (.) | (.) | (.) | (.) |
| Any New Patent Application | | | | | | |
| $y_{it}$ | -1.3513*** | -0.7851*** | -0.4702*** | -1.9613*** | -1.3426*** | -0.9691*** |
| | (0.1557) | (0.1598) | (0.1356) | (0.2116) | (0.2203) | (0.0963) |
| Additional effect (relative to quartile 4) | | | | | | |
| $y_{it}\times$ quartile 1 | 0.0469 | -0.2539 | -0.4722** | 0.2072 | -0.0034 | -0.1722 |
| | (0.2042) | (0.2082) | (0.2071) | (0.3105) | (0.3177) | (0.1612) |
| $y_{it}\times$ quartile 2 | 0.4909** | 0.4651** | 0.0321 | 0.7381*** | 0.6798** | 0.3302** |
| | (0.1973) | (0.2030) | (0.1891) | (0.2696) | (0.2771) | (0.1344) |
| $y_{it}\times$ quartile 3 | -0.0073 | 0.1437 | 0.1815 | 0.2875 | 0.5396* | 0.2685** |
| | (0.2131) | (0.2185) | (0.1817) | (0.2875) | (0.2958) | (0.1308) |
| Mean \|quartile 4 | .1448382 | .082274 | .0678597 | .1031698 | .0559353 | .046911 |
| N | 633858 | 53060 | 25046 | 671293 | 34578 | 105222 |
| Pseudo $R^2$ | .0397005 | .0758365 | .0342579 | .0272517 | .0439756 | .0344894 |

Notes: This table shows the estimated Poisson regression (3.3) of any movement between firms in a year ($j(i,t+1) \neq j(i,t)$) on whether a worker applies for a new patent and its interactions with the quartile of her current employer, ranked by mean coworker wages (excluding her wage) in a year. The estimation sample is at the person × year level. Models (1) and (4) are estimated on all potential inventors. (2) and (5) are restricted to matched inventors, and (3) and (6) are restricted to experienced inventors, who have already applied for patents at former employers. Significance: * 0.10 ** 0.05 *** 0.010.

Table 6: Upward Mobility in a Year, by Quartile of Firms and Age Group

| | Upward Move in 1 Year | | | | | |
|---|---|---|---|---|---|---|
| | Age $\leq$ 35 | | | Age > 35 | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Quartile of Coworker Mean Wage | | | | | | |
| quartile 1 | 0.5518*** | 0.9397*** | 0.4546*** | 0.2734*** | 0.3331*** | 0.2401*** |
| | (0.0157) | (0.0727) | (0.1353) | (0.0169) | (0.1009) | (0.0711) |
| quartile 2 | 0.0756*** | 0.1655** | 0.3838*** | -0.1468*** | -0.0666 | 0.0922 |
| | (0.0172) | (0.0829) | (0.1278) | (0.0166) | (0.1105) | (0.0693) |
| quartile 3 | -0.3218*** | -0.5089*** | -0.2040 | -0.5445*** | -0.6808*** | -0.2760*** |
| | (0.0195) | (0.0999) | (0.1534) | (0.0188) | (0.1297) | (0.0724) |
| quartile 4 | 0 | 0 | 0 | 0 | 0 | 0 |
| | (.) | (.) | (.) | (.) | (.) | (.) |
| Any New Patent Application | | | | | | |
| $y_{it}$ | -1.4982*** | -0.8753*** | -0.4985** | -2.1905*** | -1.4364*** | -1.0742*** |
| | (0.2756) | (0.2839) | (0.2178) | (0.3526) | (0.3657) | (0.1510) |
| Additional Effect (relative to quartile 4) | | | | | | |
| $y_{it} \times$ quartile 1 | 0.4659 | 0.0484 | -0.0840 | 0.3461 | 0.0982 | 0.1816 |
| | (0.3158) | (0.3228) | (0.2823) | (0.4725) | (0.4829) | (0.2204) |
| $y_{it} \times$ quartile 2 | 0.8597*** | 0.7748** | 0.0465 | 0.9401** | 0.8586* | 0.5611*** |
| | (0.3211) | (0.3305) | (0.2956) | (0.4365) | (0.4482) | (0.1994) |
| $y_{it} \times$ quartile 3 | 0.2087 | 0.4255 | 0.1752 | 0.3857 | 0.6585 | 0.2827 |
| | (0.3833) | (0.3946) | (0.3172) | (0.5165) | (0.5327) | (0.2183) |
| Mean \|quartile 4 | .0545131 | .0290004 | .0270464 | .0494281 | .0246957 | .0204835 |
| N | 620048 | 52445 | 24749 | 661445 | 33853 | 104243 |
| Pseudo $R^2$ | .0502368 | .0990209 | .0425966 | .0366167 | .0643001 | .0417684 |

Notes: This table shows the estimated Poisson regression (3.3) of upward mobility in 3 years ($Q(i, t+1) > Q(i, t)$ or $Q(i, t+1) = Q(i, t) = 4$) on whether a worker applies for a new patent and its interactions with the quartile of her current employer, ranked by mean coworker wages (excluding her wage) in a year. The estimation sample is at the person $\times$ year level. Models (1) and (4) are estimated on all potential inventors. (2) and (5) are restricted to matched inventors, and (3) and (6) are restricted to experienced inventors, who have already applied for patents at former employers. Significance: * 0.10 ** 0.05 *** 0.010.

# Appendix A: Model Details

## A0. Model Timeline & Information Structure

There are two discrete periods in this model, as illustrated in Figure 7.

1. (**$t = 1$**) Employers start with zero employees. All workers are on the labor market looking for jobs.
   (a) Given initial information $\{I_{i1}\}$ about workers, employers share belief $\pi_{i1} = Pr(H|I_{i1})$ and post contracts $\{\underline{w}_{i1j}, \gamma_{i1j}\, \tau_{i1j}\}$ simultaneously, in which the base wage, the bonus for patenting, and investment on innovation $\underline{w}_{ij}$, $\gamma_{ij}\, \tau_{i1j}\ \geq 0$.
   (b) Each worker observes the wages posted by all firms, draws idiosyncratic preferences (4.2), and chooses the employer $j(i,1)$ that maximizes her utility (4.5) at $t = 1$. She will make effort $e_{i1j}$ on innovation conditional on choosing $j = j(i,1)$.
   (c) Whether there is a public innovation, $y_{i1} \in \{0,1\}$, is realized by the end of $t = 1$. A worker receives a wage increase of $\gamma_{i1j} \times \underline{w}_{i1j}$ if $y_{i1} = 1$.
2. (**$t = 2$**) Let $I_{i2}$ denote the information about $i$ at the beginning of $t = 2$ (symmetric among all firms and workers).

$$\begin{aligned} y_{i1} &= 1 \rightarrow \text{public } I_{i2} = \{H\} \\ y_{i1} &= 0 \rightarrow \text{public } I_{i2} = I_{i1} \cup \{j(i,1), y_{i1} = 0\} \end{aligned} \tag{7.1}$$

   (a) Given information $I_{i2}$, firms post new contracts simultaneously by solving (4.8).
   (b) A worker reenters the job market with probability $\lambda \in [0,1]$. If she is on the market, she observes the new contracts, draws new preferences from (4.2), and chooses the employer that maximizes her expected utility (4.3). Otherwise, $j(i,2) = j(i,1)$ and she makes effort that maximizes her utility conditional on staying.
   (c) Repeat 1(c). The model concludes.

