Labor Mobility, Human Capital Investment, and Technological Change*

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Firms actively use investment types (general vs. firm-specific) to affect their labor hiring and retention process, which, in turn, has implications on innovation and technological change in the economy. We develop a model in which workers accumulate both portable general and non-portable firm-specific human capital through working on R&D projects assigned by the firm. Firms choose the scope their innovation activities by balancing the benefit of increased asset redeployability and the increased employee retention cost. We estimate the model using granular innovation production and mobility data of three million inventors. Our model closely matches the observed mobility and innovation specificity over inventors' life cycle. Empirical estimates of the model parameters imply that 37% of observed innovation specificity among U.S. firms is driven by their labor market considerations, which enhances the firm value but lowers the inventors' surplus.

Keywords: Human Capital, Labor Mobility, Innovation, Inventors

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1. Introduction

Human capital is key for modern firms. Firms rely on human capital for their innovation and production (i.e., using human capital); while during production and innovation, human capital is further accrued to the employees through on-the-job learning (i.e., creating human capital). A key feature in the human capital-firm relation is the inalienability of human capital (Hart and Moore, 1994). That is, firms do not have full control of the employees and their human capital—even those that were accrued within the firm through the firm's own investment—and those employees and human capital could leave the firm.

Firms thus face an interesting trade-off when making investments: on the one hand, they benefit from investment and human capital accumulation; on the other hand, when making investment decisions, firms should take into account their potential separations with labor, the loss of human capital, and the replacement cost. The latter cost is particularly salient for human capital that is more specific to the firms (Becker, 1962; Hashimoto, 1981; Lazear, 2009), in which case the separation will be more costly.

How should firms match investment types and labor, accounting for these forces? How does this affect the path of human capital accumulation of workers and of the economy? What kind of policy interventions may impact firm investment and human capital accumulation?

In this paper, we tackle these questions by developing and estimating a dynamic model wherein firms hire inventors to perform innovative activities. Importantly, firms can influence the scope of their innovative activities—they can either engage the inventor to produce knowledge specifically tied to the firm, or they can choose to research subjects with more general applications. The investment decisions factor in classic economic forces such as heterogeneous risk and return profiles associated with different innovation projects, as modeled in Akcigit and Kerr (2018).

The key economic mechanism operates through firms' interaction with inventors and the competition from the labor market. On the one hand, when a firm engages in specific innovation, such investments and the resulting knowledge capital accumulated will become less redeployable, which increases the cost in the event of an employee turnover. On the other hand, as a firm directs its innovation to be more general, it enables the inventor to accumulate knowledge that he can use equally productively in other firms, thereby increasing the value of his outside option. As a result, the inventor is more likely to be poached by other competitors in the labor market, and the firm also needs to concede more rent to the inventor to fend off the increased labor market competition.

Importantly, the cost and benefit associated with specific innovation are state-dependent and vary significantly with an inventor's life(tenure) cycle. When a firm first hires an inventor, there exists larger uncertainty regarding the quality of the new hire and whether he is well suited to the specific position and task, thereby making retaining flexibility a first-order concern for the firm. As the inventor's tenure increases, the uncertainty resolves, and he accumulates human capital. Meanwhile, he is likely to be poached by outside firms, in which case he might choose to switch employment or use such outside options to bargain with the current firm to increase his rent. At this point, retaining valuable employees and bargaining efficiently with them become firms' primary concerns. As firms shift their focus, they also tilt their innovation toward a more specific spectrum, facilitating their retention and bargaining decisions.

We estimate the model using granular data on corporate patenting activities and inventors. This setting is useful for both its economic importance and empirical properties. First, inventors are a key set of high human capital labor that have long-term impact on the economy through their patenting activities. Second, for empirical analysis, we can track inventor mobility, output, and the generality/specificity of the output patents, allowing us to map to the theoretical model closely.

Our model matches key patterns observed in the data regarding firms' innovative activities, outputs, and inventor mobility. To further validate the model and highlight the key mechanisms at work, we examine the life cycle patterns of inventor mobility and innovation specificity. These conditional moments are not directly targeted in our estimation procedure. First, we document that inventors' mobility exhibits a hump-shaped pattern. When an inventor is newly hired by a firm, the likelihood of a turnover will stay low initially and keep increasing for the first few years. The turnover probability will peak among inventors with medium tenure, followed by a monotonic decline as inventors' tenure increases. Second, as inventors' tenure increases, the scope of their innovation also becomes increasingly firm-specific.

These patterns are present both in our simulated panel and the actual data.

Using the estimated model as a laboratory, we examine the degree to which innovation specificity can influence the value of the firm and the surplus accrues to inventors. To this end, we perform a sequence of counterfactual analyses by comparing our baseline model predictions to cases when the inventors' specificity is reduced exogenously. Our results suggest that lowering the innovation specificity by half will lead to a 17% increase in workers' surplus, while firms' surplus will decline, but by a smaller extent. The results imply that the firm is choosing an innovation scope that is too narrower, the helps the firm to establish better bargaining positions with employees at the expense of a lower joint surplus.

This paper connects to the recent literature on labor mobility and firm investments. Empirical explorations in this literature often use changes in the enforceability of non-compete agreements. For example, Jeffers (2019) finds that increases in the enforceability of such agreements lead established firms relying more on knowledge-intensive occupations to increase their investment rate. The contribution of our paper is two-fold. First, we deviate from the reduced-form approach and build a structural model that can help us estimate important economic parameters and consider counterfactual economic scenarios. Second, we use detailed innovation data and measurements to dive deep into not only the levels and rates of investment but also the composition of general and firm-specific types.

This paper is also related to the literature related to on-the-job learning and human capital accumulation within a firm. This literature shows that on-the-job human capital accumulation drives early career outcomes and wage dynamics (Rubinstein and Weiss, 2006). Firms as a driver of variation in on-the-job learning has long received theoretical attention (e.g. Rosen (1972), Gibbons and Waldman (2006)), but accompanying empirical studies on this front is still limited. The key contribution of our paper is to argue that firms, through investment decisions, play an active role in determining the type of human capital accumulated on the job, and to provide a model to quantify the impact of this effect on innovation.

2. Data and Measurements

2.1. Data on Patents and Inventors

Patent data are obtained from the United States Patent and Trademark Office (USPTO).[1] The database provides detailed patent-level records on nearly seven million patents granted by the USPTO between 1976 and 2020. It includes information on the patent assignee and on the patent's application and grant year. The data on individual inventors are also from PatentsView. These data are based on information from the USPTO patent applications and encompass around three million inventors between 1975 and 2020. The dataset contains disambiguated inventor names and identifiers, which permit us to track successful inventions and careers of inventors across time and employers. Inventor age data are from Kaltenberg, Jaffe and Lachman (2021), and the data are collected by the authors through a wide data collection effort using directory websites, Radaris, Spokeo, and Beenverified.

This database is linked to Compustat using the bridge file provided by NBER (up to the year 2006) and KPSS's data repository.[2] For later years, we complete the link using a fuzzy matching method based on company name, basic identity information, and innovation profiles, similar to Ma (2020), Bernstein, McQuade and Townsend (2021), and Ma (2021). Many firm-level analyses focus on US public firms between 1986 and 2016. Standard firm-level information is obtained from Compustat in this case, and variable definitions are provided in the Appendix.

To link inventors and their employers, we use the patent assignment information. We define that inventor i works in firm f if i applied for a patent that is assigned to firm f. For example, if John Smith filed a patent with firm A in 1999 and one with firm B in 2000, John Smith is designated as an employee of firm A in 1999 and as an employee of firm B in 2000. Inventors are included in the sample for their entire active career, defined as the years between their first and last patent filings.

Even though these data provide a in-depth and credible look at careers of inventors, we

[1] We obtain the patent data from the USPTO PatentsView platform, accessible at https://www.patentsview.org/download/.

