Steering Labor Mobility through Innovation*

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This paper argues that firms proactively use innovation decisions to influence the mobility and human capital accumulation of their workers. We develop a dynamic model in which workers conduct R&D projects, accumulating both general and firm-specific human capital. Firms choose the scope of innovation, influencing the type of human capital workers accumulate during the process. Pursuing more general innovation leads to increased knowledge redeployability for the firm at the cost of more difficult employee retention. 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 cycles. Empirical estimates of the model parameters imply that 24% 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.

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1. Introduction

Human capital is essential for firms, particularly for activities like research and development (R&D) and innovation. Unlike physical capital, firms do not own their employees, who have the flexibility to leave with their inalienable human capital. While some separations reflect organic reallocation of labor that could be beneficial to both the firm and the worker, many labor departures are costly to the firms—especially if the human capital is valuable and irreplaceable. Naturally, firms rank labor mobility as a top consideration, and economists have studied how firms use wages and non-wage benefits to achieve the goal of talent retention. It remains underexplored, however, how firms may strategically make operational decisions to affect labor mobility and the long-term consequences of such decisions.

In this paper, we build a model to demonstrate that firms actively use their R&D decisions, specifically the decision on the scope of innovation (general vs. specific innovation), to impact labor mobility and talent retention. Our mechanism builds on a key premise of how firms can affect human capital accumulation in the economy—much of the human capital of workers is built on the job through carrying out tasks for the employer firms (Rosen, 1972). By assigning workers to innovations with different scopes, these workers and firms accumulate different types of knowledge capital—either narrowly focused and more specific to the firm, or with more general applications and redeployable outside the firm.

The key mechanism of our model is a labor-based tradeoff behind a firm's innovation decisions. In specific, firms optimize the scope of R&D activities to influence the knowledge capital their workers accumulate in conducting these tasks, which is key in determining firm's separation cost with labor, labor mobility, talent retention cost, and ultimately firm value. General innovation fosters knowledge capital that is more redeployable for both the firm and the worker, so workers who accumulate such capital are more likely to be poached. Specific innovation activities, on the other hand, ties the worker more closely to the firm, but it incurs larger knowledge destruction and higher separation cost if the worker turns out to be a bad fit with the firm. Moreover, such trade-off varies endogenously with the workers' career stages. When a worker is young with limited track record, the firm's own separation cost concern dominates, while as the worker becomes more seasoned with proven quality, managing his outside option for retention purposes becomes the primary concern. Thus, our model predicts changes in innovation scope with the worker's tenure. Quantitatively, our model estimation suggests that such a labor-based tradeoff is crucial, influencing 24% of observed innovation specificity among U.S. firms.

Our model has several important motivations. First, it shows that firms go beyond utilizing traditional labor-market tools, such as wages or benefits, to exert impacts on the human capital fronts. This echoes the literature that shows firms use operational and financing tools to affect the labor market (Matsa, 2010). Second, even though the mechanism could apply to any human capital-intensive tasks, we use corporate innovation as our setting. This provides superior data availability for our empirical and quantitative analysis. Importantly, this is motivated by the broad literature on the importance of innovation and innovative labor, and the recent literature that argues that not only the amount but also the direction and scope of innovation are crucial (Acemoglu and Cao, 2015; Akcigit and Kerr, 2018; Mezzanotti and Simcoe, 2023). Last but not least, the mechanism is influenced by the long-lasting literature on general vs. firm-specific human capital (Becker, 1962; Hashimoto, 1981; Lazear, 2009). Recent studies estimate the extent to which human capital is specific and thus non-portable, taking it as an exogenous feature associated with the firm or the task (Yamaguchi, 2012; Gathmann and Schönberg, 2010; Huckman and Pisano, 2006). Our results extend the idea and imply that the portability of human capital is an active choice made by the firm.

Now we elaborate on our model. A firm hires inventors to perform innovative activities. These activities may lead to profitable innovation; meanwhile, they also accumulate knowledge capital for both the firm (new research process, new proprietary ideas, organizational capital) and the inventors (i.e., new knowledge acquired in conducting the research). Importantly, besides the level of R&D considered in classic innovation models, firms in our model also decide on the scope of the innovative activities—they can engage the inventor to produce either innovation specifically tied to the firm (specific innovation) or research with more general applications (general innovation).

Inventors and firms face uncertainty regarding the match quality between them. High match quality can be thought of as an inventor being well suited for the firm's research culture, environment, and direction. Neither the inventor nor the firm observes the match quality directly, but they can learn about it through the realized innovation outcomes. The uncertain nature associated with innovation activities, however, hinders the learning process, making the belief updating process gradual and slow-moving as in Moscarini (2005).

Each period, upon updating its belief of match quality, a firm can choose to terminate a position if it is deemed sufficiently unprofitable and receive the scraping value of the knowledge capital embodied in the firm. In the meantime, an inventor can be poached. Upon receiving an outside offer, he can use it as a benchmark to negotiate higher compensation with his current employer, or he can switch employment. A job switch will happen when the present value generated with the current employer falls below the expected value arising from matching the inventor with the outside firm; the latter depends on the amount of human capital that the inventor can bring to his prospective employment.

Separation can lead to knowledge capital destruction, which is costly to both the firm and the worker. Importantly, accumulating more specific knowledge capital can add to this cost. When a firm engages in specific innovation, the resulting knowledge capital is less redeployable, reducing the scrapping value to the firm in the event of job separations—we call this the *knowledge retention channel* as it is related to how much a firm can redeploy the knowledge. Concretely, one can think of these knowledge capital as new special equipments, processes, and ideas that are harder for other researchers to redeploy when a key employee with specific knowledge leaves.

Concurrently, as employees engage in highly specialized projects, they accumulate human capital that is narrowly tailored and less effectively utilized in other firms, thereby reducing the value associated with the outside offers. Moreover, from the perspective of the firm, the workers' devalued outside options can be construed as advantageous, helping it retain the workers more easily. As the retained workers' outside option becomes less valuable, it also weakens their ability to bargain with the firm, leading to a larger share of the value created accruing to the firm's shareholders—we call this the *labor retention channel* as it is related to the ability and cost associated with keeping an employee. Our model predicts that firms will actively take into account these labor-based tradeoffs when choosing their innovation specificity.

Importantly, the cost and benefit associated with the scope of innovation vary significantly with an inventor's tenure cycle. When a firm first hires an inventor, there exists large 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 gradually resolves. He also accumulates higher human capital and thus is more likely to be poached by outside firms. When such outside opportunities arise, the inventor can choose to switch employment or use them to bargain with the current firm to increase his rent. At this point, retaining valuable employees and bargaining efficiently with them become the firm's primary concerns. As the firm shifts its focus, it also tilts its innovation toward a more specific spectrum, facilitating its retention and bargaining decisions.

To gauge the empirical relevance of the channels described above, we estimate the model using granular data on corporate patenting activities and inventors' career trajectories. Our data set includes more than 7 million US inventors who filed and were successfully granted at least one patent at the United States Patent and Trademark Office (USPTO) from 1976 to 2018. For each inventor, we observe the patent production records filed with USPTO, from which we can track the firms she/he worked at, and we also infer the tenure of an investor in a firm and the mobility from such records by tracing changes of employer firms (Bernstein, 2015; Brav, Jiang, Ma, and Tian, 2018). Inventor age data are from Kaltenberg et al. (2021). We also observe the characteristics and nature of the innovation, patent specificity in particular. Using patent citation information, we construct patent specificity following Hall (2007) by capturing the scope of the patent as potentially useful for other technological fields.

Importantly, our estimation allows different firms to have comparative advantages with respect to innovations with varying scopes, which echoes Akcigit and Kerr (2018). Such comparative advantages can help explain the observed specialization of innovation scope across firms, as shown in Akcigit and Kerr (2018). On top of that, firms will also actively deviate from their most efficient area, considering the labor-based tradeoff. The direction and extent of the deviation can vary across inventors working for the same firm and for the same inventor-firm pair over different years of the inventor's tenure cycle. In our estimation, we allow the two mechanisms to jointly shape the model-predicted innovation scope, which we then map to the data. In the subsequent counterfactual analysis, we will keep firms' innovation comparative advantage as given while varying frictions that govern the labor-based tradeoff, thus teasing out the effect of the latter.

Overall, our model matches key patterns observed in the data regarding firms' innovative activities, patenting output, and inventor turnovers. 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 a firm newly hires an inventor, the likelihood of a turnover will stay low initially due to the large uncertainty pertaining to the investor's quality, and it keeps increasing for the first few years as additional information arrives. The turnover probability will peak among inventors with medium tenure, followed by a monotonic decline as inventors' tenure further increases. Second, as inventors' tenure increases, the scope of their innovation also becomes increasingly firm-specific, which partially contributes to the declining trend of inventor mobility later in their careers. These patterns capture key predictions from the model and are also present in the actual data.

Using the estimated model as a laboratory, we examine the extent to which firms' labor market considerations shape their innovation decisions using two sets of counterfactual analyses. First, we make inventors' quality fully revealing to the firm, thus eliminating any uncertainty and the resulting need to retain flexibility. Firms' innovation scope would become 14% more specific in this case, and the change is mainly concentrated among inventors with shorter tenures. Second, we remove the rent splitting consideration by letting firms re-optimize, maximizing the joint surplus between the firm-inventor pair (instead of focusing on the firm value only). The result shows that firms' innovation would become 24% less specific, with the effect showing up most strongly among more seasoned inventors.

Next, we examine how such choices of innovation specificity, in turn, influence the value of the firm and the surplus accrues to the inventors. To this end, we perform additional 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 a quarter will lead to a 21% 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 narrow, which helps them to establish better bargaining positions with employees at the expense of a lower joint surplus.

Lastly, we validate our model mechanism by examining the impact of changes in the enforceability of noncompete agreements across different states in the US. Such changes affect firms' concerns regarding employee mobility and retention, which ultimately leads to changes in their innovation scope as our model predicts. Indeed, we find that firms broaden their innovation scope when the enforcement of noncompete agreements becomes stricter, with the effect being particularly pronounced among seasoned inventors. The result confirms the model premise that firms actively choose their innovation scope to address labor-related concerns.

This paper contributes to the literature on 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; Arellano-Bover, 2024). Firms as a driver of variation in on-the-job learning have long received theoretical attention (e.g. Rosen (1972), Gibbons and Waldman (2006)), but accompanying empirical studies on this front are still limited. The key contribution of our paper is to argue that firms, through proactive operational decisions, R&D in particular, 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 channel.

A key component in our mechanism is the economic properties of firm-specific human capital, a classic idea dating back to at least to Becker (1962). Numerous theories suggest that firm-specific human capital impacts employee mobility and career outcomes. Recent studies use structural analysis to gauge the extent of firm-specific human capital within certain occupations, like cardiology surgeons and finance professionals (Huckman and Pisano, 2006; Gao et al., 2023). Just as we deviate from the on-the-job learning literature above, the proactive role of firm decisions is the key new insight in our paper. Instead of estimating the proportion of firm-specific human capital as an exogenous parameter, we endogenize the fraction of firm-specific human capital as a result of the different innovative activities undertaken by firms.

