Non-Competes, Worker Mobility, and Productivity Growth: Theory and Evidence [*]

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Abstract

This paper demonstrates that increased worker mobility between employers promotes innovation and accelerates growth. In the US, metropolitan areas subject to state-level court rulings that reduced the enforceability of non-compete (NC) clauses experienced increases in employment-to-employment (EE) hire rates. These areas also produced higher-quality patents and achieved faster productivity growth. Motivated by these empirical results, this paper develops an endogenous growth model with a frictional labor market and worker-embodied knowledge that increases innovation efficiency. Accelerated knowledge flows associated with EE transitions increase innovation and growth. The calibrated model shows that a permanent ban on NC clauses raises the annual growth rate by 0.2–0.3 percentage points, and the effect strengthens over time. Without the knowledge channel, the increase in growth rate is underestimated by more than 50%.

Keywords: Non-competes, Worker mobility, Innovation
JEL codes: J24, J31, O33, O47

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1 Introduction

The mobility of workers plays a central role in the diffusion of knowledge and the reallocation of workers between firms, thereby influencing innovation and long-term economic growth. In many labor markets, however, contractual restrictions such as non-compete (NC) clauses limit workers' ability to switch employers. While these contracts are often justified as a means to protect business secrets and guarantee monopolistic profits for innovation, they may also hinder the efficient allocation of workers and slow the pace of innovation. Understanding the growth implications of labor mobility frictions is therefore critical for both theory and policy.

This paper investigates how promoting worker mobility, specifically by removing NC clauses, shapes innovation and productivity growth in the short and long run. Previous studies on labor mobility and growth often focus on the reallocation channel, where labor moves from less- to more-productive firms or from slow- to fast-growing firms (Acemoglu et al., 2018; Lentz and Mortensen, 2008). Beyond these margins, this paper identifies a novel channel: how labor reallocation influences the rate of innovation by incumbent firms, proxied by quality-adjusted patent counts. In the US, over 70% of manufacturing productivity growth occurs within jobs held by incumbents (Baily et al., 1992), and more than 90% of patents are assigned to incumbent firms with a prior patenting history. Thus, determining how incumbent innovation responds to changes in NC clauses is crucial for quantifying aggregate growth responses.

First, this paper establishes robust empirical evidence using variations at the metropolitan statistical area (MSA) level in the US. We exploit the same state-level institutional changes in NC agreements as Jeffers (2024) to capture exogenous shocks to worker turnover rates. Following state-level court rulings that reduced the enforceability of NC contracts, MSAs in treated states experienced increased employment-to-employment (EE) hire rates. These MSAs did not necessarily exhibit higher innovation intensity, measured by patents per worker. Instead, they produced patents of significantly higher quality, as measured by the difference between forward and backward similarities and the number of citations received. Crucially, labor produc-

tivity in these areas grew faster relative to MSAs in control states.

Motivated by these facts, this paper constructs an endogenous growth model with a frictional labor market. Firms choose the rate of technology upgrades to increase their idiosyncratic productivity. While technology upgrades incur monetary R&D costs, they allow firms to utilize better technologies with current and future employees. In this setting, young and old firms face different returns to innovation. Young firms expect more future hires but have less stable current matches, whereas old firms have fewer future hires but more stable existing matches. We find that the recruitment effect dominates, generating large returns to technology upgrades for young firms.

We further introduce a knowledge stock that increases returns to R&D investments, or equivalently, reduces the cost of R&D. Because knowledge is worker-embodied, shared with the firm, and persistent (remaining even after the worker quits), the knowledge stock increases with gross hires rather than the firm's net employment. Consequently, a higher degree of worker mobility reduces the cost of innovation and accelerates productivity growth. This mechanism distinguishes our work from existing studies that emphasize labor reallocation to high-productivity firms (Lentz and Mortensen, 2008), fast-growing entrants (Acemoglu et al., 2018; Alon et al., 2018), or entrepreneurship (Engbom, 2020).

The calibrated model reproduces salient features of the relationship between firm age and worker turnover. Compared to old firms, young firms hire a disproportionately larger share of workers hired from unemployment than they poach from employment. Under random search with a balanced offer distribution, this implies that old firms possess a higher match surplus. The calibration strategy infers the underlying productivity distribution between firm ages based on NE and EE shares.

The key parameter for the quantitative impact of non-competes on growth is the elasticity of innovation costs with respect to worker-embodied knowledge. We calibrate this parameter to match the 0.2 percentage point increase in the annual productivity growth rate observed in the data after the reduction in NC enforceability. Specifically, we target this productivity response following an unexpected increase

of 25% in the match rate of employed workers, which mirrors the empirical increase in the EE hire rates.

Finally, the model is used to quantify the impact of a complete ban on NC clauses. In the transition to a new steady state without NC contracts, worker transitions from low- to high-productivity firms directly increase the productivity growth rate. Simultaneously, increased worker turnover reduces the cost of technology upgrades, especially for old firms earlier in the transition. The aggregate effect of boosting within-job productivity growth is particularly pronounced later in the transition and in the long run, as young firms grow faster and gain a larger employment share. Without the knowledge channel, the productivity effect decreases below 50%.

Related Literature

This paper augments an endogenous growth model with labor market frictions and specific human capital. The Schumpeterian growth literature, dating back to Aghion and Howitt (1992), emphasizes the reallocation of production inputs between producers as the key driver of innovation and long-run growth (Aghion et al., 2001; Klette and Kortum, 2004; Lentz and Mortensen, 2008; Coles and Mortensen, 2016; Acemoglu et al., 2018). In these models, innovation is motivated by monopolistic profits, and net labor reallocation emerges as a byproduct of idiosyncratic innovation processes. Recent papers, such as Engbom (2019, 2020) and Bilal et al. (2021), incorporate gross worker turnover into endogenous growth models to study how labor market frictions affect creative destruction by entrants. We extend this line of research by examining the role of gross turnover in innovation choices made not only by entrants but also by incumbents. Given that within-job productivity growth among incumbents accounted for 70% of manufacturing productivity growth in the 1980s (Baily et al., 1992), and that reallocating inputs among incumbents contributed another 32% (while net entry contributions were negative), incumbent responses are critical but often overlooked in growth analyzes.

This paper emphasizes gross worker turnover between employers as a novel determinant of innovation. Previous studies typically focus on input reallocation

across firms with innate differences in innovation efficiency (Lentz and Mortensen, 2008; Acemoglu et al., 2018) A few papers highlight market conditions, such the degree of market competition (Aghion et al., 2001, 2005; Hashmi, 2013), as determinants of innovation. In terms of cyclicality, Klenow (1998) notes that if skills are accumulated via learning-by-doing, firms innovate more during booms when production volumes allow faster learning. Hershbein and Kahn (2018) show that metropolitan areas hit harder by the Great Recession increased skill requirements in job postings, consistent with the recession reducing the opportunity cost of adopting routine-biased technologies. We complement these findings by showing that market conditions governing gross worker turnover facilitate innovation through knowledge flows embodied in workers.

We also add endogenous within-job productivity dynamics to models of frictional labor markets with on-the-job search. Traditionally, search friction models assume productivity is either fixed or subject to exogenous shocks (Postel-Vinay and Robin, 2002; Cahuc et al., 2006; Menzio and Shi, 2011), focusing on worker allocation across matches. Recent models emphasizing firm-level responses also assume exogenous productivity processes (Kaas and Kircher, 2015; Elsby and Michaels, 2013; Elsby and Gottfries, 2022; Bilal et al., 2022). While micro-founded papers like Bagger et al. (2014) and Lise and Postel-Vinay (2020) model within-job productivity growth via worker human capital accumulation, this paper integrates endogenous innovation choices to capture the interplay between worker turnover and growth, generating rich dynamics over the firm life cycle.

Finally, this paper broadens the understanding of the economic effects of non-compete agreements. Existing literature examines the effects of non-competes on wages and match-specific investments (Shi, 2023), consumer welfare (Lipsitz and Tremblay, 2024), and innovation (Jeffers, 2024). We extend Jeffers (2024), who found an insignificant effect of NC enforceability changes on firm-level patent counts, by analyzing the quality margin of patents and MSA-level productivity growth. Our findings are comparable to those of Shi (2023), who argues that non-competes help current matches extract rents from future employers, thereby increasing returns to match-specific investments. We show that this effect is attenuated when R&D

investments are firm-specific, and firms also hire workers from other employers. In our setting, restrictions on mobility may dampen incentives to innovate to increase poaching. Furthermore, if reduced worker mobility limits the diffusion of the knowledge, non-competes can increase innovation costs and slow down growth. These margins are likely stronger for the production and R&D workers considered here than for the executives studied in Shi (2023).

The remainder of this paper is organized as follows. Section 2 documents how the lower enforceability of non-compete clauses affects innovation activities and labor productivity. Section 3 develops a model of technology upgrades in a frictional labor market to reconcile these empirical facts. Section 4 details the calibration. Section 5 quantifies the implications of banning non-competes for growth. Section 7 concludes.

2 Empirical Analysis

We first study the empirical relationship between worker mobility and innovation using geographic variations at the MSA level. We exploit institutional changes in the enforceability of non-compete agreements from Jeffers (2024), who captures exogenous shifts in worker turnover rates and argues causal effects. The effects on economic activities are estimated using the method proposed by Callaway and Sant'Anna (2021), which provides unbiased estimates in treatment effect models with two-way fixed effects and staggered adoption.

2.1 Data

Worker turnover variables are constructed using data from Job-to-Job Flows (J2J), based on the Longitudinal Employer-Household Dynamics (LEHD) program of the US Census Bureau. This dataset provides the gross number of workers who change their primary source of labor income at the Metropolitan Statistical Area (MSA) level in each quarter. From these data, we construct four variables to measure worker turnover in the local labor market of MSA i at time t: the Nonemployment-to-

Employment (NE) hire rate, $NE_{i,t}$; the Employment-to-Nonemployment (EN) separation rate, $EN_{i,t}$; the Employment-to-Employment (EE) hire rate, $EEh_{i,t}$; and the Employment-to-Employment (EE) separation rate, $EEs_{i,t}$. The quarterly turnover rates are aggregated to the yearly level by taking averages.

$$NE_{i,t} = \frac{\text{Number of NE Hires}_{i,t}}{\text{Number of Main E Jobs}_{i,t}} \tag{1}$$

$$EEh_{i,t} = \frac{\text{Number of Job-to-Job Hires}_{i,t}}{\text{Number of Main E Jobs}_{i,t}}. \tag{2}$$

Data on granted patents and their citations are obtained from *PatentsView*[1], which is derived from public patent data from the US Patent and Trademark Office (USPTO). The patent data are merged with the location data of patent assignees and aggregated to the year and MSA level. Both the number of patents and the number of citations received by patents assigned to an MSA in a given year are normalized by the number of employed workers.[2]

We employ two measures to evaluate the quality of patents granted in an MSA. The first is the number of citations per patent, a metric also used by Acemoglu et al. (2022). The second is a text-based patent importance measure following Kelly et al. (2021). This measure is defined as the difference between the backward and forward similarity of a patent relative to other patents granted in the same MSA.[3] Backward similarity considers patents applied for up to five years prior to the application, while forward similarity considers patents applied for up to five years later. We calculate the cosine similarity between patents based on the bigrams of patent texts, similar to Kelly et al. (2021), weighting each bigram with its term frequency-inverse document frequency.

Labor productivity is measured by GDP per worker, using MSA-level GDP data from the Bureau of Economic Analysis (BEA). Net turnover rates, specifically job

[1] `https://www.patentsview.org`

[2] If a patent is assigned to $n > 1$ assignees, we assign $1/n$ patents to each assignee and to the corresponding MSA. The number of citations is adjusted similarly.

[3] We compute the difference, rather than the ratio as in Kelly et al. (2021), between the two similarities because the ratio tends to exaggerate the importance of a patent with low backward similarity.

creation and destruction rates, are obtained from the Business Dynamics Statistics (BDS) of the Census Bureau.

2.2 Regression Model

Jeffers (2024) analyze state-level court rulings that alter the enforceability of NC agreements, concluding that departure rates at knowledge-intensive firms decline (increase) following increases (decreases) in NC enforceability. We take advantage of the same institutional setting, but analyze the responses of aggregate variables at the MSA level. We focus on two specific court rulings—in South Carolina (2010) and Montana (2011)—that reduced the enforceability of NC agreements.[4]

We employ the following difference-in-difference model to estimate the 'treatment effect' of lower NC enforceability:

$$y_{i,t} = \alpha_i + \beta_h(\text{treated}_{i \in s} \cdot h \text{ years to treatment}) + X_{i,t} + \delta_t + \varepsilon_{i,t}.$$

Here, i denotes the MSA and t denotes the year. The indicator 'treated' takes a value of one if MSA i is located in a state s where the enforceability of NC agreements decreased before year t. Unless otherwise noted, $X_{i,t}$ includes unemployment rates, GDP growth rates, and the employment share of entrant firms. We exclude MSAs that span multiple states or belong to states that experienced court rulings increasing NC enforceability in Jeffers (2024).

The standard OLS estimATE of this difference-in-difference equation may not produce an unbiased estimate of the average treatment effect (ATE) if the treatment effects are heterogeneous and the treatment timing is staggered (Goodman-Bacon, 2021). Therefore, we utilize the estimation method proposed by Callaway and Sant'Anna (2021) to estimate the average effect of institutional change. This

[4]These states include Wisconsin, Colorado, Illinois, Texas, Virginia, and Georgia. Illinois experienced a court ruling that increased enforceability in 2011, but another ruling reduced enforceability in 2013. Other states experienced court rulings that strengthened NC enforceability. In these states, EE turnover rates *increased* rather than *decreased* following the rulings. Jeffers (2024) argue that the effect of enforceability is ambiguous if employees can negotiate to remove non-compete clauses. Consequently, these states are excluded from the analysis. However, the results regarding patents and citations remain consistent with the baseline results. For details, see Appendix A.1.

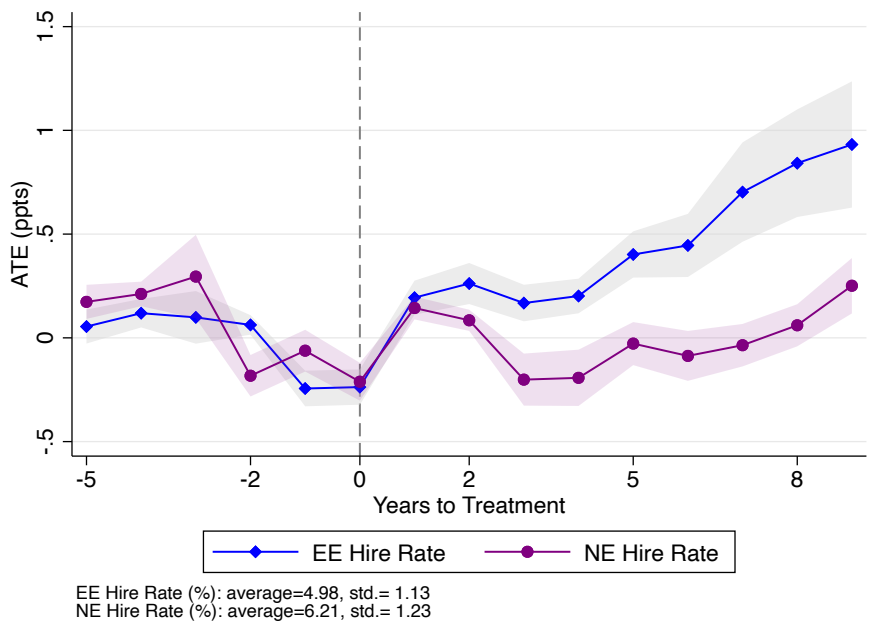


Figure 1: Effect of Lower NC Enforceability on Worker Turnover

Notes: Treatments are the court rulings that reduced the enforceability of NC contracts in South Carolina (2010) and Montana (2011). Shaded areas represent the 95% confidence interval of the estimates. Standard errors are clustered at the state level.

method uses not-yet-treated or never-treated control groups to generate an interpretable ATE. The baseline results presented here are based on never-treated control groups, although the results are quantitatively similar when using not-yet-treated groups.

2.3 Results

Figure 1 presents the ATE estimates for EE and NE hire rates. First, lower NC enforceability leads to an increase in EE hire rates, an effect that accumulates dynamically over time (see Figure 1). One year after the court ruling, the EE hire rate increases by only about 0.25 percentage points per quarter. After eight years, however, the effect quadruples; the rate increases by nearly one percentage point per quarter. Unlike the strong response to the EE hire rates, the NE hire rates do not change significantly. These results imply that NC agreements were more binding

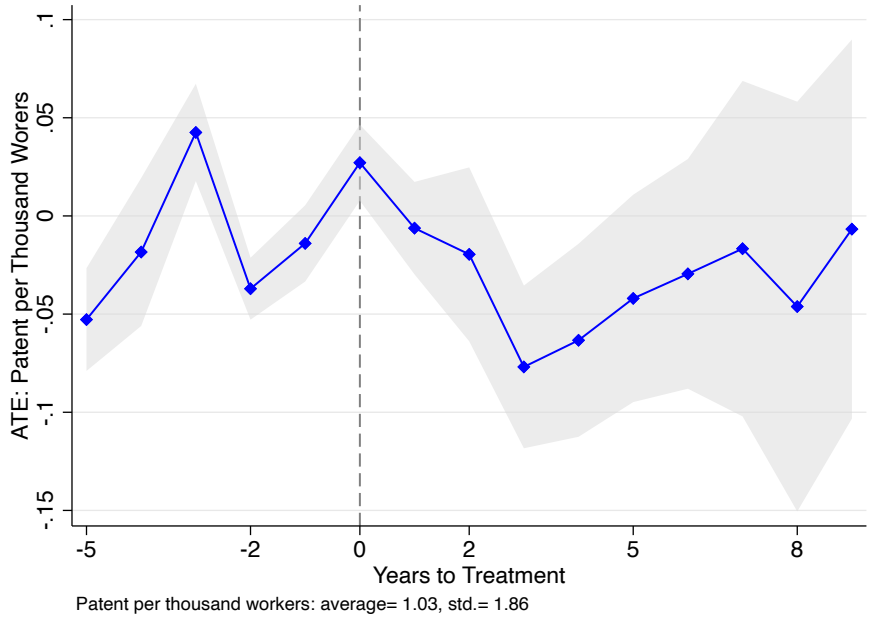


Figure 2: Effect of Lower NC Enforceability on Patents

Notes: Treatments are the court rulings that reduced the enforceability of NC contracts in South Carolina (2010) and Montana (2011). Shaded areas represent the 95% confidence interval of the estimates. Standard errors are clustered at the state level.

for employed workers than for unemployed workers.

Figure 2 shows that the number of patents per thousand workers does not respond significantly to the institutional change; in fact, the point estimates decrease modestly. This aligns with Jeffers (2024), who find that the number of patents granted to knowledge-intensive firms did not exhibit a significant increase.

In contrast, Figure 3 and 4 demonstrate that the quality of granted patents improves following court rulings in treated states. The number of citations per thousand workers and per patent increases significantly three years after the reduction in NC enforceability, and this effect persists thereafter. This increase corresponds to approximately 28% of the average and 11% of the standard deviation of the number of citations per thousand workers, respectively.

Moreover, the importance of patents increases after the reduction in the enforce-

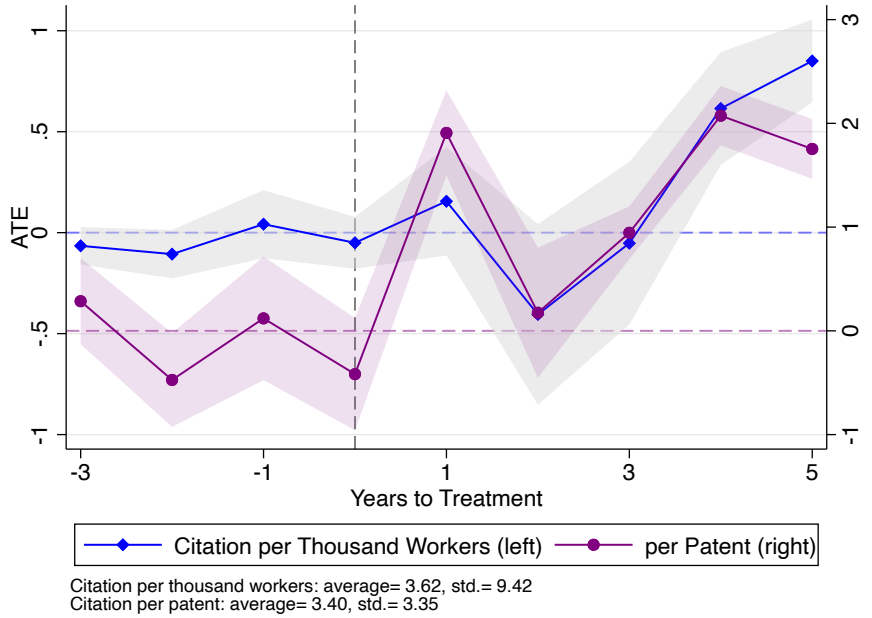


Figure 3: Effect of Lower NC Enforceability on Citations and Impacts

Notes: Treatments are the court rulings that reduced the enforceability of NC contracts in South Carolina (2010) and Montana (2011). Shaded areas represent the 95% confidence interval of the estimates. Standard errors are clustered at the state level.

ability of non-competes. The average importance of patents increases by 0.8 standard deviations two years after the court ruling and remains persistently higher. As shown in Figure 5, both increases in forward similarity and decreases in backward similarity contribute to the increase in patent importance.[5] In general, locally produced patents become more impactful after the change in enforceability.