## A1. Backward Induction

We clarify some notations that are used throughout the model.

$$\triangle_y f := E[f|y = 1] - E[f|y = 0] \tag{7.2}$$

Workers:

$$E[u_{i2j}|I_{i2}] = b \times E[ln(w_{i2j})|I_{i2}]$$

$$\overline{\Omega}(I_{i2}) = ln(\sum_j exp(E[u_{i2j}|I_{i2})) \text{ value on market (Emax)}$$

$$p_{2j}(I_{i2}) = exp(E[u_{i2j}] - \overline{\Omega}(I_{i2})), \text{ incumbent: } p_{2j}^{(1)}(I_{i2}) = 1 - \lambda \times p_{2j}(I_{i2})$$

$$\Omega_j(I_{i2}) = (1-\lambda) \times E[u_{i2j}] + \lambda \times \overline{\Omega}(I_{i2})$$

$$\triangle_y \Omega_j = \Omega_j(H) - \Omega_j(\pi(0)) = (1-\lambda) \times b \triangle_y E[ln(w_{i2j})] + \lambda \times \triangle_y \overline{\Omega}$$

Firms:

$$v_{2j}^{(1)}(I_{i2}) = p_{2j}^{(1)}(I_{i2}) \times E[MP_j - w_{2j}|I_{i2}]$$

$$\text{"}EV2\text{"} = E[v_{2j}^{(1)}(\pi_{i2})|\pi_{i1}, \tau_{i1j}, e_{i1j}] = v_{2j}^{(1)}(\pi_{i2}(0)) + \pi_{i1} h(\tau_{i1j}, e_{i1}) \times \triangle_y v_{2j}^{(1)}$$

We have stated the problems facing workers and firms in each period in Section 4.2. We complete the backward induction below.

**Optimization at $t = 2$**

At $t = 2$, workers who are on the job market solve (4.3), and the optimal effort at firm $j$ satisfies:

$$\begin{aligned}
e_{i2j} &= argmax_e \, E[b\, ln(w_{i2j}) \,|\, \pi\, e, \tau] - c(e) \\
&= \pi_{i2} \underbrace{\frac{\partial h(\tau, e)}{\partial e}}_{\downarrow \text{as } \tau\uparrow \text{ if } h_{12}<0} \times \frac{b\, ln(1+\gamma_{i2j})}{c} \\
\frac{\partial e_{i2j}}{\partial \gamma} &= \pi \frac{\partial h(\tau, e)}{\partial e} \times \frac{b}{c} \times \frac{1}{1+\gamma} \\
\frac{\partial e_{i2j}}{\partial \tau} &= \pi \boldsymbol{h_{12}(\tau, e)} \times \frac{b\, ln(1+\gamma)}{c}
\end{aligned}$$

Firms solve (4.8) for incumbent ($\delta_{ij} = 1$) and new ($\delta_{ij} = 0$) employees, respectively. The first-order conditions for incumbent employees are:

$$\frac{\partial}{\partial \underline{w}} = \frac{\partial p_{2j}^{(1)}}{\partial \underline{w}} \times \left(MP_j - E_y[w_{2j}]\right) - p_{2j}^{(1)} \times (1 + \gamma \times \pi\, h(\tau, e))$$
$$= \lambda p_{2j} \times (1 - p_{2j}) \frac{b}{\underline{w}} \times \left(MP_j - \underline{w}(1 + \gamma \times \pi\, h(\tau, e))\right) - (1 - \lambda(1 - p_{2j})) \times (1 + \gamma \times \pi\, h(\tau, e)) =$$

$$\rightarrow \underline{w}_{2j}^{(1)}(\pi) = \frac{\xi_{2j}^{(1)}}{\xi_{2j}^{(1)} + 1} \frac{MP_j}{(1 + \gamma \times \pi\, h(\tau, e))} \text{ where elasticity } \boldsymbol{\xi_{2j}^{(1)} := \frac{\lambda p(1-p) \times b}{1 - \lambda(1-p)} = \frac{\lambda\, p(1-p) \times b}{p_{2j}^{(1)}}} \tag{7.3}$$

$$\text{and } MP_j - E_y[w_{2j}] = \frac{(1 + \gamma\pi\, h(\tau, e)) \times \underline{w}}{\xi_{2j}^{(1)}}$$

$$\frac{\partial}{\partial \gamma} = \frac{\partial p_{2j}^{(1)}}{\partial \gamma} \times \left(MP_j - E_y[w_{2j}]\right) - p_{2j}^{(1)} \times \left(\underline{w}\pi\, h(\tau, e) + \frac{\partial MP_j - E[w_{2j}]}{\partial e} \frac{\partial e}{\partial \gamma}\right)$$
$$= \lambda \left(\frac{\partial p_{2j}}{\partial \gamma} + \underbrace{\frac{\partial p_{2j}}{\partial e} \frac{\partial e}{\partial \gamma}}_{=0}\right) \times \left(MP_j - E_y[w_{2j}]\right) + p_{2j}^{(1)} \times \left(-\underline{w}\pi\, h(\tau, e) + \pi \frac{\partial h(\tau, e)}{\partial e} (f_j \theta - \gamma \underline{w}) \frac{\partial e}{\partial \gamma}\right)$$

$$0 = -\gamma\, \underline{w} h(\tau, e)\ (1 - \pi h(\tau, e)) + \left(f_j \theta - \gamma \underline{w}\right) \pi \left(\frac{\partial h(\tau, e)}{\partial e}\right)^2 \frac{b}{c} \tag{7.4}$$