Our findings also connect to recent studies on labor mobility and firm investments.

Empirical investigations 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.

Finally, our paper adds to the discussion of firms' endogenous policy design in the presence of labor market frictions (Matsa, 2010). More recent studies, including Michaels et al. (2019) and Monacelli et al. (2023), estimate models with firms' endogenous investment and financing decisions, illustrating that firms actively use leverage to influence their bargaining position with workers. In their models, labor market considerations can also trigger an impact on firms' real decisions through financing. Marimon and Quadrini (2011) and Chen et al. (2023) show that contracting and agency frictions between firms and workers affect the efficiency of firm investment and the resulting human capital accumulation. We show that firms can directly influence their interaction with workers by choosing the type of innovation. We explore how the influence of such decisions varies over workers' life cycles and examine the implications on worker surplus.

2. An Illustrative Example

Let's consider a scenario where a firm hires an inventor to pursue innovation activities. On day 1, the firm determines the type of innovation to pursue. On day 2, the pair produces innovation output, which results in an immediate cash flow and simultaneously fosters the accumulation of knowledge capital. On day 3, the inventor receives an outside offer and has to decide if he wants to switch job or keep his current employment. The firm and inventor then receive their final cash flows. For simplicity, we assume there is no discounting.

We model the firm's innovation decision as a binary choice. They can opt to pursue either specific or general innovation. Both of these activities result in the production of q units of innovation output during the second period. The output is then split 50-50 between the inventor and the firm. Here, q can take one of two values: $\{\bar{q}, \underline{q}\}$, which correspond to the quality of the match between the firm and inventor being good or bad, respectively. The firm and inventor can have their priors about the likelihood of a high-quality match on day 1, but the uncertainty cannot be fully resolved until the output is realized on day 2.

Pursuing specific innovation generates 1 unit of specific knowledge capital. The utilization of the specific knowledge capital depends significantly on both the firm's infrastructure and the expertise of the inventor. Therefore, if the inventor chooses to change job, this specific knowledge capital will be lost and will not generate any future value for either the firm or the inventor. Alternatively, the firm can opt for more general innovation, which yields 1 unit of general knowledge capital. In this case, we assume that half of the general knowledge capital is embodied in the firm, and the other half in the inventor. This means that if the inventor decides to leave the firm on day 3, he can take 0.5 unit of the accumulated general human capital with him to the new employer, while the firm retains the remaining 0.5 unit.

On day 3, if the firm and inventor stay matched, they generate an additional cash flow of q. The inventor will also receive an outside offer at the beginning of day 3. He can bring any general knowledge he has accumulated to the new firm, where it can generate a return of ξ^+ per unit of knowledge. If the inventor chooses to switch to the new employer, the firm will terminate the project prematurely, resulting in a liquidation value of ξ^- per unit of general knowledge capital. The firm also has the option to terminate a project even without an outside offer. We assume $\xi^+ > \bar{q} > \xi^- > \underline{q} > 0$, suggesting that for any firm and inventor who have pursued general innovation in period 2, it is strictly more rewarding for the inventor to take the outside opportunity, and therefore, separation will always happen. However, separation will be in the firm's best interest only if the match quality is low. Conservely, if the firm and inventor have engaged in specific innovation previously, they should always maintain the match, as separating would lead to zero values for both parties. In this case, the firm and inventor will receive the project cash flow, contingent on the quality of their match.

The table below outlines the payoffs for the firm and the inventor, taking into account the separation decision on day 3 analyzed above:

	Firm's payoff		Inventor's payoff	
	$q=\bar{q}$	$q=\underline{q}$	$q=\bar{q}$	$q=\underline{q}$
General	$0.5\bar{q}+0.5\xi^{-}$	$0.5\underline{q}+0.5\xi^{-}$	$0.5\bar{q}+0.5\xi^{+}$	$0.5\underline{q}+0.5\xi^{+}$
Specific	$0.5\bar{q}+0.5\bar{q}$	$0.5\underline{q}+0.5\underline{q}$	$0.5\bar{q}+0.5\bar{q}$	$0.5\underline{q}+0.5\underline{q}$

The results presented above indicate that the choice of innovation scope can significantly impact the firm's overall payoff, primarily through two channels. The first one is the separation cost channel—when the firm pursues more specific innovation, that makes it more difficult for the firm to redeploy the knowledge capital accumulated during the process when the position is terminated, either due to the inventor switching jobs or the firm liquidating the project. The second channel operates through employee retention, which suggests that more specific innovation not only hinders the firm's ability to redeploy knowledge but also reduces the value of the inventor's human capital to outsider firms. This, in turn, decreases the likelihood of the firm losing its valuable employee to a labor market competitor. The relative significance of the two channels can vary among firms and inventors. The separation cost channel can become the dominant force when $q=\underline{q}$, or in general, when the quality of the match is relatively low and job termination is likely to take place. The employee retention channel, instead, will become a more important concern if the match quality is likely good, so the firm has a strong desire to keep the current employee and to fend off the potential competition from the labor market.

3. Model

In this section, our goal is to develop a dynamic model in which heterogeneous innovation activities that firms pursue result in distinct effects on their labor separation cost and retention decisions. Our model formalizes the intuition from Section 2, embedding factors such as endogenous R&D activities, human capital accumulation, and wage setting. The richness of these features allows us to match the observed patterns on firm R&D activities. Using this framework, we analyze, quantitatively, the potential impact of shifts in these activities on the firm value and the career outcomes of the inventors. Within this model, workers choose where to supply their human capital, considering the possibility of transitioning to new employers when such opportunities arise. They might also leverage these outside opportunities to renegotiate wages with their current employers. Firms make decisions on their R&D investment, and dynamically adjust the type of their innovation activities, anticipating how such decisions will interact with the workers' choices.

3.1. Producing innovation

Our model features a continuum of innovative jobs in an economy. Each job consists of a firm, f, that hires an inventor, j, to engage in research and development activities. Let $n_{j,f,t}$ to denote the unit of innovative output generated by inventor j, who works for firm f at time t:

$$n_{j,f,t} = Poisson\left(a \cdot e^{\kappa \cdot \mu_{j,f,t}} \cdot \Phi_{j,f,t}\right). \tag{1}$$

We use a Poisson process to reflect that innovation occurs only infrequently and is associated with uncertainty. The intensity of innovation, characterizing the frequency at which an inventor-firm pair realizes innovative outcomes, equals $(a \cdot e^{\kappa \cdot \mu_{j,f,t}} \cdot \Phi_{j,f,t})$, where a is a constant, scale parameter, and $\mu_{j,f}$ represents the match quality of the inventor-firm pair, which we discuss below in Section 3.1.1. Holding all else equal, a better quality match is associated with heightened intensity to produce innovation. $\Phi(\cdot)$ is the knowledge-to-innovation function:

$$\Phi_{j,f,t} = k_{j,f,t}^{1-\rho}, r_{j,f,t}^{\rho}, \tag{2}$$

where k stands for the level of knowledge capital stock owned by the firm-inventor pair at the start of period t, which includes the firms' research notes, existing programs, specific research practices, and the workers' human capital. A firm can also boost its innovation output in a given year by increasing its R&D expenditure, $r_{j,f,t}$.

Firms' innovation activities in our model differ in their scope. A firm-inventor pair can engage in more targeted innovative activities, leading to innovation outputs with a narrower scope, or they can choose projects with broader applications, which leads to innovations that can be applied widely across disciplines. We use $\omega_{j,f,t}$ to denote the scope (specificity) of innovation projects pursued by the inventor-firm pair in period t. Like a firm's R&D spending, its scope of innovation is also a choice variable that the firm needs to decide every period.

The return from the inventor-firm's current period of innovation activities equals:

$$y_{j,f,t} = \pi \cdot n_{j,f,t} - r_{j,f,t} - f, \tag{3}$$

where π measures the capitalized return per unit of innovation output (i.e., the discounted future cash flow generated by the innovation), and f is the fixed operating cost per period.

3.1.1. Match quality. We model the quality of an inventor-firm pair, $\mu_{j,f}$ as a binary variable—with $\{\mu = 1\}$ indicating a good quality match and $\{\mu = 0\}$ 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; 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 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 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:

$$P\{\mu = 1\} = 1 - P\{\mu = 0\} = q. \tag{4}$$

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, wherein all agents extract information about the match quality from observed signals and learn in a Bayesian fashion. As Equation (1) suggests, the innovation intensity is contingent upon μ, and hence, the realized innovation output can serve as a signal to infer $\mu_{i,b}$. When a firm and inventor experience high levels of innovative activity, they are more inclined to associate a greater likelihood with the match being of good quality. We use $p_{j,f,t}$ to denote the perceived probability that an inventor-firm pair is good quality based on the current information set, $\mathcal{F}_t$. Bayesian updating implies:

$$p_{j,f,t+1} = \frac{p_{j,f,t} \cdot \mathbb{P}\left\{n_{j,f,t} | \mu_{j,f} = 1, \mathcal{F}_t\right\}}{p_{j,f,t} \cdot \mathbb{P}\left\{n_{j,f,t} | \mu_{j,f} = 1, \mathcal{F}_t\right\} + (1 - p_{j,f,t}) \cdot \mathbb{P}\left\{n_{j,f,t} | \mu_{j,f} = 0, \mathcal{F}_t\right\}}. \tag{5}$$

3.1.2. Knowledge capital accumulation. Knowledge capital depreciates at a rate δ, and the law of motion for knowledge capital can be characterized by:

$$k_{j,f,t+1} = (1 - \delta) \cdot k_{j,f,t} + L_{i,f,t}. \tag{6}$$

Here, $L_{j,f,t}$ stands for the new knowledge capital acquired in the current period:

$$L_{j,f,t} = e^{-\ell \cdot k_{i,j,t}} \cdot n_{i,j,t}. \tag{7}$$

The firm and the inventor gain knowledge through their experience of producing innovation, $n_{i,j,t}$. ℓ determines the speed at which knowledge capital accumulates. If $\ell = 0$, then knowledge capital is accrued at a steady rate. If $\ell < 0$, then the accumulation of knowledge capital decelerates as the level of existing knowledge grows. Figure 5 illustrates the law of motion for knowledge capital as described above.

The specificity of the newly accumulated knowledge capital, $L_{j,f,t}$, is determined by the firms' endogenous choice, $\omega_{j,f,t}$. If a firm chooses to engage the inventor in more specific scientific exploration in the current period, that results in more specific knowledge capital being accumulated. Conversely, if a firm chooses a broader scope, it helps accumulate more general knowledge. Given the law of motion for knowledge capital specified by equation (6), we can derive the relation that governs the firm's choice of $\omega_{j,f,t}$, and the specificity of the knowledge capital stock, χ:

$$\chi_{j,f,t+1} = \frac{\chi_{j,f,t} \cdot (1-\delta)k_{j,f,t} + \omega_{j,f,t} \cdot L_{j,f,t}}{k_{j,f,t+1}}, \tag{8}$$

where $\chi_{j,f,t}$ serves as an indicator for the blend of knowledge capital types—namely, general and specific—that the firm-inventor pair possesses. The utilization of specific knowledge capital pivots on the firms' infrastructure and the inventors' expertise; hence, such knowledge capital is embodied in the firm-inventor pair. Regarding general knowledge capital, we need to distinguish its ownership more precisely because the firm or the inventor can keep using it upon a turnover. Therefore, ownership would play a critical role in shaping the firm and inventor's respective outside options.