Finally, Figure 6 shows that labor productivity increased faster in MSAs within treated states compared to MSAs in control states. Labor productivity was significantly lower three to four years prior to treatment, implying that the treated states experienced a sharper decline in GDP per worker during the Great Recession. However, control and treated states exhibit similar trends as they approach the treatment year, and labor productivity increases more rapidly in treated states

[5]Because the data contain a significantly smaller number of patents applied after 2020, forward similarity is calculated up to 2016, whereas backward similarity is calculated up to 2019.

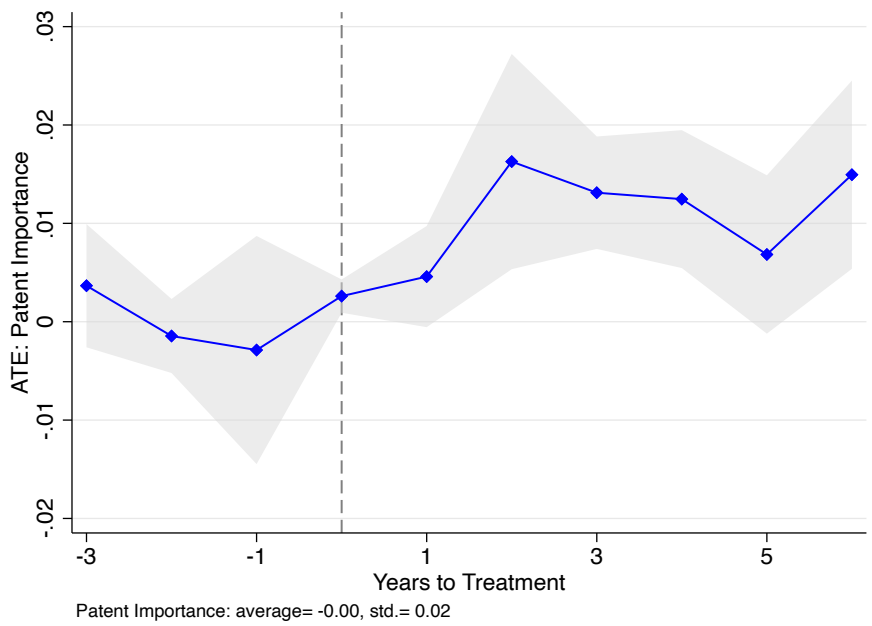


Figure 4: Effect of Lower NC Enforceability on Patent Importance

Notes: Treatments are the court rulings that reduced the enforceability of NC contracts in South Carolina (2010) and Montana (2011). Shaded areas represent the 95% confidence interval of the estimates. Standard errors are clustered at the state level.

after treatment.

In Appendix A.2, we further show that MSAs in treated states experienced large and significant increases in total employment, but small and insignificant responses in wages. In addition, the results in Appendix A.3 and Appendix A.4 indicate that these responses come more significantly from industries with higher returns to employer tenure and mature incumbents. Lastly, estimates in Appendix A.5 suggest that the gross turnover of production workers, but not the net turnover of labor or inventor mobility, likely drives these results.

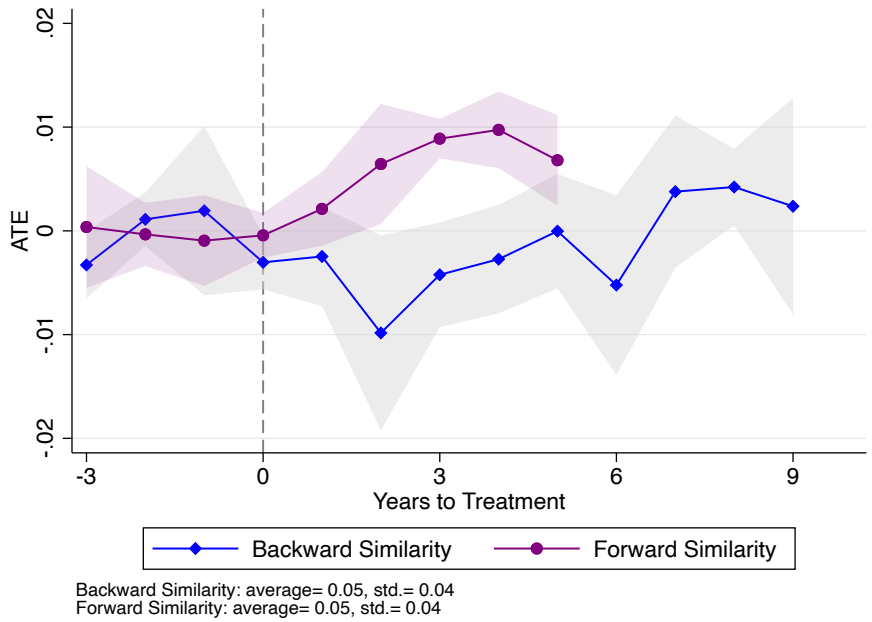


Figure 5: Effect of Lower NC Enforceability on Patent Similarity

Notes: Treatments are the court rulings that reduced the enforceability of NC contracts in South Carolina (2010) and Montana (2011). Shaded areas represent the 95% confidence interval of the estimates. Standard errors are clustered at the state level.

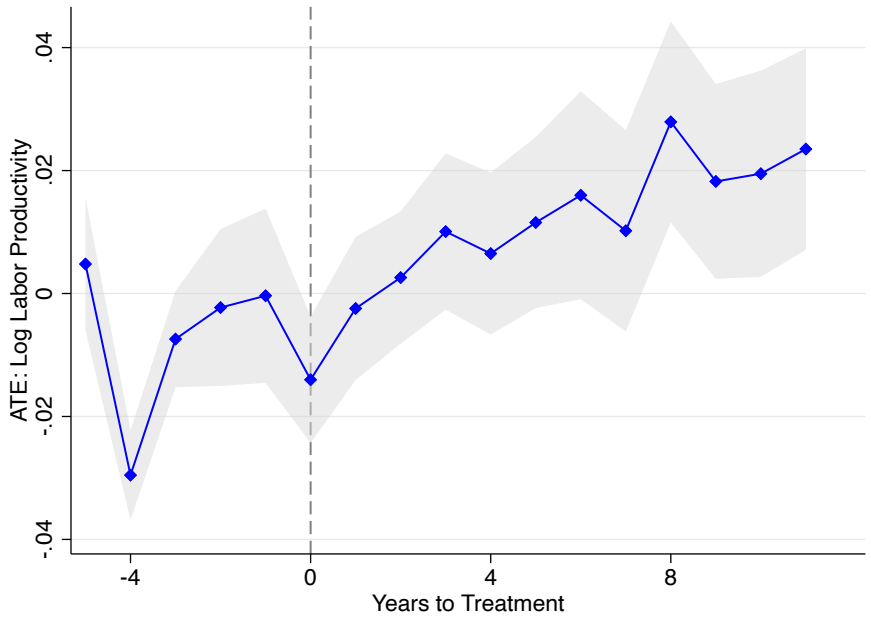


Figure 6: Effect of Lower NC Enforceability on Labor Productivity

Notes: Treatments are the court rulings that reduced the enforceability of NC contracts in South Carolina (2010) and Montana (2011). Shaded areas represent the 95% confidence interval of the estimates. Standard errors are clustered at the state level.

3 Model

The economy consists of workers and firms operating in a frictional labor market. A unit mass of workers are either employed or unemployed. Unemployed workers receive an unemployment benefit $b\bar{z}_t$ per unit of time and find a job at a rate p^U.

Employed workers are matched with other firms with a rate p^E, and current and potential employers compete for the worker as in Postel-Vinay and Robin (2002). After the employer competition, the worker works with the firm with a higher match value at the maximum value that the firm with a lower match value could offer. This condition remains unchanged when the worker approaches the firm with a credible offer from an outside employer. Without a credible outside offer, unemployed workers receive a zero surplus from the match.

Since productivity is positively correlated with the match value, the non-random EE transition often leads to increases in productivity. However, in the data, the contribution of the EE transition to growth is small despite a large productivity dispersion between employers. Consequently, we also allow random EE transitions that are orthogonal to productivity growth. Specifically, with a rate $\tilde{p}^E$, two workers switch their employers regardless of differences in match values. Without a credible outside option, workers hit by random EE shocks receive zero surplus from the new employer.

Firms are distinguished by types that represent their age. All firms enter as type 1 and switch to type 2 stochastically with a constant Poisson rate θ. Type 1 firms, or young firms, have higher job destruction and vacancy rates per existing worker than type 2 firms, which constitute a disproportionately large share of older firms. This assumption captures the stylized fact that younger firms have higher worker turnover rates.

A firm with an idiosyncratic level z and employment n produces a zn amount of output per unit of time. In order to increase z, firms choose the speed of technology upgrades $g \geq 0$. Then, the change in z is characterized by the following

equation.

$$dz = g\bar{z}_t dt + \sigma \bar{z}_t dW_t,$$

where $\bar{z}_t$ is the cross-sectional average of z at time t, W_t is a random shock that evolves following the standard Wiener process, and σ governs the magnitude of the productivity shock.

Technology upgrades incur monetary R&D costs for the firm $\bar{z}_t C(g; n, K)$, where K is the knowledge stock the firm has accumulated. This R&D cost function is increasing and convex in g. It also increases in employment n but decreases in knowledge stock K. Importantly, the cost increases linearly in $\bar{z}_t$. If g is constant, this assumption implies that the growth of idiosyncratic productivity exhibits a negative serial correlation at the worker level. In a standard model of firm growth such as Luttmer (2007), on the other hand, a firm's idiosyncratic productivity features a random growth.[6] The specification with negative autocorrelation is preferred because worker-level wage growth is negatively auto-correlated, in contrast to firm size growth.

Incumbent firms post vacancies to hire workers. Type 1 and type 2 firms post 1 and $v_1 < 1$ vacancies per existing worker, respectively. Because unemployed workers always choose to work with the matched firm, the number of vacancies is proportional to the number of NE hires. Unlike NE hires, vacancies matched to employed workers undergo employer competition, where firms with higher match surplus win the worker. Consequently, a higher share of EE hires than the NE hire share reflect a higher match surplus, which is more likely when firms have higher productivity.

Knowledge for innovation, K, is embodied in workers and spreads as workers move. Because firms can retain knowledge even after workers move to another job, knowledge increases with the number of gross hires, rather than the net employ-

[6] In general, firm-level idiosyncratic productivity can be expressed as $dz = (g - \mu)zdt + \sigma z dW_t$. When firms choose the same level of $g < \mu$ regardless of their current z, the resulting process exhibits geometric Brownian motion with negative drift. This process yields a Pareto distribution of firm-level productivity if we further introduce an exit threshold for z (Gabaix, 2009).

ment of the firm. Without loss of generality, a unit of hire is associated with an increase in knowledge stock of one unit. At the same time, a constant fraction δ of knowledge stock becomes obsolete during a unit period of time. The evolution of K is expressed as in the following equation.

$$\frac{dK}{dt} = -\delta K + nv_j \left(q^U + q^E \mathbb{P}[\text{hire}|\text{EE contact}] \right) + n\tilde{p}^E. \tag{3}$$

Entrant firms also post a fixed fraction of vacancies v_0 relative to the incumbent vacancies. They obtain initial productivity from $\mathbf{f}_{0,t}(z)$, contact with employed or unemployed workers, and start production with hired workers. Entrants are always type 1 firms and start with zero knowledge stock.

Firms lose workers if their match is separated exogenously or the match does not produce a positive surplus. They also lose workers if new employers poach their workers. The contract space is complete, which implies that the firms and workers mutually agree to maximize the joint surplus and separate if the joint surplus increases with the new employer. This assumption also makes firms choose g which maximizes the collective match surplus. Because of this property, it suffices to determine the joint surplus of the match to characterize the equilibrium and determine worker flows.

3.1 Values

3.1.1 Simplification

Following Coles and Mortensen (2016), this paper aims to simplify the analysis by making the value at the firm level homogeneous of degree one with respect to employment. This specification is supported by empirical evidence that firm growth is not correlated with size (Axtell, 2001). In addition, this feature successfully reduces the dimension of the state variable at the match level and improves the tractability of the model. This property holds if the R&D cost function is homo-

geneous of degree one with respect to K and n.

$$C(g; n, K) = nc(g; k), \tag{4}$$

where $k := K/n$ is the level of knowledge stock per current employee.

Consequently, the state of a match is reduced from (n, K, z) to (k, z). Then, the value of all matches that belong to a firm is simply the match value multiplied by the employment size.

$$\bar{\mathbf{M}}_{j,t}(K, z, n) = \mathbf{M}_{j,t}(k, z)\, n.$$

We focus on the Balanced Growth Path (BGP) where $\bar{z}_t$ grows at a constant rate μ and all other macroeconomic variables are constant. In this case, the gross match value is a time-invariant function of relative productivity $x = z/\bar{z}_t$.

$$\mathbf{M}_{j,t}(k, z) = M_j(k, x)\, \bar{z}_t.$$

Similarly, the value of unemployment, $\mathbf{U}_t$, can be expressed as $\bar{z}_t U$. Finally, we define the surplus of the match net of the unemployment value as

$$S_j(k, x) = M_j(k, x) - U.$$

3.1.2 The HJB Equation

Conditional on the continuation, the average match surplus of a firm type j, the knowledge stock per worker k, and the productivity x is characterized by the fol-

lowing HJB equation. Appendix B.1 shows the derivation of the HJB equation.

$$
\begin{aligned}
(r-\mu)\, S_j\left(k,x\right) = \max_{g} \Bigg\{ & x - b - c(g;k) - \chi_j S_j^{old}\left(k,x\right) \\
& + \theta_j \left(S_{-j}\left(k,x\right) - S_j\left(k,x\right) \right) \\
& + v_j \left(q^U S_j^{new}\left(k,x\right) + q^E \int \max\left\{ S_j^{new}\left(k,x\right) - S_{j'}^{old}\left(k',x'\right), 0 \right\} dF_{j'}\left(k',x'\right) \right) \\
& + \left(g-\mu x\right) \partial_x S_j\left(k,x\right) + \frac{\sigma^2}{2} \partial_x^2 S_j\left(k,x\right) + \left(\tilde{p}^E - \delta k \right) \partial_k S_j\left(k,x\right) \Bigg\}
\end{aligned} \tag{5}
$$

In this equation, r is the interest rate, χ_j is the type-specific separation rate, and b is the unemployment benefit rate relative to the output per worker. θ_j is the rate of the type j firm that switches to $-j$.[7] q^U and q^E are the rates at which a vacancy meets an unemployed and employed worker, respectively. Lastly, ∂_y and ∂_y^2 are the first and second partial derivative operators with respect to a variable y.
The marginal values of new and existing workers, $S_j^{new}(k,x)$ and $S_j^{old}(k,x)$ can be expressed as follows.

$$S_j^{new}\left(k,x\right) = S_j\left(k,x\right) + \left(1-k\right) \partial_k S_j\left(k,x\right) \tag{6}$$

$$S_j^{old}\left(k,x\right) = S_j\left(k,x\right) - k \partial_k S_j\left(k,x\right) \tag{7}$$

A new worker with new knowledge is more valuable than existing workers, and the difference in marginal values is the value of new knowledge $\partial_k M_j(k,x)$. Because knowledge stays persistently in the firm even after the worker leaves, the marginal value of an existing worker is smaller than the average value of an existing worker.

The evolution of knowledge per worker can be described as in the following

[7] This specification implies that $\theta_1 = \theta$, and $\theta_2 = 0$

equation.

$$\frac{dk}{dt} = -\delta k + v_j \left(q^U + q^E P_j\left(k,x\right)\right)\left(1-k\right) + \left(\chi_j + p^E O_j\left(k,x\right)\right)k + \tilde{p}^E. \tag{8}$$

In this equation, $P_j(k,x) = \int \mathbf{1}\{S_j^{new}(k,x) > S_{j'}^{old}(k',x')\}dF_{j'}(k',x')$ and $O_j(k,x) = \int \mathbf{1}\{S_j^{old}(k,x) < S_{j'}^{new}(k',x')\}dH_{j'}(k',x')$ are the probabilities that a firm poaches an employed worker and a worker leaves to another employer conditional on a contact. The offer density, $h_j(k,x)$, is proportional to the number of vacancies posted by incumbents and entrants, which is described below. For notational simplicity, we denote this change in knowledge per worker by $a_j\left(k,x\right)$.

To continue the match without, the surplus with the existing worker must be positive.

$$S_j^{old}\left(k,x\right) \geq 0. \tag{9}$$

Because the match surplus increases in x for a given level of k and firm type j, we can define the cutoff level of productivity for continuation; $\underline{x}_j(k) := \inf\{x' | S_j(k,x') > 0\}$. The match chooses to separate if the firm productivity hits this threshold for each level of k. Furthermore, because $\partial_k S_j(k,x) \geq 0$, the marginal surplus of new workers $S_j^{new}(k,x)$ and the average surplus $S_j(k,x)$ are strictly positive whenever the boundary condition (9) holds with inequality.

The type of firm affects the surplus of the match in several ways. First, type 2 firms, which account for disproportionately more in old matches, have lower job destruction rates χ_j. Second, type 2 firms have a lower vacancy rate per worker v_j. Thus, old firms have longer durations for current matches, but smaller values from future hires. Because of this, type 1 firms accumulate knowledge more rapidly, as in Equation (8), and their stationary level of knowledge is higher.

3.2 Distribution

In the BGP equilibrium, the probability density of employed workers, $f_j(k,x)$, is time-invariant. Conditional on continuation of the match, the density is characterized by the following Kolmogorov forward equation augmented with the extensive margin of worker hires and separations.

$$\begin{aligned} 0 = & -\partial_x \left[\left(g_j\left(k,x\right) - \mu x \right) f_j\left(k,x\right) \right] + \partial_x^2 \left[\frac{\sigma^2}{2} f_j\left(k,x\right) \right] \\ & - \partial_k \left[a_j\left(k,x\right) f_j\left(k,x\right) \right] - \theta_j f_j\left(k,x\right) + \theta_{-j} f_{-j}\left(k,x\right) \\ & + q^U V h_j\left(k,x\right) + q^E V P_j\left(k,x\right) h_j\left(k,x\right) \\ & - \chi_j f_j\left(k,x\right) - p^E O_j\left(k,x\right) f_j\left(k,x\right) \end{aligned} \tag{10}$$

The first line shows the evolution of x within each job from technology upgrades, obsolescence, and productivity shocks. In this line, $g_j(k,x)$ denotes the optimal rate of technology upgrades specified in Equation (5). The second line describes the change in worker density due to within-job changes in k and type-switching. The third and fourth lines correspond to the increase in density due to the NE and EE hires and the decrease in density from the EN and EE separations, respectively.

The following equations characterize the mass of vacancies relative to total employment, V, the unemployment rate u and the offer density $h_j(x,y)$.

$$V = \left(1 + v_0\right) \bar{v}, \tag{11}$$

$$u p^U = \left(1 - u\right) \left(\bar{\chi} + \varphi \right), \tag{12}$$

$$h_j\left(k,x\right) \propto v_j f_j\left(k,x\right) + v_0 f_0\left(x\right) \mathbf{1}\left[k = 0, j = 1\right]. \tag{13}$$

In the above equations, $\bar{v} = \int v_j dF_j\left(k,x\right)$ is the average intensity of vacancy, $\bar{\chi} = \int \chi_j dF_j\left(k,x\right)$ is the average rate of exogenous separation, and φ is the rate of endogenous separation. $f_0(x) := \mathbf{f}_{0,t}(x\bar{z}_t)/\bar{z}_t$ is the productivity distribution of entering firms, which is parameterized further in Section 4.

The match rates are consistent with each other.

$$p^U u = q^U V(1-u), \tag{14}$$

$$p^E = q^E V. \tag{15}$$

The growth rate, μ, is expressed as in the following equation.[8]

$$\begin{aligned}\mu = & \int g_j(k,x)\, dF_j(k,x) \\ & + p^U u/(1-u)\, \mathbb{E}_H[x] - (\bar{\chi}+\varphi)\, \mathbb{E}_{\chi+\varphi}[x] \\ & + p^E \iint (x-x')\, \mathbf{1}\left[S_j^{new}(k,x) > S_{j'}^{old}(k',x')\right] dH_j(k,x)\, dF_{j'}(k',x')\end{aligned} \tag{16}$$

where $\mathbb{E}_H[x]$ is the average productivity of new jobs distributed as $H_j(k,x)$. Similarly, $\mathbb{E}_{\chi+\varphi}[x]$ is the average productivity of matches separated endogenously or exogenously. Consequently, Equation (16) decomposes the long-run growth rate into three margins: i) within-job technology upgrades, ii) transmission of better technologies through the NE and EN transitions, and iii) transmission of better technologies through the EE transitions. Firms with better technologies tend to hire workers more from firms with lower productivity. In addition, matches of separated workers have different average productivity from matches of workers hired from unemployment. Thus, worker turnover directly contributes to productivity growth. By construction, random EE transitions do not generate productivity growth *per se*. However, similar to non-random employer contacts, random EE transitions also transmit knowledge for innovation between firms and promote within-job technology upgrades.

[8] This equation is derived formally in Appendix B.2.

4 Quantification

To quantify the model, we assume the following parametric form for the R&D cost function:

$$c(g;k) = \frac{\varepsilon\kappa}{\varepsilon+1}\frac{\exp(-\alpha k)+\nu}{1+\nu}g^{\frac{\varepsilon+1}{\varepsilon}}. \tag{17}$$

The first-order condition that determines the optimal rate of technology upgrades is then given by:

$$g_j(k,x) = \left(\frac{1+\nu}{\exp(-\alpha k)+\nu}\frac{\partial_x S_j(k,x)}{\kappa}\right)^{\varepsilon} \tag{18}$$

In this equation, ε governs the elasticity of technology upgrades with respect to marginal R&D costs. The parameters α and ν govern the knowledge elasticity of R&D costs. The efficiency shifter in Equation (18), $(1+\nu)/(exp(-\alpha k)+\nu)$, originates at one (when $k=0$) and converges to $(1+\nu)/\nu$ as $k\to\infty$. The speed of this convergence is determined by α.