$$\frac{\partial}{\partial \tau} = \frac{\partial p_{2j}^{(1)}}{\partial \tau} \times \left(MP_j - E_y[w_{2j}]\right) + p_{2j}^{(1)} \times \left(\frac{\partial MP_j - E[w_{2j}]}{\partial \tau} + \frac{\partial MP_j - E[w_{2j}]}{\partial e} \frac{\partial e}{\partial \tau}\right)$$
$$= \lambda \underbrace{\left(\frac{\partial p_{2j}}{\partial \tau} + \frac{\partial p_{2j}}{\partial e} \frac{\partial e}{\partial \tau}\right)}_{=0} \times \frac{(1 + \gamma\pi\, h(\tau, e)) \times \underline{w}}{\xi_{2j}^{(1)}} + p_{2j}^{(1)} \times \left(\pi \underbrace{\frac{\partial h(\tau, e)}{\partial \tau}}_{h_1} (f_j \theta - \gamma \underline{w}) - \zeta \tau + \frac{\partial MP_j -}{\ldots}\right.$$

$$\rightarrow \tau_{i2j}(\pi) = \frac{\pi\ \left(f_j \theta - \gamma \underline{w}\right)}{\zeta} \times \left(h_1 + \pi\, h_2\, \boldsymbol{h_{12}}\, \frac{b\ ln(1 + \gamma)}{c}\right) \tag{7.5}$$

**Optimization at $t = 1$**

At $t = 1$, workers take into account the option value at $t = 2$ if choosing a firm $j$, denoted by $\Omega_j$. The optimal effort she would choose at firm $j$, as shown in (4.5) given the contracts firms posted, satisfies:[22]

$$\begin{aligned}
e_{i1j} &= argmax_e \; \pi h(\tau_{i1j}, e) \times b\, ln(1+\gamma_{i1j}) - c(e) + \beta_W E_y[\Omega_j(\pi_{i2}) | \pi_{i1}, \tau_{i1j}, e] \\
&= \pi_{i1} \times \frac{\partial h(\tau_{i1j}, e)}{\partial e} \times \frac{\left(b\, ln(1+\gamma_{i1j}) \; + \beta_W \triangle_y \Omega_j\right)}{c} \qquad (7.6)\\
\rightarrow \frac{\partial e_{i1j}}{\partial \underline{w}_{1j}} &= 0 \\
\frac{\partial e_{i1j}}{\partial \gamma_{i1j}} &= \pi_{i1} h_2 \times \frac{b/c}{1+\gamma} \approx \frac{e_{i1j}}{\gamma_{i1j} + (1+\gamma_{i1j})\beta_W / b \times \triangle_y \Omega_j} \\
\frac{\partial e_{i1j}}{\partial \tau_{i1j}} &= \pi_{i1} h_{12} \times \frac{\left(b\, ln(1+\gamma_{i1j}) \; + \beta_W \triangle_y \Omega_j\right)}{c} = e_{i1j} \times \frac{h_{12}}{h_2}, < 0 \text{ if } h_{12} < 0
\end{aligned}$$

Firms solve (4.9). Let $EV2$ denote the expected continuation value from incumbent employees who stay at $t = 2$: $EV2 := E[v_{2j}^{(1)}(\pi_{i2}) | \pi_{i1}, \tau_{i1j}, e_{i1j}]$. The optimal contract set by firm $j$ at $t = 1$ satisfy: (ignoring $i$ for a worker in the subscripts):

$$\frac{\partial}{\partial \underline{w}} = \frac{\partial p_{1j}}{\partial \underline{w}} \times \left(MP_j(\pi_1) - \underline{w}\left(1 + \gamma \times \pi_1 h(\tau, e_{1j})\right) + \beta_J EV2\right) - p_{1j} \times (1 + \gamma \times \pi_1 h(\tau, e_{1j})) = 0$$

$$\rightarrow \underline{w}_{1j}(\pi) = \frac{b(1-p_{1j})}{\left(1 + b(1-p_{1j})\right) \times (1 + \gamma \times \pi_1 h(\tau, e_{1j}))} \times \left(f_j(1-\tau) + f_j \theta \pi_1 h(\tau, e_{1j}) - \frac{\zeta}{2}\tau^2 + \beta_J EV2\right) \qquad (7.7)$$

$$MP_j - E[w_{1j}] + \beta_J EV2 = \underline{w}_{1j} \times \frac{(1 + \gamma \times \pi_1 h(\tau, e_{1j}))}{b(1-p_{1j})}$$

$$\frac{\partial}{\partial \gamma} = \frac{\partial p_{1j}}{\partial \gamma} \times \left(MP_j - E[w_{1j}] + \beta_J EV2\right) + p_{1j} \times \left(-\underline{w} \times \pi_1 h(\tau, e_{1j}) + \frac{\partial (MP_j - E[w_{1j}] + EV2)}{\partial e} \times \frac{\partial e_{1j}}{\partial \gamma}\right) =$$

$$\text{where } \frac{\partial p_{1j}}{\partial \gamma} = \frac{\partial p_{1j}}{\partial \gamma} + \frac{\partial p_{1j}}{\partial e}\frac{\partial e}{\partial \gamma} = p_{1j}(1-p_{1j}) \times \left(\pi h(\tau, e)\frac{b}{1+\gamma} + 0 \times \frac{\partial e}{\partial \gamma}\right)$$

$$\rightarrow 0 = -\gamma \times \underline{w}\; h(\tau, e)\,(1 - \pi_1 h(\tau, e)) + \left(f_j \theta - \gamma \underline{w} + \beta_J \triangle_y v_{2j}^{(1)}\right) \times \frac{\pi\, b}{c}\,(h_2)^2 \qquad (7.8)$$

[22]Note worker effort $e$ is more elastic w.r.t. wage incentive $\gamma$ at $t = 2$ than $t = 1$: $\frac{\partial ln\, e_{i1j}}{\partial ln\, \gamma_{i1j}} < \frac{\partial ln\, e_{i2j}}{\partial ln\, \gamma_{i2j}} \approx 1$. In the first period, workers are motivated by an increase in their option values if they successfully innovate.