To this end, we assume that in every period, a fraction, η, of the newly accumulated knowledge resides with the firm and is embedded in the firm's intangible capital stock—one can think of these as research notes generated in the process, improved research practice within the firm, or knowledge accumulation to other research staff in the firm. The remaining $(1-\eta)$ fraction goes to the inventor and becomes his human capital. We use $\lambda_{j,f,t}$ to measure the fraction of total knowledge capital embodied in the firm. Equation (6) implies that:

$$\lambda_{j,f,t+1} = \frac{\lambda_{j,f,t} \cdot (1-\delta)k_{j,f,t} + \eta \cdot L_{j,f,t}}{k_{j,f,t+1}}. \tag{9}$$

A unique feature of our framework is that we separately model the scope and ownership of knowledge capital. The scope of knowledge capital will influence innovation production, as we allow heterogeneous productivity of specific versus general knowledge capital stock, and the relative productivity can also vary endogenously as firms choose projects with varying scopes. The specificity of human capital also has important implications when a firm and its inventor separate, in which case, both parties will find it difficult to redeploy the knowledge if it is associated with a high degree of specificity. Thus, there will be more substantial costs in the job transitioning process. In contrast, the ownership of knowledge capital does not directly influence production. However, it will become consequential when the possibility of separation arises, in which case, both parties are entitled to redeploy the knowledge capital embodied in them.

3.1.3. Job separation and the loss of knowledge capital. The evolution of knowledge capital is also influenced by separations between firms and workers. In our model, job separations arise endogenous for two reasons. First, an inventor may be poached by a competitor in the labor market, leading to the dissolution of the current inventor-firm pairing if the current employer is unable to match the competitor's offer. The conditions under which such separation occurs are derived in Section 3.3 below. Second, a firm may terminate a position if it becomes unprofitable.

When an inventor is poached by an outside firm, he can bring the fraction of his human capital that is general to the prospective employer. Consequently, the inventor's continuation value is contingent upon the productivity of this newly formed employment pair. The firm that loses the inventor has to terminate the position and receive a liquidation value from the knowledge capital that is embodied in the position. A firm also has the option to voluntarily terminate a position, even when the inventor does not receive an outside offer. In such cases, the firm receives the same liquidation value, and the inventor exits the market[1] and receive his reservation utility, which we normalize to zero.

To simplify the notation throughout the remainder of this paper, we will also use $\left(k^F_{f,t}\right)$ and $\left(k^I_{j,t}\right)$ to denote the knowledge capital owned by the firm and the inventor, respectively:

$$k^F_{f,t} \equiv \lambda_{j,f,t}(1-\chi_{j,f,t}) \cdot k_{j,f,t} \tag{10}$$

$$k^I_{f,t} \equiv (1-\lambda_{j,f,t})(1-\chi_{j,f,t}) \cdot k_{j,f,t}, \tag{11}$$

Let ξ be the price of knowledge capital. The cash flow that the firm receives from either a voluntary or involuntary liquidation equals $\xi \cdot k^F_{f,t}$, where $k^F_{f,t}$ is the amount of knowledge capital embodied in the firm, specified by equation (10). This liquidation value constitutes the firm's outside option.

Lastly, jobs can also be destroyed for exogenous reasons, which occurs at an annual rate of τ. The inventors who exit due to job terminations or for exogenous reasons will be replaced by a group of novice inventors joining the industry, each of whom is endowed with $\mathring{k}$ units of

[1] This assumption is not restrictive as termination only occurs for inventors with relatively low levels of human capital. Therefore, we can interpret their exits as them rejoining the labor force and behaving similarly to the novice inventors.

general human capital.

There is also a large number of potential entrant firms that will create new jobs upon entry, and existing firms can also open up new positions. Both new entrants and existing firms pay a sunk cost of ι to create a new job and participate in the labor market. We use ϕ to denote the mass of new jobs created in the industry. Given ι, ϕ is determined in the equilibrium by the job creators' indifference condition. When a new position is created, we assume that the firm will first try to poach a seasoned inventor, in which case, they receive an additional signal regarding his potential match quality: $\mathring{\nu} \sim N\left(\mathring{\mu}, \sigma_\nu^2\right)$. If $\sigma_\nu \to \infty$, it means that the signal is uninformative, and if $\sigma_\nu \to 0$, it means the match quality is fully revealed. We use $\mathring{p}$ to denote the posterior probability that the new match has good quality:

$$\mathring{p} = \frac{q \cdot \mathrm{pdf}\left(\mathring{\nu}|\mathring{\mu} = 1\right)}{q \cdot \mathrm{pdf}\left(\mathring{\nu}|\mathring{\mu} = 1\right) + (1-q) \cdot \mathrm{pdf}\left(\mathring{\nu}|\mathring{\mu} = 0\right)}. \tag{12}$$

If the investor declines the offer, the firm will turn to a novice inventor, in which case, they start with an uninformed prior—the probability of the match being good equals the unconditional mean of q.

The firms that have successfully recruited either a reasoned or a novice inventor will acquire knowledge capital from the market, which we denote as $\mathring{k}$. This newly acquired knowledge $\mathring{k}$ is then combined with the inventor's human capital and forms the knowledge base of the new inventor-firm pair. $\mathring{k}$ is an endogenous decision to be made by the job creator. We use ξ to denote the market price at which firms liquidate or acquire knowledge capital, which is pinned down in the equilibrium by the market clearing condition.

3.2. Value function

The timeline of the model is as follows. At the beginning of each period, the firm makes its decision on R&D expenditure (r) and sets innovation scope (ω). The firm and inventor then produce and collect innovation outputs. In the meantime, existing knowledge capital depreciates, and the firm inventor pair also accumulates new knowledge through their innovation activities. At the end of the period, inventors receive external offers and decide if they switch to the new firm or stay with their current employer; the firm decides whether or not to terminate the position.

In this section, we introduce the value function for a firm-inventor pair at the beginning of a period, represented in a recursive formula. We drop the time subscript by using prime to denote the next period variables. We first take as given the firm's decisions related to R&D and the choices governing the separation of the inventor-firm, collectively referred to as Ω. We discuss the endogenous determination of these decisions below in Section 3.3.

We define $V(\cdot)$ of an inventor-firm pair as the present value of all cash flows received by the shareholders of the firm plus the discounted lifetime wage income received by the inventor. we define the net value, $\tilde{V}(\cdot)$ as the pair's $V(\cdot)$ minus the liquidation price of capital:

$$\begin{aligned} V(p,k,\lambda,\chi;\Omega) =& y + \beta(1-\tau)\cdot\mathbb{E}\{V(p',k',\lambda',\chi';\Omega') + \Sigma^1(p',k',\lambda',\chi';\Omega')\cdot\mathbf{1}_{d=1} \\ & + \Sigma^2(p',k',\lambda',\chi';\Omega')\cdot\mathbf{1}_{d\neq 1}\cdot\mathbf{1}_{d=2}\}, \end{aligned} \tag{13}$$

$$\tilde{V}(p,k,\lambda,\chi;\Omega) \equiv V(p,k,\lambda,\chi;\Omega) - \xi k^F, \tag{14}$$

where y is the per-period return generated by the inventor-firm pair as defined in equation (3), and β is the discount factor. The value of the firm-inventor pair equals the flow profit plus the continuation value if the pair is maintained in the next period, plus the gain or losses from separation. k^F is the general knowledge capital that the firm can redeploy upon separation as defined in equation (10). Our model features three types of separations as described in section 3.1.3.τ captures the rate at which an inventor exits the market for exogenous reasons; $\mathbf{1}_{d=1}$ is an indicator function for the inventor receiving an outside offer[2] and subsequently deciding to switch employment; $\mathbf{1}_{d=2}$ corresponds to the firm's decision to terminate the current project; otherwise, we use $d = 0$ to denote no endogenous separation.

In equation (13), the expectation is taken w.r.t. two factors. The first is the stochastic evolution of states for the current inventor-firm pair due to the uncertainty embedded in their innovation output process, and the second is the pool of outside offers that the inventor might receive. $\Sigma^1(p',k',\lambda',\chi')$ denotes the gain when the inventor takes the outside offer, and $\Sigma^2(p',k',\lambda',\chi')$ corresponds to the value change when the position is terminated by the

[2]Outside offer arrives at the probability ϕ, which measures the mass of new firms actively searching to hire, and thus the probability of an inventor receiving an outside offer.

firm or due to exogenous inventor exit:

$$\Sigma^1(p', k', \lambda', \chi'; \Omega') = \theta \left\{ \tilde{V}\left(\mathring{p}, \mathring{k} + k^I, \mathring{\lambda}, 0; \mathring{\Omega}\right) - \tilde{V}(p', k', \lambda', \chi'; \Omega') \right\} \tag{15}$$

$$\Sigma^2(p', k', \lambda, \chi'; \Omega') = -\tilde{V}(p', k', \lambda', \chi'; \Omega'), \tag{16}$$

θ captures the inventor's relative bargaining power—when an inventor switches employment. When this happens, the inventor and his original firm will be compensated on par with their outside options, which equals $\tilde{V}(p', k', \lambda', \chi')$. In addition, the inventor will capture a θ fraction of the gain generated by reallocating to the new employer, which equals $\tilde{V}(\cdot)$ generated by the new pair minus that if the inventor stays matched with the current employer. When the inventor switches employment, the perceived match quality of the new pair is given by equation (12), and initial knowledge capital is entirely general, which equals the firm's initial investment, $\mathring{k}$, plus the human capital that the inventor can bring to the new employment, k^I (as specified in equation 11). $\mathring{\lambda}$ measures the share of knowledge capital contributed by the firm, which equals $\frac{\mathring{k}}{\mathring{k}+k^I}$.

3.3. Wage, R&D, and separation decisions

In this section, we delve into the wage negotiation between the inventor and the firm, establishing how they divide the value they jointly create. This division is crucial, as it shapes the optimal decisions for the firm and the inventor, based on their stake in the total value generated.