Lastly, we assume that an entrant firm randomly meets an existing match, learns about its technology, and imitates that technology imperfectly, scaling it by a factor $\lambda < 1$. This implies that the productivity distribution of entrants is expressed as:

$$f_0(x) \propto \sum_j \int f_j\left(k, \frac{x}{\lambda}\right) dk. \tag{19}$$

The parameter λ governs the contribution of NE-EN transitions to aggregate growth.

4.1 Calibration

We employ indirect inference to calibrate the model parameters. Specifically, we select a parameter set that minimizes the distance between data moments and model-based ones and summarize them in Table 1.

Panel A displays moments targeted directly without numerical simulation. With

a target annual growth rate of 2% and a risk-free interest rate of 6%, the discount rate $r - \mu$ is calibrated at 4% annually. The monthly NE hire rate, p^U, is calibrated to 19%. This figure is lower than the typical 30–35% job-finding rate for unemployed workers, as it implicitly accounts for the non-participation margin.

Table 1: Calibration Results

Symbol	Parameter	Value	Target	Data	Model
A. External Calibration					
$r - \mu$	Discount Rate	3%	Interest Rate	5.0%	5.0%
p^U	Job-Finding Rate	18.7%	-	-	-
B. Internal Calibration					
θ	Switching Rate	1.9%	NE Hire Share (Middle)	10.9%	14.7%
v_2	Vacancy (Type 2)	26.0%	NE Hire Share (Old)	69.2%	63.6%
v_0	Entrants Vacancy	3.9%	NE Hire Share (Start-up)	8.7%	9.1%
χ_1	Separation Rate (Type 1)	4.8%	EN Rate (Young)	3.8%	3.7%
χ_2	Separation Rate (Type 2)	1.9%	EN Rate (Middle)	3.2%	3.0%
b	Unempl. Benefit	0.15	EN Rate (Old)	2.2%	2.3%
q^E	Vacancy Match Rate (Employed)	0.5%	Within Contribution	69.3%	70.1%
$\tilde{p}^E$	Random EE	2.0%	EE Rate	2.0%	2.1%
κ	Upgrade Cost Shifter	6.33e+06	Growth Rate	2.0%	2.0%
ε	Upgrade Elasticity	0.69	EE Hire Share (Middle)	10.1%	12.4%
ν	R&D Cost Difference	0.4%	EE Hire Share (Old)	72.1%	76.0%
λ	Mean Productivity (Entrant)	0.95	EE Hire Share (Start-up)	7.7%	2.9%
α	R&D Cost Elasticity	2.73	Δ GDP in Year 0-10	2.0ppt	1.9ppt
δ	Knowledge Depreciation	0.11	Employment Share (Middle)	8.6%	12.2%
σ	Productivity Shock	0.54	Employment Share (Old)	80.0%	77.1%

Notes: This table describes calibration targets in the data and model, and the resulting calibrated parameters. Discount, interest, and growth rates are annual. All other rates are monthly. Start-ups are firms under the age of one. Young, Old, and Middle refer to firms with ages between two and five, over ten, and between six and ten, respectively. Short matches are employed workers with job tenures shorter than five years. Within-contribution is the contribution of within-job technology upgrades to the growth rate of the BGP, as shown in Equation (16).

Panel B of Table 1 presents the parameters calibrated by solving the full model. The last two columns compare the target values in the data with their model counterparts. The calibrated model matches the moments closely, despite the numerical noises associated with the firm simulation.

First, we normalize the vacancy postings of type 1 firms per existing worker to one. We then calibrate the vacancy rate of type 2 firms and the probability of switch-

ing from type 1 to type 2 to match the Non-Employment-to-Employment (NE) hire shares of firms aged six to ten and those over ten years old. Assuming a random search where unemployed workers always accept an offer, the number of NE hires is proportional to the number of vacancies. Similarly, the number of vacancies posted by entering firms is targeted to match their observed NE hire share. The vacancy rate per worker for type 2 firms is calibrated to be only 26% of that for type 1 firms. This reflects the fact that young firms account for a disproportionately larger share of NE hires compared to their employment share. Meantime, the monthly number of vacancies posted by entering firms amounts to 4% of the vacancies by incumbents.

EN separation rates for different age groups of firms are directly mapped to the probabilities of exogenous and endogenous separation for matches between types of firms and productivity levels. Since the magnitude of the unemployment benefit determines the endogenous separation rate—by setting the threshold where marginal match surplus equals zero—the NE separation rates of different firm age groups are targeted to match the three exogenous separation parameters and the unemployment benefit. The NE separation rate for type 2 firms is 1.9% per month, 60% lower than that of type 1 firms. The low calibrated value for the unemployment benefit—15% of average productivity—implies that most separations are driven by exogenous shocks.

We target a 69.3% contribution of within-job technology upgrades to aggregate growth to calibrate q^E, the rate of vacancies matching with employed workers. This target is derived from the accounting decomposition of Baily et al. (1992), which breaks down manufacturing productivity growth ($\Delta \mathbf{A}_t$) into four margins:

$$\Delta \mathbf{A}_t = \underbrace{\sum_{i \in \mathbf{C}_t} \mathbf{s}_{it-1} \Delta \mathbf{a}_{it}}_{\text{Within}} + \underbrace{\sum_{i \in \mathbf{C}_t} \mathbf{a}_{it-1} \Delta \mathbf{s}_{it}}_{\text{Between}} + \underbrace{\sum_{i \in \mathbf{C}_t} \Delta \mathbf{a}_{it} \Delta \mathbf{s}_{it}}_{\text{Cross}} + \underbrace{\sum_{i \in \mathbf{E}_t} \mathbf{s}_{it} \mathbf{a}_{it} - \sum_{i \in \mathbf{X}_t} \mathbf{s}_{it-1} \mathbf{a}_{it-1}}_{\text{Net Entry}}$$

In this Baily-Campbell-Hulten decomposition, $\mathbf{s}_{it}$ is the share of plant i in year t, $\Delta\mathbf{a}_{it}$ is the change in plant-level productivity, $\Delta\mathbf{s}_{it}$ is the change in share, $\mathbf{C}_t$ is the set of continuing plants, $\mathbf{E}_t$ is the set of entrants, and $\mathbf{X}_t$ is the set of exiting plants. Baily et al. (1992) find that 69.3% of growth is attributable to within-plant productivity growth (with fixed shares) during the 1972–1987 period.

A traditional approach to calibrating the EE match rate is to directly target the monthly EE transition rate observed in the data (Petrongolo and Pissarides, 2001). However, recent literature emphasizes the importance of amenities and non-monetary motivations for on-the-job moves (Sorkin, 2018; Bagga et al., 2023), which do not necessarily contribute to technology diffusion or long-run growth. In our model, on-the-job search drives long-run growth because worker transitions from lower- to higher-productivity firms increase the economy's average productivity. Therefore, we target the contribution of within-employer productivity growth to calibrate the search efficiency of employed workers, allowing the random EE shock rate to account for the residual EE transitions. The high monthly EE rate, combined with the relatively small contribution of EE transitions to growth, suggests that most EE transitions are associated with random employer-switching behavior that is orthogonal to productivity growth *per se*.

When employed workers match with a new employer in the absence of a random EE shock—occurring at Poisson rate p^E—they move only if the surplus is higher at the new firm. This is more probable if the new firm has higher productivity. Consequently, conditional on the NE hire share, higher EE hire and employment shares imply higher productivity. The calibration strategy leverages these moments to infer the underlying differences in productivity distribution and its growth profile between firms of different ages.

Since young firms have lower employment shares relative to their NE hire shares, they must start with lower productivity. Our calibration suggests that the average productivity of start-ups is 95% that of incumbents. The curvature of the R&D cost function, ε, governs how firms of different types differentially invest in R&D. With higher returns to R&D driven by future employment growth, young firms invest more in technology upgrades and grow faster than old firms. As ε increases, the

rate of technology upgrades rises, widening the productivity gap between young and old firms. The cost shifter for technology upgrades, κ, is set to match the annual aggregate growth rate of 2%.

The presence of worker-embodied knowledge reduces the gap in technology upgrade rates between young and old firms. With an accumulated knowledge stock, old firms conduct R&D more efficiently. The cost differential between firms with varying knowledge levels is dictated by the parameter ν in Equation (17). As the knowledge stock k approaches infinity, the R&D cost decreases by a factor of $\nu/(1+\nu)$ relative to start-ups.

The growth effect of labor mobility depends heavily on α, the elasticity of R&D costs with respect to the knowledge stock. We calibrate this using the treatment effect estimate of NC enforceability from Section 2. Following court rulings that lowered NC enforceability, EE transition rates increased by 25%. At the same time, productivity grew at an annual rate 0.2 percentage points higher than in control states over ten years. We match this additional productivity growth. Specifically, we introduce an unexpected, permanent 25% increase in both the match rate of employed workers and the random EE switching rate. We then calibrate α such that the model generates the additional productivity increase of 2 percentage points during the first ten years of the transition path to the new BGP relative to the baseline BGP.

Finally, the rate at which knowledge becomes obsolete, δ, alters the knowledge stock and productivity growth differentials between young and old firms. A higher δ reduces the knowledge stock and consequently the average productivity of old firms. In parallel, a larger productivity shock magnitude is associated with slower productivity growth over the firm's life cycle. These parameters serve to increase the EE separation rate of old firms and reduce their employment shares.

5 Long-run Effect of Banning Non-Competes

In this section, we use the calibrated model to quantify the long-run impact of banning NC contracts. Specifically, we model a complete ban on NC clauses as a 25% increase in the match rate of employed workers, p^E. This magnitude is equivalent to the increase in the EE transition rate observed following the institutional changes described in Section 2. It is modestly higher than the 18% of workers reported to be subject to non-compete clauses in Starr et al. (2021).[9]

We introduce a one-time, unexpected permanent increase in p^E to the stationary equilibrium and compute the transition path to the new stationary equilibrium associated with the higher match rate. The entry vacancy rate, v_0, is kept fixed at its baseline value throughout this exercise. As shown in Appendix A.4, the share of job creation by entrant firms does not increase—and in fact decreases marginally—following the reduction in non-compete enforceability.

5.1 Productivity Growth

Table 2 summarizes the 10-year additional growth in productivity following a complete ban on non-competes. The productivity response remains positive throughout the periods considered. During the first 10 years after the ban, the model generates an additional 0.19 percentage points of annual growth, matching the treatment effect estimated in Figure 6. The majority of this productivity response comes from technology upgrades within the job. Specifically, 64% of the total productivity response arises from within-job growth, whereas the direct effect of EE transitions accounts for only 42%. This result extends the findings of Schumpeterian growth models, where net resource reallocation from less to more productive producers is a key driver of long-run growth (Acemoglu et al., 2018). In our model, the gross reallocation of workers facilitates knowledge diffusion, thereby promoting growth.

[9] Based on the Survey of Household Economics and Decisionmaking (SHED), Boesch et al. (2023) show that mid-career workers (ages 25–44) are more likely to be bound by non-competes than older workers. Given that these workers also exhibit higher probabilities of switching jobs, the fraction of EE contacts affected by non-competes is adjusted accordingly.

Table 2: Productivity Responses after Banning Non-Competes (%)

	Full Model				Without Knowledge Transfer			
	Within	EE	NE	Total	Within	EE	NE	Total
Years 0-10	1.24	0.81	-0.12	1.94	0.44	0.33	-0.14	0.62
Years 10-20	1.42	0.91	0.26	2.59	0.48	0.35	0.09	0.92
Long-run	1.45	0.89	0.36	2.71	0.49	0.35	0.11	0.93

Notes: This table summarizes the 10-year difference in labor productivity relative to the baseline economy with the low match rate to employed workers. The Within, EE, and NE margins of productivity growth are expressed in Equation (16). The full model is calibrated with the knowledge effect ($\alpha > 0$) and targets the productivity increase during the first ten years after the mobility change. The model without knowledge transfer is re-calibrated without the knowledge effect (i.e., $\alpha = 0$) and does not target the productivity increase.

The effect is further amplified in the medium run (10 to 20 years after the ban) and in the long run. Both within-job and NE transition margins contribute to this amplification. These dynamics are driven by compositional changes in the firm distribution: early in the transition, the distribution becomes more skewed toward old firms, as shown in Figure 7. Because old firms are more productive on average, an increase in the match rate for employed workers allows them to modestly increase their employment share. Since old firms hire fewer workers relative to their existing workforce and have lower job destruction rates, this shift reduces the overall volume of NE-NN transitions. Meanwhile, old firms invest less in within-job productivity upgrades per worker. This compositional shift initially dampens the productivity increase within jobs. However, as young firms also benefit from knowledge transfer and accelerate their growth, this compositional effect dissipates.

In the absence of knowledge transfer, the growth response is significantly underestimated, as shown in the right panel of Table 2. All three margins contribute less to growth in this scenario. Not only is knowledge transfer embodied in EE transitions crucial for reducing innovation costs and accelerating technology upgrades, but it also leads to a more dispersed productivity distribution among workers. Because knowledge transfer confers additional value to new workers compared to old ones,

some non-random employer contacts result in EE transitions despite negative productivity changes. Consequently, less productive firms are more likely to maintain worker inflows. In stationary equilibrium, the standard deviation of the productivity distribution is 0.24 with knowledge transfer, compared to the value of 0.23% without it.

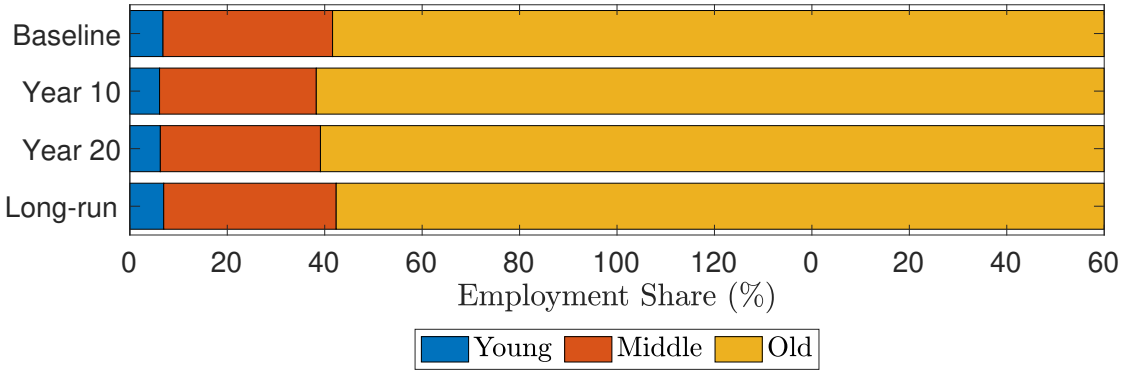


Figure 7: Employment Share across Firm Age

Notes: This figure shows the employment share of firms grouped by their age in the baseline case with lower worker mobility, ten and twenty years after the change in worker mobility, and in the new BGP with higher worker mobility. Young, Middle, and Old refer to firms with ages below five, between six and ten, and above eleven, respectively.

Figure 8 decomposes the change in average upgrade rates for young and mature firms—ages below five and above six, respectively. As indicated by the solid lines, the effects are larger for young firms. This occurs primarily because young or type 1 firms have a higher vacancy intensity, causing their returns to innovation to increase disproportionately more. However, average upgrade rates among old firms also increase substantially because they possess a higher knowledge stock due to the increased volume of gross EE transitions. The dashed lines in Figure 8 show that changes in within-job upgrades stem from both compositional changes among workers and changes in optimal upgrade rates conditional on match-level variables. When the upgrade policy function is fixed at the baseline level, the increase in average rates is 45% and 50% for young and old firms, respectively. The difference between young and old firms is much narrower with fixed upgrade rates, imply-

ing that the upgrade rates of type 1 firms respond more elastically to the change in contact rates due to their higher recruitment intensity per existing workers.

6 Robustness

6.1 Explicit Formulation of Non-Competes

In the baseline model, non-competes are equivalent to an exogenous reduction in match rates. In this section, we adopt the interpretation of Shi (2023) that non-competes function as a tool to extract rents from future employers through buyout fees.[10] To facilitate the analysis, we introduce four parameters: η, the probability that a job starts with a non-compete clause; ς, the probability that NC clauses are enforceable for a job offer received during employment; ϕ, the payment required to buy out the non-compete clause; and τ, the rate at which the non-compete clause expires. For a detailed description of the model of explicit non-competes, see Appendix C.2.

We set $\tau = 1/24$, implying an average non-compete duration of 24 months. We calibrate $\eta = 0.48$ to target a share of 25% of workers constrained by non-compete clauses. To match the 25% increase in EE transition rates after the removal of NCs, given that 25% of workers are covered, ς is set to 0.8. We then vary the value of ϕ to examine the implications of non-compete buyouts for growth.

We consider four values for ϕ, expressed as proportions of the economy's average surplus $\bar{S}$ in the baseline case with $\phi = 0$, and summarize their impact on EE transitions and growth rates in Table 3. The EE rate decreases only marginally between different values of ϕ because most of the EE transitions in the model are associated with random shocks. Consequently, buyout payments in this exercise have almost purely redistributive effects and their impact on actual worker mobility is limited. The analysis in Section 5 captures the impact of non-competes through changes in

[10] Specifically, if a worker is subject to an enforceable non-compete clause, the new firm must pay a buyout to hire the worker. Following the employer auction à la Postel-Vinay and Robin (2002), if the new firm poaches the worker, it pays the worker the maximum match surplus the current firm can offer and makes the buyout payment to the current firm.

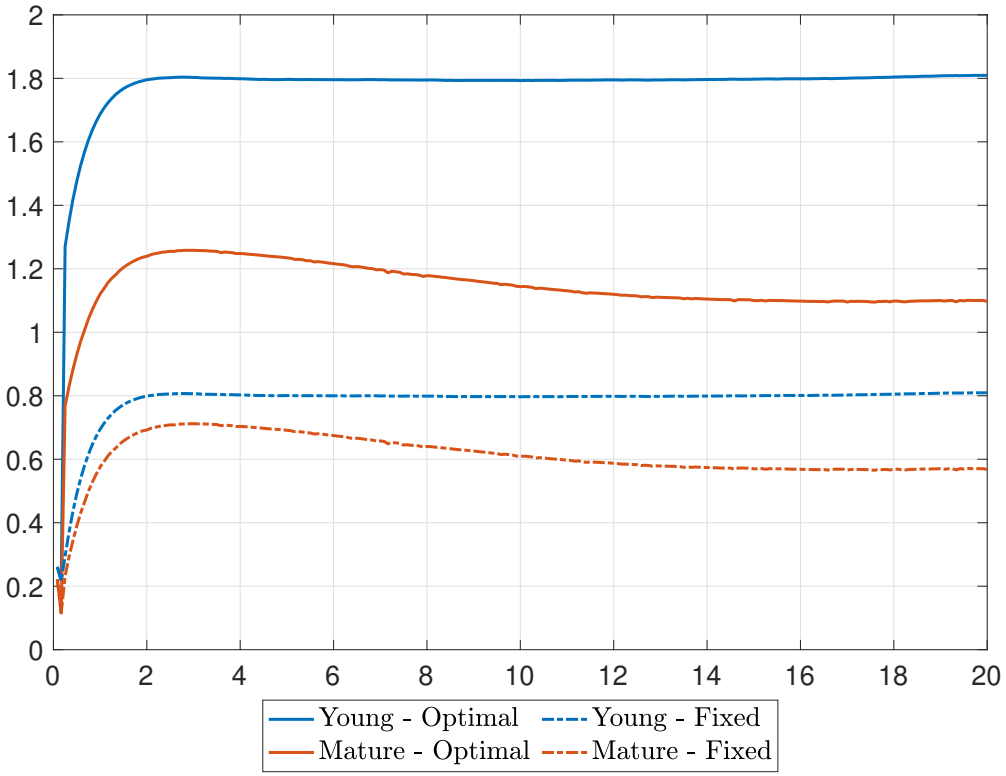


Figure 8: Changes in Average Upgrade Rates by Firm Age

Notes: This figure shows the increase in average technology upgrade rates of firms grouped by their age over the years following the change in worker mobility, relative to the baseline BGP with lower mobility. The change is measured using upgrade rates averaged over ten years. Young and Mature refer to firms with ages below five and above six, respectively. "Optimal" refers to technology upgrade rates chosen optimally as in Equation (5), while "Fixed" refers to rates fixed at the baseline level conditional on match-level variables.

	Baseline	$\phi = 0.1\bar{S}$	$\phi = 0.5\bar{S}$	$\phi = \bar{S}$	$\phi = 1.5\bar{S}$
EE Rate	2.139%	2.128%	2.128%	2.128%	2.128%
Growth	2.093%	2.082%	2.080%	2.083%	2.093%
Within	1.441%	1.445%	1.443%	1.441%	1.441%
EE	0.281%	0.281%	0.281%	0.281%	0.281%
NE	0.371%	0.356%	0.356%	0.361%	0.371%

Table 3: Different Values of Buyout Fees and Growth

Notes: This table summarizes the growth rate and its components between BGP with different values for buyout fees of non-compete agreements. EE rates are monthly, and growth rates are annual. $\bar{S}$ is the average surplus of the baseline economy.

worker mobility channels.

A key result in Shi (2023) is that buyout of non-competes allows firms to extract rents from future matches with more productive producers, thereby encouraging match-specific investments—similar to within-job technology upgrades in our framework. In contrast, this paper finds that such buyout fees have a negligible impact on the average rate of within-job upgrades, as shown in the third row of Table 3. Unlike Shi (2023), our model incorporates the increase in firm value derived from future hires.[11] Since firms must also pay buyouts to hire workers subject to non-competes from other firms, the net increase in match surplus associated with buyout fees is substantially smaller. In this setting, firms with lower match surpluses gain disproportionately more because their workers are more likely to be poached. However, this redistribution of match surplus has negligible effects on rates of within-job upgrades and the productivity distribution. Consequently, the contributions of EE and NE transitions to growth remain largely unchanged. Since the reference economy remains virtually the same, the quantitative responses to banning non-competes barely change from the results in Table 2.