$$\frac{\partial}{\partial \tau} = \frac{\partial p_{1j}}{\partial \tau} \times \left(MP_j - E[w_{1j}] + \beta_J EV2\right) + p_{1j} \times \left(\frac{\partial(MP_j - E[w_{1j}] + EV2)}{\partial \tau} + \frac{\partial(MP_j - E[w_{1j}] + EV}{\partial e}\right.$$

$$\text{where } \frac{\partial p_{1j}}{\partial \tau} = p_{1j}(1 - p_{1j}) \times \left(\frac{\partial u_{1j}}{\partial \tau} + 0 \times \frac{\partial e}{\partial \tau}\right) = p_{1j}(1 - p_{1j}) \times \pi h_1 \left(b\, ln(1+\gamma) + \beta_W \triangle \Omega_j\right)$$

$$\rightarrow \tau_{1j}(\pi) = \frac{\pi}{\zeta} \times \left[\left(f_j\theta + \beta_J \triangle v_{2j}^{(1)} - \gamma \underline{w}\right)(h_1 + e h_{12}) + \underline{w}\,(1 + \gamma\,\pi h) h_1 \left(ln(1+\gamma) + \frac{\beta_W \triangle \Omega_j}{b}\right)\right] \tag{7.9}$$

## A2. Proof of Propositions

### Proof of Proposition 1: Base Wages Increasing in Firm Productivity

**Proof (sketch):**
From 7.3 and 7.7, we can see the base wages set by firms in equilibrium are strictly increasing in productivity $f_j$, as the expected marginal revenue product of labor $MP_j$ increases faster in productivity $f_j$ than equilibrium $\gamma$ or the inverse of labor supply elasticity.

### Proof of Proposition 2: Heterogeneity in Firm Investment on Innovation

**Proof (sketch):**
In an imperfectly competitive labor market, we have $f_j\theta - \gamma\underline{w}$ to be increasing in firm productivity $f_j$. The optimal investment on innovation at $t = 2$ is shown in (7.5), and it is increasing in $f_j$ under the assumption that $h_1 + h_2\frac{\partial e}{\partial \tau} = h_1 + \pi h_2\, h_{12}\frac{b\, ln(1+\gamma)}{c} > 0$. Similarly, (7.9) shows the optimal investment at $t = 1$, in which we have the each component to be increasing in $f_j$.

### Proof of Proposition 3: Heterogeneity in Wage Returns to Innovation

***(a)***
From (7.8), we have

$$\gamma_{1j}(\pi) = \frac{\pi b}{c} \times \frac{\left(f_j\theta + \beta_J \triangle_y v_{2j}^{(1)}\right)}{\underline{w}} \times \frac{(h_2)^2}{h - \pi h^2 + \frac{\pi b}{c}\,(h_2)^2} \tag{7.10}$$

$$\frac{\partial \gamma_{1j}}{\partial \lambda} \propto \beta_J \frac{\partial}{\partial \lambda}\left(\frac{\triangle_y v_{2j}^{(1)}}{\underline{w}_{1j}}\right) < 0 \tag{7.11}$$

$$\text{note } \frac{\partial \triangle_y v_{2j}^{(1)}}{\partial \lambda} = -\triangle_y \left[(1-p_{2j})\left(MP_j - E[w_{2j}]\right)\right]$$

***(b)***

From the FOC at $t = 1$ w.r.t. $\gamma$ (7.8), we have:

$$\begin{aligned}
\frac{\partial ln(\gamma_{1j})}{\partial f_j} &= \frac{\partial\, ln\left(\frac{f_j\theta + \beta_J \triangle_y v_{2j}^{(1)}}{\underline{w}}\right)}{\partial f_j} + \frac{\partial}{\partial f_j} ln\left(\frac{(h_2)^2}{h - \pi h^2 + \frac{\pi b}{c}(h_2)^2}\right) \\
&= \frac{\partial\, \mathbf{ln}\left(\frac{\mathbf{f_j}\theta + \beta_\mathbf{J} \triangle_\mathbf{y} \mathbf{v}_{\mathbf{2j}}^{(\mathbf{1})}}{\underline{\mathbf{w}}}\right)}{\partial \mathbf{f_j}} - \underbrace{\frac{\partial \tau_{1j}}{\partial f_j}}_{>0 \text{ Prop } 2} \times \frac{2\left(h_{12} + h_{22}\frac{\partial e}{\partial \tau}\right)\frac{(h-\pi h^2)}{h_2} - \left((1-2\pi h)\left(h_1 + h_2 \frac{\partial e}{\partial \tau}\right)\right)}{h - \pi h^2 + \frac{\pi b}{c}(h_2)^2}
\end{aligned} \tag{7.12}$$

We have $\frac{\partial \gamma_{1j}}{\partial f_j} < 0$ iff

$$\frac{\partial\, \mathbf{ln}\left(\frac{\mathbf{f_j}\theta + \beta_\mathbf{J} \triangle_\mathbf{y} \mathbf{v}_{\mathbf{2j}}^{(\mathbf{1})}}{\underline{\mathbf{w}}}\right)}{\partial \mathbf{f_j}} < \frac{\partial \tau}{\partial f_j} \times \frac{-2\left(h_{12} + h_{22}\frac{\partial e}{\partial \tau}\right)\frac{(h-\pi h^2)}{h_2} + \left((1-2\pi h)\left(h_1 + h_2 \frac{\partial e}{\partial \tau}\right)\right)}{h - \pi h^2 + \frac{\pi b}{c}(h_2)^2}$$

***(c)***

From a firm's FOC w.r.t. $\gamma$ at $t = 2$ (7.4), we have:

$$\gamma_{2j} = \frac{\pi b \theta}{c} \times \frac{f_j}{\underline{w}} \times \frac{(h_2)^2}{h - \pi h^2 + \frac{\pi b}{c}(h_2)^2} \tag{7.13}$$

When $\lambda \uparrow$, the only object that varies on the RHS is $\underline{w}$, which increases according to (7.3). Hence we have:

$$\frac{\partial \gamma_{2j}}{\partial \lambda} < 0 \tag{7.14}$$

***(d)***

Differentiating both sides of (7.4) over firm productivity $f_j$, we have:

$$\frac{\partial ln(\gamma_{2j})}{\partial f_j} = \frac{\partial\, ln\left(\frac{f_j}{\underline{w}}\right)}{\partial f_j} + \frac{\partial}{\partial f_j} ln\left(\frac{(h_2)^2}{h - \pi h^2 + \frac{\pi b}{c}(h_2)^2}\right) \tag{7.15}$$
$$= \frac{1}{f_j} - \frac{\partial ln(\underline{w}_{2j})}{\partial f_j} - \underbrace{\frac{\partial \tau_{2j}}{\partial f_j}}_{>0 \text{ Prop } 2} \times \frac{2\left(h_{12} + h_{22}\frac{\partial e}{\partial \tau}\right)\frac{(h-\pi h^2)}{h_2} - \left((1-2\pi h)\left(h_1 + h_2\frac{\partial e}{\partial \tau}\right)\right)}{h - \pi h^2 + \frac{\pi b}{c}(h_2)^2}$$

$$\frac{\partial \gamma_{2j}}{\partial f_j} \propto \underbrace{\frac{\partial (f_j/\underline{w})}{\partial f_j}}_{>\mathbf{0}} \times \left(\frac{(h_2)^2}{h - \pi h^2 + \frac{\pi b}{c}(h_2)^2}\right) + \frac{f_j}{\underline{w}} \times \underbrace{\left[\frac{\partial}{\partial \tau} + \frac{\partial}{\partial e} \times \frac{\partial e}{\partial \tau}\right]}_{(***)} \times \frac{\partial \tau}{\partial f_j} \tag{7.16}$$