[2] The extended data for KPSS can be accessed at https://github.com/KPSS2017/Technological-Innovation-Resource-Allocation-and-Growth-Extended-Data.

also want to highlight that those inventor careers are only imperfectly tracked by patent data. These limitations may affect our analysis later to different degrees, and we want to briefly overview them here. First, this is an "observation by inventing" type of data. That is, we only observe inventors as frequent as they innovate. This is particularly relevant when linking inventors and firms. If more than one year passes between two patent filings, we assume that the employment transition between the two firms occurs at the midpoint between the patent application years if the inventor switched employers; we impute the employer is the starting and the ending point employer is the same firm. Next, some inventors show up only once or for a very few times (47% of the inventors patented only once, more specifically, 1.45 out of 3.07 million). In some cases, it may make more sense to focus only on those inventors with a long-enough tenure as an inventor, defined based on frequency of patenting, or based on overall patenting quantify. At last, the disappearance of an inventor from the data set, i.e., no future patent filings, could be due to many potential reasons—promotion (to non-R&D positions), productivity and creativity dry, retirement or death, and etc.

2.2. Measuring Generality of Innovation and Human Capital

Central to our analysis, for each patent p, we observe all the citations it makes to prior patents; and similarly, we also observe all the citations it receives from future patents up to the year 2020. For the former, those patents cited by p can be considered as the prior arts of p, as they capture the broad set of knowledge and technologies used in developing this new technology p—we call these backward citations made by p. On average, each patent makes fifteen backward citations. For the latter, we observe all cases when p is cited by a successfully granted patent and the timing of those citations. These are forward citations received by p.[3]

A wide variety of citations-based measures can be defined and computed in order to examine different aspects of the patented innovations and their links to other innovations. We have computed and integrated into the data "Generality" as suggested in Trajtenberg,

[3]The forward citation process has a well known right-truncation problem (Hall, Jaffe and Trajtenberg, 2001), because patents, particularly recently approved ones, could receive many citations in the unobserved future. We will discuss this issue in the context of the analysis.

Jaffe and Henderson (1997) and Hall, Jaffe and Trajtenberg (2001).

$$Generality_p = 1 - \sum_{j \in J} Citation_{pj}^2, \tag{1}$$

where $Citation_{pj}$ denotes the percentage of citations received by patent p that belong to patent class j, out of J patent classes (note that the sum is the Herfindahl concentration index). Thus, if a patent is cited by subsequent patents that belong to a wide range of fields the measure will be high, whereas if most citations are concentrated in a few fields it will be low (close to zero). Thinking of forward citations as indicative of the impact of a patent, a high generality score suggests that the patent presumably had a widespread impact, in that it influenced subsequent innovations in a variety of fields (hence the "generality" label).

Generality varies across industries. The traditional fields Mechanical and Others are at the bottom in terms of generality, whereas Computers and Communications is at the top, with Chemical and Electrical and Electronics in between. Surprisingly perhaps, Drugs and Medical is also at the bottom. Also somewhat surprisingly, Chemical (that we regard as a traditional field) stands high. The fact that Computers and Communications scores highest in terms of generality fits well the notion that this field may be playing the role of a "General Purpose Technology" (see Bresnahan and Trajtenberg, 1995) and the centrality of different fields in innovation network (Acemoglu, Akcigit and Kerr, 2016; Liu and Ma, 2021). Likewise, the low scores of Mechanical and Others correspond to expectations, in terms of the low innovativeness and restricted impact of those fields. In that sense, this constitutes a sort of "validation" of the measures themselves.

At last, we want to note that the construction of generality depends to a large extent upon the patent classification system, and hence there is an inherent element of arbitrariness in them. Thus, a "finer" classification within a field, in terms of number of 3-digit patent classes available, will likely result ceteris paribus in higher generality measures, and one may justly regard that just as an artifact of the classification system (that may be the case for example with Chemicals). In this paper, we will use the International Patent Classification (IPC) system which include more than six hundred classes.

The *Generality* measure has been constructed and discussed at the level of each patent

p. It can intuitively be aggregated to inventor-year it level by averaging among all patents that inventor i produces in year t. We can also do so at the firm-year ft level. Those are all properties of flows of new innovation production. We can also construct the human capital (for an inventor) or knowledge capital (for a firm) by aggregating among patent *up to* year t.

3. Stylized Facts

Fact 1: Inventor's patents become less and less general over time (both in terms of inventor age and inventor's tenure in a firm).

[Insert Figure 1 Here.]

Figure 1 shows that for a given inventor, innovation generality decreases with both age and tenure within a firm. This effect is robust to the subsample of inventors who frequently patent during the covered sample period.

Fact 2: Inventors with more general human capital have higher job transition rates.

[Insert Figure 2 Here.]

Figure 2 shows the relation between inventor mobility and inventor general human capital (upper panel) and between inventor mobility and inventor age (bottom panel). The upper panel demonstrates that inventors with more general human capital have higher mobility. The bottom panel demonstrates a more nuanced message—younger and older inventors have lower mobility, while inventors between the age of 35 to 40 have the highest mobility.

Fact 3: General human capital is associated with more general patents in the future.

[Insert Figure 3 Here.]

Figure 3 shows that at both inventor- and firm-levels, more general human capital, as captured using past patent generality, is associated with more general innovation in the future.

Fact 4: After NC enforcement strengthens, patent generality increases.

Fact 5: Inventors become more productive after changing to a new job.

[Insert Figure 4 Here.]

Figure 4 shows that after an inventor changes his/her job, conditional on that transition, they become more productive. This result is robust to different measures of inventor productivity, including patent counts and forward citations of produced patents.

4. Model

4.1. Model setup

We model a continuum of innovative projects. Each project consists of an inventor and a firm that hires the inventor in a position to engage in research and development activities and produce innovative outputs. We use $n_{j;f;t}$ to denote the unit of innovative output generated by inventor j, who works for firm f at time t:

$$n_{j;f;t} = Poisson\left(\alpha_{j;f;t} \quad k_{j;f;t}\right) \tag{2}$$

where $k_{j;f;t}$ is the stock of knowledge capital and $\alpha_{i;f;t}$ stands for the utilization of knowledge capital, which, in turn, is characterized by:

$$\log \alpha_{j;f;t} = a_0 \quad \mu_{j;f;t} + a_1 \quad \omega_{j;f;t} + a_2 \quad j\omega_{j;f;t} \quad \chi_{j;f;t}j. \tag{3}$$

$\mu_{j;f}$ is the match quality of the inventor-firm pair; higher match quality leads to higher utilization of existing knowledge capital. $\omega_{j;f;t}$ measures the specificity of the pair's target output in the current period. A pair engaging in more specific innovation could face lower competition from potential rivals; thus, their existing knowledge capital would translate into a higher arrival rate of innovation output. $\chi_{j;f;t}$ measures the specificity of the knowledge capital stock for an inventor-firm pair. The smaller deviation between $\omega_{j;f;t}$ and $\chi_{j;f;t}$, as measured by the absolute value of the pair-wise difference, indicates the types of existing knowledge capital and target output are better aligned, thus leading to high utilization.

The current period flow profit from innovative activities can be written as:

$$\pi_{j;f;t} = b_{j;f;t} \quad n_{j;f;t} \quad i_{j;f;t} \quad c, \tag{4}$$

where $b_{j;f;t}$ measures the return per unit of innovation output, which takes the following functional form:

$$b_{j;f;t} = b_0 + b_1 \quad \omega_{j;f;t}, \tag{5}$$

Note that if b_1 in Equation (5) and a_1 in Equation (3) take opposite signs, it will imply a risk-return tradeoff between doing specific and general innovations. For example, if $b_1 < 0$ and $a_1 > 0$, pursuing general innovation would be more risky, associated with a lower output arrival rate, but the outputs, once materialized, will bring higher returns to the firm. c is a fixed per-period operation cost. $i_{j;f;t}$ is the firm's current period R&D expenditure.