Wage is determined in a sequential auction bargaining framework (Cahuc et al., 2006; Jarosch, 2023), which builds on prior works of Postel-Vinay and Robin (2002a,b). We define u as the best external offer (the one associated with the highest $\tilde{V}$) that inventor j has ever received during his employment with firm f, which we also refer to as inventor j's bargaining capital. A rookie inventor has a bargaining capital of zero when first joining the labor market. Let $W(\cdot)$ and $J(\cdot)$ denote the value functions of the inventor and the firm, respectively, which satisfy:

$$W(p,k,\lambda,\chi,u;\Omega)=u+\theta\left[\tilde{V}(p,k,\lambda,\chi;\Omega)-u\right], \tag{17}$$

$$J(p,k,\lambda,\chi,u;\Omega)=\xi k^{F}+(1-\theta)\left[\tilde{V}(p,k,\lambda,\chi;\Omega)-u\right], \tag{18}$$

where θ is the inventor's relative bargaining power. Equations (17) and (18) imply that the inventor will be compensated on par with his bargaining capital, plus θ share of the surplus generated from maintaining the match with the current employer. The firm will be compensated on par with its liquidation price, plus the remaining $1-\theta$ share of the surplus. When an inventor receives an outside offer, his bargaining capital, u, evolves as follows:

$$u'=\begin{cases} u & \text{if } u>\tilde{V}\left(\mathring{p},\mathring{k}+k^{I},\mathring{\lambda},0;\mathring{\Omega}\right), \\ \tilde{V}\left(\mathring{p},\mathring{k}+k^{I},\mathring{\lambda},0;\mathring{\Omega}\right) & \text{if } \tilde{V}(p,k,\lambda,\chi;\Omega)\geq\tilde{V}\left(\mathring{p},\mathring{k}+k^{I},\mathring{\lambda},0;\mathring{\Omega}\right)>u, \\ \tilde{V}(p,k,\lambda,\chi;\Omega) & \text{if } \tilde{V}\left(\mathring{p},\mathring{k}+k^{I},\mathring{\lambda},0;\mathring{\Omega}\right)>\tilde{V}(p,k,\lambda,\chi;\Omega). \end{cases} \tag{19}$$

Intuitively, an inventor can initiate a negotiation with the employer only if there is a credible threat (receiving an outside offer). He will do so only if the outside offer beats his current bargaining capital, leading to better compensation upon the wage negotiation. More specifically, case one of equation (19) suggests that if the net value generated from the inventor taking the outside offer is lower than his current bargaining capital, then the inventor will choose to do nothing, in which case, his bargaining capital stays unchanged. In the second case, if the outside offer is better than the inventor's bargaining capital, the inventor will initiate a wage negotiation with the current employer. The current employer will make a counteroffer, where the inventor will be compensated on par with the entire net value generated from taking the outside offer, which forms the inventor's new bargaining capital, plus θ share of the surplus. Note that in this case, the outside firm cannot match this offer because, with any $\theta>0$, it would entail the outside firm's value J to fall below its liquidation price. This offer is sustainable for the current inventor-firm pair, as both parties enjoy a positive surplus in addition to their respective outside options. If the outside offer generates a high $\tilde{V}$ exceeding that created by the current inventor-firm pair, the current firm will be unable to counter. Hence, the inventor will separate from the current employer and join the new firm, in which case, he uses the net value generated by his current employment as his bargaining capital with the new employer.

This above process implies that the inventor will accumulate bargaining capital, which allows him to move up to better-paying positions gradually. However, an exception exists when the current firm-inventor pair creates a strictly positive $\tilde{V}$, but it falls below the inventor's bargain capital u. In this case, without lowering the inventor's bargaining capital, the firm would end up with a J below its liquidation price. However, it is also sub-optimal for the firm to liquidate because the pair still creates a positive net value. In this case, we allow the firm to initiate a negotiation with the inventor such that the entire net value created accrues to the inventor, and the firm is just indifferent between liquidating the position or not, in which case, we assume the position will be maintained[3].

When the net value of the current inventor-firm pair falls below zero, no $u > 0$ exists that permits the firm to achieve a $J(\cdot)$ equivalent or greater than its liquidation price. Consequently, the firm will liquidate the project. The following summarizes the inventor-firm's endogenous separation decision:

$$d = \begin{cases} 1 & \text{if } \tilde{V}\left(\mathring{p}, \mathring{k} + k^I, \mathring{\lambda}, 0; \mathring{\Omega}\right) > \tilde{V}\left(p, k, \lambda, \chi; \Omega\right), \\ 2 & \text{if } \tilde{V}\left(p, k, \lambda, \chi; \Omega\right) < 0, \\ 0 & \text{if otherwise.} \end{cases} \tag{20}$$

This implies that a separation between the inventor and the firm only occurs if the net value of maintaining the match is lower than that generated by matching the inventor with the prospective new employer or if the net value is strictly below zero. Given the R&D expenditure and scope choices made by the firm and the wage negotiation process, such a separation decision is bilaterally efficient, serving the best interest of both the firm and the inventor concurrently.

[3]This situation can be triggered when the posterior of the match quality, p', is adjusted downward sharply due to low current-period output. Allowing the firm to lower the wage while maintaining the position helps us to ensure that job termination decisions in our model are always efficient, conditional on the current states and policies

Finally, we analyze the firm's optimal decisions on R&D expenditure and specificity. For an incumbent firm, these choices are made to maximize its value J:

$$\{i, \omega\} = \arg\max J(p, k, \lambda, \chi, u; \Omega). \tag{21}$$

These choices related to firms' R&D strategies, along with the separation decision described in equation (20) close the loop for the endogenous determination of Ω.

For a new entrant in the industry, after successfully recruiting a seasoned or novice inventor, the firm will choose the amount of knowledge capital to purchase at the market price ξ to maximize the value of the firm net any investment costs:

$$\mathring{k} = \arg\max J(\mathring{p}, \mathring{k} + k^I, \mathring{\lambda}, 0, u; \mathring{\Omega}) - \xi\mathring{k}. \tag{22}$$

3.4. Stationary equilibrium

For each investor-firm pair, their continuation value is forward-looking. It depends on firms' choices on future R&D expenditure and specificity, also considering potential gains from future separations. The expected gain of separation, in turn, depends on the firm's liquidation value and the outside opportunities available to the inventor. We use Γ_t to denote the distribution of incumbent inventor-firm pairs and new entrants, and we use P^Γ to denote the probability law that governs the transition of Γ :

$$\Gamma_{t+1} = P^\Gamma(\Gamma_t) \tag{23}$$

A stationary equilibrium exists if the following conditions are satisfied:

1. All incumbent inventor-firm pairs follow the optimal separation decision described in equation (20).

2. All incumbent firms make the optimal R&D expenditure and specificity choices as described in equation (21),

3. All entrants with accepted offers choose the optimal amount of knowledge capital to acquire as described in equation (22).

4. All agents have rational expectations of the other agents' actions in the economy.

5. The market for knowledge capital clears—the demand by new entrants equals the supply by firms who experience inventor turnovers.

6. All new entrant firms break even in expectation.

7. The probability law governing the evolution of the states, P^{Γ}, is consistent with agents' optimal decisions.

8. The distribution of firms and inventors is stationery, $\Gamma_{t+1} = \Gamma_t$.

3.5. Model mechanism

The model features a labor-based tradeoff when firms choose the type of innovation activities to engage in. If the firm pursues specific innovation, the cost is the loss of specific knowledge capital in the event of an inventor turnover; the benefit is that it lowers the inventor's general human capital and, thus, the value of his outside opportunities. As a result, separation becomes less likely, and the firm can retain a larger share of the value creation. Importantly, this trade-off is time-varying. When the current perceived match quality is low, separation (or job termination if the inventor does not receive an outside offer) is likely, and the firm is more concerned about maintaining flexibility; when the current perceived match quality becomes high, employee retention and rent splitting 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.

4. Data and Measurements

4.1. Data on patents and inventors

Patent data are obtained from the United States Patent and Trademark Office (USPTO).[4] The database provides detailed patent-level records on nearly seven million patents granted

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

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 et al. (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.[5] For later years, we complete the link using a fuzzy matching method based on the company name, basic identity information, and innovation profiles, similar to Ma (2020), Bernstein et al. (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. For example, we define that inventor i works in Firm f in year t if i applied for a patent in year t that is assigned to firm f. If two or more years pass between two patent filings, and if the employer inferred from these two filings are the same, we impute the employer for all the years in between as this employer. This information can also allow us to identify job switches. For example, if Jane Smith filed a patent with Firm A in 1999 and one with Firm B in 2000, Jane Smith is designated as an employee of Firm A in 1999 and as an employee of Firm B in 2000. If the employers change between two filings that are two or more years apart, we assume that the employment transition between the two firms occurs at the midpoint between the patent application years. Inventors are included in the sample for their entire active career as an inventor, defined as the years between their first and last patent filings.

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

4.2. 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; 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.[6]

A wide variety of citation-based measures can be defined and computed in order to examine different aspects of patented innovations and their links to other innovations. We have computed and integrated into the data "Generality" as suggested in Trajtenberg et al. (1997) and Hall et al. (2001).

$$Generality_p = 1 - \sum_{j \in J} Citation_{pj}^2, \tag{24}$$

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 of Mechanical and Others are at the bottom in terms of generality, whereas Computers and Communications are 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

[6] The forward citation process has a well-known right-truncation problem (Hall et al., 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.

"General Purpose Technology" (see Bresnahan and Trajtenberg, 1995) and the centrality of different fields in innovation network (Acemoglu et al., 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 the number of 3-digit patent classes available, will likely result 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 includes 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 the 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.

4.3. Summary statistics

In Table 1, we report summary statistics of our sample. We report both at the inventor level (Panel A), at the patent level (Panel B), and then at the firm level (Panel C).

[Insert Table 1 Here.]

4.4. 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: 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.

5. Estimation

In this section, we present the model estimates and discuss the intuition behind the estimation process.

To facilitate the estimation, we make two extensions to the baseline model. These extensions do not change the main tradeoff described in Section 3.5. They help us to account for additional factors pertaining to firms' innovation decisions, thus permitting closer matches on the related empirical patterns. We start by re-defining the knowledge-innovation function, $\Phi(\cdot)$ as follows:

$$\Phi\left(k_{j,f,t}, \chi_{j,f,t}, r_{j,f,t}, \omega_{j,f,t}\right) = \left(e^{-b\cdot|\chi_{j,f,t}-\omega_{j,f,t}|} \cdot k_{j,f,t}\right)^{1-\rho} \cdot \left(r_{j,f,t}\right)^{\rho}, \tag{25}$$

where $|\chi_{j,f,t} - \omega_{j,f,t}|$ represents the "distance" between the current innovation scope and the scope of the accumulated knowledge capital. Given the current period $\chi_{j,f,t}$, if a firm and inventor engage in innovation activities more "aligned" with their accumulated knowledge, it enables more efficient utilization of existing knowledge, leading to higher outputs. Conversely, if the alignment is poor, that leads to a productivity "discount" of existing knowledge. The parameter b controls the strength of the "alignment" effect, thereby allowing us to more precisely match the persistence of innovation scope in the data, which can be partially driven by such an "alignment" effect.

Next, we extend the baseline model by permitting firms to have varying comparative advantages with respect to different scopes of innovation. To this end, we modify the return of innovation activities (equation 3) into:

$$y_{j,f,t} = \pi \cdot n_{j,f,t} - e^{c_j\cdot\omega_{j,f,t}} \cdot r_{j,f,t} - f. \tag{26}$$

For any given firm j, a negative c_j implies that the firm holds a comparative advantage in conducting more focused research, leading to innovation in a narrowly defined technological category, while a positive c_j suggests the opposite. It is crucial to acknowledge that our main mechanism, outlined in section 3.5, does not depend on general and specific innovations having differing cost efficiencies. However, introducing this heterogeneity enables our model to align more accurately with the data. Akcigit and Kerr (2018) provides evidence indicating that firms with varying sizes and ages possess comparative advantages in generating innovations with varying scopes. Hence, by explicitly accounting for such comparative advantages, we are able to better match the model to data and isolate the decisions of firms' optimal innovation scope that are driven by our novel, labor-related tradeoff.