Hence we have:

$$\frac{\partial ln\gamma_{2j}}{\partial f_j} < 0 \iff \underbrace{\frac{\partial}{\partial f_j} ln(f_j/\underline{w})}_{=\frac{1}{f_j} - \frac{\partial ln w}{\partial f_j}} < \frac{\partial}{\partial \tau} ln\left(\frac{h - \pi h^2 + \frac{\pi b}{c}(h_2)^2}{(h_2)^2}\right) \times \frac{\partial \tau_{2j}}{\partial f_j} \tag{7.17}$$

The condition is satisfied when $(\tau, e)$ are substitutes with $h_{12} \ll 0$, in which case

- High-$f_j$ firms are setting lower $\gamma$ to avoid excessive efforts from workers (diminishing return to effort as $h_{12} < 0$).
- Low-$f_j$ firms on the other hand set lower $\tau$ but higher $\gamma$ to elicit more efforts from workers, whose $h_2$ are higher when $\tau$ is low.

## Appendix B: Additional Empirical Results

Appendix Table B1: Poisson Regressions of Ever Inventing

| | Full Sample | |
|---|---|---|
| | (1) | (2) |
| **Demographics** | | |
| Female | -1.29809 | -1.22436 |
| | (0.00849) | (0.00857) |
| Age (normalized at 35) | -1.18215 | -0.49511 |
| | (0.06283) | (0.06022) |
| $Age^2$, $Age^3$ | X | X |
| **Job Characteristics** | | |
| Tenure | 0.16152 | 0.26883 |
| | (0.03540) | (0.03514) |
| $Tenure^2$, $Tenure^3$ | X | X |
| Blue Collar | -0.49502 | -0.80953 |
| | (0.03692) | (0.04304) |
| White Collar | 1.25696 | 1.10266 |
| | (0.04116) | (0.04033) |
| Blue/White × Age | X | X |
| Permanent Contract | 0.45127 | 0.05251 |
| | (0.03263) | (0.03210) |
| Temporary Contract | 0.03128 | 0.01116 |
| | (0.02861) | (0.02793) ) |
| Seasonal Contract | -1.58927 | -1.19540 |
| | (0.29588) | (0.34350) |
| Contract Type × Age | X | X |
| **INPS Sample (1987-2009)** | | |
| Min(Yr \| INPS)=1987 | -0.17688 | -0.15301 |
| | (0.00974) | (0.00946) |
| Min(Age \| INPS) | 0.66709 | 0.50071 |
| | (0.00971) | (0.00966) |
| (Min(Yr)=1987) × Min(Age) | 0.02812 | 0.01559 |
| | (0.00834) | (0.00809) |
| Constant | -4.74880 | -3.51388 |
| | (0.04737) | (0.04647) |
| **Fixed Effects** | | |
| Year | X | X |
| Industry and Region | X | |
| Firm | | X |
| N | 1.25e+07 | 8,434,000 |
| Pseudo R2 | 0.10132 | 0.22189 |

Notes: This table shows the estimated Poisson regression (2.1) of $Inv_i = 1$ if person $i$ has any patent application and she is matched to INPS. About 1.5 million workers: have ≥ 5 years of employment in the INPS data between 1987 and 2009, entered the sample between age 14 and age 55, and have worked in more white-collar than blue-collar jobs (see summary statistics in Column 1 of Table 1). The estimation sample is at the person × year level. We use the estimated p-scores from column (2) conditional on firm fixed effects to select potential inventors (Section 2.2).

Appendix Table B2: Firm Characteristics by Quartile of Coworker Wages, Restricted to Firms Matched to INVIND

| | Quartile 1 | | Quartile 2 | | Quartile 3 | | Quartile 4 | |
|---|---|---|---|---|---|---|---|---|
| | mean | sd | mean | sd | mean | sd | mean | sd |
| **Num. Unique Firms** | 796 | | 767 | | 732 | | 741 | |
| Log Wage | 7.797 | 0.262 | 7.848 | 0.208 | 7.907 | 0.202 | 7.967 | 0.238 |
| Num. Potential Inventors | 65.619 | 290.740 | 112.765 | 423.677 | 121.525 | 377.785 | 94.394 | 332.056 |
| Age of Employees | 37.638 | 3.676 | 38.143 | 3.199 | 38.604 | 3.054 | 39.026 | 3.324 |
| Age of Employees When Applying for a Patent | 43.092 | 6.968 | 43.072 | 6.295 | 43.533 | 6.150 | 43.959 | 6.319 |
| **Patent Applications (per worker-year)** | | | | | | | | |
| Num. Patent Apps | 0.040 | 0.077 | 0.041 | 0.065 | 0.044 | 0.072 | 0.046 | 0.080 |
| Num. Patent Apps, Age<=35 | 0.021 | 0.092 | 0.021 | 0.062 | 0.023 | 0.064 | 0.024 | 0.097 |
| Num. Patent Apps, Age>35 | 0.056 | 0.119 | 0.057 | 0.095 | 0.058 | 0.100 | 0.061 | 0.117 |
| Any Patent App | 0.024 | 0.036 | 0.025 | 0.030 | 0.025 | 0.033 | 0.026 | 0.036 |
| Any Patent App, Age<=35 | 0.013 | 0.046 | 0.013 | 0.029 | 0.014 | 0.030 | 0.014 | 0.046 |
| Any Patent App, Age>35 | 0.033 | 0.056 | 0.033 | 0.045 | 0.033 | 0.046 | 0.035 | 0.052 |
| **Industry (grouped by csc code):** | | | | | | | | |
| Electronics/Telecom | 0.117 | 0.321 | 0.126 | 0.332 | 0.142 | 0.350 | 0.097 | 0.296 |
| Pharmaceutical | 0.031 | 0.173 | 0.057 | 0.232 | 0.073 | 0.260 | 0.083 | 0.276 |
| Automobile | 0.053 | 0.223 | 0.078 | 0.268 | 0.063 | 0.243 | 0.050 | 0.219 |
| Other Manufacturing | 0.512 | 0.500 | 0.535 | 0.499 | 0.466 | 0.499 | 0.499 | 0.500 |
| Services and Others | 0.287 | 0.453 | 0.203 | 0.403 | 0.255 | 0.436 | 0.271 | 0.444 |
| **Characteristics from INVIND:** | | | | | | | | |
| Revenue (in thousands) | 132 | 419 | 190 | 739 | 288 | 1,560 | 274 | 1,542 |
| Num. Employees | 695 | 5,428 | 711 | 2,092 | 888 | 3,108 | 812 | 3,025 |
| Num. White-collar Employees | 201 | 451 | 281 | 589 | 484 | 2,592 | 455 | 2,594 |
| Num. Blue-collar Employees | 296 | 502 | 404 | 1,437 | 480 | 1,665 | 442 | 1,617 |
| Investment on Machinery | 4891.837 | 18195.751 | 6635.252 | 28080.389 | 12693.249 | 134746.087 | 12231.338 | 133354.893 |
| Investment on Material | 144.780 | 464.780 | 296.684 | 3102.310 | 320.908 | 3150.547 | 309.891 | 3116.939 |
| Investment on Immaterial | 662.042 | 4900.004 | 1706.398 | 18997.465 | 2482.956 | 22626.553 | 2062.077 | 19192.780 |
| Investment on Housing | 915.557 | 4312.087 | 900.268 | 3907.318 | 1174.762 | 5736.162 | 1123.742 | 5706.287 |
| Investment on R&D | 1818.462 | 14984.238 | 4645.302 | 36650.753 | 4961.548 | 35389.903 | 4576.242 | 34768.882 |