Knowledge capital depreciates at a rate $(1 \quad \rho)$, and the accumulation of new knowledge capital in the current period, $y_{j;f;t}$, is given by:

$$y_{j;f;t} = \ell_1 \quad n_{i;f;t} + \ell_0 \quad i_{i;f;t}. \tag{6}$$

Equation (6) implies that knowledge capital can be accumulated through both direct R&D investments and learning from past innovative activities (learning-by-doing). If $\ell_0 >> \ell_1$, it implies that knowledge capital accumulation is determined mostly by innovation inputs regardless of whether the inputs lead to successful outputs or not; otherwise if $\ell_1 >> \ell_0$, it implies that firms and inventors only accumulate knowledge from successes in their previous innovation activities. The law of motion for knowledge capital can be characterized by:

$$k_{j;f;t+1} = \rho \quad k_{j;f;t} + y_{j;f;t}. \tag{7}$$

4.2. Knowledge capital specificity

Knowledge capital in our model differs in its specificity. A firm-inventor pair can engage in more targeted innovative activities that have narrower scope, which allows the firm and inventor to accumulate more specific knowledge capital or they can choose projects that have broader applications, which leads to the resulting knowledge capital accumulated being more general. We specify the law of motion of the knowledge capital specificity as a weighted average of the historical knowledge capital specificity and the specificity of current period innovation activities:

$$\chi_{j;f;t+1} = \chi_{j;f;t} \quad \frac{\rho k_{j;f;t}}{k_{j;f;t+1}} + \omega_{j;f;t} \quad \frac{y_{j;f;t}}{k_{j;f;t+1}}. \tag{8}$$

Note that in Equation (8), we allow the specificity of innovation, $\omega_{j;f;t}$ to be a dynamic choice that varies across time even for a given inventor-firm pair; the historical choices of $\omega_{j;f;t}$, in return, influence the dynamics of the pair's knowledge capital specificity.

For each inventor-firm pair, its knowledge capital can either reside with the firm and embeds in the firms' intangible capital stock $\left(k^F_{f;t}\right)$, or reside with the the inventor becomes his human capital $\left(k^I_{j;t}\right)$:

$$k_{j;f;t} = k^F_{f;t} + k^I_{j;t} \tag{9}$$

More specifically, we assume that a fraction, η, of the newly acquired knowledge capital resides with the firm. All knowledge capital shares the same depreciation rate $(1 \quad \rho)$, thus we can write:

$$k^F_{f;t+1} = \rho k^F_{f;t} + \eta y_{j;f;t}, \tag{10}$$

$$k^I_{j;t+1} = \rho k^I_{j;t} + (1 \quad \eta) y_{j;f;t}, \tag{11}$$

We use $\left\{\chi^F_{f;t}, \chi^I_{j;t}\right\}$ to denote the specificity of the firm's intangible capital and the inventor's human capital. Equations (7) through (11) imply the following relationship:

$$\left\{\chi^F_{f;t}, \chi^I_{j;t}\right\} = \left\{\frac{\eta \quad \chi_{j;f;t} k_{j;f;t}}{k^F_{f;t}}, \frac{(1 \quad \eta) \quad \chi_{j;f;t} k_{j;f;t}}{k^I_{j;t}}\right\} \tag{12}$$

The specificity of knowledge capital influences the transition of $\left\{k^F_{f;t}, k^I_{j;t}\right\}$ when the firm hires a new inventor and when the inventor switches employment in the future. If the knowledge capital is associated with a high degree of specificity, it implies that both the worker and the firm find it hard to redeploy the knowledge that they have accumulated from their past joint projects. Thus, there will be a larger loss in the job transitioning process.

4.3. Match quality

We model the quality of an inventor-firm pair, $\mu_{j;f}$ as a binary variable—with $f\mu = 1g$ indicating a good quality match and $f\mu = 0g$ indicating otherwise. We allow $\mu_{j;f}$ to vary across inventors and over time when the same inventor is hired by different firms. Hence, as in previous studies (see e.g., Jovanovic (1979) and Nagypál (2007)), our modeling of μ carries a pair-specific component.

Empirically, we can think of μ as capturing whether an inventor's research style and interest fit the institution's future direction and strategic priorities. For example, is there potential synergy with his future teammates and team knowledge? Does the working environment (collaborative style, value, etc.) fit with the inventor's production process? Does the position provide the appropriate incentive for the inventor to work hard to accumulate human capital, and whether such incentives align with his career objectives? These factors are hard to observe or ascertain ex-ante, but nevertheless, they play a crucial role in shaping the productivity of individuals at their workplaces.

When an inventor is first matched with a firm, the pair-specific true match quality follows a common Bernoulli distribution:

$$P\{\mu = 1\} = 1 - P\{\mu = 0\} = q. \tag{13}$$

The distribution is common knowledge, but the realization of $\mu_{j,t}$ is *unobservable* to any agents in the model. Hence, our model features symmetric learning, where all agents extract information about the match quality from observed signals and learn in a Bayesian fashion. We use $p_{j,f,t}$ to denote the perceived probabilitiy that an inventor-firm pair is good quality. If an inventor-firm pair is maintained in a current period, Bayesian updating implies:

$$p_{j,f,t+1} = \frac{p_{j,f,t} \times P\{n_{j,f,t} | \mu_{j,f} = 1\}}{p_{j,f,t} \times P\{n_{j,f,t} | \mu_{j,f} = 1\} + (1 - p_{j,f,t}) \times P\{n_{j,f,t} | \mu_{j,f} = 0\}}. \tag{14}$$

4.4. Outside opportunity

There is a probability λ that an inventor can land an outside offer at the end of each period. We use $\mathring{\mu}$ to denote the match quality of the outside offer, which follows the common Bernoulli distribution in equation 13. Upon receiving an offer, the inventor can observe an additional signal on the quality of the potential match with the outside firm: $\mathring{\nu} \sim N(\mathring{\mu}, \sigma^2)$. If $\sigma \to \infty$, it means that the signal is uninformative and if $\sigma \to 0$, it means that the match quality is fully revealed to the inventor. (Note that if we prefer to maintain the outside option constant, we can do so by setting $\sigma \to \infty$). We use $\mathring{p}$ to denote the perceived probability that the new match is good quality:

$$\mathring{p} = \frac{q \cdot \mathrm{pdf}\left(\mathring{\nu} | \mathring{\mu} = 1\right)}{q \cdot \mathrm{pdf}\left(\mathring{\nu} | \mathring{\mu} = 1\right) + (1 - q) \cdot \mathrm{pdf}\left(\mathring{\nu} | \mathring{\mu} = 0\right)}. \tag{15}$$

When a firm-inventor pair separates at the end of period t, the firm can liquidate its intangible capital on the market—only a fraction, $1 - \chi^F_{f,t+1}$, of the firm's intangible capital is redeployable and will be priced. Let ξ be the price of knowledge capital that clears the market. The firm will receive $\xi\left(1 - \chi^F_{t+1}\right) k^F_{t+1}$ from liquidating its knowledge capital, which constitues the firm's outside option.

4.5. Bellman equation

We use prime to denote values of variables at the beginning of the next period. We define the surplus of an inventor-firm pair as the discounted present value of innovative outputs created by the pair minus their respective outside options, as discussion in section 4.4, which we can express in a recursive way:

$$\begin{aligned} S\left(p, k^F, k^I, \chi\right) = \mathsf{E}\Big\{\pi - \left[\xi\left(1 - \chi^F\right) k^F - \beta\xi\left(1 - \chi^{F'}\right) k^{F'}\right] + \beta\left(1 - \tau\right) \cdot \\ \left[S\left(p', k^{F'}, k^{I'}, \chi'\right) + \lambda \cdot \mathsf{I}_{d=1} \cdot \Sigma_1\left(p', k^{F'}, k^{I'}, \chi'\right) + \mathsf{I}_{d=2} \cdot \Sigma_2\left(p', k^{F'}, k^{I'}, \chi'\right)\right]\Big\} \end{aligned} \tag{16}$$

where π is the flow profit generated by the inventor-firm pair as defined in equation 4, and $\mathsf{E}\left\{\xi\left(1 - \chi^F\right) k^F - \beta\xi\left(1 - \chi^{F'}\right) k^{F'}\right\}$ captures the user cost of knowledge capital due to delayed liquidation. If the firm liquidates today, it will receive $\xi\left(1 - \chi^F\right) k^F$ dollars; if the firm continues to operate for one more period, the expected value from liquidation will be $\mathsf{E}\left\{\xi\left(1 - \chi^{F'}\right) k^{F'}\right\}$ one year later, where the expectation is taken w.r.t. the stochastic evolution of the firms' intangible capital.