More specifically, we model c_j as being drawn from a normal distribution with mean zero and variance σ_c^2; that is, $c_j \sim N(0, \sigma_c^2)$, and it is time-invariant for a given firm. The cost structure closely follows that in Akcigit and Kerr (2018).

5.1. Identification

We estimate the model parameters using the 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 employed in the estimation and explain how they help identify the model parameters.

As a preliminary step, we set the discount factor β to 0.9, a value commonly used in the literature. We calibrate the exogenous job dissolution probability, τ, so that the model predicts an average dropout rate of 6% among inventors, which includes firms' endogenous termination of unprofitable positions and exogenous job dissolution. We set the entry cost, ι, so that the model implies an annual job creation rate, ϕ, that also equals 6%. We set the return to innovation outputs, π, to 6.8 to match the average market value of patents. The unconditional probability of high match quality, denoted as q, is set to 0.5, and thus, we effectively discretize the match quality in the model based on the median of its empirical counterpart. Lastly, we set θ, the relative bargaining power of inventors, to 0.5, which is consistent with the estimated bargaining power of highly skilled workers in Cahuc et al. (2006). The remaining 11 parameters are estimated within an SMM system. These parameters are summarized in Table 2. 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 fit the data as closely as possible.

First, we focus on moments related to the observed patent counts. We match patents' mean and standard deviation at the inventor-firm level to identify a and ℓ. When a becomes higher, it increases both the level of patents and the dispersion of patents among inventor-firms. Conversely, a rise in ℓ implies that it is more difficult for high-productivity pairs to gain additional knowledge, thereby shrinking the variation of patent outputs in the cross section. We rely on the autocorrelation of patent counts to identify δ, the depreciation rate of knowledge capital. We calculate the average number of patents filed by novice inventors during the first three years of their employment spell to identify $\mathring{k}$, which controls their initial human capital. We calculate the fraction of inventor-firm-years with zero patent to identify the fixed cost parameter, f. With an increment in f, a firm will find it increasingly more costly to sustain low productivity years, prompting more timely job terminations and, consequently, a reduction in the occurrence of zero patent years.

We then focus on features related to patent specificity. We use the auto-correlation of patent generality to identify b, which captures the importance of "scope alignment" in firms' innovation production function. Higher b implies that it enhances productivity when the scope of current innovation is closely aligned with that of pre-existing knowledge, leading to high persistence in firms' specificity decisions. To identify the heterogeneity in firms' innovation expertise, we focus on the dispersion of innovation specificity at the firm level. If firms have varied comparative advantages with respect to different innovation scopes, it will translate into more substantial variations in their realized specificity choices.

To identify the next class of parameters, we focus on moments pertaining to firms' R&D expenditure. We use the average R&D expenditure to patent output ratio, $\frac{e^{c_j \cdot \omega_{j,f,t}} \cdot r_{j,f,t}}{\pi n_{j,f,t}}$ to identify the parameter η. A higher η suggests that the firm can internalize more of its R&D, leading to enhanced incentives and increased R&D-associated expenses. We further include the standard deviation of the R&D expenditure ratio. ρ controls the elasticity of R&D in the firm's production function; we construct its data counterpart by regressing patent counts on log R&D expenditure and use the regression coefficient as the identifying moment.

Lastly, we come to parameters that govern the match quality. We use the average inventor relocation rate to identify κ. Our model suggests that job relocation occurs when inventors move to prospective employers that offer a better match quality. An increase in the value of parameter κ indicates that match quality plays a more significant role in the innovation production process. This, in turn, provides inventors with a stronger incentive to relocate, leading to a higher mobility rate. If the value of κ falls to zero, it means that the innovation output is not affected by the current match quality. In such a scenario, inventors would strictly prefer to stay with their current employer to maintain the specific knowledge capital they have accumulated over the past. As a result, the model would predict a mobility rate of zero. Next, conditional on a separation taking place, we count the number of years that an inventor works 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 a very precise signal about whether he is a good match with the current employer or not, in which case, he always stays with the current employer if the match is good quality and separates immediately if the match quality is bad. Thus, the model will generate short employment spells for those who eventually decide to take an outside offer. Finally, we include a moment corresponding to the change in patent counts around inventors' job relocation, defined as:

$$\Delta n_{j,f,t} = \frac{n_{j,f,t+1} + n_{j,f,t+2} + n_{j,f,t+3}}{3} - \frac{n_{j,f,t-1} + n_{j,f,t-2} + n_{j,f,t-3}}{3}, \tag{27}$$

where year t is the year when an inventor changes employment. The change in patent counts reflects the impacts of inventors migrating to positions that better fit their talent. Furthermore, the change can also be driven by investors forfeiting their specific human capital amid the job transition process; the magnitude of the effect is contingent on the historical specificity choices made by the firms. Therefore, we match this moment to ensure that our model can also accurately predict the relative magnitudes of these important channels. Note that we omit year t from our calculation of Δn to avoid any mechanical changes in productivity caused by the transition disruptions.

Table 2 presents the parameter estimates for the model.

[Insert Table 2 Here.]

In Table 3, we compare the empirical and model-implied moments.

[Insert Table 3 Here.]

5.2. Re-scaling the variables to match model setup

In our model, patents do not vary in value and quality, but such variations exist in the 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 variations in patent market value. Instead, we adjust our measure by assigning a higher patent count to the firm-inventor pair if the output patents are of higher value. For example, a $10 \times v$ million patent can be viewed as a portfolio of ten patents, each with a v million market value. We choose the unit of measurement, v, to match the average patent value in industries with the lowest per-patent value.

We also need to adjust the number of inventors. For example, if a patent is assigned to 10 people, then each one of them is considered to have contributed to 0.1 patent in the given year. We perform this adjustment because 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, to be consistent with the way that we count patents.

6. Model Implication

6.1. Inventor turnover and the value of specificity

As a preliminary step, we verify in Figure 6 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 relative to that with a more general scope. To facilitate the comparison, we first define a "specificity premium" measure at the firm level:

$$\frac{\mathbf{E}J\left(p', k', \lambda', \chi'; u' | p, k, \lambda = 0.5, \chi = 1; u = \bar{u}\right) - \mathbf{E}J\left(p', k', \lambda', \chi'; u' | p, k, \lambda = 0.5, \chi = 0; u = \bar{u}\right)}{\mathbf{E}J\left(p', k', \lambda', \chi'; u' | p, k, \lambda = 0.5, \chi = 0; u = \bar{u}\right)}. \tag{28}$$

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 ($\lambda = 0.5$), and asks what would be the percentage change in the firm's continuation value 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 7 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. On the one hand, when the perceived match quality of the inventor-firm pair is low, and they have relatively little knowledge capital, that implies a high separation probability, partially due to the firm’s decision to terminate. As a result, maintaining flexibility is valuable for the firm. On the other hand, when the match quality and knowledge both increase, the separation probability declines while the value created by the pair hikes, making employee retention and rent-splitting the primary concerns, thereby increasing the value of specificity. The results thus highlight the change in firms’ preference regarding the type of innovation activities to pursue as their relationship with the inventor evolves.

[Insert Figure 7 Here.]

Figure 8 further illustrates how the value of a firm changes continuously with varying levels of knowledge capital specificity. This analysis considers three distinct scenarios, each reflecting a combination of an inventor-firm pair’s perceived match quality and knowledge capital: high, medium, and low. These scenarios represent cases where worker retention concerns outweigh the separation cost, when these concerns are equally important, and when worker retention and subsequent rent-splitting decisions become predominant. Consistent with the results from Figure 7, the firm’s value is monotonically increasing/decreasing in the knowledge capital specificity when either the worker retention or the separation cost concern dominates. In the intermediate case, when the two are of comparative significance, the change in firm value tends to be less pronounced as knowledge capital specificity varies. Moreover, this scenario admits an interior optimal knowledge capital specificity that optimally balances the labor-based tradeoffs and delivers the highest value for the firm.

[Insert Figure 8 Here.]

6.2. Knowledge specificity over life cycle

Next, we examine how firms' varying preference for innovative activities relates to inventors' tenure. As inventors' tenure with a firm increases, they accumulate more human capital by learning from previous innovation activities. In addition, the perceived match quality also increases due to the selection effect—long tenure with the current firm implies that this is likely to be a good match (otherwise, he would have been terminated or out-hired by the other firms in previous years). These forces imply that the inventor-firm pair will move from the bottom right corner towards the top left corner of Figure 7.

Accompanying such a move, Panel A of Figure 9 shows that the inventor's mobility first rises 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 instead of a bad match. Therefore, the firm would tolerate initial failures before finding 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 keeps increasing, the match quality among the remaining inventors grows due to selection, and their knowledge capital also increases, leading to persistent mobility declines. We also plot the inventor's cumulative probability of making at least one job transfer within the next five years, which declines monotonically over their life cycle.

[Insert Figure 9 Here.]

The above results imply that as inventors get more seasoned, maintaining the redeployability of knowledge capital becomes less important relative to other considerations, such as retaining inventors and lowering the compensation costs, resulting in reduced attractiveness of engaging in general innovations. This effect is amplified by an additional force, operating through inventors accumulating outside offers over the years and building bargain capital. In Figure 7, we hold the current period ν of an inventor constant (at $\bar{\mu}$) and allow the expectation of future bargain capital to change due to the arrival of outsider opportunities in the next period. When we track an inventor over the life cycle, we recognize that his current bargain capital itself also increases (almost) monotonically over the life cycle,[7], Consistently, Panel B of Figure 9 shows that as inventors become more seasoned, they keep receiving outside offers, which they can use to bargain with their current employers. Hence, their bargain capital grows, implying that firms must 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 extract a higher surplus.

In Figure 10, we partition inventors by their tenure with the current employers and plot the model implied innovation specificity within each tenure quartile. The results reveal a monotonic relationship. Quantitatively, as the inventors' tenure grows from the bottom to the top quartile, the specificity of innovation projects they engage in will shift correspondingly by almost two quartiles. This shift is significant and aligns with the lifecycle patterns observed in Figure 9.

[Insert Figure 10 Here.]

6.3. Counterfactuals

Quantitatively, how much of the observed variations in innovation specificity can be attributable to firms actively using such decisions to influence workers' mobility and outside opportunities? We perform a series of counterfactual analyses to answer this question, with the results presented in Table 4. In row (1), we reproduce the results in Figure 10, reporting the innovation specificity for inventors with varying tenure. In row (2), we explore a hypothetical scenario: what if the liquidation of specific knowledge capital came without any discount? In this case, the firm need not be concerned about increased separation costs even if they engage the inventor in highly specific projects. In row (3), we consider another counterfactual scenario where we shut down firms' incentives to retain and bargain with

[7] We say it is "almost" because there are rare incidences when the pair is close to a termination boundary when a firm can initiate a negotiation with the inventor to lower his surplus.

inventors by assuming that they design the innovation specificity to maximize the lifetime value of the inventor-firm pair (V, as defined in equation 13), not just the portion that accrues to firms' shareholders. Under this premise, we let firms re-optimize their innovation specificity and compare it against the prediction from the baseline model.