Notes: This table is restricted to firms that are matched to INVIND by fiscal code or by firm name, and displays the mean characteristics of firms (to be compared to those shown in Table 2).

Appendix Table B3: First Patent Application at the Current Employer, by Quartile of Firms and Age Group

| | First Patent Application at the Current Employer | | | | | |
|---|---|---|---|---|---|---|
| | Age ≤ 35 | | | Age > 35 | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Quartile of Mean Wage | | | | | | |
| quartile 1 | -0.4228*** | -0.2131*** | 0.1361 | -0.0640 | -0.0963** | 0.0034 |
| | (0.0439) | (0.0382) | (0.1574) | (0.0453) | (0.0385) | (0.0670) |
| quartile 2 | -0.1260*** | -0.1734*** | 0.2363** | -0.1047*** | -0.0931*** | 0.2169*** |
| | (0.0403) | (0.0364) | (0.1184) | (0.0386) | (0.0339) | (0.0501) |
| quartile 3 | 0.1028*** | -0.1179*** | 0.2093* | -0.0484 | -0.0839** | 0.2423*** |
| | (0.0391) | (0.0372) | (0.1170) | (0.0372) | (0.0337) | (0.0452) |
| quartile 4 | 0 | 0 | 0 | 0 | 0 | 0 |
| | (.) | (.) | (.) | (.) | (.) | (.) |
| Mean \|quartile 4 | .0103621 | .1264715 | .0707749 | .0071 | .1620197 | .0734755 |
| N | 644238 | 52843 | 5869 | 744670 | 34735 | 33170 |
| Pseudo $R^2$ | .0659837 | .1086511 | .08996 | .0399946 | .0729018 | .0836694 |

Notes: This table shows the estimated Poisson regression (3.1) of whether a worker files her first patent application at her current employer on the quartile of her employer, ranked by mean coworker wages (excluding her wage) in a year. The estimation sample is at the person × year level, including the years until each worker's first patent application at the current employer. All regressions control for sex, a cubic polynomial in age (relative to age 35), indicators for white/blue collar and permanent/temporary contract interacted with age, and fixed effects of the calendar year, 2-digit industry, and geographic region. Models (1) and (4) are estimated on potential inventors who have not applied for patents before. (2) and (5) are restricted to matched inventors who have not applied for patents yet but will do so during the sample period. (3) and (6) are restricted to experienced inventors, who have already applied for patents at former employers. Significance: * 0.10 ** 0.05 *** 0.010.

Appendix Table B4: First Patent Application by Younger Potential Inventors, by Industry

| | First Patent Application at the Current Employer | | | | |
|---|---|---|---|---|---|
| | (1) Electronics | (2) Pharma | (3) Auto | (4) Oth Manufact. | (5) Services |
| Quartile of Coworker Mean Wage | | | | | |
| quartile 1 | 0.0677 | -0.3528** | 0.1187 | -0.6426*** | -0.1225 |
| | (0.0729) | (0.1527) | (0.1759) | (0.0774) | (0.1087) |
| quartile 2 | 0.0846 | -0.0712 | 0.2397 | -0.0603 | 0.4115*** |
| | (0.0861) | (0.1163) | (0.1520) | (0.0662) | (0.1039) |
| quartile 3 | -0.1062 | -0.1335 | 0.5462*** | 0.0962 | 0.9114*** |
| | (0.1055) | (0.1077) | (0.1565) | (0.0671) | (0.0899) |
| quartile 4 | 0 | 0 | 0 | 0 | 0 |
| | (.) | (.) | (.) | (.) | (.) |
| Mean \|quartile 4 | .0138093 | .0107692 | .0103342 | .0083069 | .0057378 |
| N | 124095 | 59791 | 66472 | 244943 | 146877 |
| Pseudo $R^2$ | .0540683 | .0848628 | .0815984 | .0506165 | .1004004 |

Notes: This table shows the estimated Poisson regression (3.1) of whether a worker files her first patent application at her current employer on the quartile of her employer, ranked by mean coworker wages (excluding her wage) in a year. We fit separate regressions for younger potential inventors in each industry, which are grouped by csc code in the INPS data. "Other Manufacturing" includes manufacturing industries that are not in electronics, pharmaceutical or automobile. See notes under Table 3 for additional details on the regressions. Significance: * 0.10 ** 0.05 *** 0.010.