τ in equation 16 captures the rate at which an inventor exits the market for exogenous reasons. In addition, a firm-inventor pair can also separate for endogenous reasons—we use $d = 1$ to denote the decision that the inventor departs the current employer to take an outside offer, and $d = 2$ to denote a firm's decision to liquidate the current project, otherwise, we set $d = 0$ if no separation occurs. $\mathsf{I}_{d=1}$ and $\mathsf{I}_{d=2}$ are indicator functions for the inventor taking an outside offer and the firm liquidating the current project; $\Sigma^{1}\left(p^{0}, k^{F^{\theta}}, k^{I^{\theta}}, \chi^{0}\right)$ and $\Sigma^{2}\left(p^{0}, k^{F^{\theta}}, k^{I^{\theta}}, \chi^{0}\right)$ denote the expected gains from doing so, respectively:[4]

$$\Sigma^{1}\left(p^{0}, k^{F^{\theta}}, k^{I^{\theta}}, \chi^{0}\right) = \mathsf{E}\theta \left\{ S\left(\mathring{p}, \mathring{k}, k^{I^{\theta}}\left(1 \quad \chi^{I^{\theta}}\right), 0\right) \quad S\left(p^{0}, k^{F^{\theta}}, k^{I^{\theta}}, \chi^{0}\right)\right\}, \tag{17}$$

$$\Sigma^{2}\left(p^{0}, k^{F^{\theta}}, k^{I^{\theta}}, \chi^{0}\right) = \quad S\left(p^{0}, k^{F^{\theta}}, k^{I^{\theta}}, \chi^{0}\right), \tag{18}$$

When an inventor separates from his original employer, he carries over a fraction,1 χ^{I}, of his human capital to the new employment. The perceived match quality between the worker and new employer is denoted by $\mathring{p}$, and the outside firm has a stock of $\mathring{k}$ units of general intangible capital that the pair can employ for production. The expectation in equation 17 is taken w.r.t. two things—the first is the stochastic evolution of states for the current inventor-firm pair, and the second is the pool of outside offers that the inventor can receive;θ in equation 17 captures the inventor's bargain power—when an inventor switches employment, the inventor and his original firm will be compensated on par of their outside options, which equals the joint surplus generated by the original firm-inventor pair. In addition, the inventor will capture θ fraction of the total surplus generated by reallocating to the new employer, which equals to forward looking surplus generated by the new pair minus the new employer's outside option of staying unmatched.

4.6. Wage Determination

Define u to be the best outside offer that inventor j has received during his employment with firm f, which we also refer to as inventor j's bargain capital. Let $W\left(p^{0}, k^{F^{\theta}}, k^{I^{\theta}}, \chi^{0}; u\right)$ and $J\left(p^{0}, k^{F^{\theta}}, k^{I^{\theta}}, \chi^{0}; u\right)$ to denote the value function of an inventor and that of a firm, respectively. We can write:

$$W\left(p^{0}, k^{F^{\theta}}, k^{I^{\theta}}, \chi^{0}; u\right) = u + \theta\left[S\left(p^{0}, k^{F^{\theta}}, k^{I^{\theta}}, \chi^{0}\right) \quad u\right], \tag{19}$$

[4] $\chi^{I'}$ and $\chi^{F'}$ in equations 17 and 18 can be calculated based on the current firm-inventor states using equation 12 .

$$J\left(p^{0}, k^{F^{0}}, k^{I^{0}}, \chi^{0}; u\right) = \xi\left(1 \quad \chi^{F^{0}}\right) k^{F^{0}} + (1 \quad \theta)\left[S\left(p^{0}, k^{F^{0}}, k^{I^{0}}, \chi^{0}\right) \quad u\right], \tag{20}$$

where the outside option u evolves according to:

$$u^{0} = \begin{cases} u, & \text{if } u > S\left(p^{0}, \mathring{k}, k^{I^{0}}, \mathring{\chi}\right), \\ S\left(p^{0}, \mathring{k}, k^{I^{0}}, \mathring{\chi}\right) & \text{if } S\left(p^{0}, k^{F^{0}}, k^{I^{0}}, \chi^{0}\right) \quad S\left(p^{0}, \mathring{k}, k^{I^{0}}, \mathring{\chi}\right) > u, \\ S\left(p^{0}, k^{F^{0}}, k^{I^{0}}, \chi^{0}\right) & \text{if } S\left(p^{0}, \mathring{k}, k^{I^{0}}, \mathring{\chi}\right) > S\left(p^{0}, k^{F^{0}}, k^{I^{0}}, \chi^{0}\right). \end{cases} \tag{21}$$

The above wage setting equation implies that the inventor will choose to bargain with the firm only if it is in his favor to do so, namely it generates higher $W(\ )$ for the worker, with one exception, that is when the joint surplus $S(\ )$ falls below the worker's bargain capital u. When that happens, the firm can negotiate with the worker such that all surplus goes to the worker and the firm will just be indifferent between liquidating the project and maintaining it for on more period:

$$u^{0} = S\left(p^{0}, k^{F^{0}}, k^{I^{0}}, \chi^{0}\right), \text{if } S\left(p^{0}, k^{F^{0}}, k^{I^{0}}, \chi^{0}\right) < u. \tag{22}$$

When the joint surplus $S(\ )$ falls below zero, there will be no $u > 0$ that gives the firm a $J(\ )$ that is higher than its value from liquidation, in which case, the firm will liquidate the project; the inventor receives a zero surplus and exits the market.

When the joint surplus of a firm-inventor pair fall below that generated by the inventor matched with his potential outside offer, the inventor will separate with the current employer and join the outsider firm. We can verify that such switching decisions are bilateral efficient, given the bargain protocol described in equations 19 to 22. Hence, the firm and inventor will always agree on such separation decisions.

$$d = \arg\max S(p, k^{F}, k^{I}, \chi) \tag{23}$$

Each firm who is currently matched with an inventor will choose the level and specificity of investment in order to maximize the value that accrues to the firm:

$$\{i, \omega\} = \arg\max J(p', k^{F'}, k^{I'}, \chi'; u) \tag{24}$$

Each new entrant with an accepted offer will choose the amount of knowledge capital to install to maximize its value net of any investment costs:

$$\mathring{k} = \arg\max J(p', \mathring{k}, k^{I'}, 0; u) \quad \xi \mathring{k} \tag{25}$$

4.7. Stationery Equilibrium

For each investor-firm pair, their continuation value is forward looking and depends on firms' choices on future R&D investments and specificity, and it takes into account the gains from future separations. The expected gain of separation, in turn, depends on the liquidation value of the firm and the outside opportunities available to the inventor. We use Γ_t to denote the distribution of inventor-firm pairs and we use P to denote the probability law that governs the transition of Γ :

$$\Gamma_{t+1} = P(\Gamma_t) \tag{26}$$

A stationery equilibrium exists if the following conditions are satisfied:

1. All inventor-firm pairs solve the optimal separation decision as described by equation 23, taken as given the evolution of knowledge capital, and the distribution of inventor-firm states.

2. All matched firms make the optimal choices of R&D investment and specificity as described in equation 24, and all entrants with accepted offers choose the optimal amount of knowledge capital to acquire as described in equation 25, taken as given future separation probabilities and the distribution of inventor-firm states.

3. All agents have rational expectations.

4. The supply of knowledge capital from liquidated projects equals the demand by new entrants, so the market clears.

5. The probability law governing the the evolution of the states, P ,is consistent with agents' optimal decisions.
6. The distribution of firms and inventors is stationery, $\Gamma_{t+1} = \Gamma_t$.

4.8. Model mechanism

Our model features the two potential trade-offs when the firm and inventor choose the type of innovation activities. The first one relates to the success probability and the return on innovation as governed by Equations (5) and (3). One type of innovation can be more challenging, leading to a lower probability of success, but it can generate higher returns once the firm and inventor establish an exclusionary right. Similar channels related to the varying success probability and returns of different innovations have been emphasized in prior studies (e.g. Akcigit and Kerr, 2018) as an important determinant for the optimal type of innovation that firms choose to pursue.