[11] Shi (2023) study how non-competes mitigate the hold-up problem associated with match-specific investments. In our framework, R&D investments are firm-specific and have lasting effects on future hires.

7 Conclusion

Despite the presence of significant labor market frictions, the interaction between these frictions, innovation, and productivity growth remains underexplored. This paper demonstrates that the diffusion of knowledge associated with worker mobility can lower innovation costs for the broader economy. This effect complements the usual channel where worker turnover can stimulate growth by reallocating labor from less productive, slow-growing firms to more productive, fast-growing ones.

This paper provides empirical evidence that innovation responds endogenously to changes in labor market frictions. Institutional changes that facilitate EE transitions lead to higher-quality innovations and faster growth of labor productivity. Motivated by these general equilibrium responses in data, we develop an endogenous growth model with a frictional labor market and technology upgrade choices. The model highlights that worker turnover not only increases the returns to innovation by allowing productive firms to expand, but also reduces the costs of innovation through knowledge diffusion.

Our quantitative results suggest that incumbent innovation is essential in shaping the aggregate response of productivity growth to economic shocks. Despite the secular decline in worker turnover rates since the late 20th century, aggregate growth rates have decreased only moderately. This implies that the contribution of changes in productivity within the job to growth is likely to become more critical than before. This empirical pattern calls for continued research on the determinants of incumbent innovation and productivity growth and the role of the labor market in this process.

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A Data Appendix

A.1 Other NC Changes

This appendix examines the effects of state-level institutional changes that *increased* the enforceability of NC contracts, as identified by Jeffers (2024). As argued by Jeffers (2024), higher state-level NC enforceability does not necessarily imply more binding restrictions if workers sort into sectors that do not require NC clauses. Indeed, Figure A.1 shows that EE hire rates in MSAs within states with increased NC enforceability became marginally higher, rather than lower, following the court rulings.

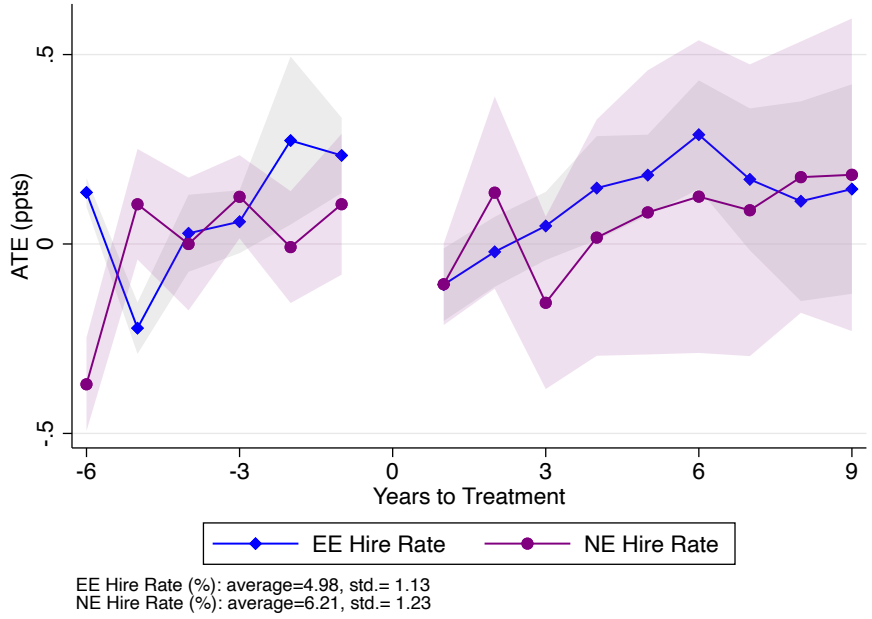


Figure A.1: Effect of Higher NC Enforceability on Gross Turnover

Notes: Treatments are the court ruling that increases the enforceability of NC contracts in Wisconsin (2009), Georgia (2010), Colorado (2011), Texas(2011), and Virginia (2013). Shaded areas represent the 95% confidence interval of the estimates. Standard errors are clustered at the state level.

Consistent with the results in Section 2.2, the number of patents in these states does not increase significantly (see Figure A.2). However, the number of citations

per patent increases significantly four years after the institutional changes. Although insignificant, citations per thousand workers increase marginally. Similarly, the importance of local patents increases following court rulings that alter enforceability.

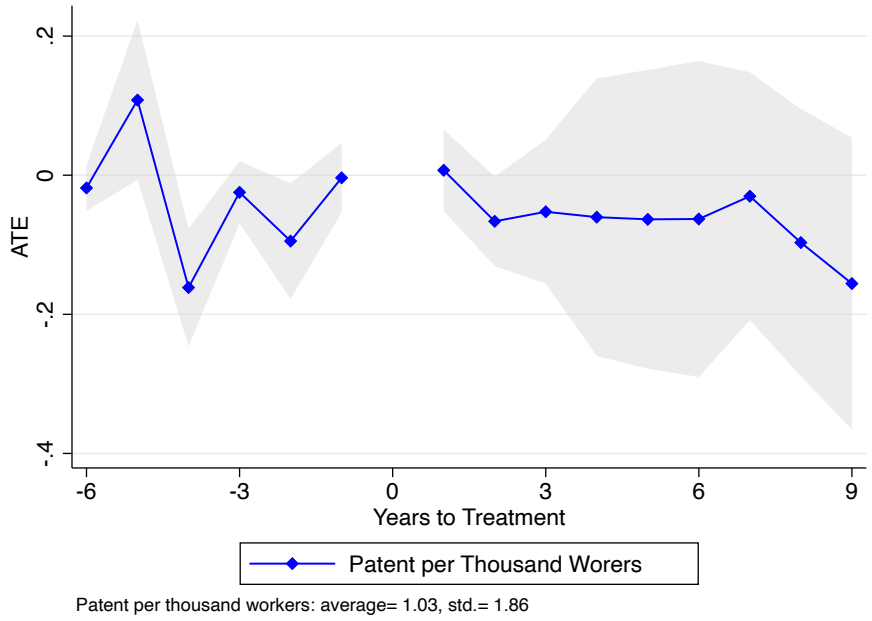


Figure A.2: Effect of Higher NC Enforceability on Patents

Notes: Treatments are the court ruling that increases the enforceability of NC contracts in Wisconsin (2009), Georgia (2010), Colorado (2011), Texas(2011), and Virginia (2013). Shaded areas represent the 95% confidence interval of the estimates. Standard errors are clustered at the state level.

In Figure A.5, the labor productivity response is mostly insignificant, with negative point estimates. This result is consistent with higher enforceability of the NC forcing workers into less productive and restricted jobs, potentially mitigating the growth benefits of quality innovation.

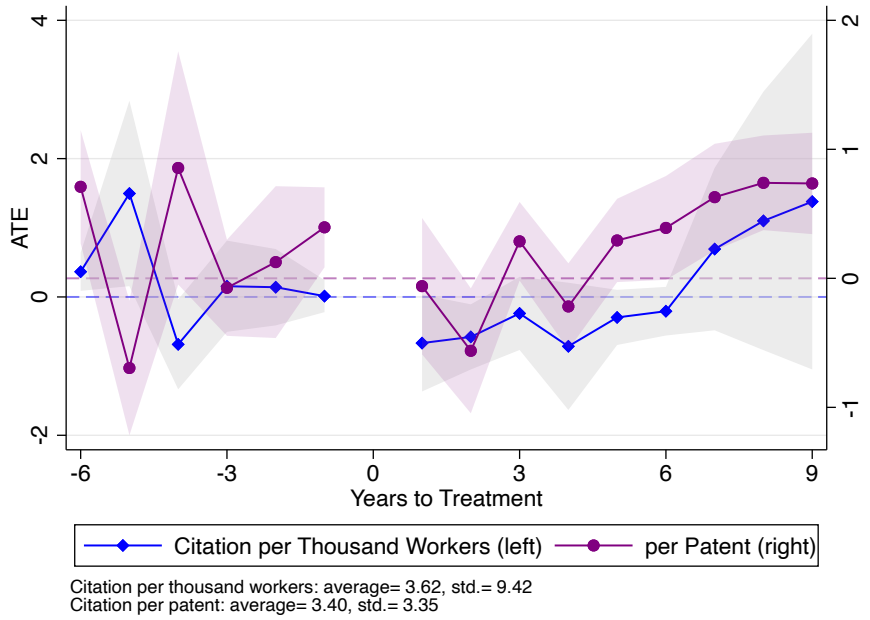


Figure A.3: Effect of Higher NC Enforceability on Citations

Notes: Treatments are the court ruling that increases the enforceability of NC contracts in Wisconsin (2009), Georgia (2010), Colorado (2011), Texas(2011), and Virginia (2013). Shaded areas represent the 95% confidence interval of the estimates. Standard errors are clustered at the state level.

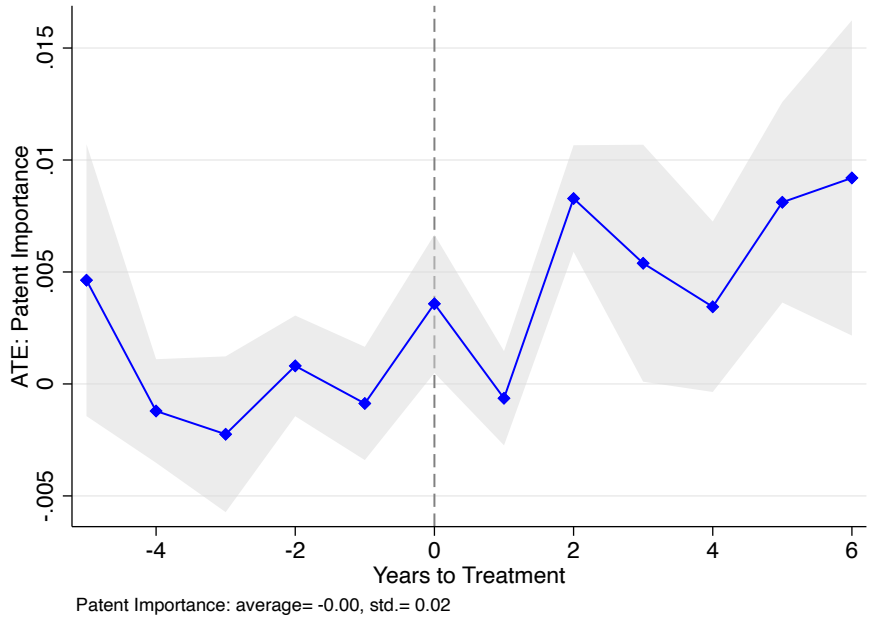


Figure A.4: Effect of Higher NC Enforceability on Patent Importance

Notes: Treatments are the court ruling that increases the enforceability of NC contracts in Wisconsin (2009), Georgia (2010), Colorado (2011), Texas(2011), and Virginia (2013). Shaded areas represent the 95% confidence interval of the estimates. Standard errors are clustered at the state level.

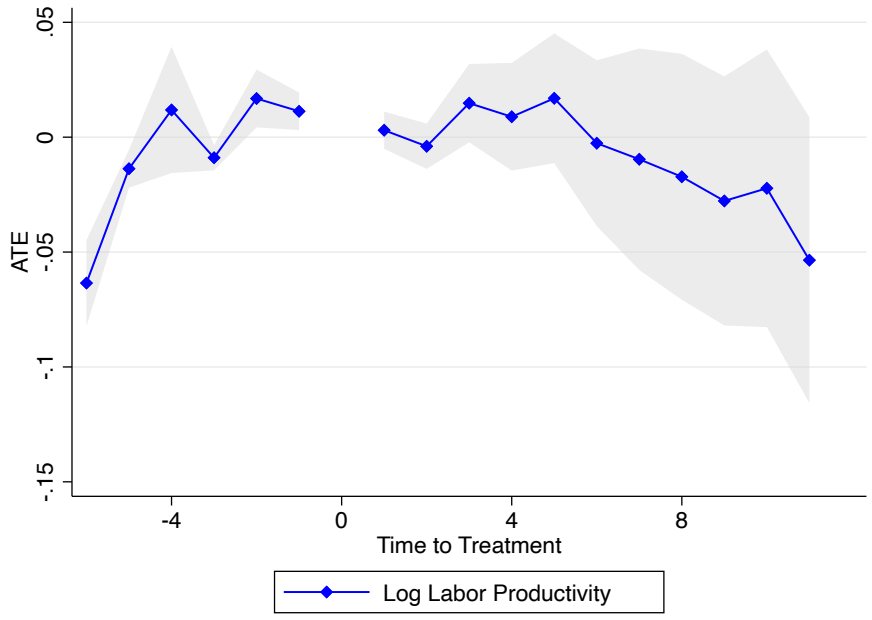


Figure A.5: Effect of Higher NC Enforceability on Labor Productivity

Notes: Treatments are the court ruling that increases the enforceability of NC contracts in Wisconsin (2009), Georgia (2010), Colorado (2011), Texas(2011), and Virginia (2013). Shaded areas represent the 95% confidence interval of the estimates. Standard errors are clustered at the state level.

A.2 Additional Treatment Effects

Figure A.6 displays changes in log employment for MSAs in treated states following changes in NC enforceability. MSA-level employment increases by nearly 4% five years after court rulings, and this positive effect is statistically significant at the 5% level, although the confidence bands widen over time.

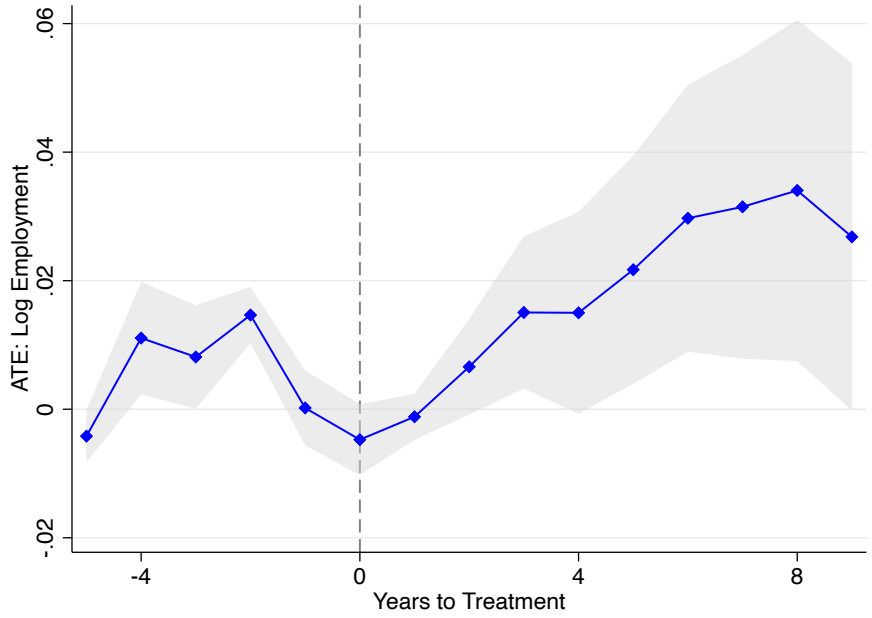


Figure A.6: Effect of Lower NC Enforceability on Employment

Notes: Treatments are the court rulings that reduced the enforceability of NC contracts in South Carolina (2010) and Montana (2011). Shaded areas represent the 95% confidence interval of the estimates. Standard errors are clustered at the state level.

Figure A.7 presents the coefficient estimates for log wages at the MSA level. The effect is generally small and statistically insignificant.

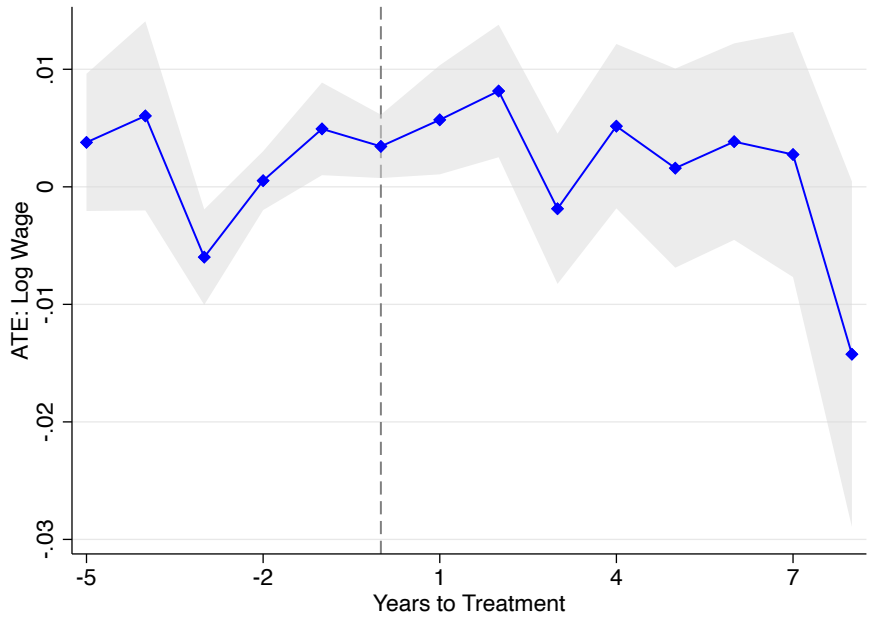


Figure A.7: Effect of Lower NC Enforceability on Wage

Notes: Treatments are the court ruling that reduces the enforceability of NC contracts in South Carolina (2010) and Montana (2011). Shaded areas represent the 95% confidence interval of the estimates. Standard errors are clustered at the state level.

A.3 Treatment Effect by Tenure Group

Figure A.8 illustrates the responses of patent impact by industry groups, sorted by the magnitude of the wage-tenure premium.[12] The average patent impact, defined as the average number of citations per granted patent, increases more significantly and rapidly in high-tenure-premium industries. The difference in the average treatment effect is significant at the 1% level.

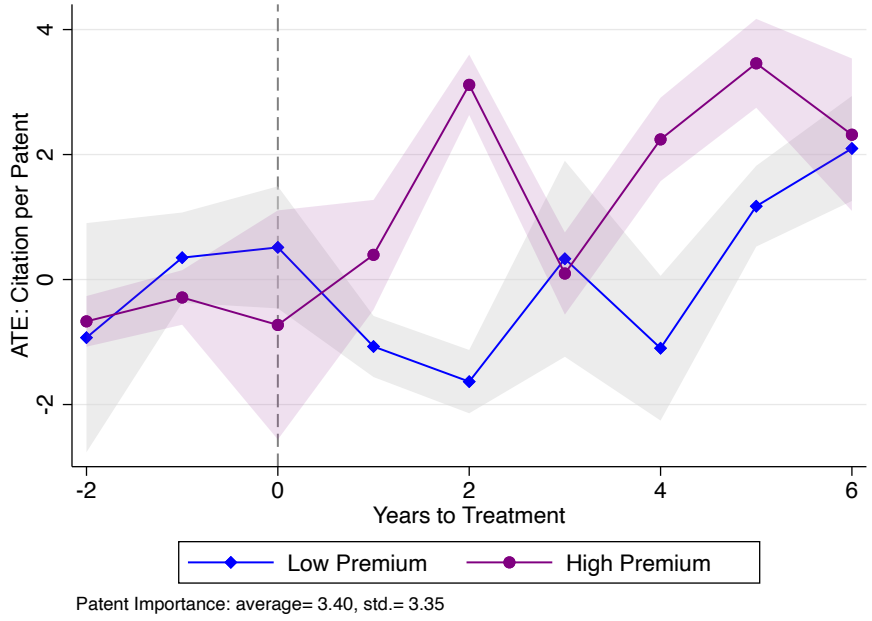


Figure A.8: Effect on Patent Impact by Tenure Premium

Notes: Treatments are the court ruling that reduces the enforceability of NC contracts in South Carolina (2010) and Montana (2011). Shaded areas represent the 95% confidence interval of the estimates. Standard errors are clustered at the state level.

[12]Specifically, we regress the log wage of a worker on tenure at the current job, controlling for demographics, education level, and fixed effects for year, industry, and occupation, using combined data from the Annual Social and Economic Supplement and the Job Tenure and Occupational Mobility Supplement. The tenure premium, measured by the coefficient on tenure, is estimated separately for each industry. We map the tenure premium at the Census 1990 industry level to three-digit 2007 NAICS codes using the correspondence in the American Community Survey 2008–2012. We then convert the 2007 NAICS codes to Cooperative Patent Classification (CPC) codes using crosswalks developed by Goldschlag et al. (2020). Finally, we define the low-tenure-premium group as CPC codes with premiums smaller than the employment-weighted median, and the high-tenure-premium group as the remainder.

Next, in Figure A.9, we show that the increase in patent importance is larger and more significant for industries with a higher tenure premium on wages. The difference in average treatment effect is significant at the 10% level. These results imply that the effects are greater for industries with a higher emphasis on human capital and are consistent with innovation activities encouraged with knowledge or human capital embodied in workers. If human capital not only increases productivity but also reduces innovation costs through the diffusion of knowledge, it contributes to faster productivity growth within jobs.