Appendix Table B5: Wage Returns to New Patent Application, by Quartile of Firms and Age Group

| | Log Annual Wages | | | | | |
|---|---|---|---|---|---|---|
| | Age ≤ 35 | | | Age > 35 | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Quartile of Coworker Mean Wage | | | | | | |
| quartile 1 | -0.2228*** | -0.1450*** | -0.1796*** | -0.3667*** | -0.1918*** | -0.3275*** |
| | (0.0013) | (0.0043) | (0.0128) | (0.0019) | (0.0082) | (0.0084) |
| quartile 2 | -0.1225*** | -0.0697*** | -0.1143*** | -0.2597*** | -0.1296*** | -0.2209*** |
| | (0.0012) | (0.0040) | (0.0113) | (0.0016) | (0.0074) | (0.0079) |
| quartile 3 | -0.0794*** | -0.0517*** | -0.0926*** | -0.1817*** | -0.0869*** | -0.1803*** |
| | (0.0013) | (0.0040) | (0.0105) | (0.0016) | (0.0073) | (0.0075) |
| quartile 4 | 0 | 0 | 0 | 0 | 0 | 0 |
| | (.) | (.) | (.) | (.) | (.) | (.) |
| Any New Patent Application | | | | | | |
| $y_{it}$ | 0.0160** | 0.0270*** | 0.0372 | 0.0592*** | 0.0076 | -0.0160 |
| | (0.0079) | (0.0083) | (0.0253) | (0.0128) | (0.0137) | (0.0178) |
| Excess Returns (relative to quartile 4) | | | | | | |
| $y_{it}\times$ quartile 1 | 0.1348*** | 0.0518*** | 0.0426 | 0.1958*** | 0.0232 | 0.1411*** |
| | (0.0102) | (0.0107) | (0.0419) | (0.0193) | (0.0203) | (0.0304) |
| $y_{it}\times$ quartile 2 | 0.0760*** | 0.0107 | 0.0053 | 0.1561*** | 0.0451** | 0.1107*** |
| | (0.0104) | (0.0107) | (0.0343) | (0.0170) | (0.0180) | (0.0260) |
| $y_{it}\times$ quartile 3 | 0.0584*** | 0.0114 | -0.0190 | 0.0474*** | -0.0098 | 0.0159 |
| | (0.0100) | (0.0104) | (0.0320) | (0.0165) | (0.0174) | (0.0231) |
| Mean \|quartile 4 | 7.6783 | 7.626333 | 7.877535 | 8.22946 | 8.212372 | 8.486808 |
| N | 649892 | 53108 | 6300 | 746369 | 34750 | 33402 |
| Adjusted $R^2$ | .4125289 | .4444977 | .3205998 | .1985601 | .2018522 | .2287792 |

Notes: This table shows the estimated OLS regression (3.2) of log annual wages on whether a worker applies for a new patent and its interactions with the quartile of her current employer, ranked by mean coworker wages (excluding own wage) in a year. The estimation sample is at the person × year level. All models control for the covariates listed under Table 3, including year/region/2-digit ateco (industry) fixed effects, but no person effects as in Table 4. Models (1) and (4) are estimated on all potential inventors. (2) and (5) are restricted to matched inventors, and (3) and (6) are restricted to experienced inventors, who have already applied for patents at former employers. Significance: * 0.10 ** 0.05 *** 0.010.

Appendix Table B6: Wage Returns to New Patent Application, by Lagged Quartile of Firms and Age Group

| | Log Annual Wages | | | | | |
|---|---|---|---|---|---|---|
| | Age ≤ 35 | | | Age > 35 | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Lagged Quartile of Mean Wage | | | | | | |
| quartile 1 | -0.1177*** | -0.0756*** | -0.0496*** | -0.0981*** | -0.0653*** | -0.0920*** |
| | (0.0016) | (0.0054) | (0.0139) | (0.0014) | (0.0054) | (0.0064) |
| quartile 2 | -0.0692*** | -0.0306*** | -0.0315*** | -0.0605*** | -0.0339*** | -0.0447*** |
| | (0.0014) | (0.0044) | (0.0120) | (0.0011) | (0.0041) | (0.0050) |
| quartile 3 | -0.0467*** | -0.0158*** | -0.0130 | -0.0383*** | -0.0164*** | -0.0170*** |
| | (0.0013) | (0.0040) | (0.0095) | (0.0010) | (0.0038) | (0.0042) |
| quartile 4 | 0 | 0 | 0 | 0 | 0 | 0 |
| | (.) | (.) | (.) | (.) | (.) | (.) |
| Any New Patent Application | | | | | | |
| $y_{it}$ | 0.0360*** | 0.0310*** | 0.0462** | 0.0294*** | 0.0085 | 0.0054 |
| | (0.0063) | (0.0068) | (0.0224) | (0.0049) | (0.0052) | (0.0086) |
| Excess Returns (relative to quartile 4) | | | | | | |
| $y_{it}\times$ quartile 1 | 0.0418*** | 0.0247*** | -0.0726* | 0.0264*** | 0.0167* | 0.0043 |
| | (0.0086) | (0.0088) | (0.0435) | (0.0085) | (0.0087) | (0.0179) |
| $y_{it}\times$ quartile 2 | 0.0166** | -0.0076 | -0.0481 | 0.0106 | 0.0021 | 0.0109 |
| | (0.0080) | (0.0083) | (0.0301) | (0.0069) | (0.0070) | (0.0130) |
| $y_{it}\times$ quartile 3 | 0.0094 | -0.0093 | -0.0209 | -0.0056 | -0.0118* | -0.0094 |
| | (0.0080) | (0.0085) | (0.0294) | (0.0065) | (0.0067) | (0.0117) |
| Mean \|quartile 4 | 7.721059 | 7.66655 | 7.890526 | 8.260885 | 8.249698 | 8.519439 |
| N | 600776 | 47589 | 4847 | 706316 | 31590 | 29095 |
| Adjusted $R^2$ | .7159351 | .753993 | .8123083 | .8689091 | .9072654 | .8800531 |

Notes: This table shows the estimated OLS regression (3.2) of log annual wages on whether a worker applies for a new patent and its interactions with the quartile of her current employer, ranked by mean coworker wages (excluding own wage) in a year. The estimation sample is at the person × year level. All models control for the covariates listed under Table 3, including year/region/2-digit ateco (industry) fixed effects, but no person effects as in Table 4. Models (1) and (4) are estimated on all potential inventors. (2) and (5) are restricted to matched inventors, and (3) and (6) are restricted to experienced inventors, who have already applied for patents at former employers. Significance: * 0.10 ** 0.05 *** 0.010.

Appendix Table B7: Between-Firm Job Mobility in 3 Years, by Quartile of Firms and Age Group

| | Move in 3 Years: $j(i,t+3) \neq j(i,t)$ | | | | | |
|---|---|---|---|---|---|---|
| | Age ≤ 35 | | | Age > 35 | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Quartile of Coworker Mean Wage | | | | | | |
| quartile 1 | -0.1126*** | 0.1286*** | -0.2028*** | -0.1020*** | -0.0057 | -0.0687** |
| | (0.0057) | (0.0276) | (0.0564) | (0.0074) | (0.0425) | (0.0322) |
| quartile 2 | -0.1644*** | -0.1207*** | 0.0161 | -0.1517*** | -0.1212*** | 0.0056 |
| | (0.0060) | (0.0305) | (0.0509) | (0.0069) | (0.0441) | (0.0303) |
| quartile 3 | -0.0882*** | -0.1159*** | -0.0069 | -0.1313*** | -0.2031*** | -0.0504* |
| | (0.0060) | (0.0312) | (0.0511) | (0.0067) | (0.0448) | (0.0287) |
| (base) quartile 4 | 0 | 0 | 0 | 0 | 0 | 0 |
| | (.) | (.) | (.) | (.) | (.) | (.) |
| Any New Patent Application | | | | | | |
| $y_{it}$ | -0.7363*** | -0.1297* | -0.3459*** | -1.2551*** | -0.5314*** | -0.6719*** |
| | (0.0705) | (0.0738) | (0.0798) | (0.0956) | (0.0998) | (0.0558) |
| Additional Effects (relative to quartile 4) | | | | | | |
| $y_{it}\times$ quartile 1 | -0.2259** | -0.4978*** | -0.1903 | 0.2564* | -0.0031 | -0.1387 |
| | (0.1018) | (0.1052) | (0.1201) | (0.1408) | (0.1465) | (0.0950) |
| $y_{it}\times$ quartile 2 | 0.2215** | 0.1790* | -0.0082 | 0.3814*** | 0.3087** | 0.2371*** |
| | (0.0940) | (0.0983) | (0.1160) | (0.1319) | (0.1377) | (0.0801) |
| $y_{it}\times$ quartile 3 | 0.0226 | 0.1308 | 0.1629 | 0.1592 | 0.3231** | 0.2825*** |
| | (0.0960) | (0.1005) | (0.1083) | (0.1332) | (0.1395) | (0.0760) |
| Mean \|quartile 4 | .348879 | .1983226 | .1758764 | .2680996 | .1389503 | .1241034 |
| N | 588284 | 52714 | 21648 | 532345 | 33837 | 81894 |
| Pseudo $R^2$ | .0325828 | .0551437 | .0292374 | .0272774 | .03805 | .0320218 |

Notes: This table shows the estimated Poisson regression (3.3) of any movement between firms in 3 years ($j(i,t+3) \neq j(i,t)$) on whether a worker applies for a new patent and its interactions with the quartile of her current employer, ranked by mean coworker wages (excluding own wage) in a year. The estimation sample is at the person × year level. Models (1) and (4) are estimated on all potential inventors. (2) and (5) are restricted to matched inventors, and (3) and (6) are restricted to experienced inventors, who have already applied for patents at former employers. Significance: * 0.10 ** 0.05 *** 0.010.

Appendix Table B8: Upward Mobility in 3 Years, by Quartile of Firms and Age Group

| | Upward Move in 3 Years | | | | | |
|---|---|---|---|---|---|---|
| | Age ≤ 35 | | | Age > 35 | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Quartile of Coworker Mean Wage | | | | | | |
| quartile 1 | 0.5234*** | 0.9021*** | 0.2748*** | 0.3102*** | 0.4395*** | 0.2741*** |
| | (0.0097) | (0.0451) | (0.0839) | (0.0110) | (0.0618) | (0.0479) |
| quartile 2 | 0.1080*** | 0.1705*** | 0.1699** | -0.1247*** | -0.0179 | 0.1444*** |
| | (0.0105) | (0.0515) | (0.0796) | (0.0110) | (0.0694) | (0.0464) |
| quartile 3 | -0.3338*** | -0.5742*** | -0.3914*** | -0.5275*** | -0.6068*** | -0.3411*** |
| | (0.0121) | (0.0636) | (0.0930) | (0.0124) | (0.0822) | (0.0497) |
| (base) quartile 4 | 0 | 0 | 0 | 0 | 0 | 0 |
| | (.) | (.) | (.) | (.) | (.) | (.) |
| Any New Patent Application | | | | | | |
| $y_{it}$ | -0.7775*** | -0.1119 | -0.6006*** | -1.2580*** | -0.3970*** | -0.8307*** |
| | (0.1210) | (0.1264) | (0.1359) | (0.1446) | (0.1520) | (0.0914) |
| Additional Effects (relative to quartile 4) | | | | | | |
| $y_{it}\times$ quartile 1 | -0.1547 | -0.5008*** | 0.1048 | -0.1443 | -0.4514** | 0.0772 |
| | (0.1527) | (0.1590) | (0.1782) | (0.2195) | (0.2291) | (0.1366) |
| $y_{it}\times$ quartile 2 | 0.2864* | 0.2776* | 0.2795 | 0.4102** | 0.2869 | 0.4336*** |
| | (0.1531) | (0.1609) | (0.1834) | (0.1998) | (0.2102) | (0.1234) |
| $y_{it}\times$ quartile 3 | -0.0593 | 0.2620 | 0.3361* | 0.2454 | 0.4311* | 0.4316*** |
| | (0.1817) | (0.1913) | (0.1995) | (0.2211) | (0.2342) | (0.1303) |
| Mean \|quartile 4 | .1402386 | .0739971 | .0789845 | .1315743 | .0610061 | .0548166 |
| N | 567938 | 51977 | 21333 | 518716 | 33287 | 80667 |
| Pseudo $R^2$ | .0506328 | .0954508 | .038297 | .0412972 | .064989 | .0378604 |

Notes: This table shows the estimated Poisson regression (3.3) of upward mobility in 3 years ($Q(j(i,t+3)) > Q(i,t)$ or $Q(j(i,t+3)) = Q(i,t) = 4$) on whether a worker applies for a new patent and its interactions with the quartile of her current employer, ranked by mean coworker wages (excluding own wage) in a year. The estimation sample is at the person × year level. Models (1) and (4) are estimated on all potential inventors. (2) and (5) are restricted to matched inventors, and (3) and (6) are restricted to experienced inventors, who have already applied for patents at former employers. Significance: * 0.10 ** 0.05 *** 0.010.