The second trade-off focus on the interaction between firms and inventors. If the firm chooses to engage in specific innovation, the cost is the loss of specific knowledge capital embodied with the firm; the benefit is that it lowers the inventor's general human capital and, thus, his outside opportunities. As a result, separation becomes less likely, and the firm can keep a larger share of the surplus. Note that this trade-off is time-varying. When the current perceived match quality is low, separation (or layoff when the inventor does not receive a good outside option) is likely, and the firm is more concerned about maintaining flexibility; when the current perceived match quality becomes high, employee retention and wage setting become the firm's first-order consideration, especially given that the inventor could have accumulated high levels of bargain capital over the time. The firm will optimally tilt its innovation activity to a more specific spectrum in anticipation of the labor market effect.

5. Estimation

5.1. Identification

We estimate the model using simulated method of moments (SMM), which chooses parameter values that minimize the distance between the moments generated by the model and their counterparts in the data. In this subsection, we present the data moments used in the estimation and explain how they help identify the model parameters.

In the initial step, we set the discount factor β to be 0.9, a value commonly used in the literature. We calibrate the exogenous exit rate, τ, to X% per year, to match the average dropout rate among inventors. We estimate the remaining 11 parameters in an SMM system. These parameters include: γ, the curvature of innovation production function; b, the return on each unit of innovation output; c, the fixed cost of operation; ρ the depreciation rate of knowledge capital; η, fraction of knowledge capital that accrues to the firm; q, the prior probability of good-quality match between any inventor-firm pair, and σ_v, the precision of an inventor's signal on the match quality. In addition. In addition, $f a_1, a_2 g$, determines the utilization of knowledge capital stock for an inventor-firm pair, and $f \ell_0, \ell_1 g$ controls the accumulation of knowledge capital through learning and through firms' R&D investments. Parameter identification in SMM requires choosing moments whose predicted values are sensitive to the model's underlying parameters. Our identification strategy ensures that there is a unique parameter vector that makes the model match the data as closely as possible.

First, we use the annual patent counts by high, medium, and low R&D firms (75th, 50th, 25th percentile) to identify γ and c; if the innovation outputs has strong decreasing return to scale (high γ), then the firms with high R&D should experience modest abnormal patent counts relative to an average firm; on the other hand, if firms have lower operating cost, they tend to hold back investments and wait for longer until they liquidate a projects, which leads to sharper declines in the patent counts by firms with low R&D investments relative to the average.

We use the change in patent counts around the time when an inventor switches job to identify the parameter a_1. When a inventor switches employment, they are able to break the bad match the current employer and experience, on average, an increase in the match quality.

Therefore, if match quality is an important determinant of human capital utilization, we should observe a large increase in deal number following an inventor reallocation. We use the persistence in patent specificity to identify the parameter a_2. Intuitively, if adjustments of the knowledge capital specificity is costly and and severely impact the utilization of knowledge capital, then as should observe a high auto correlation in output specificity

We use the market value of patents to determine the return per unit of innovation, b. We use firms' R&D expenditure to identify the parameter, η. If a larger fraction of knowledge capital accrues to the firm, then the firm will have stronger incentives to invest in R&D.

To identify accumulation and depreciation of knowledge capital, we run the following regression:

$$n_{j;f;t} = \varrho_{i;} \quad \sum_{=1}^{3} i_{j;f;t} \quad + \sum_{=1}^{3} \varrho_{n;} \quad n_{j;f;t} \quad + \varepsilon_{j;f;t}, \tag{27}$$

where $n_{j;f;t}$ is the number of patents produced by inventor j, firm f, in year t, $i_{j;f;t}$ is the amount of R&D invested on this inventor-firm pair, and $\tau = 1, 2, 3$ denotes a 1-year to a 3-year lag, respectively. If a firm's knowledge capital accumulation relies heavily by the R&D investments (ℓ_0 is larger), the accumulated knowledge capital will lead to subsequent higher innovation outputs, generating a higher $f \varrho_{i;} \; g$. Therefore, we use the average coefficient, $\frac{1}{3}\sum^{3}_{=1} \varrho_{i;}$ to identify ℓ_0. Similarly, if successful prior innovation is key to subsequent knowledge capital accumulation (ℓ_1 is high), then we should observe higher persistence in deal numbers, and thus we use the average coefficient, $\frac{1}{3}\sum^{3}_{=1} \varrho_{n;}$ to identify ℓ_1. The parameter ρ controls for the speed of human capital depreciation, with a higher (lower) value indicating slower (faster) decay in human capital. We therefore use spread of deal persistence, $\varrho_{n;1} \quad \varrho_{n;3}$, to identify ρ. Intuitively, a smaller spread implies a higher value of ρ.

We use the average relocation rate to identify parameter q. A low unconditional probability of good-quality match (q) means that alternative employments are less attractive ex ante, and it takes longer for an inventor to location a good future employer. Therefore, the relocation rate should decrease with q and the employment duration should increase with q. Next, conditional on a separation taking place, we count the number of years that an inventor work for the firm until the separation happens. This conditional employment duration helps to identify the precision of the signal, σ_v. If σ_v is small, it implies that an inventor can receive very precise signal about whether he is a good match with the current employer or not, in which case, he always stay with the current employer if the match is good quality and separates immediate if the match quality is bad.Thus, the model will generate short employment spells for those who separate from their employers.

5.2. Re-scaling the Variables to Match Our Model Setup

In our model, patents do not vary in their value and quality, which is an important dimension in patent data. For example, as documented in Kogan et al. (2017), the market value of each patent is on average 10 million (in 1982 dollars), and the standard deviation is 32 million.

To account for this dimension, we re-scale our patent counts to reflect their value. We do not keep track of this market value. Instead, we measure it by assigning a higher patent count to the firm-inventor pair if the output patents are of higher value. For example, a 10 v million patent can be viewed a portfolio of ten patents, each with v million market value. We choose the unit of measurement, v to match average patent value in industries with the lowest per-patent value.

We also need to adjust for the number of inventors. For example, if a patent is assigned to 10 people then each on of them contribute to 0.1 patent in the given year. At the end of the day, we want the patent measure to be at the inventor level. Similarly, we calculate the per-capita R&D expenses as the average R&D expense, which will be used in some later calculation.

6. Model Implication

6.1. Inventor turnover and the value of specificity

As a preliminary step, we verify in Figure 5 that inventors who have accumulated high levels of human capital and those who have high perceived match quality with their current employers exhibit low mobility. Their mobility will be amplified if they receive a good outside option, as suggested by a noisy signal indicating a high probability of a good match between the inventor and the potential outside employer. On the opposite side, their mobility will be dampened if a larger fraction of the human capital that inventors accumulate is firm-specific, making it more costly to redeploy and leading to a higher loss in the event of a turnover.

After validating the primary mechanisms in the model, we next examine the implications on the value of firm-specific knowledge capital, as opposed to more general ones. To facilitate the comparison, we first define a "specificity premium" measure at the firm level:

$$\frac{J\left(p^0, k^{F^0}; \chi^0 = 1; u = \bar{u}, k^{I^0} = k^{F^0}\right) \quad J\left(p^0, k^{F^0}; \chi^0 = 0; u = \bar{u}, k^{I^0} = k^{F^0}\right)}{J\left(p^0, k^{F^0}; \chi^0 = 0, u = \bar{u}, k^{I^0} = k^{F^0}\right)}. \tag{28}$$

Intuitively, the measure takes a firm-inventor pair with an average level of bargain capital ($u = \bar{u}$), and where the firm and inventor have accumulated an equal amount of knowledge capital ($k^{I^0} = k^{F^0}$), and asks what would be the percentage change in the firm's surplus if we counterfactually reset all of the knowledge capital to be firm-specific, relative to the case if we counterfactually make the knowledge capital base to be entirely general. If the resulting change is positive, it implies that having firm-specific knowledge capital carries a "premium" from the firm's perspective, leading to a higher surplus received by the firm; otherwise, knowledge capital specificity is associated with a discount that can lower firm value.