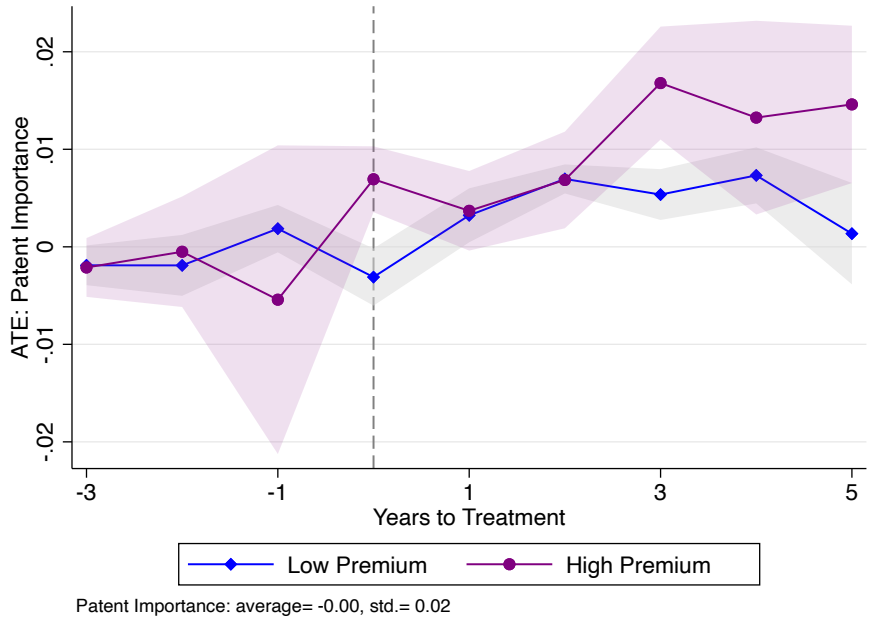


Figure A.9: Effect on Patent Importance by Tenure Premium

Notes: Treatments are the court ruling that reduces the enforceability of NC contracts in South Carolina (2010) and Montana (2011). Shaded areas represent the 95% confidence interval of the estimates. Standard errors are clustered at the state level.

A.4 Entrants vs. Incumbents

The MSA-level responses to institutional changes in NC agreements are driven primarily by incumbents rather than entrants. First, all regressions in Section 2.2 control the entrant share of job creation in the BDS. Moreover, the share of employment creation does not increase after the change in NC enforceability; rather it decreases (see Figure A.10). Lastly, when we restrict our analysis to incumbent patents—defined as patents granted to assignees appearing in the USPTO data more than two years prior to the grant year—the results regarding patents, citations, and importance remain virtually unchanged (see Figure A.11–A.13). This result arises because incumbents dominate patenting activity: between 2000 and 2019, 91.5% of patents were granted to incumbents.

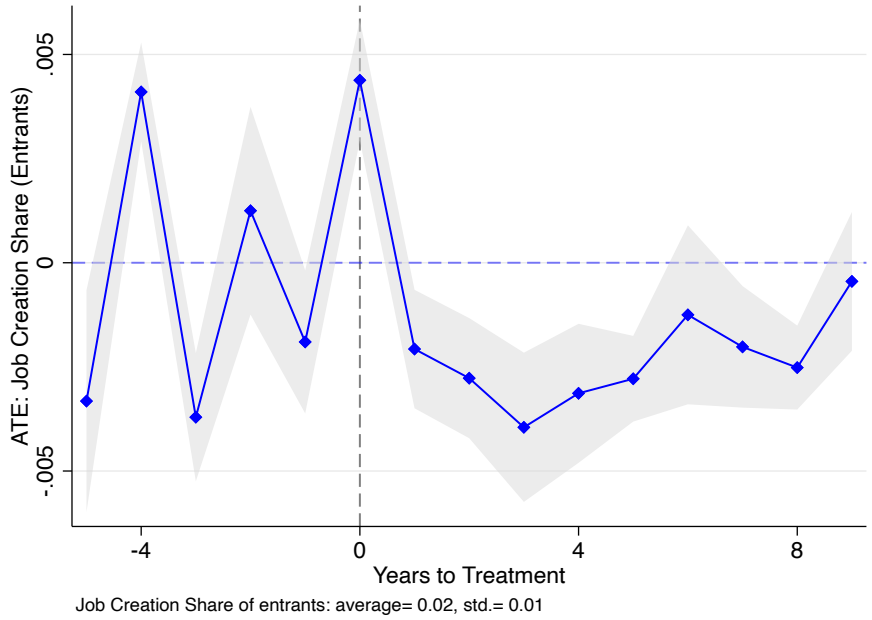


Figure A.10: Effect of Lower NC Enforceability on Job Creation of Entrants

Notes: Treatments are the court ruling that reduces the enforceability of NC contracts in South Carolina (2010) and Montana (2011). Shaded areas represent the 95% confidence interval of the estimates. Standard errors are clustered at the state level.

Figure A.14 displays the treatment effect estimates by assignee age. The age of the assignee is defined as the difference between the first appearance of the assignee in

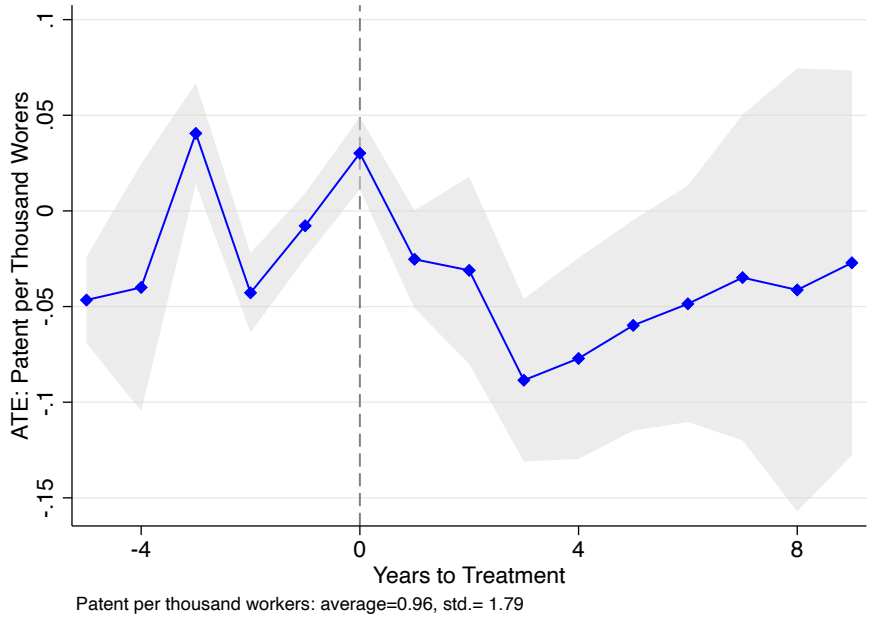


Figure A.11: Effect of Lower NC Enforceability on Incumbent Patents

Notes: Treatments are the court ruling that reduces the enforceability of NC contracts in South Carolina (2010) and Montana (2011). Shaded areas represent the 95% confidence interval of the estimates. Standard errors are clustered at the state level.

the patent data and the grant year. The results indicate that the effect of the NC enforceability change is quantitatively stronger for older assignees, although the effect on younger ones is also significant but smaller in magnitude. The results of patent importance are largely consistent with the results of the citation in Figure A.15.

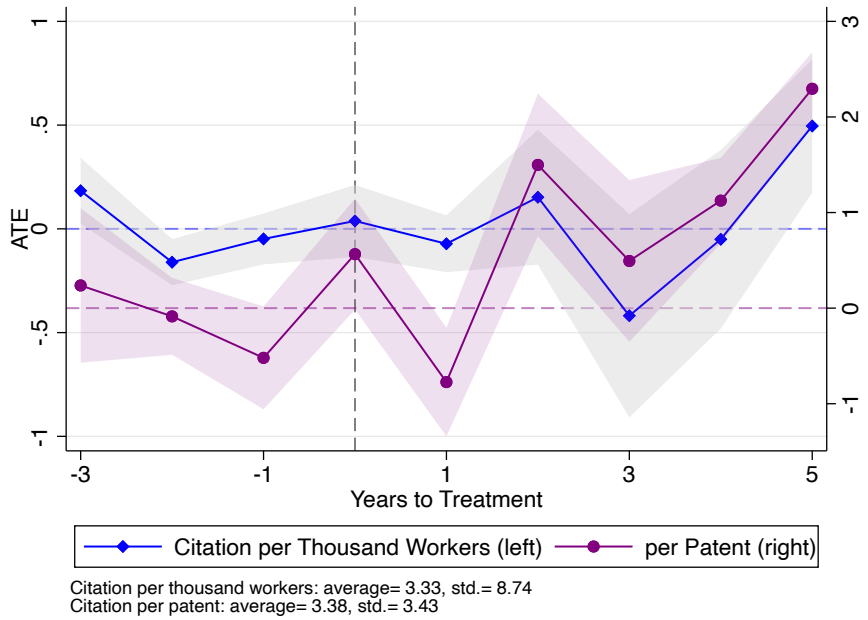


Figure A.12: Effect of Lower NC Enforceability on Incumbent Citations and Impacts

Notes: Treatments are the court ruling that reduces the enforceability of NC contracts in South Carolina (2010) and Montana (2011). Shaded areas represent the 95% confidence interval of the estimates. Standard errors are clustered at the state level.

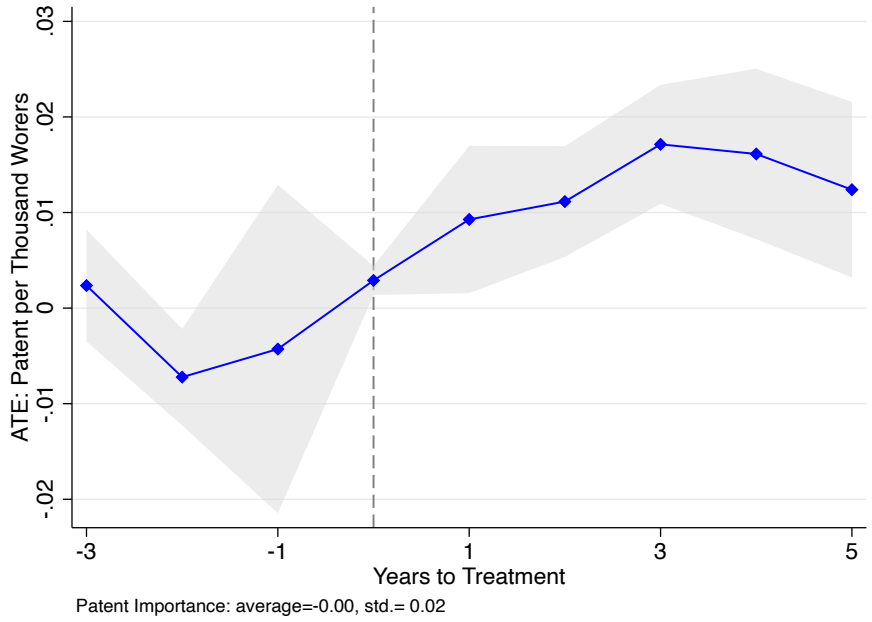


Figure A.13: Effect of Lower NC Enforceability on Incumbent Patent Importance

Notes: Treatments are the court ruling that reduces the enforceability of NC contracts in South Carolina (2010) and Montana (2011). Shaded areas represent the 95% confidence interval of the estimates. Standard errors are clustered at the state level.

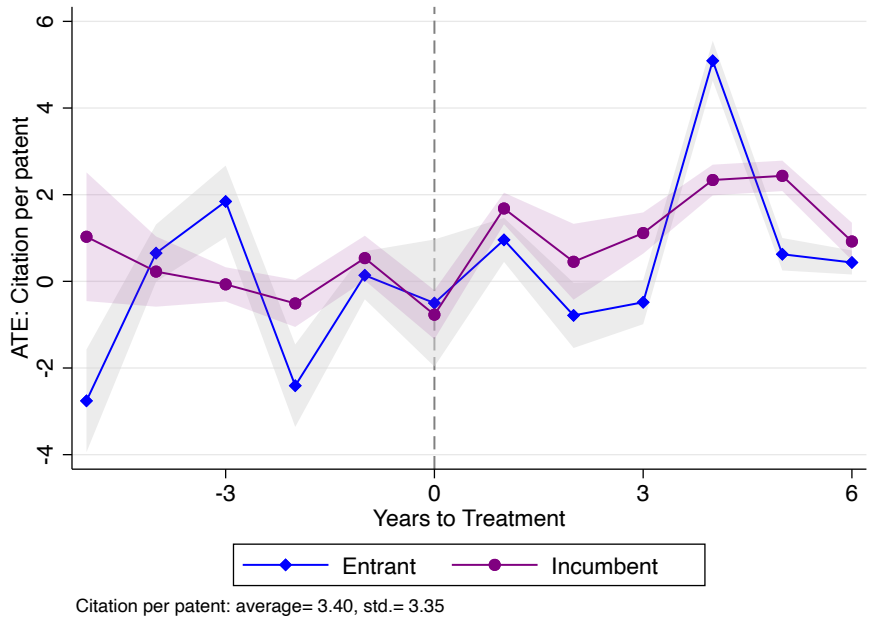


Figure A.14: Effect of Lower NC Enforceability on Citations per Patent by Age

Notes: Treatments are the court ruling that reduces the enforceability of NC contracts in South Carolina (2010) and Montana (2011). Shaded areas represent the 95% confidence interval of the estimates. Standard errors are clustered at the state level.

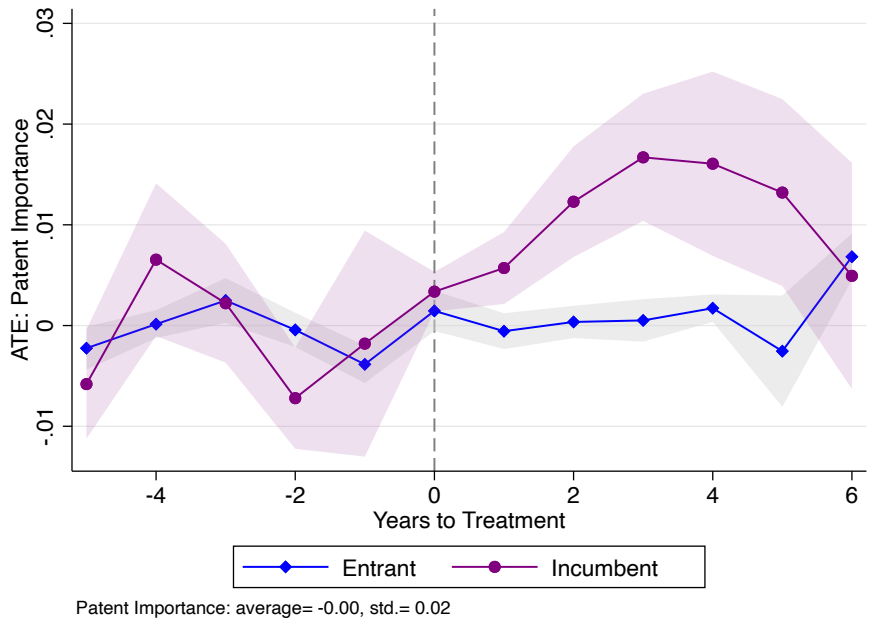


Figure A.15: Effect of Lower NC Enforceability on Patent Importance by Age

Notes: Treatments are the court ruling that reduces the enforceability of NC contracts in South Carolina (2010) and Montana (2011). Shaded areas represent the 95% confidence interval of the estimates. Standard errors are clustered at the state level.

A.5 Net vs. Gross

The results of patents and citations in Section 2.2 are likely driven by gross turnover of workers rather than net turnover of jobs. As shown in Figure A.16, the rates of job creation and destruction do not respond significantly to changes in NC enforceability.

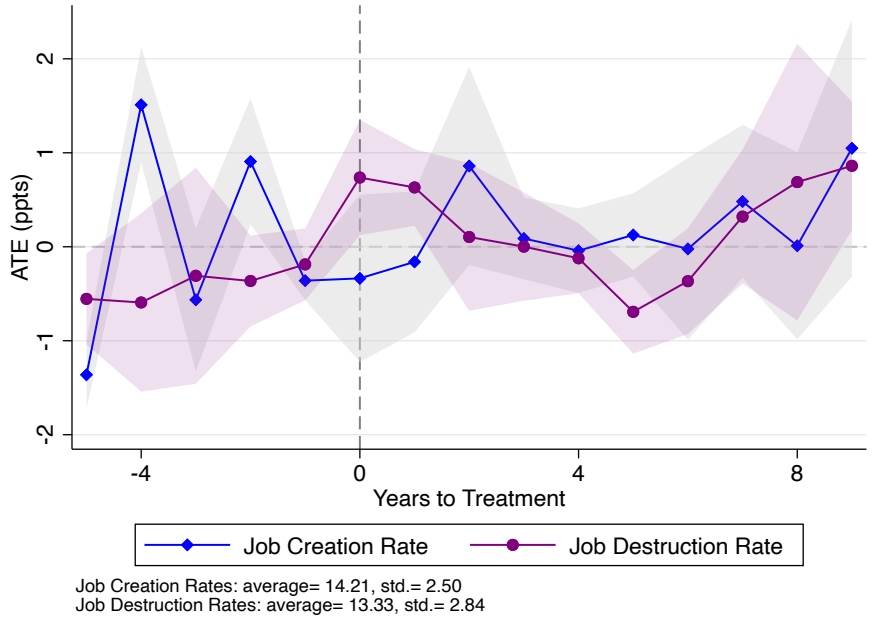


Figure A.16: Effect of Lower NC Enforceability on Net Labor Turnover

Notes: Treatments are the court ruling that reduces the enforceability of NC contracts in South Carolina (2010) and Montana (2011). Shaded areas represent the 95% confidence interval of the estimates. Standard errors are clustered at the state level.

A.6 Inventor Mobility

The existing literature often emphasizes the role of inventor mobility in promoting innovation. In this appendix, we show that inventor mobility likely does not drive the citation results observed after NC enforceability changes, as inventor mobility itself did not increase in response to these institutional shifts.

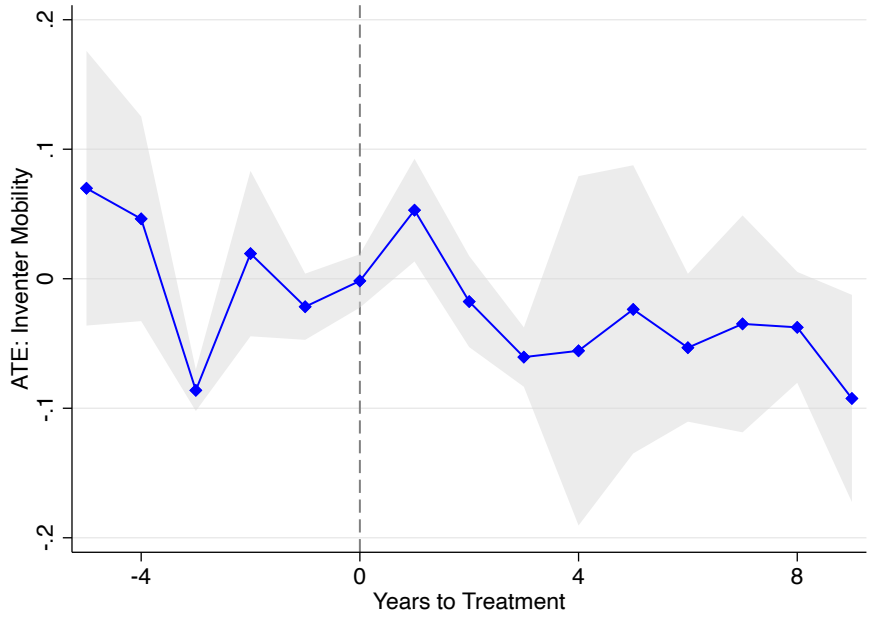


Figure A.17: Effect of Lower NC Enforceability on Inventor Mobility

Notes: Treatments are the court ruling that reduces the enforceability of NC contracts in South Carolina (2010) and Montana (2011). Inventor mobility is defined as the fraction of inventors with nonzero patent applications in a year that switch from one assignee to another. Standard errors are clustered at the state level.

Figure A.17 presents the regression results. For inventors appearing in the patent application data in a given year and MSA, inventor mobility is defined as the share of inventors associated with multiple assignees in that year or who switched assignees between the current and prior year. Inventor mobility does not change systematically after changes in enforceability; if anything, it decreases modestly.

A.7 Correlation between Worker Turnover and Growth

In this appendix, we employ the local projection method of Jordà (2005) to estimate the dynamic correlation of worker turnover rates with labor productivity and patenting activities. Specifically, we estimate the following equation using OLS for each horizon $h \in 1, \ldots, 7$:

$$y_{i,t+h} = \alpha_{i,h} + \delta_{t+h} + \beta_h r_{i,t} + {}_h X_{i,t} + \tilde{}_h \tilde{X}_{i,t+h} + \nu_{i,t+h} \tag{A.1}$$

In this equation, β_h estimates the correlation between a change in the turnover rate $r_{i,t}$ in MSA i at time t and a change in the result y at time $t+h$. The specification controls for MSA and year fixed effects, as well as controls at time t and $t+h$. Controls at time t, $X_{i,t}$, include lagged log labor productivity, manufacturing employment share, and the entrant share of job creation.[13] Controls at time $t+h$, $X_{i,t+h}$, include the unemployment rate, GDP growth between $t+h$ and $t+h-1$, and lagged log labor productivity. These variables are included to control for cyclical components that might induce correlations between turnover, productivity, and innovation, as well as MSA heterogeneity in industry and firm age composition.

Figure A.18–A.21 display the estimation results for log labor productivity, patents per worker, citations per worker, and citations per patent. In Figure A.18, a one percentage point increase in EE and NE hire rates in an MSA is initially associated with a 3% decrease in labor productivity. However, over time, the sign of the correlation flips; by the fifth year following the increase in $r_{i,t}$, the regression estimates become positive. Thus, the correlation with productivity growth becomes positive in the medium run.

The response of patents per thousand workers is generally small and statistically insignificant, except in the sixth and seventh years (see Figure A.19). In contrast to the raw patent count, the number of citations per patent increases significantly through the second year. Moreover, the short-term correlation is substantial: a one percentage point increase in the EE hire rate is associated with 0.4 additional citations per thousand workers, equivalent to 11% of the sample standard devia-

[13] Entrants are defined in the BDS as firms that entered the labor market in the current or prior year.