[Insert Table 4 Here.]

The results in Table 4 suggest that in the baseline model, the potential separation cost induces firms to assign junior inventors to perform general tasks, even when certain firms might have a comparative advantage in more specialized areas of innovation. Conversely, for more seasoned workers, the desire to influence their outside options and retain them more effectively leads firms to involve them in overly specific projects. This effect is particularly pronounced among inventors in the top tenure quartile. Quantitatively, their innovation projects become 32% more specific compared to the baseline model. By comparing the outcomes in rows (2) and (4) to those of the baseline model, we come to the conclusion that the matching and incentive frictions in the labor market can distort the type of investment and the resultant accumulation of human capital. This effect varies with the career stages of workers and is most pronounced among senior employees with the highest levels of human capital.

We further explore the value implication of firms' innovation specificity choice, quantifying how it affects the distribution of value between inventors and firms. To answer this question, we perform additional counterfactual analyses, wherein we exogenously change the innovation specificity for firms in our simulated economy by 25% to 100%. In the latter scenario, we essentially make innovation entirely general. The results are presented in Table 5, indicating that firm value decreases as we change the scope of their innovation. This result is unsurprising since we are moving further away from firms' "optimal" innovation specificity, which they choose endogenously in the baseline to maximize value. When the innovation specificity decreases, however, it enhances inventors' outside options, leading to increased wage income for them. When we add up the inventor and firm values, the sum initially rises as we decrease specificity, followed by a monotonic decline. This suggests that firms are directing their inventors towards a somewhat excessively narrow scope.

[Insert Table 5 Here.]

7. External Validation: The Effect of Noncompete Agreement

In this section, we examine whether the type of R&D projects that firms pursue vary in response to shocks to labor mobility and their employee retention concerns. This reduced-form analysis shed light on our main model mechanism that firms actively choose their innovation scope to influence the labor-based tradeoff.

To explore variation in labor market mobility and firms' concerns about employee retention, we rely on changes in the enforceability of noncompete agreements (NCs) across US states, which restricts labor mobility and lowers the probability that a worker chooses to leave a firm. In our model, there is a negative relation between age/tenure and the specificity of innovation, and this is because inventors who have stayed in a firm longer have a lower probability of future separation—more specific investment could further lower the probability that such good-quality worker chooses to leave. With stricter NC enforcement, firms are less worried about good-quality workers leaving, making it less rewarding to use R&D investment (and the resulting knowledge capital) to retain good-quality workers. In other words, it would be a confirmation of our mechanism if we find the age/tenure-innovation scope relation becoming weaker after NCA enforcement strengthens.

The empirical design follows Jeffers (2019), who compile a list of changes in the enforceability of NCs that mainly come from state-level court rulings that overturn precedent and cause a sudden change in the enforceability of NC contracts. In column (1) of Table 6, we first show that with stricter enforcement of NCs, there is a significantly lower annual job transition rate among inventors. The 0.6 percentage points in economic magnitude translated to a 15% lower from the base transition probability. This evidence is consistent with prior findings on the impact of NCs and validates the relevance of this variation in our empirical setting.

[Insert Table 6 Here.]

Our key empirical analysis is based on the following model:

$$PatentGenerality = \alpha + \beta_1 \cdot Tenure/Age + \beta_2 \cdot Tenure/Age \cdot NC + \theta \cdot NC + \varepsilon. \quad (29)$$

In this model, β_1 tests our model prediction pertaining to the age/tenure-specificity relation (similar to that in Figure 1). β_2 tests the impact of changes in labor mobility and retention concerns. In columns (2) and (3), we show that tenure in a firm and inventor age are both negatively related to patent generality, consistent with our model mechanism. Importantly, we show that this relation is mitigated when NC enforcement becomes stricter, flattening the relation by roughly 25%.

Our results further suggest that NCs have a negative impact on generality for new and young workers (e.g., tenure = 1); while the effect is positive on older workers. For example, for a worker with tenure equal to 5, the net change of generality would be $5 \times 0.012 - 0.020 = 0.040$. Therefore, the aggregate impact of NC enforcement on each firm (not inventor-firm pairs) is likely to differ based on the worker composition.

To put the results in a broader perspective, our model sheds light on the nuances in the mechanisms behind the firm responses following changes in the enforcement of NCs. In particular, our results show the heterogeneous effects among different groups of workers with varying seniority and outside opportunities because they have different departure probabilities and knowledge capital. So, a broad takeaway is that for NC-related policy discussions, one needs to take into account firm-level motives for knowledge and labor retention due to labor composition.

8. 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.

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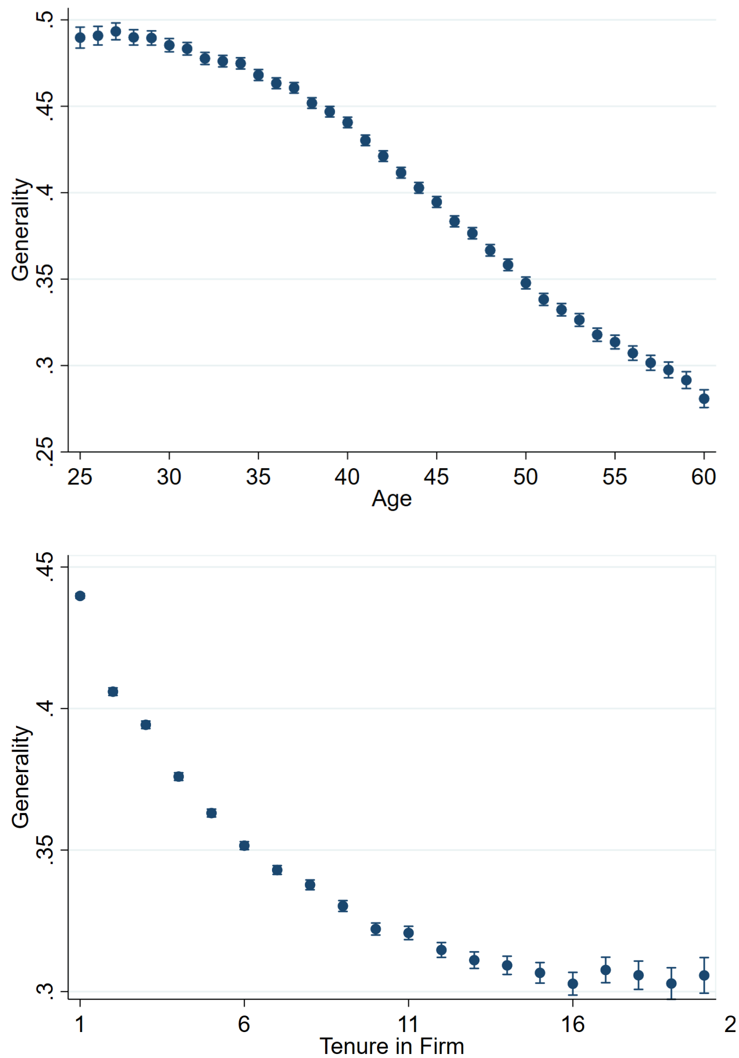