Our results in Figure 6 show there is no "one size fits all" story— firm-specific human capital can carry either a "premium" or a "discount", depending on the current state of the inventor-firm pair. As a result, firms' preference for the type of innovation activities to engage in also changes as their relationship with the inventor evolves.

6.2. Optimal specificity over life cycle

Next, we examine how firms' varying preference for different types of innovative activities relates to inventors' tenure. As inventors' tenure with a firm increases, it is accompanied by two key changes. First, as shown in panel A of Figure 7, the inventors' mobility first shoots up and then decreases gradually over time. When an inventor newly joins a firm, there exists great uncertainty regarding his fit with the firm. Even if he fails to become productive immediately, it could reflect bad luck, as opposed to a bad match. Therefore, the firm would tolerate initial failures before they would find a turnover warranted. As the inventor's tenure with the firm increases, the luck component in his performance gets washed out, and the firm starts to have a more precise estimate of its match quality with the inventor. They would fire an inventor if the match quality is sufficiently bad or choose not to make a retention offer if the worker is poached by an outside firm where he seems a better fit, leading to sharp increases in the realized mobility.

As inventors' tenure further increases, mobility will start to decline, mainly due to two forces. First, as inventors' tenure increases, they accumulate more human capital by learning from successful innovation experiences and failed ones. A fraction of the human capital they accumulate is firm-specific and will be lost in the event of a job turnover. The second force is due to selection. The fact that an inventor has maintained a long tenure with the current firm implies that this is likely to be a good match (otherwise, he would have been out-hired by the other firms in previous years). The high match quality also predicts that he is less likely to depart from the firm in the current and future years.

Panel B of Figure 7 shows that as inventors become more seasoned, they also keep receiving outside offers, which they can use to bargain with their current employers. Hence, their bargain capital increases monotonically with their tenure.

How do these life cycle changes influence the firms' scope of innovation? On the one hand, as inventors' mobility declines over time, maintaining the redeployability of knowledge capital becomes a less important concern, thus lowering the attractiveness of engaging in general innovation. On the other hand, as inventors' outside options increase, it implies that firms need to concede more rent to the inventors. Tilting innovation in a more specific spectrum will help to alleviate this concern by reducing the portion of knowledge capital that an inventor can bring to his next employment, thus reducing the value of his outside employment opportunities. The less valuable outside options would, in turn, weaken the inventor's bargaining position, allowing the firm to expect higher rent. Our results in Figure 8 show that, indeed, as inventors' tenure increases, firms optimally choose to narrow down the scope of their innovation activities. As influenced by the firms' choices, inventors' own stock of human capital also exhibits a similar pattern.

6.3. Surplus analysis

How does firms' choice of innovation specificity influence their surplus and the surplus of their inventors? To answer this question, we perform a set of counterfactual analysis, where instead of letting firms optimally choose their innovation specificity, we force specificity to range from zero to 75% of their chosen level. In each counterfactual scenario, we calculate the average surplus accruing to the firm, the inventor, and the pair. The results are reported in Table 2, which suggest firms' value would decrease when their choice of knowledge specificity deviates from the optimal level. The lower specificity, in turn, would increase the inventors' outside options, thereby boosting their surplus. When we add up the inventor and firms' surplus, the sum initially increases as we choose lower specificity, followed by a monotonic decline, implying that firms can be choosing a scope of innovation that is too narrow.

7. Conclusion

Labor market forces are important in explaining firm investment decisions and have long-term consequences on the economy. When firms choose the type of innovation activities to engage in, they tradeoff the benefit of increased asset redeployability from general innovation with the associated higher employee retention cost. Such choices, in turn, influence the type of knowledge capital that workers will accumulate and their subsequent innovation activities.

Over time, the U.S. labor market is becoming increasingly competitive. In the meantime, academics and policymakers complain that firms are researching in an overly narrow scope, contributing little to fundamental science and technological breakthroughs. Our paper provides a new angle that explains these phenomena based on firms' labor market considerations, and our results also bear important policy implications.

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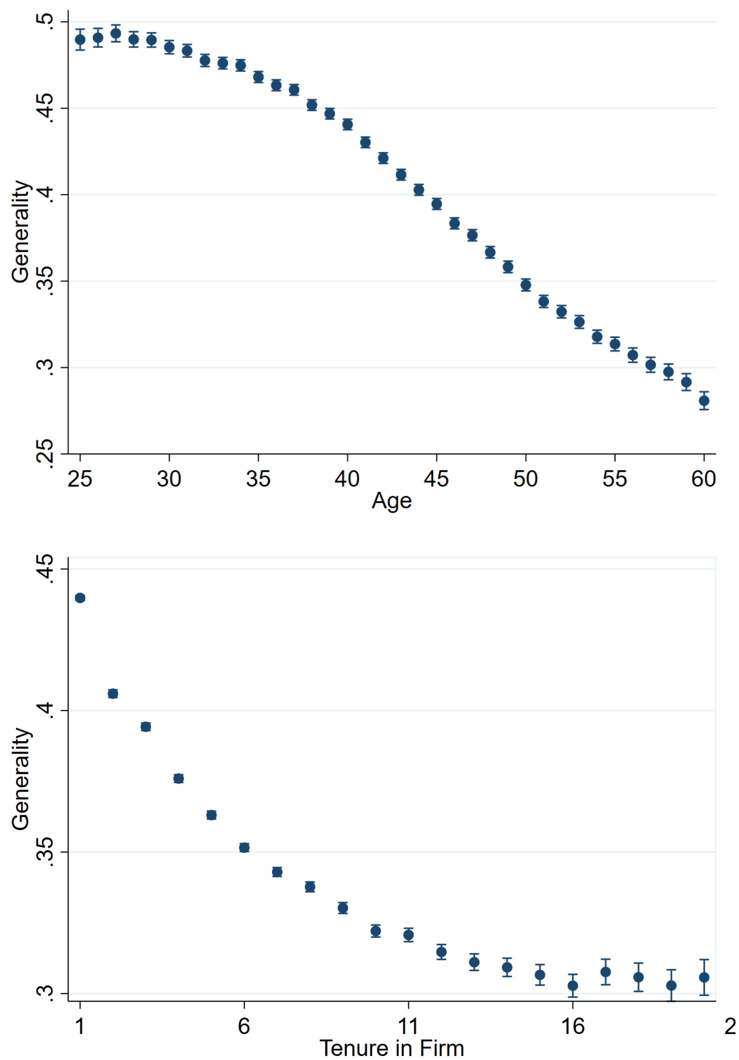