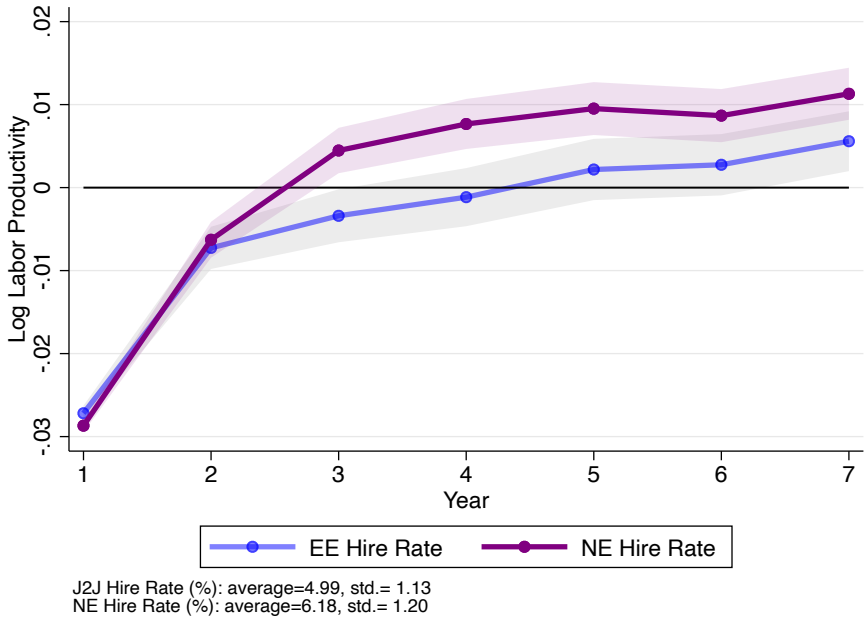


Figure A.18: Local Projection of Turnover Rates on Labor Productivity

Notes: Local projection coefficients are from the estimation of Equation (A.1). Shaded areas represent the 95% confidence interval of the estimates.

tion. The results are quantitatively smaller but qualitatively similar for NE hire rates.

Consequently, the number of citations per thousand workers increases with higher rates of EE and NE hires. A one percentage point increase in the EE hire rate corresponds to 1.5 additional citations per thousand workers, or 15% of the standard deviation. This effect remains significantly positive until the third year. The results for NE hire rates are smaller but follow a similar pattern. Unlike in Section 2, the importance of patents does not exhibit a significant correlation with changes in local EE and NE hire rates.

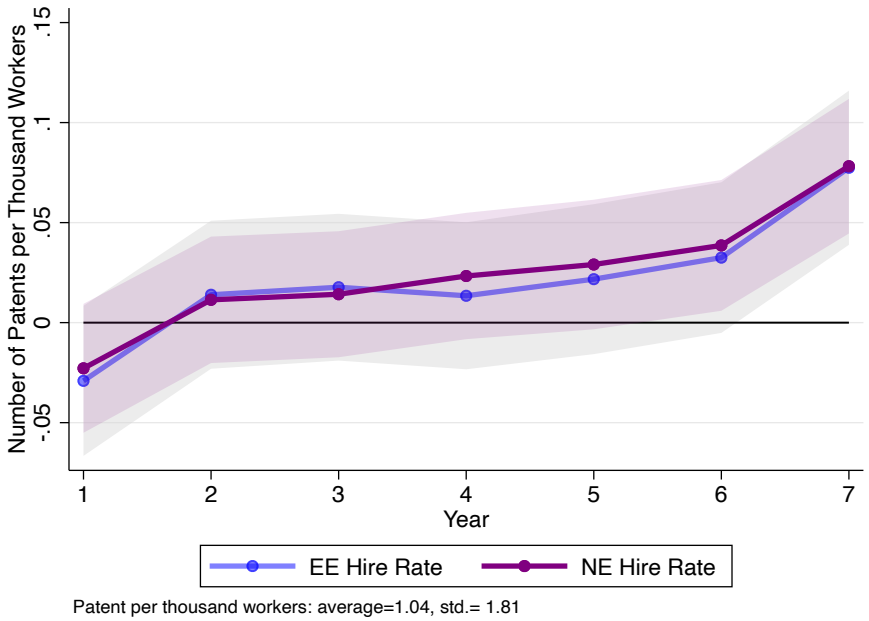


Figure A.19: Local Projection of Turnover Rates on Patents

Notes: Local projection coefficients are from estimation of Equation (A.1). Shaded areas represent the 95% confidence interval of the estimates.

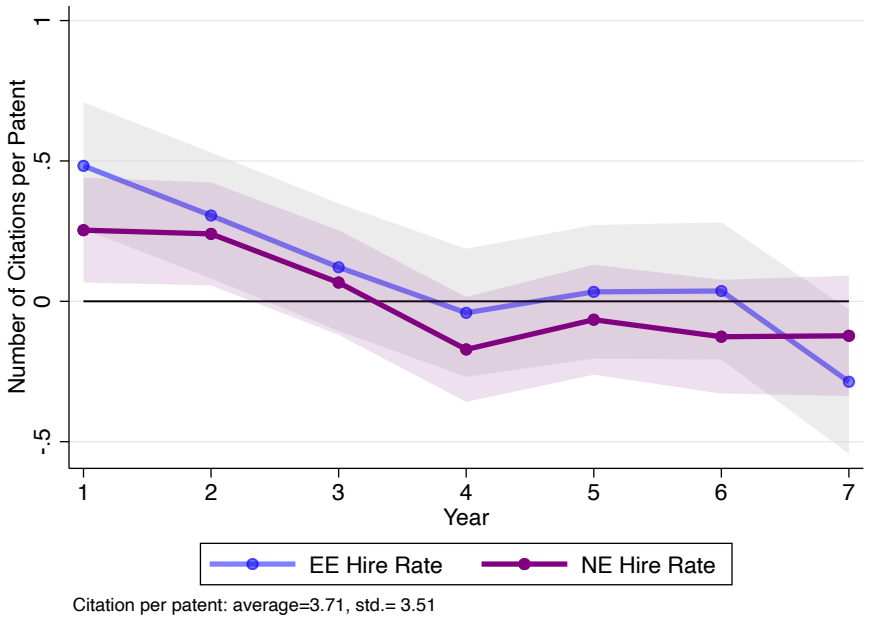


Figure A.20: Local Projection of Turnover Rates on Patent Impact

Notes: Local projection coefficients are from estimation of Equation (A.1). Shaded areas represent the 95% confidence interval of the estimates.

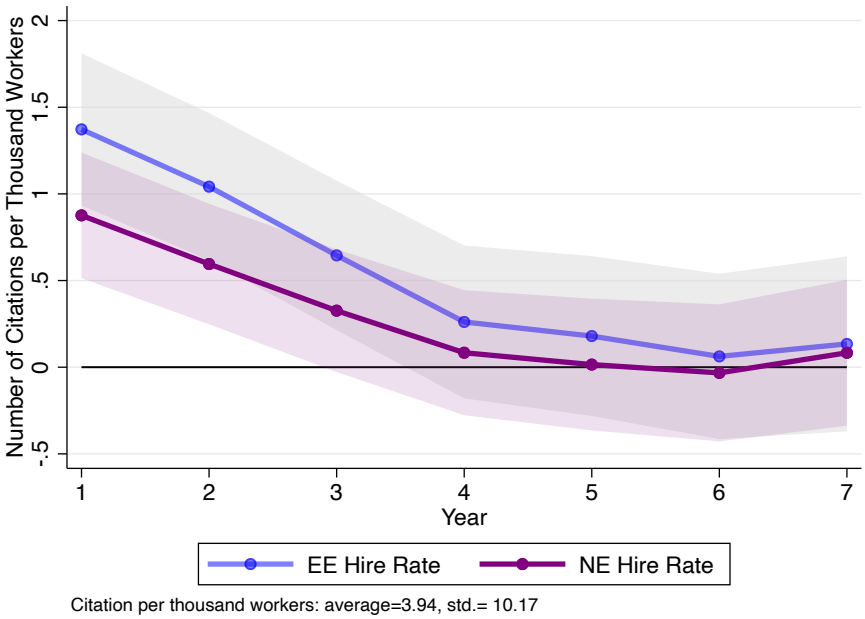


Figure A.21: Local Projection of Turnover Rates on Citations

Notes: Local projection coefficients are from estimation of Equation (A.1). Shaded areas represent the 95% confidence interval of the estimates.

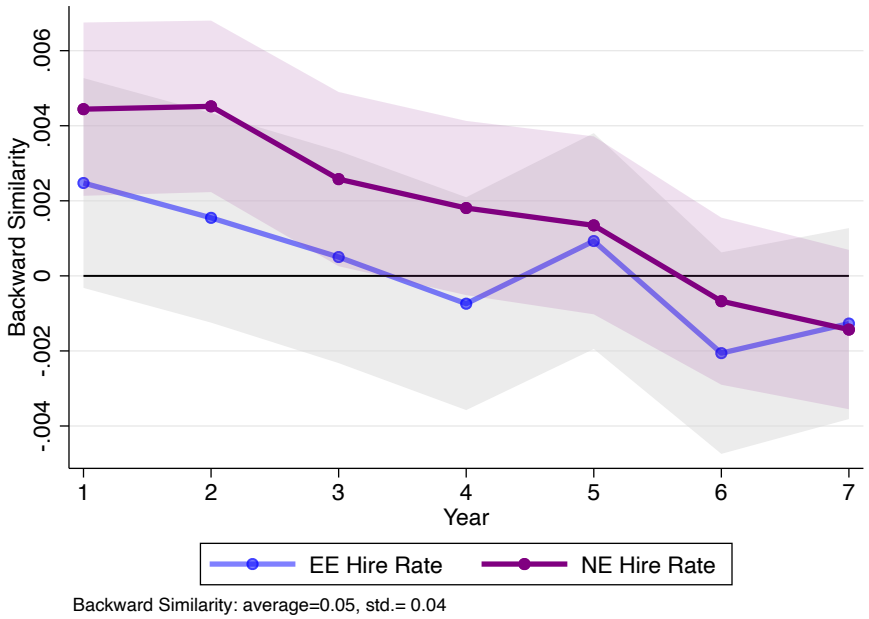


Figure A.22: Local Projection of Turnover Rates on Citations

Notes: Local projection coefficients are from estimation of Equation (A.1). Shaded areas represent the 95% confidence interval of the estimates.

A.7.1 Robustness of LP Correlations

The local projection estimates remain robust to controlling for job creation and job destruction rates. Figure A.23–A.26 present the results when net labor turnover rates (job creation and destruction) are included as additional controls. The coefficient estimates are virtually unchanged compared to the baseline specification in Appendix A.7.

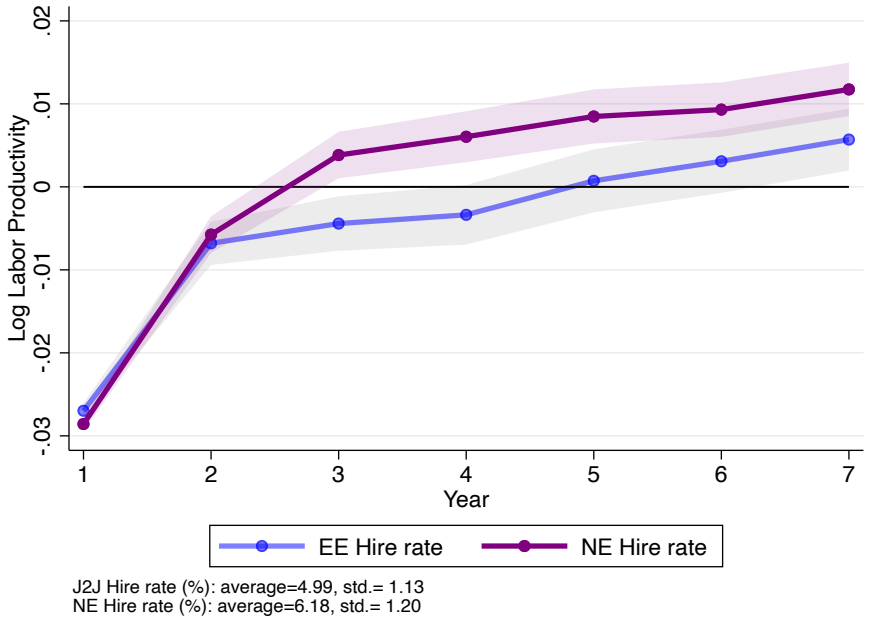


Figure A.23: Robustness: Local Projection of Turnover Rates on Labor Productivity

Notes: These estimates are made after controlling for the MSA-level job creation and destruction rates in addition to the baseline local projection regression in Appendix A.7. Shaded areas represent the 95% confidence interval of the estimates.

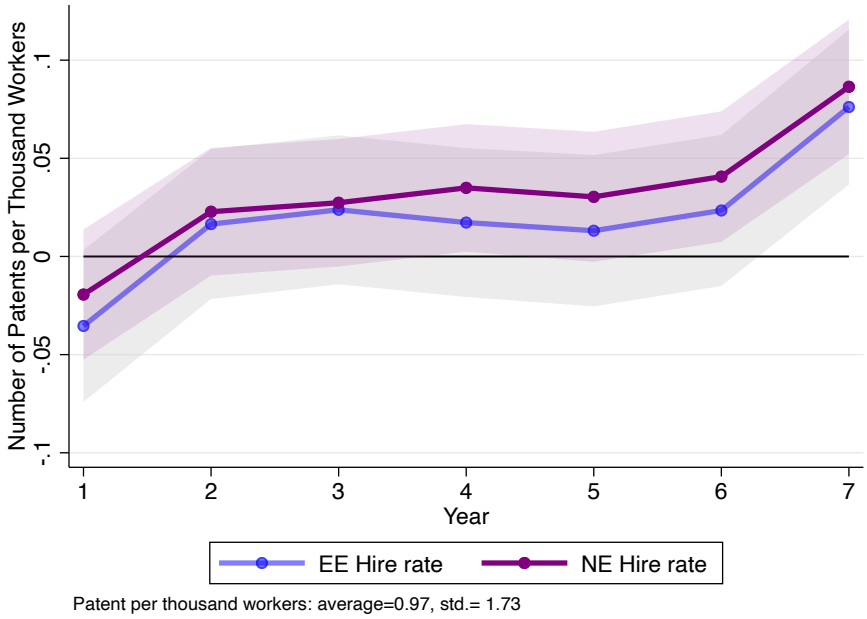


Figure A.24: Robustness: Local Projection of Turnover Rates on Patents

Notes: These estimates are made after controlling for the MSA-level job creation and destruction rates in addition to the baseline local projection regression in Appendix A.7. Shaded areas represent the 95% confidence interval of the estimates.

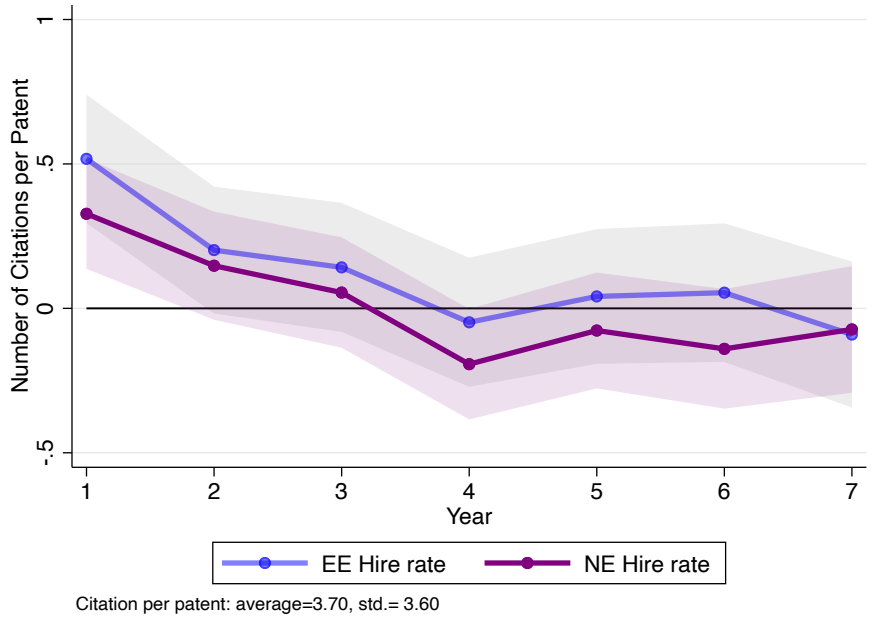


Figure A.25: Robustness: Local Projection of Turnover Rates on Patent Impact

Notes: These estimates are made after controlling for the MSA-level job creation and destruction rates in addition to the baseline local projection regression in Appendix A.7. Shaded areas represent the 95% confidence interval of the estimates.

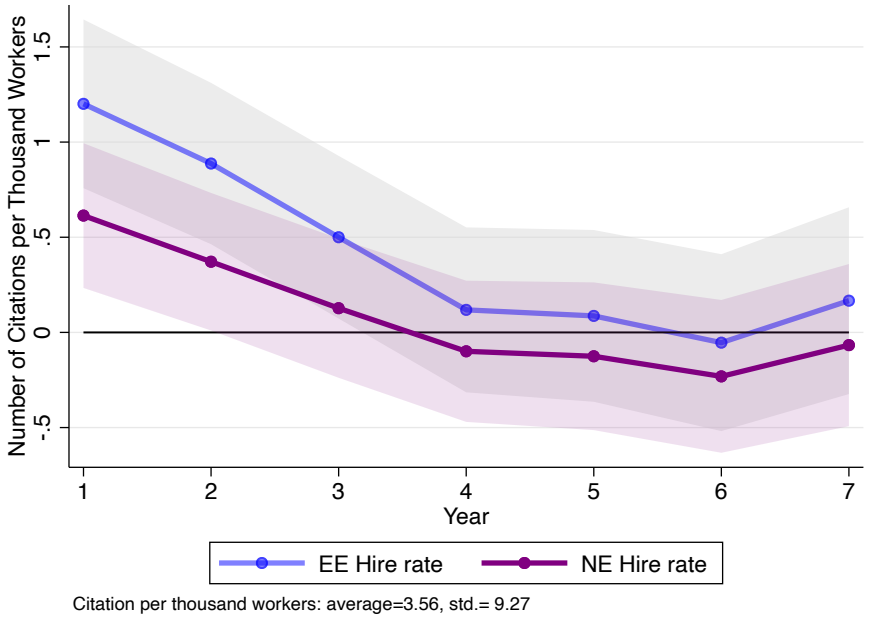


Figure A.26: Robustness: Local Projection of Turnover Rates on Citations

Notes: These estimates are made after controlling for the MSA-level job creation and destruction rates in addition to the baseline local projection regression in Appendix A.7. Shaded areas represent the 95% confidence interval of the estimates.