Figure 1. Innovation Generality and Inventor Experience

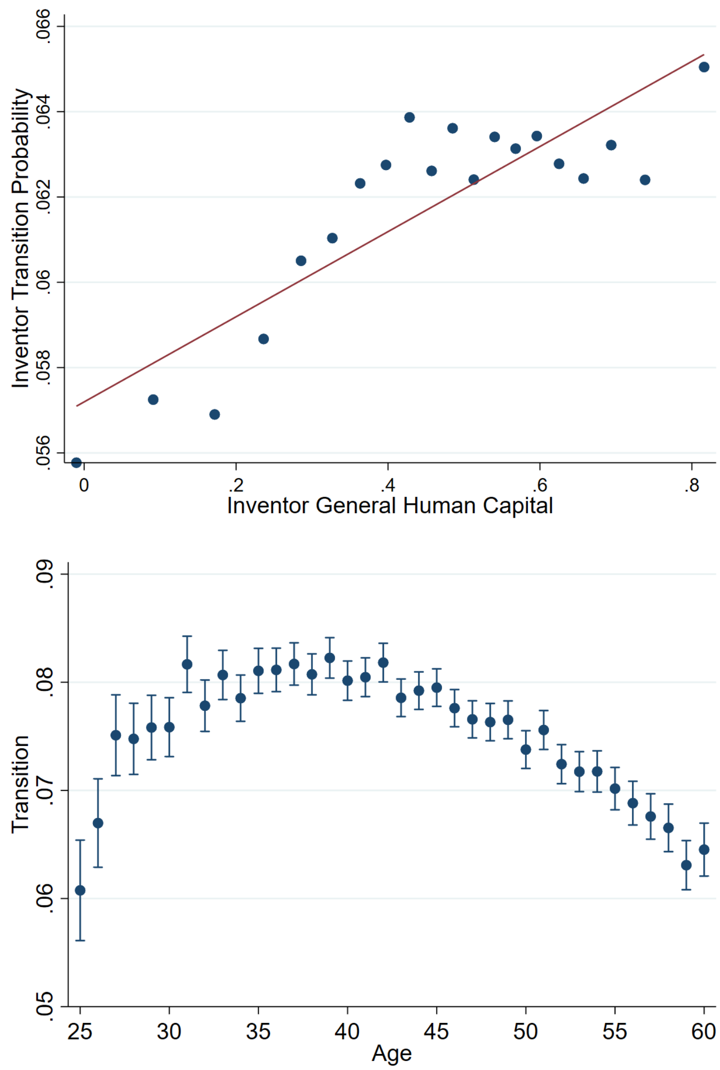

Figure 2. Inventor Mobility, Experience, and Human Capital Generality

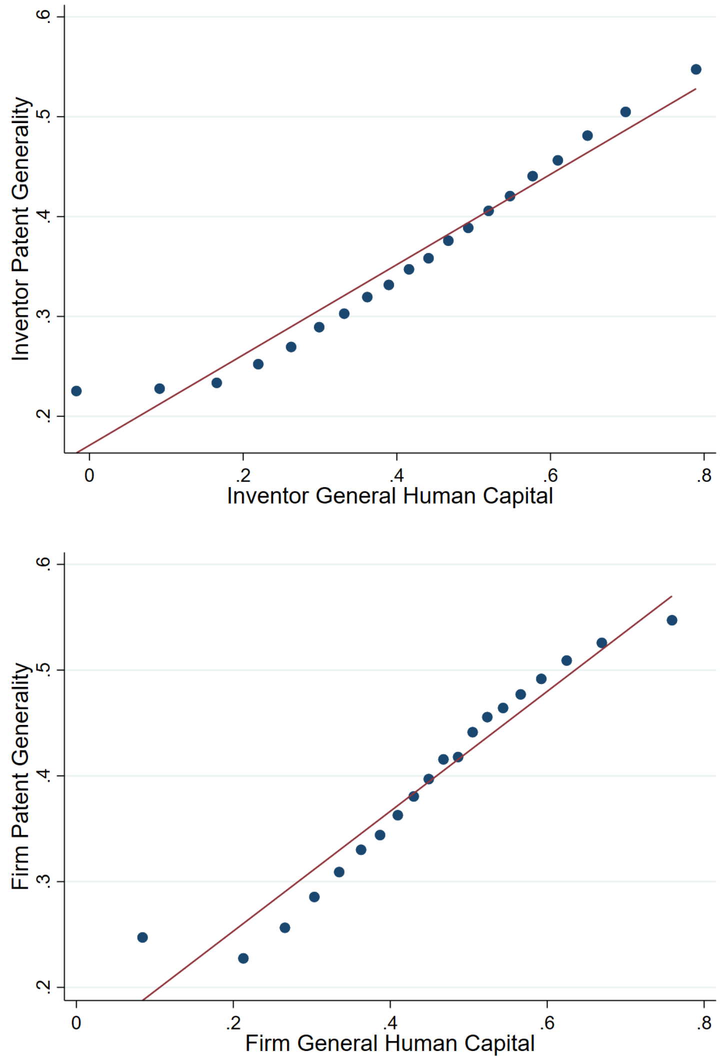

Figure 3. Inventor General Human Capital and Firm's Future Patent Generality

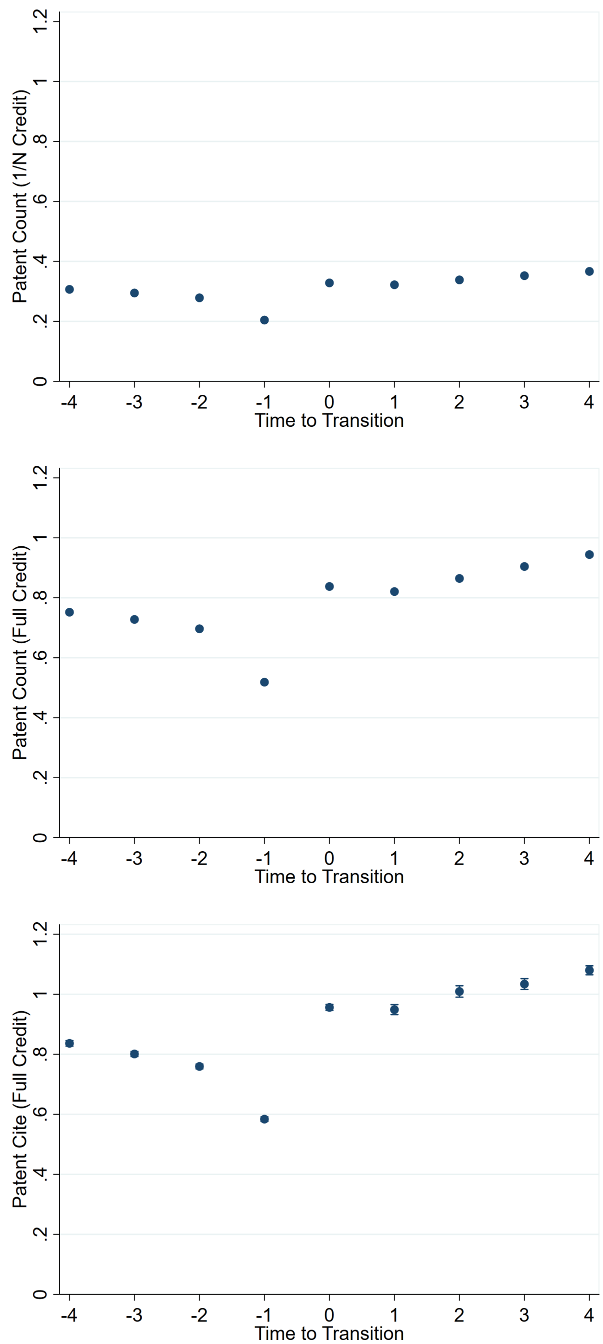

Figure 4. Productivity Around Transition

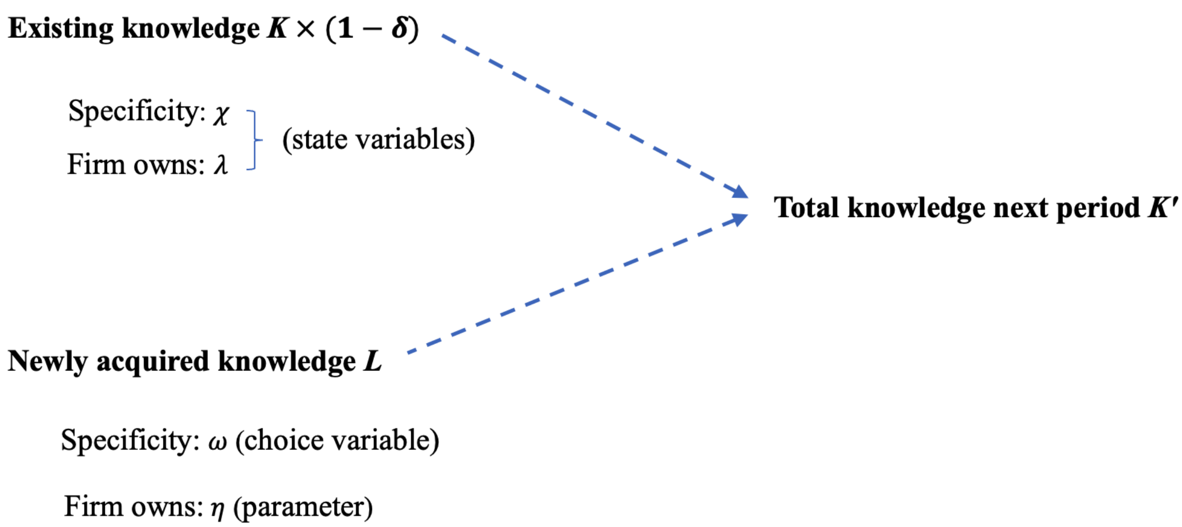

Figure 5. Law of Motion for Knowledge Capital

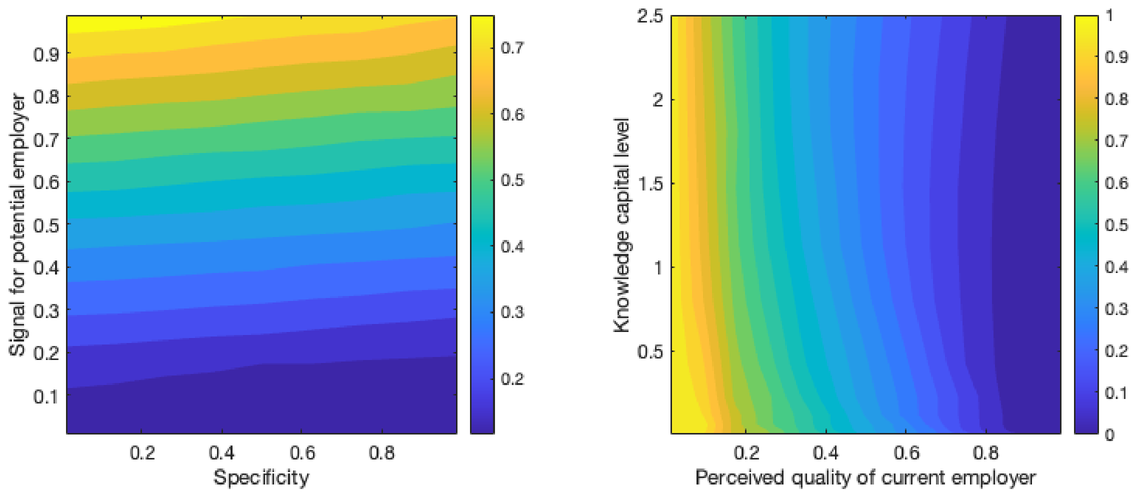

Figure 6. Match Quality, Knowledge Capital, and Inventor Turnover

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

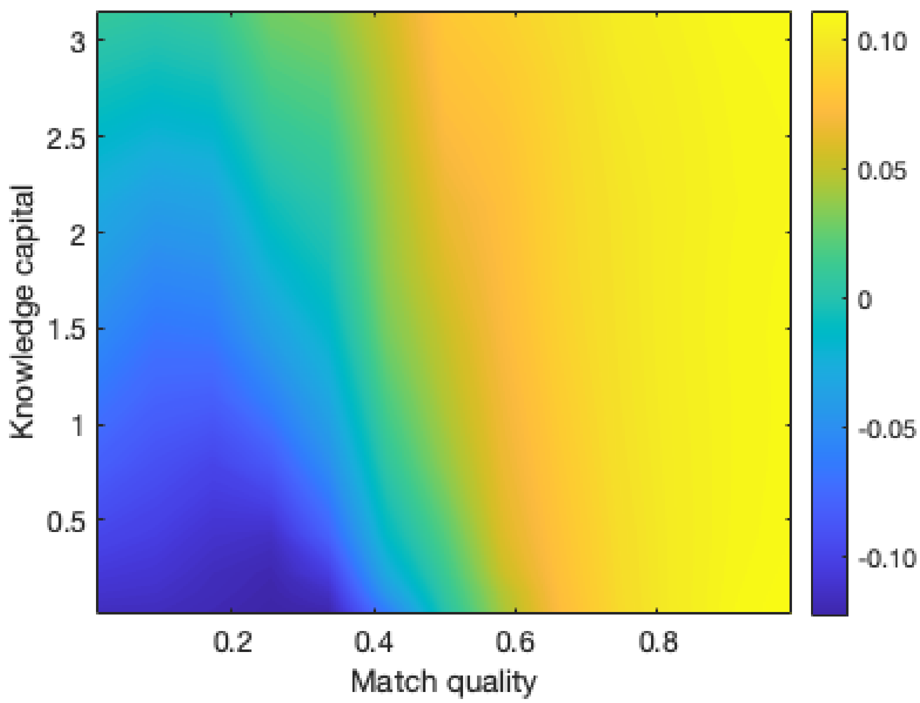

Figure 7. Knowledge Capital Specificity Premium

This figure illustrates the knowledge capital specificity premium using a heat map. The knowledge capital specificity premium is defined in Equation (28).