Figure 1. Innovation Generality and Inventor Experience

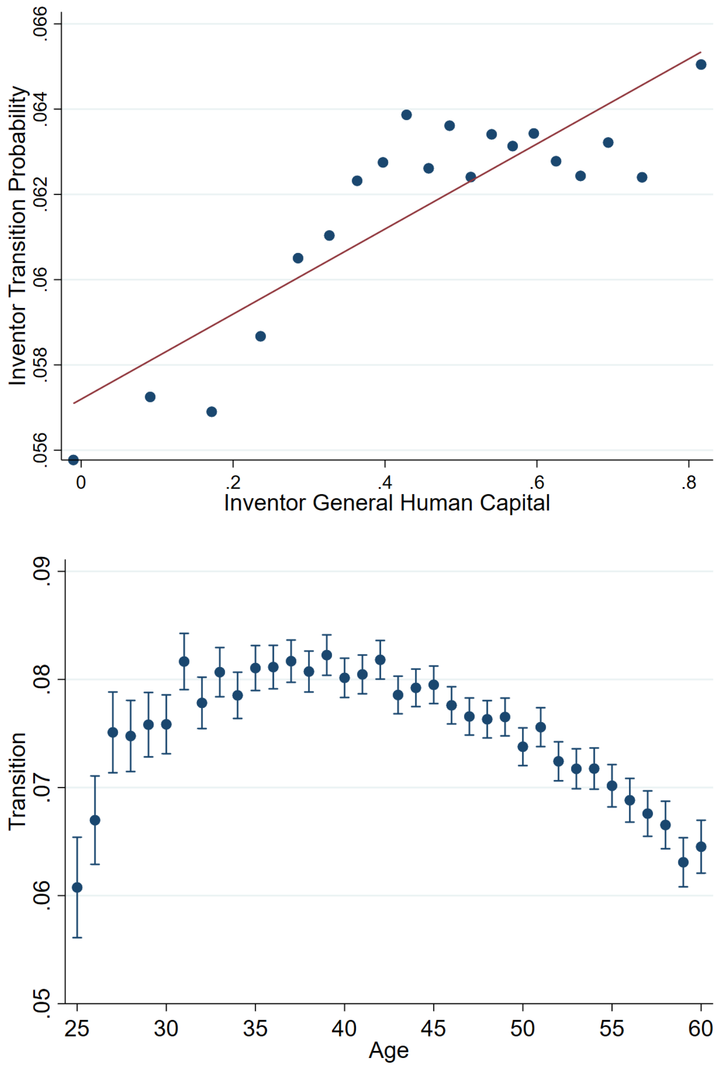

Figure 2. Inventor Mobility, Experience, and Human Capital Generality

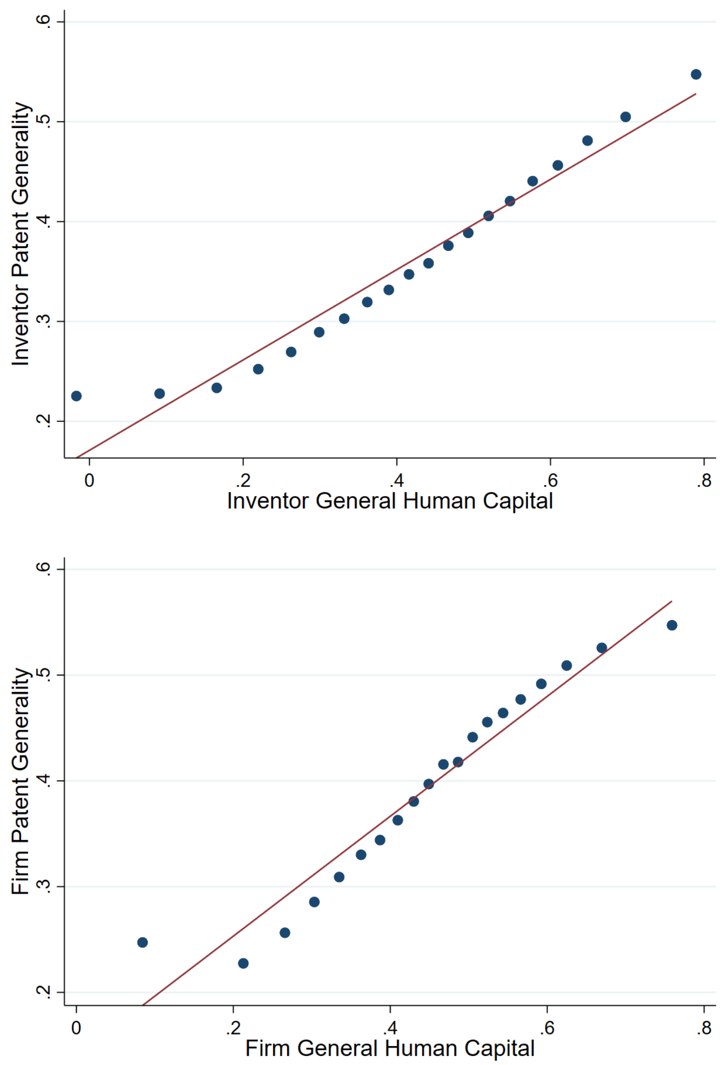

Figure 3. Inventor General Human Capital and Firm's Future Patent Generality

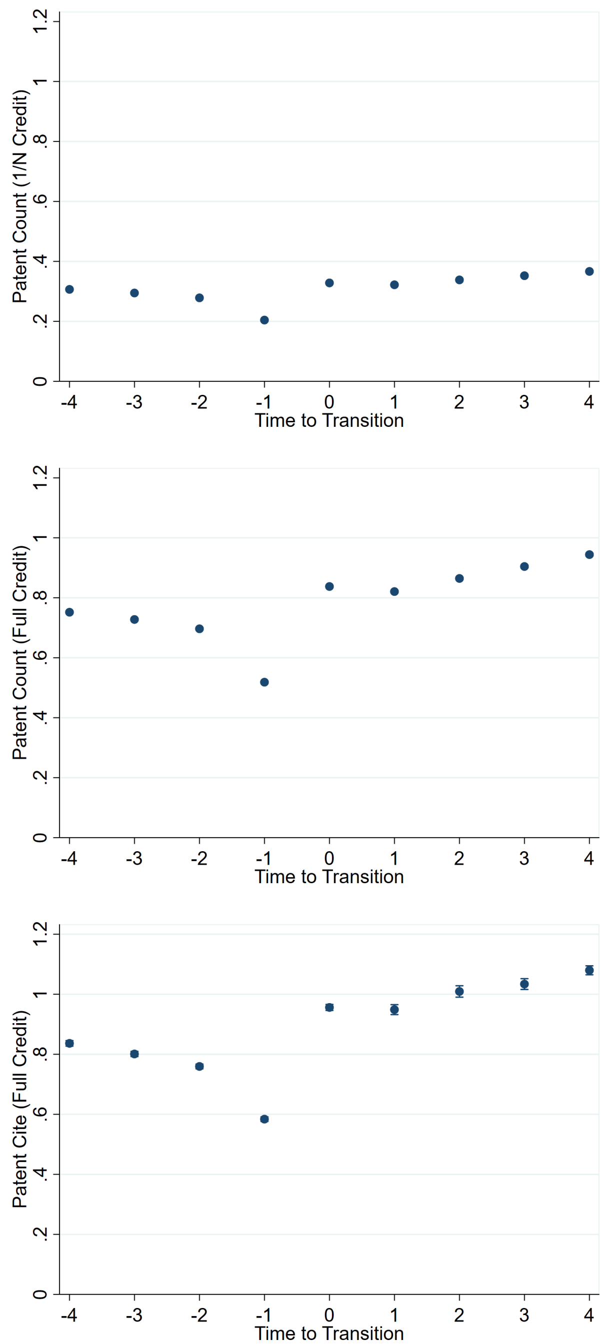

Figure 4. Productivity Around Transition

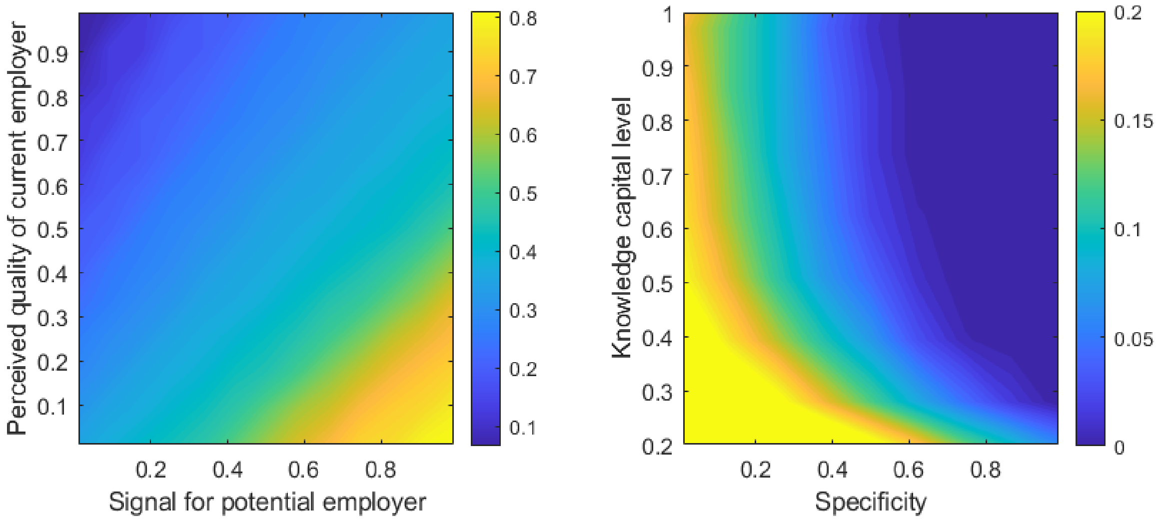

Figure 5. Match Quality, Knowledge Capital, and Inventor Turnover

This figure illustrates the mobility of inventors using heat maps. Mobility is measured as the probability that an individual inventor leaves the current position.

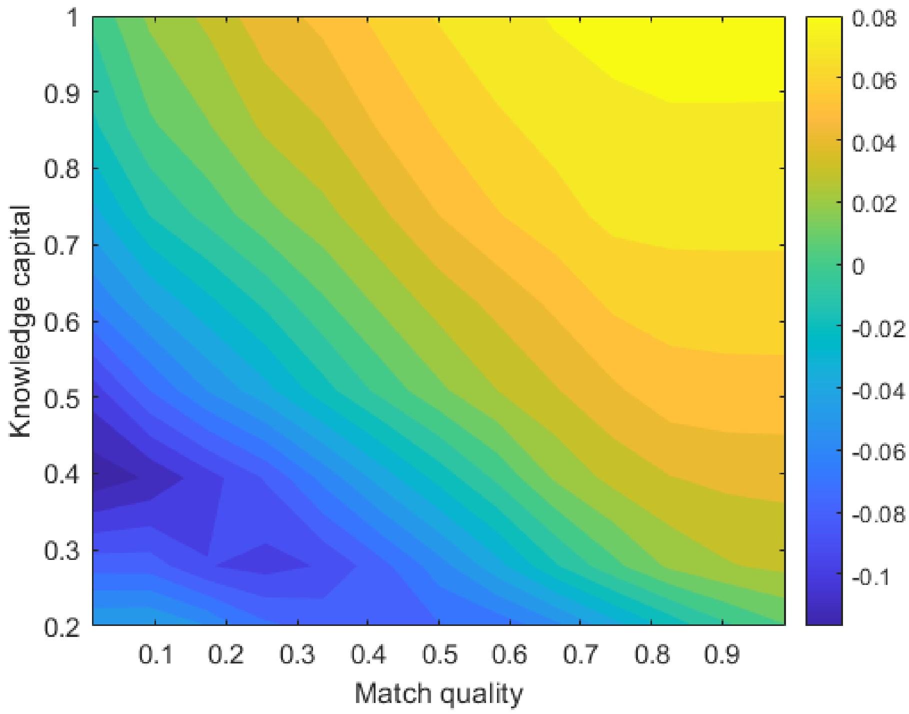

Figure 6. The Value of Knowledge Capital Specificity

This figure illustrates the value of knowledge for firms with varying inventor quality and knowledge capital. The knowledge capital "specificity premium" or "discount" is defined in Equation (28).

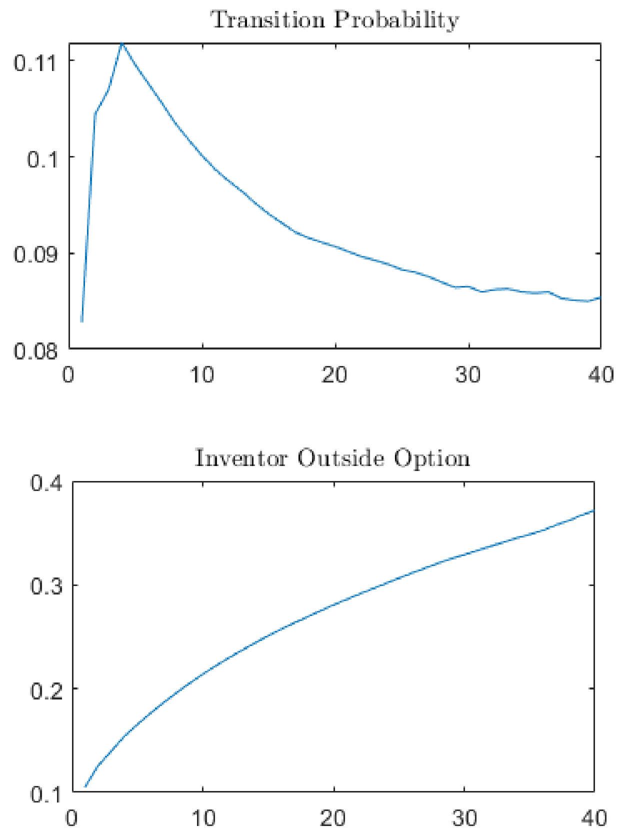

Figure 7. Inventor Turnover, Outside Option, and Tenure

This figure illustrates how inventors' transition probability and the value of their outside option evolve with their tenure.

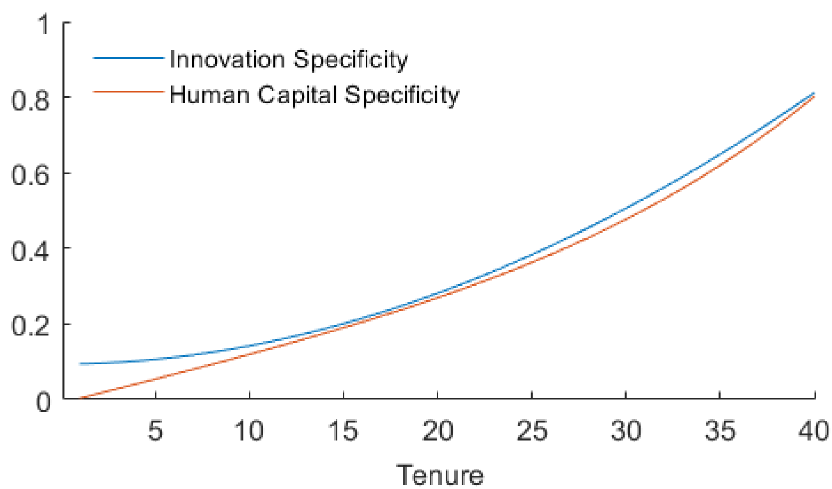

Figure 8. The Life Cycle of Innovation Specificity

This figure illustrates how the specificity of an inventor's current period innovative outputs and that of his knowledge capital stick evolves with his tenure.

Table 1. Parameters and Identifying Moments

This table summarizes the parameters we estimate in the model and the corresponding identifying moments.

Par	Description	Value	Identification
γ	Curvature of production function	0.8225	Upper 25th percentile of patent count
a	Knowledge capital utilization	f0.50, 0.10, -0.21g	Average patent count
			Loading of patent count on specificity
			Persistence of patent specificity
b	Return on innovation	f6.8, -1.2g	Average patent market value
			Loading of patent market value on specificity
c	Fixed production cost	0.01	Proportion of zero patent production
ℓ	Knowledge capital accumulation	f0.1, 0.3g	Loading of current patent counts on prior patent counts
			Loading of current patent counts on R&D investments
ρ	Depreciation rate of knowledge capital	0.8	"Term structure" for the auto-correlation of patent counts
η	Fraction of knowledge embodied in firm	0.5	R&D per capital
q	Unconditional probability of good match	0.51	Frequency of job switch
σ_v	S.d. of signal on the outside option	1	Employment duration conditional on separation
Additional moments:			
1	Average specificity of patents		
2	Patent counts conditional on inventor tenure		
3	Patent counts around inventor turnovers		

Table 2. Counterfactual

This table reports the results of counterfactual analysis, where instead of letting firms optimally choose their knowledge capital specificity (χ), we force specificity to range from zero to 75% of their chosen level. In each counterfactual scenario, we calculate the average surplus accruing to the firm, the inventor, and the pair.

	Baseline	75% χ	50% χ	25% χ	$\chi = 0$
Total surplus	2.1844	2.1920	2.1847	2.1496	2.0933
Firm surplus	2.0724	2.0318	2.0057	1.9701	1.9032
Worker surplus	0.1120	0.1602	0.1790	0.1795	0.1901