B Model Appendix

B.1 Formulation of the HJB Equation

The value function at the firm level, $\bar{\mathbf{M}}_{j,t}(K,z,n)$, satisfies the following HJB equation:

$$\begin{aligned}
r\bar{\mathbf{M}}_{j,t}(K,z,n) = &\max_{g} zn - \bar{z}_t C(g;n,K) \\
&+ n\chi_j\left(\mathbf{U}(\bar{z}_t) - \partial_n \bar{\mathbf{M}}_{j,t}(K,z,n)\right) \\
&+ \theta_j\left(\bar{\mathbf{M}}_{j,t}(K,z,n) - \bar{\mathbf{M}}_{j,t}(K,z,n)\right) \\
&+ nv_j\Bigg(q^U\left(\partial_n \bar{\mathbf{M}}_{j,t}(K,z,n) + \partial_K \bar{\mathbf{M}}_{j,t}(K,z,n)\right) \\
&\quad + q^E\int \max\Big\{\partial_n \bar{\mathbf{M}}_{j,t}(K,z,n) + \partial_K \bar{\mathbf{M}}_{j,t}(K,z,n) \\
&\qquad - \partial_{n'} \bar{\mathbf{M}}_{j',t}\left(K',z',n'\right), 0\Big\}\Bigg) d\bar{\mathbf{F}}_{j',t}\left(K',z',n'\right) \\
&+ g\partial_x \bar{\mathbf{M}}_{j,t}(K,z,n) + \frac{\sigma^2}{2}\partial_x^2 \bar{\mathbf{M}}_{j,t}(K,z,n) \\
&+ \left(\tilde{p}^E n - \delta K\right)\partial_K \bar{\mathbf{M}}_{j,t}(K,z,n) + \mu\bar{z}_t\partial_t \bar{\mathbf{M}}_{j,t}(K,z,n).
\end{aligned}$$

In this equation, $\bar{\mathbf{F}}_{j',t}(K',z',n')$ is the probability distribution of employed workers, $\bar{\mathbf{P}}_{j,t}(K,z,n)$ is the probability of poaching, and $\bar{\mathbf{O}}_{j,t}(K,z,n)$ is the probability of worker quits to other employers.
$\mathbf{U}(\bar{z}_t)$ is the value of an unemployed worker at time t, satisfying:

$$r\mathbf{U}(\bar{z}_t) = b\bar{z}_t + \mu\bar{z}_t\partial_{\bar{z}_t}\mathbf{U}(\bar{z}_t).$$

We guess and verify that $\mathbf{M}_{j,t}(k,z) := \bar{\mathbf{M}}_{j,t}(kn,z,n)/n$, where $\mathbf{M}_{j,t}(k,z)$ is characterized by the following HJB equation:

$$\begin{aligned}
(r-\mu)\mathbf{M}_{j,t}(k,z) = \max_{g} \Bigg\{ & z - \bar{z}_t c(g;k) \\
& + \chi_j \left(U - \mathbf{M}_{j,t}(k,z) + k\partial_k \mathbf{M}_{j,t}(k,z) \right) \\
& + \theta_j \left(\mathbf{M}_{-j,t}(k,z) - \mathbf{M}_{j,t}(k,z) \right) \\
& + v_j \Bigg(q^U \left(\mathbf{M}_{j,t}(k,z) + (1-k)\partial_k \mathbf{M}_{j,t}(k,z) \right) \\
& \quad + q^E \int \max \Bigg\{ \mathbf{M}_{j,t}(k,z) + (1-k)\partial_k \mathbf{M}_{j,t}(k,z) \\
& \qquad - \mathbf{M}_{j',t}\left(k',z'\right) + k'\partial_{k'} \mathbf{M}_{j',t}\left(k',z'\right), 0 \Bigg\} d\mathbf{F}_{j',t}\left(k',z'\right) \Bigg) \\
& + g\partial_z \mathbf{M}_{j,t}(k,z) + \frac{\sigma^2}{2}\partial_z^2 \mathbf{M}_{j,t}(k,z) + \left(\tilde{p}^E - \delta k \right) \partial_k \mathbf{M}_{j,t}(k,z) \Bigg\}.
\end{aligned}$$

Note that $\partial_k \mathbf{M}_{j,t}(k,z) = \partial_K \bar{\mathbf{M}}_{j,t}(K,z,n)$ and $\partial_n \bar{\mathbf{M}}_{j,t}(K,z,n) = \mathbf{M}_{j,t}(k,z) - k\partial_k \mathbf{M}_{j,t}(k,z)$. Furthermore, $\partial_n \bar{\mathbf{M}}_{j,t}(K,z,n) - \partial_{n'} \bar{\mathbf{M}}_{j',t}(K',z',n') > 0$ is mathematically equivalent to $\mathbf{M}_{j,t}(k,z) + (1-k)\partial_{k'} \mathbf{M}_{j,t}(k,z) - \mathbf{M}_{j',t}(k',z') - k'\partial_{k'} \mathbf{M}_{j',t}(k',z') > 0$. Consequently,

$$\begin{aligned}
\int \max \left\{ \partial_n \bar{\mathbf{M}}_{j,t}(K,z,n) - \partial_{n'} \bar{\mathbf{M}}_{j',t}\left(K',z',n'\right), 0 \right\} d\bar{\mathbf{F}}_{j',t}\left(K',z',n'\right) & \\
= \int \max \left\{ \mathbf{M}_{j,t}(k,z) - \mathbf{M}_{j',t}\left(k',z'\right), 0 \right\} d\mathbf{F}_{j',t}\left(k',z'\right) & \\
\bar{\mathbf{P}}_{j,t}(K,z,n) = \int \mathbf{1}\left\{ \partial_n \bar{\mathbf{M}}_{j,t}(K,z,n) > \partial_{n'} \bar{\mathbf{M}}_{j',t}\left(K',z',n'\right) \right\} d\bar{\mathbf{F}}_{j',t}\left(K',z',n'\right) & \\
= \int \mathbf{1}\left\{ \mathbf{M}_{j,t}(k,z) > \mathbf{M}_{j',t}\left(k',z'\right) \right\} d\mathbf{F}_{j',t}\left(k',z'\right) =: \mathbf{P}_{j,t}(k,z) & \\
\bar{\mathbf{O}}_{j,t}(K,z,n) = \int \mathbf{1}\left\{ \partial_n \bar{\mathbf{M}}_{j,t}(K,z,n) > \partial_{n'} \bar{\mathbf{M}}_{j',t}\left(K',z',n'\right) \right\} d\bar{\mathbf{H}}_{j',t}\left(K',z',n'\right) & \\
= \int \mathbf{1}\left\{ \mathbf{M}_{j,t}(k,z) < \mathbf{M}_{j',t}\left(k',z'\right) \right\} d\mathbf{H}_{j',t}\left(k',z'\right) =: \mathbf{O}_{j,t}(k,z). &
\end{aligned}$$

$\bar{\mathbf{H}}_{j',t}\left(K',z',n'\right)$ and $\mathbf{H}_{j',t}\left(k',z'\right)$ represent the offer distributions.

We verify that the HJB equation is homogeneous of degree one in $\bar{z}_t$ if $\mathbf{F}_{j,t}\left(k,z\right) = F_j\left(k,z/\bar{z}_t\right)$, $\mathbf{H}_{j,t}(k,z) = H_j(k,z/\bar{z}_t)$, and $\mathbf{U}(z_t) = \bar{z}_t U = \bar{z}_t b/(r-\mu)$. Define $M_j\left(k,x\right) = \mathbf{M}_{j,t}\left(k,x\bar{z}_t\right)/\bar{z}_t$ and confirm that the following equation holds:

$$\begin{aligned}
\left(r-\mu\right)M_j\left(k,x\right) = \max_g \Bigg\{ & x - c(g;k) + \chi_j\left(U - M_j^{old}\left(k,x\right)\right) \\
& + \theta_j\left(M_{-j}\left(k,x\right) - M_j\left(k,x\right)\right) \\
& + v_j\left(q^U M_j^{new}\left(k,x\right) + q^E \int \max\left\{M_j^{new}\left(k,x\right) - M_{j'}^{old}\left(k',x'\right),0\right\} dF_{j'}\left(k',x'\right)\right) \\
& + \left(g-\mu x\right)\partial_x M_j\left(k,x\right) + \frac{\sigma^2}{2}\partial_x^2 M_j\left(k,x\right) + \left(\tilde{p}^E - \delta k\right)\partial_k M_j\left(k,x\right)\Bigg\},
\end{aligned}$$

where $M_j^{new}\left(k,x\right) = M_j\left(k,x\right) + \left(1-k\right)\partial_k M_j\left(k,x\right)$ and $M_j^{old}\left(k,x\right) = M_j\left(k,x\right) - k\partial_k M_j\left(k,x\right)$.

Finally, express $S_j(k,x) = M_j(k,x) - U$ and verify that Equation (5) holds.

B.2 Derivation of the Growth Rate

For the growth rate, it is more convenient to start with the Kolmogorov forward equation for the marginal distribution of workers on x. Let $\tilde{f}_x(x) = \sum_j \lim_{k\to\infty} \partial_x F_j(k,x)$ denote the marginal distribution of workers in x.

$$
\begin{aligned}
0 = &- \left(\tilde{g}\left(x\right) - \mu x\right) \tilde{f}_x\left(x\right) + \partial_x \left[\frac{\sigma^2}{2} \tilde{f}_x\left(x\right)\right] \\
&+ p^U u / \left(1-u\right) \tilde{H}_x\left(x\right) - \tilde{\chi}\left(x\right) - \tilde{\varphi}\left(x\right) \\
&+ q^E V \iint_{s\leq x} \mathbf{1}\left[S_j^{new}\left(k,s\right) > S_{j'}^{old}\left(k',s'\right)\right] dH_j\left(k,s\right) dF_{j'}\left(k',s'\right) \\
&- p^E \iint_{s\leq x} \mathbf{1}\left[S_j^{old}\left(k,s\right) < S_j^{new}\left(k',s'\right)\right] dF_j\left(k,s\right) dH_{j'}\left(k',s'\right).
\end{aligned}
\tag{B.1}
$$

In this equation, $\tilde{g}(x) = \sum_j \int g_j(k,x) f_j(k|x) dk$ is the average upgrade rate conditional on x, and $\tilde{H}_t(x) = \lim_{k\to\infty} H(k,x)$ is the marginal distribution of offers over x. $\tilde{\chi}(x) = \sum_j \chi_j \iint_{s\leq x} f_j(k,s) ds dk$ and $\tilde{\varphi}(x) = \int \mathbf{1}[s = \underline{x}(k), s < x] \partial_x \frac{\sigma^2}{2} f_j(k,x) dk$ are the exogenous and endogenous separation rates for matches with productivity lower than x, respectively.

Integrating Equation (B.1) over $[0,\infty)$ and rearranging terms, using $q^E V = p^E$:

$$
\begin{aligned}
\mu &= \mu \int x dF_j\left(k,x\right) \\
&= \underbrace{\int \tilde{g}\left(x\right) d\tilde{F}_x\left(x\right)}_{=A} \\
&\underbrace{-q^U V \int \tilde{H}_x\left(x\right) dx + \int \chi\left(x\right) dx + \int \varphi\left(x\right) dx}_{=B} \\
&+ p^E \underbrace{\left\{ - \iint_{s\leq x} \mathbf{1}\left[S_j^{new}(k,x) > S_{j'}^{old}(k',x')\right] dH_j\left(k,s\right) dF_{j'}\left(k',s'\right) dx \right.}_{=C} \\
&+ \underbrace{\left. \iint_{s\leq x} \mathbf{1}\left[S_j(k,x) < S_{j'}^{new}(k',x')\right] dF_j\left(k,s\right) dH_{j'}\left(k',s'\right) dx \right\}}_{=D}
\end{aligned}
\tag{B.2}
$$

First, term A is simply the average rate of technological upgrades:

$$
\begin{aligned}
A = \int \tilde{g}\left(x\right) \tilde{f}_x\left(x\right) dx &= \iint \sum_j g_j\left(k,x\right) \frac{f_j\left(k,x\right)}{\tilde{f}_x\left(x\right)} dk \tilde{f}_x\left(x\right) dx \\
&= \sum_j \iint g_j\left(k,x\right) f_j\left(k,x\right) dkdx.
\end{aligned}
\tag{B.3}
$$

B is the growth from replacing low-productivity matches with high-productivity matches with the NE-EN transitions.

$$
\begin{aligned}
& q^U V = p^U u/(1-u) = \bar{\chi} + \varphi. \\
& \therefore B = q^U V \int \left(1 - \tilde{H}\left(x\right)\right) dx - \left(\bar{\chi} + \varphi\right) \int \left(1 - (\tilde{\chi}(x) + \tilde{\varphi}(x))/(\bar{\chi} + \varphi)\right) dx \\
& \quad = q^U V \mathbb{E}_H\left[x\right] - \left(\bar{\chi} + \varphi\right) \mathbb{E}_{\chi+\varphi}\left[x\right].
\end{aligned}
\tag{B.4}
$$

Lastly, term $p^E(C+D)$ corresponds to productivity growth from worker reallo-

cation to matches with the highest productivity via EE transitions:

$$
\begin{aligned}
(C+D)/p^E = & -\iint_{s\leq x} \mathbf{1}\left[S_j^{new}(k,s) > S_{j'}^{old}\left(k',s'\right)\right] dH_j(k,s)\, dF_{j'}\left(k',s'\right) dx \\
& + \iint_{s\leq x} \mathbf{1}\left[S_j^{old}(k,s) < S_{j'}^{new}\left(k',s'\right)\right] dF_j(k,s)\, dH_{j'}\left(k',s'\right) dx \\
= & \iint_{s>x} \mathbf{1}\left[S_j^{new}(k,s) > S_{j'}^{old}\left(k',s'\right)\right] dx dH_j(k,s)\, dF_{j'}\left(k',s'\right) \\
& - \iint_{s>x} \mathbf{1}\left[S_j^{old}(k,s) < S_{j'}^{new}\left(k',s'\right)\right] dx dF_j(k,s)\, dH_{j'}\left(k',s'\right) \\
= & \iint s\mathbf{1}\left[S_j^{new}(k,s) > S_{j'}^{old}\left(k',s'\right)\right] dH_j(k,s)\, dF_{j'}\left(k',s'\right) \\
& - \iint s\mathbf{1}\left[S_j^{old}(k,s) < S_{j'}^{new}\left(k',s'\right)\right] dF_j(k,s)\, dH_{j'}\left(k',s'\right) \\
= & \iint s\mathbf{1}\left[S_j^{new}(k,s) > S_{j'}^{old}\left(k',s'\right)\right] dH_j(k,s)\, dF_{j'}\left(k',s'\right) \\
& - \underbrace{\iint s\mathbf{1}\left[S_j^{old}(k,s) < S_{j'}^{new}\left(k',s'\right)\right] dF_j(k,s)\, dH_{j'}\left(k',s'\right)}_{k\leftrightarrow k', s\leftrightarrow s'} \\
= & \iint s\mathbf{1}\left[S_j^{new}(k,s) > S_{j'}^{old}\left(k',s'\right)\right] dH_j(k,s)\, dF_{j'}\left(k',s'\right) \\
& - \iint s'\mathbf{1}\left[S_j^{new}(k,s) > S_{j'}^{old}\left(k',s'\right)\right] dH_j(k,s)\, dF_{j'}\left(k',s'\right) \\
= & \iint \left(s-s'\right)\mathbf{1}\left[S_j^{new}(k,s) > S_{j'}^{old}\left(k',s'\right)\right] dH_j(k,s)\, dF_{j'}\left(k',s'\right). \qquad \text{(B.5)}
\end{aligned}
$$

The first line comes from the following condition, which implies that the number of poached workers equals the number of workers who quit for new jobs:

$$
\begin{aligned}
& \lim_{x\to\infty} q^E V \iint_{s\leq x} \mathbf{1}\left[S_j^{new}(k,s) > S_{j'}^{old}\left(k',s'\right)\right] dH_j(k,s)\, dF_{j'}\left(k',s'\right) \\
& \quad = \lim_{x\to\infty} p^E \iint_{s\leq x} \mathbf{1}\left[S_j^{old}(k,s) < S_{j'}^{new}\left(k',s'\right)\right] dF_j(k,s)\, dH_{j'}\left(k',s'\right).
\end{aligned}
$$

Combining Equations (B.2)–(B.5) yields Equation (16).

C Quantitative Appendix

C.1 Quantitative Properties of the Model

Figure C.1 displays the probabilities of EE separation implied in the model, conditional on an on-the-job contact, in relative productivity (x), knowledge stock (k), and firm type (j).

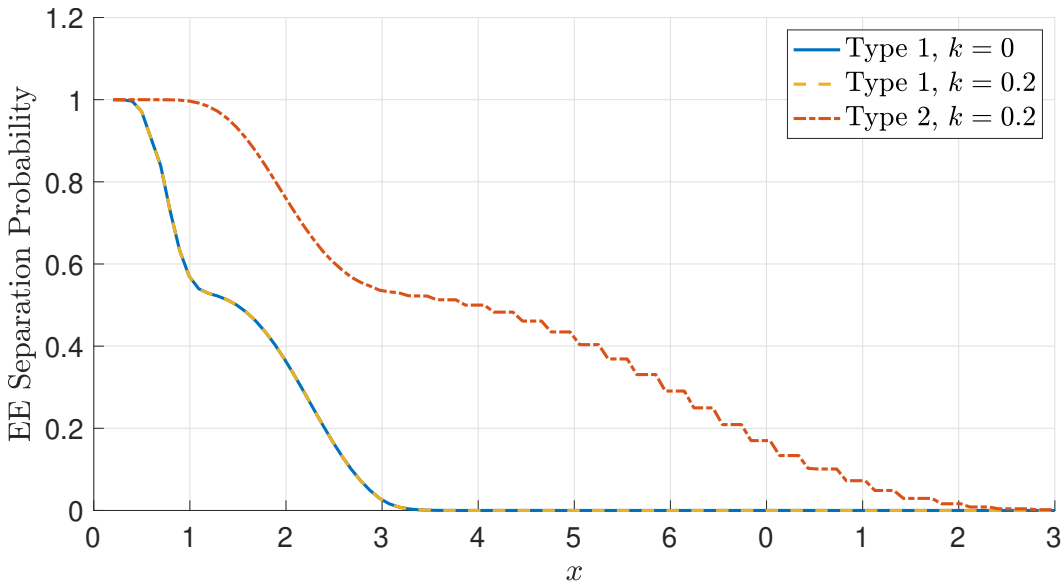


Figure C.1: Separation Probabilities

Notes: This figure shows the probabilities of worker quits to a new employer, conditional on an on-the-job contact, plotted over productivity x for selected values of knowledge stock per worker k and firm type j.

Separation rates vary significantly with respect to productivity levels and firm types, while the knowledge stock has a limited quantitative effect on match values and separation probabilities. The type of firm matters because type 1 firms derive more value from future hires and the match value internalizes this. Although a higher knowledge stock k reduces R&D costs and accelerates within-job productivity growth, the value of a match depends primarily on the current productivity level because the productivity grows slowly.

Figure C.2 illustrates the optimal technology upgrade rates, $g_j(k, x)$, as a function of knowledge stock, firm type, and productivity. Upgrade rates are higher for type 1 firms. This arises because type 1 firms face a higher return to upgrades due to expected future hires, despite their higher job destruction rates. At the same time, because knowledge reduces upgrade costs, firms with a higher k exhibit lower upgrade costs and higher upgrade rates.

Technology upgrade rates tend to be higher for firms with higher levels of productivity. Higher productivity implies a greater probability of poaching an employed worker and utilizing the new technology; thus, returns to upgrades are higher. Furthermore, because technology upgrades increase poaching probabilities, firms have additional incentives to invest, particularly when the worker density is concentrated around the level of match surplus. Quantitatively, this poaching incentive is small; the return is driven primarily by the productivity effect on current and future matches than by the increase in poaching probability itself.

Figure C.3 shows the average knowledge stock, technology upgrade rates, relative productivity, and the share of type 1 firms over the age of the firm. In the first panel, new firms accumulate knowledge stock immediately after entering the market. Due to the rapid obsolescence of knowledge, the knowledge stock per worker peaks quickly, within two years of entry. Subsequently, as firms slowly transition from type 1 to type 2 (second panel), the number of hires per existing worker declines and the remaining matches become more stable. Consequently, the knowledge stock per worker gradually decreases with firm age.

Driven by knowledge accumulation during the first two years, the rate of technology upgrades initially increases. However, after two years, as the knowledge stock per worker diminishes and firms transition to type 2, upgrade rates decline. Since entering firms start with lower productivity than incumbents but grow faster, average firm productivity increases gradually with firm age.

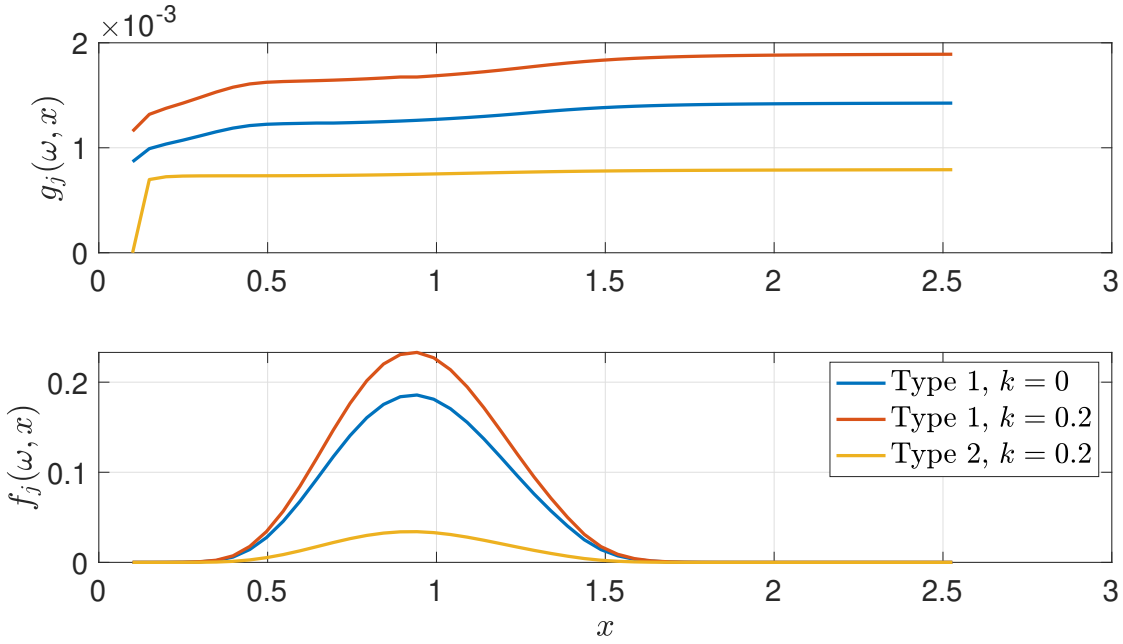


Figure C.2: Technology Upgrade Rates

Notes: This graph shows technology upgrade rates and the worker distribution over productivity x conditional on selected values for knowledge stock per worker k and firm type j.

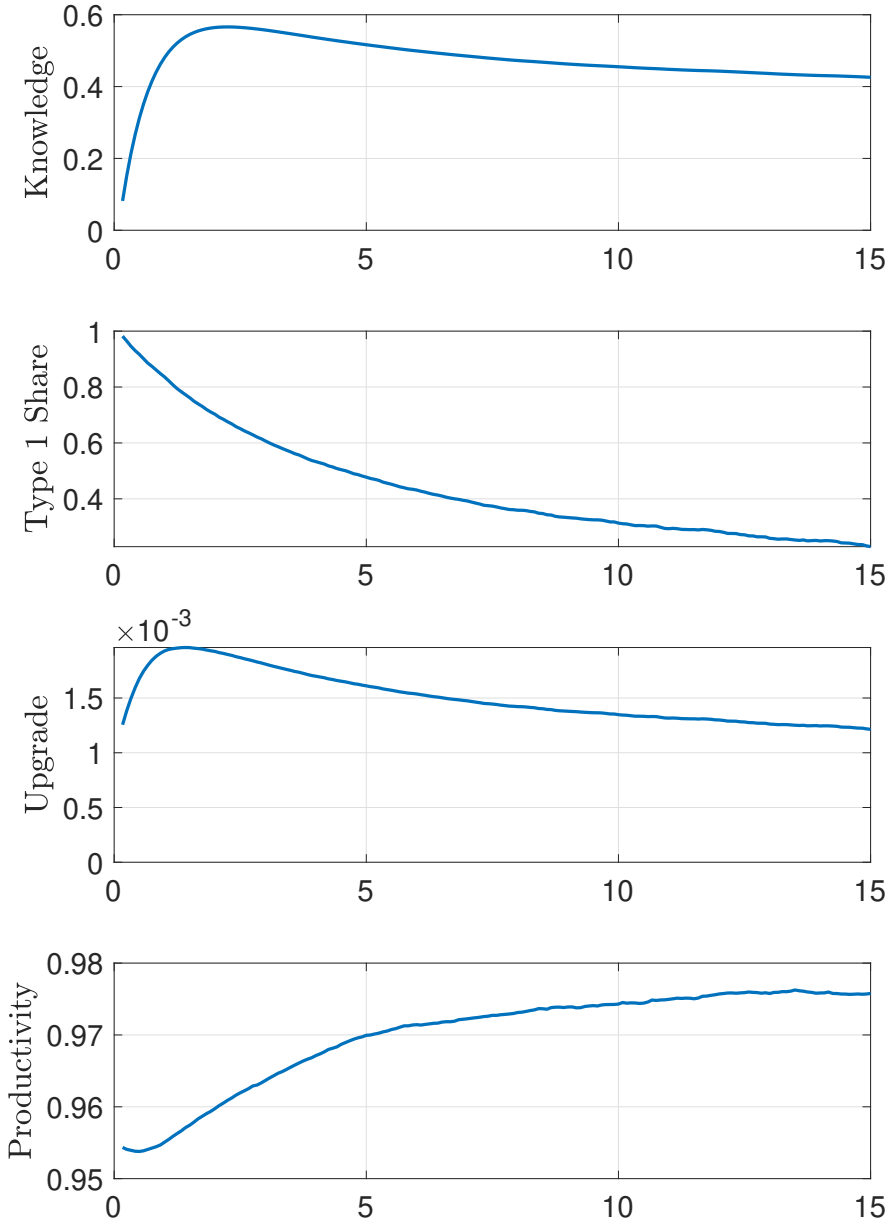


Figure C.3: Firm Characteristics over Firm Age

Notes: This graph shows the employment-weighted average knowledge stock, worker share of type 1 firms, technology upgrade rates and productivity over firm age. These series are calculated with a simulated panel of 10,000 firms.

C.2 Explicit Formulation of Non-Compete Agreement

In the baseline economy, the marginal value of a new worker differs from that of an existing worker and the average worker due to the properties of the innovation knowledge stock. In the extended model, marginal values also differ based on whether the worker is subject to a non-compete clause. Similarly, for new hires, the marginal value depends on whether the employer can impose a non-compete.

Specifically, a buyout occurs only when the worker contacted by a new employer has an enforceable non-compete clause and the new employer is willing to pay the buyout fee. This occurs when the marginal value of a new worker at the poaching firm exceeds the marginal value of an existing worker with a non-compete at the current firm. The marginal value of an unemployed worker at a firm is the weighted average of the value with a non-compete— with probability η—and without—with probability $1-\eta$. Conversely, when the firm contacts an employed worker, six scenarios are possible:

1. The worker has no NC at the current firm; the new firm imposes an NC.
2. The worker has no NC at the current firm; the new firm cannot impose an NC.
3. The worker has an unenforceable NC; the new firm imposes an NC.
4. The worker has an unenforceable NC; the new firm cannot impose an NC.
5. The worker has an enforceable NC; the new firm imposes an NC.
6. The worker has an enforceable NC; the new firm cannot impose an NC.

In cases 5 and 6, the new firm must pay ϕ to hire the worker.

The following equation describes the total value of all matches accruing to a firm with gross knowledge stock K, productivity z, employment n, and employment

subject to non-competes l:

$$
\begin{aligned}
r\bar{\mathbf{M}}_{j,t}(K,z,n,l) = & \max_{g} zn - \bar{z}_t C(g;n,K) \\
& + l\chi_j\left(\mathbf{U}(\bar{z}_t) - \partial_n\bar{\mathbf{M}}_{j,t}(K,z,n,l) - \partial_l\bar{\mathbf{M}}_{j,t}(K,z,n,l)\right) \\
& + (n-l)\chi_j\left(\mathbf{U}(\bar{z}_t) - \partial_n\bar{\mathbf{M}}_{j,t}(K,z,n,l)\right) - \delta K\partial_K\bar{\mathbf{M}}_{j,t}(K,z,n,l) \\
& + \phi p^E l\varsigma\mathbf{O}_j(K,z,n,l;\phi) - \tau l\partial_l\bar{\mathbf{M}}_{j,t}(K,z,n,l) \\
& + \phi\tilde{p}^E l\varsigma - \phi\tilde{p}^E n\bar{\omega}\varsigma \\
& + \theta_j\left(\bar{\mathbf{M}}_{j,t}(K,z,n,l) - \bar{\mathbf{M}}_{j,t}(K,z,n,l)\right) \\
& + nv_j\Bigg(q^U\left(\partial_n\bar{\mathbf{M}}_{j,t}(K,z,n,l) + \eta\partial_l\bar{\mathbf{M}}_{j,t}(K,z,n,l) + \partial_K\bar{\mathbf{M}}_{j,t}(K,z,n,l)\right) \\
& \quad + q^E\int\eta\left(\frac{n'}{n'+l'}\right)\max\Big\{\partial_n\bar{\mathbf{M}}_{j,t}(K,z,n,l) + \partial_l\bar{\mathbf{M}}_{j,t}(K,z,n,l) + \partial_K\bar{\mathbf{M}}_{j,t}(K,z,n,l) \\
& \qquad - \partial_{n'}\bar{\mathbf{M}}_{j',t}\left(K',z',n',l'\right),0\Big\} \\
& \qquad + (1-\eta)\left(\frac{n'}{n'+l'}\right)\max\Big\{\partial_n\bar{\mathbf{M}}_{j,t}(K,z,n,l) + \partial_K\bar{\mathbf{M}}_{j,t}(K,z,n,l) \\
& \qquad - \partial_{n'}\bar{\mathbf{M}}_{j',t}\left(K',z',n',l'\right),0\Big\} \\
& \qquad + \eta(1-\varsigma)\left(\frac{l'}{n'+l'}\right)\max\Big\{\partial_n\bar{\mathbf{M}}_{j,t}(K,z,n,l) + \partial_l\bar{\mathbf{M}}_{j,t}(K,z,n,l) + \partial_K\bar{\mathbf{M}}_{j,t}(K,z,n,l) \\
& \qquad - \partial_{n'}\bar{\mathbf{M}}_{j',t}\left(K',z',n',l'\right) - \partial_{l'}\bar{\mathbf{M}}_{j',t}\left(K',z',n',l'\right),0\Big\} \\
& \qquad + (1-\eta)(1-\varsigma)\left(\frac{l'}{n'+l'}\right)\max\Big\{\partial_n\bar{\mathbf{M}}_{j,t}(K,z,n,l) + \partial_K\bar{\mathbf{M}}_{j,t}(K,z,n,l) \\
& \qquad - \partial_{n'}\bar{\mathbf{M}}_{j',t}\left(K',z',n',l'\right) - \partial_{l'}\bar{\mathbf{M}}_{j',t}\left(K',z',n',l'\right),0\Big\} \\
& \qquad + \eta\varsigma\left(\frac{l'}{n'+l'}\right)\max\Big\{\partial_n\bar{\mathbf{M}}_{j,t}(K,z,n,l) + \partial_l\bar{\mathbf{M}}_{j,t}(K,z,n,l) + \partial_K\bar{\mathbf{M}}_{j,t}(K,z,n,l) \\
& \qquad - \partial_{n'}\bar{\mathbf{M}}_{j',t}\left(K',z',n',l'\right) - \partial_{l'}\bar{\mathbf{M}}_{j',t}\left(K',z',n',l'\right) - \phi,0\Big\} \\
& \qquad + (1-\eta)\varsigma\left(\frac{l'}{n'+l'}\right)\max\Big\{\partial_n\bar{\mathbf{M}}_{j,t}(K,z,n,l) + \partial_K\bar{\mathbf{M}}_{j,t}(K,z,n,l) \\
& \qquad - \partial_{n'}\bar{\mathbf{M}}_{j',t}\left(K',z',n',l'\right) - \partial_{l'}\bar{\mathbf{M}}_{j',t}\left(K',z',n',l'\right) - \phi,0\Big\}\Bigg)d\bar{\mathbf{F}}_{j',t}\left(K',z',n',l'\right) \\
& + g\partial_x\bar{\mathbf{M}}_{j,t}(K,z,n,l) + \frac{\sigma^2}{2}\partial_x^2\bar{\mathbf{M}}_{j,t}(K,z,n,l) \\
& + \left(\tilde{p}^E n - \delta K\right)\partial_K\bar{\mathbf{M}}_{j,t}(K,z,n,l) + \mu\bar{z}_t\partial_t\bar{\mathbf{M}}_{j,t}(K,z,n,l)
\end{aligned}
$$

In this equation, $\mathbf{O}_j\left(K,z,n,l;\phi\right)$ is the probability that the contacted worker has an enforceable non-compete clause and the new firm has a marginal value for new workers greater than the marginal value of existing workers in the current firm. $\bar{\omega}$ is the average share of workers subject to non-competes.

Define $\omega = l/n$ as the share of workers subject to non-competes. Then, the average match value is homogeneous of degree one in employment size n and average productivity $\bar{z}_t$; i.e., $M_j\left(k,x,\omega\right) := \bar{\mathbf{M}}_{j,t}\left(nk,z,n,n\omega\right)/n/\bar{z}_t$. Define $S_j\left(k,x,\omega\right) = M_j\left(k,x,\omega\right) - U$. The average match surplus satisfies

$$
\begin{aligned}
\left(r-\mu\right)S_j\left(k,x,\omega\right) = \max_g \Bigg\{ & x - b - c(g;k) - \chi_j\left(S_j\left(k,x,\omega\right) - \partial_k S_j\left(k,x,\omega\right)\right) \\
& + \theta_j\left(S_{-j}\left(k,x,\omega\right) - S_j\left(k,x,\omega\right)\right) - \tau\omega\partial_\omega S_j\left(k,x,\omega\right) \\
& + p^E\varsigma\omega\phi\eta\int\left[S_{j'}^{new,l}\left(k',x',\omega'\right) - \phi \geq S_j^{old,l}\left(k,x,\omega\right)\right]dH_{j'}\left(k',x',\omega'\right) \\
& + p^E\varsigma\omega\phi\left(1-\eta\right)\int\left[S_{j'}^{new,r}\left(k',x',\omega'\right) - \phi \geq S_j^{old,l}\left(k,x,\omega\right)\right]dH_{j'}\left(k',x',\omega'\right) \\
& + \tilde{p}^E\varsigma\phi\left(\omega-\bar{\omega}\right) + \tilde{p}^E\partial_k S_j\left(k,x,\omega\right) + \tilde{p}^E\left(\eta-\omega\right)\partial_\omega S_j\left(k,x,\omega\right) \\
& + v_j\Bigg(q^U\left(S_j\left(k,x,\omega\right) + \left(1-k\right)\partial_k S_j\left(k,x,\omega\right) + \left(\eta-\omega\right)\partial_\omega S_j\left(k,x,\omega\right)\right) \\
& \quad + q^E\eta\varsigma\int\omega'\max\left\{S_j^{new,l}\left(k,x,\omega\right) - \phi - S_{j'}^{old,l}\left(k',x',\omega'\right),0\right\}dF_{j'}\left(k',x',\omega'\right) \\
& \quad + q^E\left(1-\eta\right)\varsigma\int\omega'\max\left\{S_j^{new,r}\left(k,x,\omega\right) - \phi - S_{j'}^{old,l}\left(k',x',\omega'\right),0\right\}dF_{j'}\left(k',x',\omega'\right) \\
& \quad + q^E\eta\left(1-\varsigma\right)\int\omega'\max\left\{S_j^{new,l}\left(k,x,\omega\right) - S_{j',l}^{old,l}\left(k',x',\omega'\right),0\right\}dF_{j'}\left(k',x',\omega'\right) \\
& \quad + q^E\left(1-\eta\right)\left(1-\varsigma\right)\int\omega'\max\left\{S_j^{new,r}\left(k,x,\omega\right) - S_{j',l}^{old,l}\left(k',x',\omega'\right),0\right\}dF_{j'}\left(k',x',\omega'\right) \\
& \quad + q^E\eta\int\left(1-\omega'\right)\max\left\{S_j^{new,l}\left(k,x,\omega\right) - S_{j'}^{old,r}\left(k',x',\omega'\right),0\right\}dF_{j'}\left(k',x',\omega'\right) \\
& \quad + q^E\left(1-\eta\right)\int\left(1-\omega'\right)\max\left\{S_j^{new,r}\left(k,x,\omega\right) - S_{j'}^{old,r}\left(k',x',\omega'\right),0\right\}dF_{j'}\left(k',x',\omega'\right)\Bigg) \\
& + \left(g-\mu x\right)\partial_x S_j\left(k,x,\omega\right) + \frac{\sigma^2}{2}\partial_x^2 S_j\left(k,x,\omega\right)\Bigg\}.
\end{aligned}
$$

In this equation, $S_j^{new,l}$ and $S_j^{new,r}$ are the marginal values of a new worker with

and without a non-compete clause, respectively. Similarly, $S_j^{old,l}$ and $S_j^{old,r}$ are the marginal values of an existing worker with and without a non-compete clause. They satisfy the following equations in relation to the average match surplus:

$$\begin{aligned}
S_j^{new,r}(k,x,\omega) &= S_j(k,x,\omega) + (1-k)\,\partial_k S_j(k,x,\omega) - \omega\partial_\omega S_j(k,x,\omega) \\
S_j^{new,l}(k,x,\omega) &= S_j(k,x,\omega) + (1-k)\,\partial_k S_j(k,x,\omega) + (1-\omega)\,\partial_\omega S_j(k,x,\omega) \\
S_j^{old,r}(k,x,\omega) &= S_j(k,x,\omega) - k\partial_k S_j(k,x,\omega) - \omega\partial_\omega S_j(k,x,\omega) \\
S_j^{old,l}(k,x,\omega) &= S_j(k,x,\omega) - k\partial_k S_j(k,x,\omega) + (1-\omega)\,\partial_\omega S_j(k,x,\omega)
\end{aligned}$$

Because $\partial_\omega S_j(k,x,\omega) \geq 0$, the marginal value of a worker is greater with non-compete clauses. Analogously to the baseline case, because $\partial_k S_j(k,x,\omega)$, the marginal value of a new worker is greater than that of an existing worker. The change in knowledge stock per worker and the share of non-competes can be described as in the following equations:

$$\begin{aligned}
dk/dt &= -\delta k + v_j\left(q^U + q^E P_j(k,x,\omega)\right)(1-k) \\
&\quad + \left(\chi_j + p^E\omega O_j^l(k,x,\omega) + p^E(1-\omega)\,O_j^r(k,x,\omega)\right)k + \tilde{p}^E \\
&=: a_j(k,x,\omega) \\
d\omega/dt &= -\tau\omega + p^E\omega(1-\omega)\left(O_j^r(k,x,\omega) - O_j^l(k,x,\omega)\right) \\
&\quad + (\eta-\omega)\,v_j\left(q^U + q^E P_j(k,x,\omega)\right) + \tilde{p}^E(\eta-\omega) \\
&=: c_j(k,x,\omega).
\end{aligned}$$

In these equations, $F_j(k,x,\omega)$ and $H_j(k,x,\omega)$ are the distributions of workers and offers. $O_j^l(k,x,\omega)$ and $O_j^r(k,x,\omega)$ are the probabilities that the worker quits to a

new job with and without a non-compete clause.

$$
\begin{aligned}
O_j^l(k,x,\omega) = \varsigma \int \eta \left[S_{j'}^{new,l}\left(k',x',\omega'\right) > S_j^{old,l}(k,x,\omega) + \phi \right] dH_{j'}\left(k',x',\omega'\right) \\
+ \varsigma \int (1-\eta) \left[S_{j'}^{new,r}\left(k',x',\omega'\right) > S_j^{old,l}(k,x,\omega) + \phi \right] dH_{j'}\left(k',x',\omega'\right) \\
+ (1-\varsigma) \int \eta \left[S_{j'}^{new,l}\left(k',x',\omega'\right) > S_j^{old,l}(k,x,\omega) \right] dH_{j'}\left(k',x',\omega'\right) \\
+ (1-\varsigma) \int (1-\eta) \left[S_{j'}^{new,r}\left(k',x',\omega'\right) > S_j^{old,l}(k,x,\omega) \right] dH_{j'}\left(k',x',\omega'\right) \\
O_j^r(k,x,\omega) = \int \eta \left[S_{j'}^{new,l}\left(k',x',\omega'\right) > S_j^{old,r}(k,x,\omega) \right] dH_{j'}\left(k',x',\omega'\right) \\
+ \int (1-\eta) \left[S_{j'}^{new,r}\left(k',x',\omega'\right) > S_j^{old,r}(k,x,\omega) \right] dH_{j'}\left(k',x',\omega'\right).
\end{aligned}
$$

Lastly, $P_j(k,x,\omega)$ is the probability that a vacancy can poach an employed worker conditional on a contact.

$$
\begin{aligned}
P_j(k,x,\omega) = \int \omega' \varsigma \eta \left[S_j^{new,l}(k,x,\omega) > S_{j'}^{old,l}\left(k',x',\omega'\right) + \phi \right] dF_{j'}\left(k',x',\omega'\right) \\
+ \int \omega' \varsigma (1-\eta) \left[S_j^{new,r}(k,x,\omega) > S_{j'}^{old,l}\left(k',x',\omega'\right) + \phi \right] dF_{j'}\left(k',x',\omega'\right) \\
+ \int \omega' (1-\varsigma) \eta \left[S_j^{new,l}(k,x,\omega) > S_{j'}^{old,l}\left(k',x',\omega'\right) \right] dF_{j'}\left(k',x',\omega'\right) \\
+ \int \omega' (1-\eta)(1-\eta) \left[S_j^{new,r}(k,x,\omega) > S_{j'}^{old,l}\left(k',x',\omega'\right) \right] dF_{j'}\left(k',x',\omega'\right) \\
+ \int \left(1-\omega'\right) \eta \left[S_j^{new,l}(k,x,\omega) > S_{j'}^{old,r}\left(k',x',\omega'\right) + \phi \right] dF_{j'}\left(k',x',\omega'\right) \\
+ \int \left(1-\omega'\right)(1-\eta) \left[S_j^{new,r}(k,x,\omega) > S_{j'}^{old,r}\left(k',x',\omega'\right) + \phi \right] dF_{j'}\left(k',x',\omega'\right)
\end{aligned}
$$

The distribution of workers is characterized by an equation similar to Equation (10).

$$
\begin{aligned}
0 = & -\partial_x \left[\left(g_j\left(k,x,\omega\right) - \mu x \right) f_j\left(k,x,\omega\right) \right] + \partial_x^2 \left[\frac{\sigma^2}{2} f_j\left(k,x,\omega\right) \right] \\
& - \partial_k \left[a_j\left(k,x,\omega\right) f_j\left(k,x,\omega\right) \right] - \partial_\omega \left[c_j\left(k,x,\omega\right) f_j\left(k,x,\omega\right) \right] \\
& - \theta_j f_j\left(k,x,\omega\right) + \theta_{-j} f_{-j}\left(k,x,\omega\right) \\
& + q^U V h_j\left(k,x,\omega\right) + q^E V P_j\left(k,x,\omega\right) h_j\left(k,x,\omega\right) \\
& - \chi_j f_j\left(k,x,\omega\right) - p^E \left(\omega O_j^l\left(k,x,\omega\right) + \left(1-\omega\right) O_j^r\left(k,x,\omega\right) \right) f_j\left(k,x,\omega\right),
\end{aligned}
$$

where

$$
\begin{aligned}
V &= \left(1+v_0\right) \int v_j dF_j\left(k,x,\omega\right), \\
h_j\left(k,x,\omega\right) &\propto v_j f_j\left(k,x,\omega\right) + v_0 f_0\left(x\right) \mathbf{1}\left[k=0, j=1, \omega=\eta\right], \\
f_0\left(x\right) &\propto \sum_j \iint f_j\left(k, \frac{x}{\varsigma}, \omega\right) dk d\omega.
\end{aligned}
$$

The growth rate is also expressed similarly to Equation (16).

$$
\begin{aligned}
\mu = & \int g_j\left(k,x,\omega\right) dF_j\left(k,x,\omega\right) \\
& + p^U u/\left(1-u\right) \mathbb{E}_H\left[x\right] - \left(\bar{\chi}+\varphi\right) \mathbb{E}_{\chi+\varphi}\left[x\right] \\
& + p^E \iint \Bigg(\omega\varsigma\eta \mathbf{1}\left[S_j^{new,l}\left(k,x,\omega\right) > S_{j'}^{old,l}\left(k,x,\omega\right) + \phi\right] \\
& \quad + \omega\varsigma\left(1-\eta\right) \mathbf{1}\left[S_j^{new,r}\left(k,x,\omega\right) > S_{j'}^{old,l}\left(k,x,\omega\right) + \phi\right] \\
& \quad + \omega\left(1-\varsigma\right)\eta \mathbf{1}\left[S_j^{new,l}\left(k,x,\omega\right) > S_{j'}^{old,l}\left(k,x,\omega\right)\right] \\
& \quad + \omega\left(1-\varsigma\right)\left(1-\eta\right) \mathbf{1}\left[S_j^{new,r}\left(k,x,\omega\right) > S_{j'}^{old,l}\left(k,x,\omega\right)\right] \\
& \quad + \left(1-\omega\right)\eta \mathbf{1}\left[S_j^{new,l}\left(k,x,\omega\right) > S_{j'}^{old,r}\left(k,x,\omega\right)\right] \\
& \quad + \left(1-\omega\right)\left(1-\eta\right) \mathbf{1}\left[S_j^{new,r}\left(k,x,\omega\right) > S_{j'}^{old,r}\left(k,x,\omega\right)\right] \Bigg) \\
& \quad \times \left(x-x'\right) dH_j\left(k,x,\omega\right) dF_{j'}\left(k',x',\omega'\right)
\end{aligned}
$$