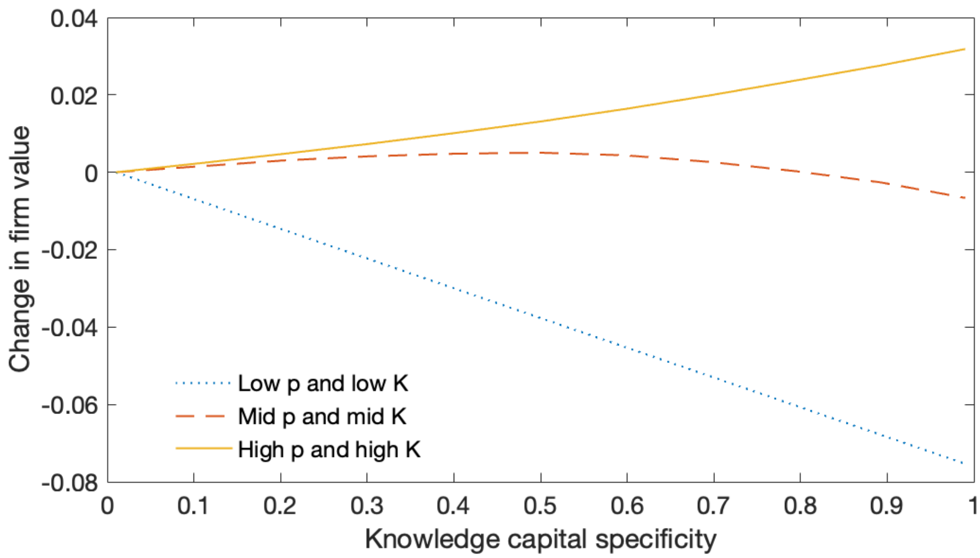

Figure 8. Firm Value and Knowledge Capital Specificity

This figure illustrates the relationship between firm value and its begin-of-period knowledge capital specificity. High, medium, and low perceived match quality (knowledge capital) corresponds to firms falling in the top, middle, and bottom terciles of the simulated model economy, based on the partitioning variables.

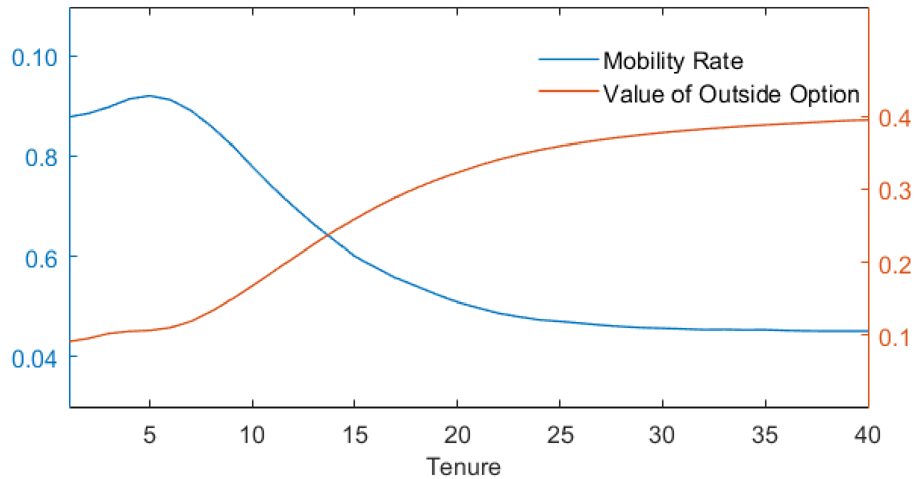

Figure 9. Inventor Turnover, Outside Option, and Tenure

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

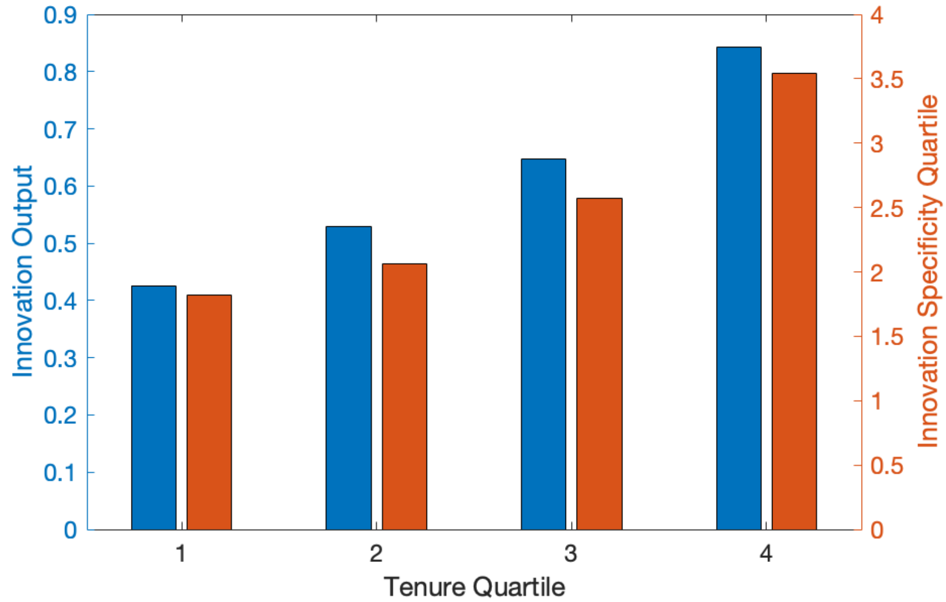

Figure 10. Innovation Specificity over Varying Career Stages

This figure illustrates how inventors' innovation output and the specificity of their innovation activities evolve with their career stages. Inventors are divided into four quartiles based on their tenure with their current employers. The left-hand-side axis corresponds to the average innovation output among inventors in a tenure group; the right-hand-side axis corresponds to the quartile ranking of their innovation specificity.

Table 1. Summary Statistics

This table summarizes key variables at the inventor-, patent-, and firm-levels.

	N	Mean	Median	Std.Dev
	a. Inventor Level (Inventor-Year Obs)			
Inventor Age	7692114	42.85	42.00	9.69
Tenure in Firm	7692114	5.10	4.00	4.46
Transition	6595233	0.08	0.00	0.27
Number of Patent Produced (Full Credit)	7692114	0.80	0.00	1.73
Number of Patent Produced (1/N Credit)	7692114	0.31	0.00	0.72
Total Past Patent Produced	7692114	2.45	1.00	5.27
Generality	2938761	0.39	0.44	0.28
General Human Capital	7597431	0.40	0.43	0.24
	b. Patent Level (Patent Obs)			
Year	6913074	2002.36	2004.00	11.66
Total Backward Citation	6913074	14.67	6.00	56.47
Total Forward Citation (up to 2021)	6913074	13.03	3.00	40.45
Generality	4965036	0.37	0.44	0.29
	c. Firm Level (Public Firm-Year Obs)			
No. of New Patents	282369	11.57	1.00	98.88
Total Forward Citations of New Patents	282369	153.81	0.00	1432.49
New Patents' Generality	137542	0.39	0.42	0.24
R&D/Assets	279914	0.07	0.04	0.16

Table 2. Parameters

In this table, we report the model parameter estimates. Panel A presents statutory parameters and those whose values can be calibrated directly from the data. Panel B reports the value of parameters we estimate via the Simulated Method of Moments (SMM).

Panel A. Statutory and Calibrated Parameters		
β	Discount factor	0.9
θ	Workers' bargaining power	0.5
q	Unconditional probability of an good match	0.5
π	Capitalized return per unit of innovation output	6.82
τ	Exogenous rate of pair dissolution	0.03
ϕ	Rate of new job creation	0.06
Panel B. Parameters Estimated via SMM		
a	Constant in knowledge production function (Eq 1).	0.53
ℓ	Curvature of knowledge accumulation (Eq 7).	0.76
δ	Depreciation rate of knowledge capital	0.15
$\mathring{k}$	Initial human capital of novice inventors	0.05
f	Fixed operating cost	0.24
b	Controls the relationship between knowledge production and the alignment of knowledge specificity (Eq 25)	0.08
σ_c	Heterogeneity in firms' specialization w.r.t innovation scopes	0.21
η	Fraction of newly acquired knowledge embodied in the firm	0.69
ρ	Elasticity of R&D in knowledge production function (Eq 25)	0.33
κ	Controls the relationship between knowledge production and firm-inventor match quality (Eq 1)	1.14
σ_v	Standard deviation of the signal on outside offer	8.22

Table 3. Moments Conditions

This table reports the simulated and actual moment conditions.

Moments	**Data**	**Simulated**
Average patent per inventor	0.8613	0.9271
Percentage of zero patent years	0.5640	0.5879
Variance of patent per inventor	0.7690	0.6851
Loadings of patent output on prior patent production	0.3001	0.2023
Dispersion of patent specificity at the firm level	0.1230	0.1293
Patent specificity persistence	0.5558	0.6247
Loadings of patent output on R&D investment	0.0600	0.0865
R&D per inventor	0.4779	0.3225
Variance of R&D per inventor	0.5210	0.5054
Frequency of job switches	0.0651	0.0703
Employment duration conditional on separation	4.7540	5.1729
Change of productivity after job switch	0.0962	0.1180
Patent output per novice inventor	0.6470	0.5083

Table 4. Innovation Specification under Alternative Models

This table reports the predicted innovation specificity for inventors in varying tenure quarterlies and under alternative model specifications. In row (1), we report the results under the baseline model; in row (2), we examine the scenario where a firm incurs no discount when liquidating its specific knowledge capital; row (4) corresponds to the scenario where the firm chooses its innovation specificity to maximize the joint value of the firm and the inventor, instead of that accruing to the firm's shareholders only. In rows (3) and (5), we calculate the percentage change in innovation specificity under alternative models, compared with their counterparts in the baseline scenario.

	Tenure Q1	Tenure Q2	Tenure Q3	Tenure Q4	Overall
Baseline	0.5192	0.5661	0.6358	0.7313	0.6131
No separation cost	0.6128	0.6597	0.7124	0.7943	0.6948
(% change)	(18.02%)	(16.53%)	(12.05%)	(8.62%)	(13.81%)
No rent splitting	0.4241	0.4416	0.4768	0.4929	0.4588
(% change)	(-18.33%)	(-22.00%)	(-25.01%)	(-32.59%)	(-24.48%)

Table 5. Innovation Specificity and the Value to Firms and Inventors

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 value of the firm (J), the wage of the inventor (W), and the value of the inventor-firm pair (V). In the bracket, we report the percentage of the total value claimed by the firm and the inventor, respectively.

	Baseline	$75\% \cdot \chi$	$50\% \cdot \chi$	$25\% \cdot \chi$	$\chi = 0$
Firm value	2.9928	2.8390	2.5721	2.3180	2.1248
Inventor wage	1.1683	1.4199	1.4646	1.6823	1.7318
Value of the pair	4.1611	4.2590	4.0367	4.0003	3.8566
Firm share	71.92%	66.66%	63.72%	57.94%	55.10%
Inventor share	28.08%	33.34%	36.28%	42.06%	44.90%

Table 6. Effect from the Enforcement of Noncompete Agreement

This table reports the effect of noncompete agreement enforcement on inventors' mobility and the generality of the patent they file. Noncompete Enforcement corresponds to changes in the enforceability of noncompete agreements across US states, following Jeffers (2019). Transition Prob is a dummy that equals one if an inventor separates from the current employer to join another company, and patent generality is defined following equation (24).

	(1) Transition Prob	(2) Patent Generality	(3) Patent Generality
Tenure In Firm x Noncompete Enforcement		0.012***	
		(0.001)	
Tenure In Firm		-0.042***	
		(0.000)	
Inventor Age x Noncompete Enforcement			0.014***
			(0.002)
Inventor Age			-0.048***
			(0.001)
Noncompete Enforcement	-0.006***	-0.020***	-0.052***
	(0.001)	(0.001)	(0.007)
Constant	0.073***	0.185***	0.296***
	(0.000)	(0.000)	(0.003)
Observations	3,606,405	4,114,604	4,114,604
R-squared	0.074	0.144	0.133
Firm FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes