Worker Turnover, Disruptive Innovation, and Productivity Growth *

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March 20, 2025

Abstract

This paper shows that faster worker turnover between employers encourages firms to make more disruptive innovations and accelerates long-run growth. In the US, state-level institutional changes that increase employment-to-employment transitions of workers make innovations more disruptive and productivity grow faster. This paper reconciles these empirical facts with an endogenous growth model with a frictional labor market where firms choose the rate of technology upgrades and new technologies make existing worker skills obsolete. The calibrated model implies a substantial compositional change in long-run growth in response to the aging population and low start-up rates.

Keywords: Disruptive Innovation, Productivity Growth, Worker Turnover
JEL codes: J24, J31, O33, O47

*We thank Davide Alonzo, Rui Castro, Joao Galindo de Fonseca, Gregor Jarosch, Fabian Lange, Giuseppe Moscarini, Markus Poschke, Serdar Ozkan, Younghun Shim for their helpful comments and suggestions. We also thank seminar participants at KAEA sessions at ASSA, Montreal Inequality Group, KWEN 2024 Summer Workshop, MES-E/SE 2024 in Ho Chi Minh city, and EWMES 2024 in Palma de Majorca.

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1 Introduction

Declining business dynamism refers to the phenomenon that firm turnover is slowed down in terms of employment, profits, and innovation, which has been a pervasive trend in developed countries since the 1980s (Decker et al., 2016; Calvino et al., 2020). At the same time, worker turnover across employers has also slowed down due to various factors, such as fewer job openings and the aging population. However, only a few papers have studied slower worker turnover as a factor in generating long-term economic changes, and most of the existing works only emphasize how firm entry margin is affected.[1]

This paper studies the effect of worker turnover on business dynamism and long-run growth by focusing on within-job productivity changes of incumbent firms. Ample empirical evidence points out the importance of incumbent firms in innovation and productivity growth. In the US, more than 90% of patents are assigned to incumbent firms that previously had more than one patent, and more than 85% of manufacturing productivity growth is made within jobs held by incumbents. Thus, how incumbent innovation responds to changes in economic conditions is crucial in quantifying aggregate responses.

In addition, this paper focuses on the role of gross worker turnover. Unlike net labor turnover, which is measured by the numbers of jobs created and destroyed at the establishment or firm level, gross worker turnover is measured by workers switching to new employers. Thus, if two firms swap equal numbers of workers, net labor turnover stays the same but gross worker turnover increases. This paper studies how gross worker turnover, not net job turnover, affects the innovation decisions made by firms.

First, this paper establishes supporting empirical evidence using variations at the metropolitan (MSA) area level in the US. We leverage the state-level institutional changes in worker turnover rates from Jeffers (2024). After state-level court rulings that lower the enforceability of non-compete (NC) contracts, MSAs in treated states experience increases in employment-to-employment (EE) hire rates. These MSAs do

[1] Engbom (2019), for example, studies how the aging population increases barriers to firm entry by improving the employment positions of wage workers. Hopenhayn et al. (2022) and Karahan et al. (2024) also study how slower population growth reduces firm entries in equilibrium.

not necessarily become more intensive in innovation, measured by the number of patents per worker. Instead, their innovations become more disruptive, measured by the difference between forward and backward similarities with other patents and the number of citations made to patents granted in those areas. Additionally, labor productivity grows faster relative to MSAs in control states.

Then, this paper constructs an endogenous growth model with a frictional labor market to incorporate the empirical relationship. Firms choose the speed of technology upgrades. Workers are either skilled or unskilled under the current technology at the job. Skills are technology-specific. If firms choose a higher technology upgrade rate, worker skills accumulated under the current technology become obsolete. At the same time, skills are job-specific. Thus, if workers move from one job to another, they become unskilled. In this case, faster worker turnover not only increases the gains of technology upgrades from production and future employment but also reduces the opportunity cost of technology upgrades by decreasing the fraction of workers skilled under the current technology. This mechanism is distinguished from existing papers that emphasize labor reallocation from low- to high-productivity firms (Lentz and Mortensen, 2008), from incumbents to fast-growing entrant firms (Alon et al., 2018), or worker sorting to entrepreneurship (Engbom, 2020).

The model parameters are calibrated to match various macro- and micro-moments of growth and worker transitions over firm age and match tenures. The key moments to infer productivity growth over firm age are the difference in net EE hire rates between firm age groups. Intuitively, if young firms have lower productivity but their productivity grows faster than old firms, net EE hire rates decrease fast with firm age. The calibrated model replicates the general equilibrium responses of disruptive innovation to changes in the enforceability of NC contracts by an exogenous shift in match rates of employed workers. The model emphasizes the role of within-job technology upgrade margin to shape overall responses of the long-run growth rate.

Lastly, the model is used to evaluate the effect of two trends in the labor market: low start-up rates and the aging population. Low start-up rates enter as an exogenous decrease in vacancies posted by entering firms. Low start-up rates imply

that fewer matches are made by start-ups whose productivity grows fast. However, if more hires can be made by incumbents instead of entering firms, low start-up rates raise the returns to technology upgrades of incumbents. In the end, the faster technology upgrades of incumbent matches boost productivity growth. The diffusion margin has a limited role in determining the overall direction of changes in response to low start-up rates.

On the other hand, the aging population is interpreted as an exogenous reduction in match and separation rates of employed workers. The aging population reduces the long-run growth rate by slowing down the diffusion of new technologies through EE transitions. Moreover, the aging population increases the share of workers attached to existing technologies. Low start-up rates and the aging population cancel out each other, leaving the stationary growth rate almost unchanged. However, the composition of long-run growth is substantially changed. The productivity growth depends more on within-job technology upgrades than on the diffusion of new technologies with the two trends in the labor market.

Related Literature

This paper contributes to the endogenous growth model with labor market turnover. The Schumpeterian growth literature since Aghion and Howitt (1992) emphasizes production input reallocation across producers as the key element 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 motives come from monopolistic profits the firms can earn after making an innovation, and innovation incurs monetary or labor costs. The net turnover of labor is a byproduct of an innovation process that is idiosyncratic across producers.

Recent papers such as Engbom (2019, 2020) and Bilal et al. (2021) incorporate gross worker turnover into endogenous growth models and study how labor market frictions affect the creative destruction from entrants. This paper also studies the role of gross turnover in innovation choices not only by entrants but also by incumbents. Within-job productivity growth of incumbents accounts for 86.5% of manufacturing productivity growth in the 1980s (Baily et al., 1992). The reallocation

of production inputs among incumbents contributes to 20% of productivity growth, and the contribution of entrants and exits is negative. Thus, incumbent responses matter in shaping the aggregate responses of the economy.

This paper emphasizes gross worker turnover across employers as a novel determinant for innovation. Previous studies often emphasize the innate differences in innovation efficiency across firms (Lentz and Mortensen, 2008; Acemoglu et al., 2018) or the degree of market competition (Aghion et al., 2001, 2005; Hashmi, 2013). A few studies emphasize the role of worker skills in innovation decisions. Klenow (1998) shows that if skills are accumulated by learning by doing, firms are more likely to innovate in booms when they can learn the new skills faster with more production volume. Hershbein and Kahn (2018), on the other hand, show that metropolitan areas hit harder by the Great Recession have more increases in skill requirements, which is consistent with recessions reducing the opportunity cost of adopting routine-biased technologies. This paper shows that gross worker turnover changes firms' incentives to try more disruptive innovations since worker skills are both job- and technology-specific. Thus, faster worker turnover reduces the opportunity cost of trying new technologies.

This paper adds endogenous within-job productivity changes to models of a frictional labor market with on-the-job search. Traditionally, labor market models with search frictions feature productivity either fixed or subject to exogenous shock over the job tenure (Postel-Vinay and Robin, 2002; Cahuc et al., 2006; Menzio and Shi, 2011). These models then study worker allocation across different productivity levels with endogenous job-switching behavior. Recent models that emphasize firm-level responses also assume an exogenous productivity process (Kaas and Kircher, 2015; Elsby and Michaels, 2013; Elsby and Gottfries, 2022; Bilal et al., 2022). More micro papers such as Bagger et al. (2014) and Lise and Postel-Vinay (2020) model within-job productivity increases through human capital accumulation for workers. This paper augments frictional labor market models with firm-side considerations on innovation and makes a rich discussion on the relationship between worker turnover and match dynamics over firm age.

The remainder of this paper is organized as follows. Section 2 explains how lower enforceability of non-compete clauses affects innovation activities and labor pro-

ductivity. Section 3 investigates a model of technology upgrade choice with the frictional labor market to reconcile the empirical facts. Section 4 calibrates the model. Section 5 and Section 6 show the implications of the quantitative model in the context of changes in NC enforceability and historical changes in the labor market, respectively. Section 7 concludes.

2 Empirical Analysis

We first study the empirical relationship between gross worker turnover and innovation using variations at the MSA level. To argue the causal effects of worker turnover on economic activities, we use institutional changes on non-compete agreements from Jeffers (2024) and capture exogenous changes in worker turnover rates. The changes in economic variables are estimated as in Callaway and Sant'Anna (2021), which propose methods for unbiased estimates in a treatment effect model with two-way fixed effects.

2.1 Data

Worker turnover variables are constructed with data from Job-to-Job Flow (J2J) based on the Longitudinal Employer-Household Dynamics (LEHD) from the US Census Bureau. The dataset offers the gross number of workers who change the main source of income at the metropolitan area (MSA) level in each quarter. From this data, four variables are constructed to measure worker turnover in the local labor market of MSA i at time t: Nonemployment-to-Employment (NE) hire, $NE_{i,t}$, Employment-to-Nonemployment (EN) separation, $EN_{i,t}$, Employment-to-Employment (EE) hire, $EEh_{i,t}$, and Employment-to-Employment (EE) separation rates, $EEs_{i,t}$. The quarterly turnover rates are aggregated to the yearly level by taking averages.

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

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

$$\tag{3}$$

Data on granted patents and their citations are from *PatentsView*.[2], which parses 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. The number of patents, as well as the number of citations on patents assigned to an MSA in a given year, are normalized by the number of employed workers[3].

We consider two measures to evaluate how disruptive local patents are. The first measure is the number of citations per patent, used by Acemoglu et al. (2022). The second one is the text-based importance measure of patents following Kelly et al. (2021). The measure is constructed as the difference between the backward and forward similarity of a patent to other patents applied in the MSA.[4] The backward similarity considers other patents applied up to five years prior to the application, and the forward similarity uses other patents applied up to five years following the application. We calculate the cosine similarity between patents based on the bigrams of patents' texts, similar to Kelly et al. (2021). Each bigram is weighted with the term frequency-inverse document frequency.

Labor productivity is measured by GDP per worker. GDP at the MSA level from the regional economic account data by the Bureau of Economic Analysis (BEA). Net turnover rates, such as job creation and destruction rates, come from the Business Dynamics Statistics (BDS) of the Census Bureau.

2.2 Regression Model and Results

Jeffers (2024) uses state-level court rulings that change the enforceability of NC agreements at the state level and show that the departure rates at knowledge-intensive firms decline (increase) after increases (decreases) in NC enforceability. We use the same institutional setting but analyze responses of aggregate variables at the MSA level. We focus on the two court ruling cases in South Carolina (2010) and Montana (2011) that reduced the enforceability of NC agreements.

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

[3] If the patents are assigned to $n > 1$ assignees, we assign $1/n$ patents to each assignee and to the MSA of each assinee. Citations are adjusted similarly.

[4] We compute the difference, not the ratio as in Kelly et al. (2021), between the two similarities because the ratio tends to overstate the importance of a patent with low backward similarity.

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

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

As before, i refers to the MSA, and t to the year. The 'treated' indicator takes the value of one when the MSA i belongs to the state in which the enforceability of NC agreements decreases. Otherwise specified, $X_{i,t}$ include the unemployment rates, GDP growth rates, and employment share of entrant firms. In the baseline case, we exclude MSAs that range over multiple states or belong to a state that experiences a court ruling that increases the enforceability of NC contracts in Jeffers (2024).[5]

The OLS estimation of this difference-in-difference equation does not yield an unbiased estimate of the average treatment effect (ATE) if the treatment effect is heterogeneous and the timing of the treatment is triggered (Goodman-Bacon, 2021). Thus, we use the estimation method in Callaway and Sant'Anna (2021) to estimate the average treatment effect of institutional changes. They show that estimates yield an unbiased estimate of an interpretable ATE when the estimation uses not-yet-treated or never-treated control groups. The baseline results are made with never-treated control groups but the results are roughly unchanged with not-yet-treated control groups.

Figures 1 show the ATE estimates on EE and NE hire rates. First, the lower enforceability of NC contracts increases the EE hire rates, and the effects accumulate over time (See Figure 1). One year after the court ruling, the EE hire rate increases only about 0.2 percentage points per quarter. After eight years, the EE hire rate increases by almost 1 percentage point per quarter. Unlike the strong responses in EE hire rates, NE hire rates do not change significantly. These results imply that the NC agreements were more binding to employed workers than to nonemployed

[5]These states include Wisconsin, Colorado, Illinois, Texas, Virginia, and Georgia. Illinois experienced a court ruling that increased the enforceability in 2011 but another court ruling that reduced the enforceability in 2013. Other states experienced court rulings that strengthened the enforceability of NC agreements. It turns out that EE turnover rates *increased*, not *decreased*, in MSAs in these states after the court rulings. Jeffers (2024) also argues that the effect of enforceability is ambiguous if the employees can negotiate to remove the non-compete clauses. Thus, these states are excluded from the analysis. However, the results on patents and citations are consistent with the baseline results. These results are described in Appendix A.2.

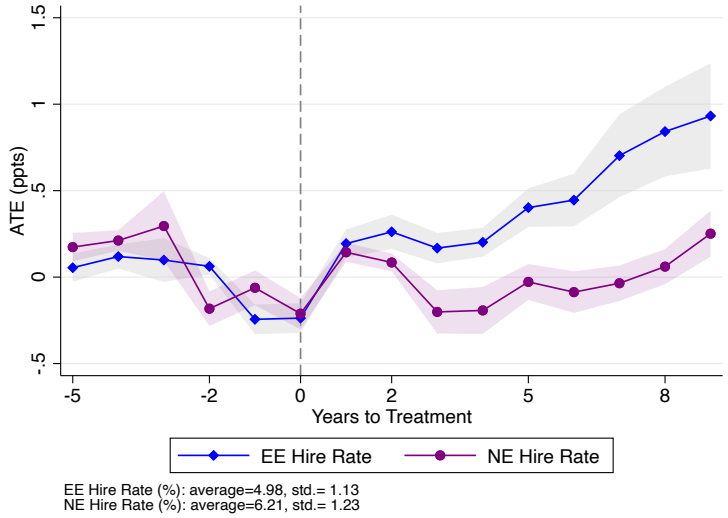


Figure 1: Effect of Lower NC Enforceability on Worker Turnover

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.

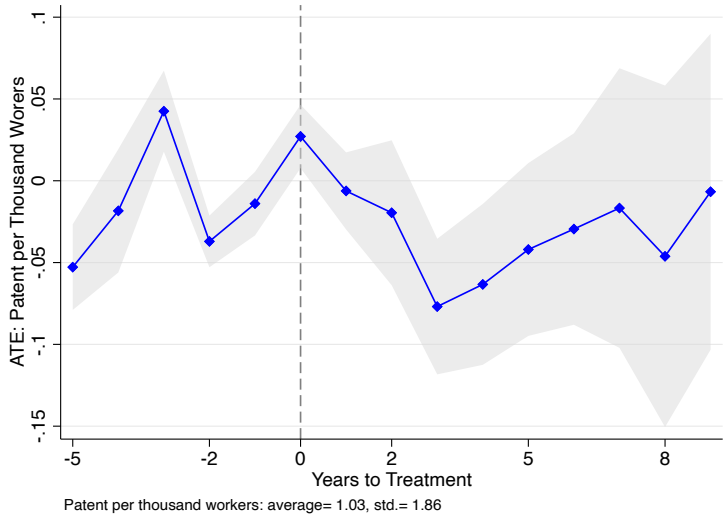


Figure 2: Effect of Lower NC Enforceability on Patents

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.

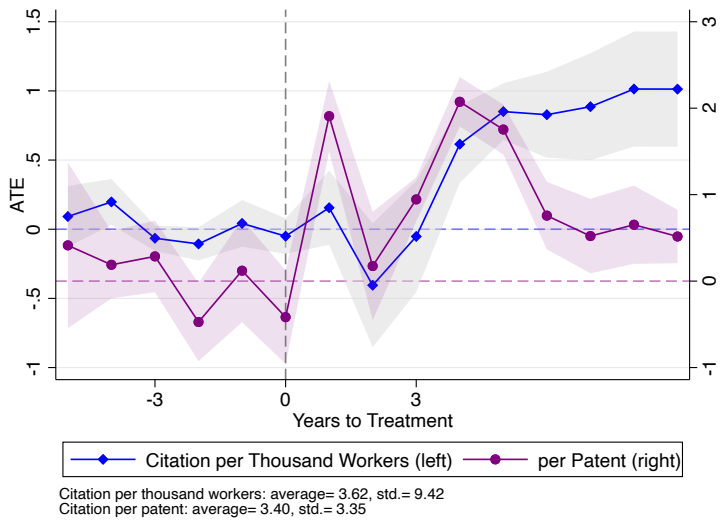


Figure 3: Effect of Lower NC Enforceability on Citations and Impacts

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.

workers.

Figure 2 shows that the number of patents per thousand workers does not respond persistently to institutional change. If anything, the number of patents modestly decrease. This is consistent with Jeffers (2024), in which the number of patents granted to knowledge-intensive firms did not exhibit a significant increase.

Contrarily, in Figures 3 and 4, patents become more disruptive after the court rulings in treated states. The number of citations per thousand workers and per patent increases after the institutional change in the enforceability of NC contracts. The average number of citations per patent increases persistently right after the change. The number of citations per thousand workers, however, increases four years later. This comes from the short-term reduction in the number of patents per thousand workers in Figure 2. After the number of patents comes back to the MSA average, the number of citations increases significantly with more citations made per patent.

Moreover, the importance of patents increases after the reduction in NC enforceability. The average importance of patents goes up by 0.8 standard deviation two

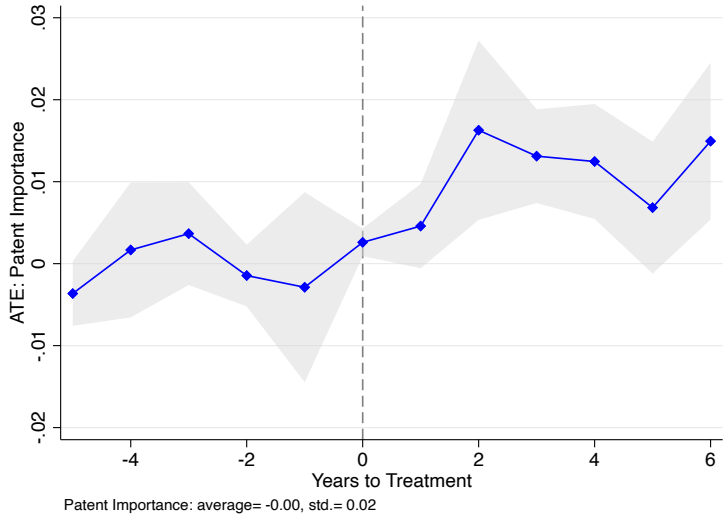


Figure 4: Effect of Lower NC Enforceability on Patent Importance

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.

years after the court ruling. In Figure 5, both increases in forward similarity and decreases in backward similarity contribute to the changes in patent importance.[6] Overall, locally produced patents become less incremental and more disruptive after the institutional change.

Figure 6 shows that labor productivity grew faster in MSAs of the states that had a decrease in enforceability of NC contracts compared to the metropolitan areas of control states. The labor productivity was significantly lower four and three years before the treatment, implying that the treated states experienced a sharp decline in GDP per worker during the Great Recession. Nonetheless, control and treated states have similar trends near the treatment year, and labor productivity grows faster in treated states after the treatment.

What is the mechanism behind these general equilibrium responses in the local labor market? Additional results in Appendix A.3 and A.4 show that this response comes from old incumbents, not entrants, and gross worker turnover, not net labor

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

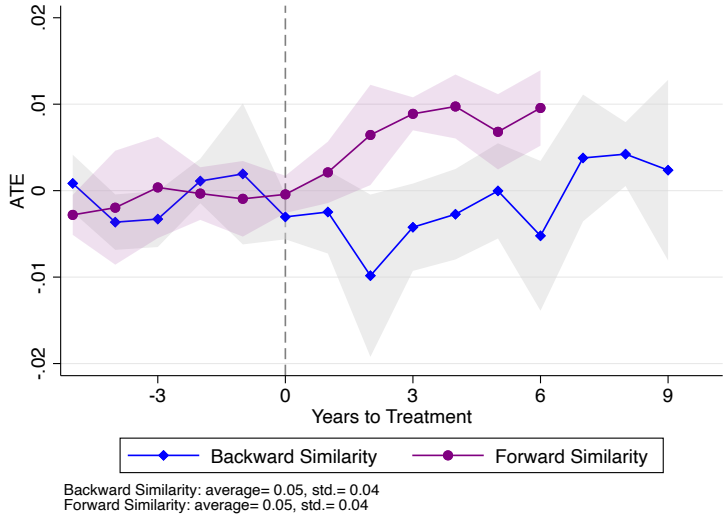


Figure 5: Effect of Lower NC Enforceability on Patent Similarity

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.

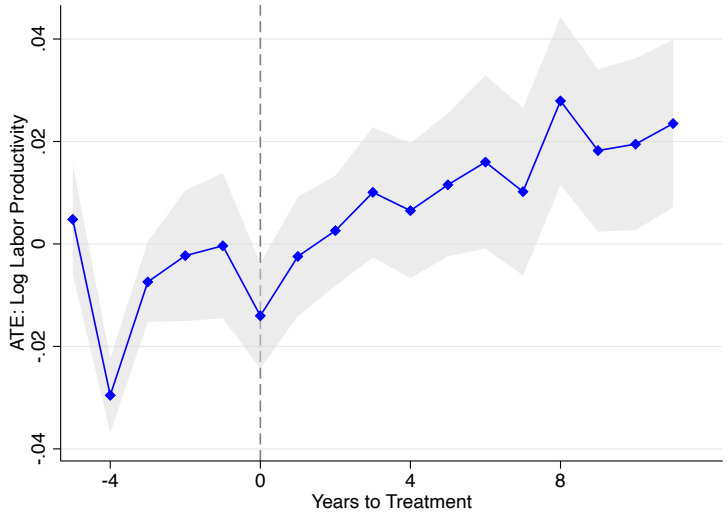


Figure 6: Effect of Lower NC Enforceability on Labor Productivity

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.

turnover, drives these results.

2.3 Discussion

In this section, we briefly discuss the key assumptions of the model that derive the positive correlation between worker turnover and within-job technology upgrades: the job- and technology-specificity of worker skills. The job-specificity of worker skills comes from the occupation-specificity of worker skills and increased occupational mobility after EE transitions. Also, recent empirical works suggest that new technologies make some worker skills obsolete.

Kambourov and Manovskii (2009b) show that wage growth is the most strongly associated with occupation tenure, as opposed to industry and employer tenure. They argue this is consistent with worker skills, or human capital in their paper, more occupation-specific. Nonetheless, job switching is closely related to occupation switching. Kambourov and Manovskii (2009a) report that "*less than 30% of nonemployed workers find a job in their desired occupation in PSID*". Also, 35% of job switchers move to different occupations, compared to 14% of job stayers (See Groes et al. (2015), Appendix A5.4).

Furthermore, a recent paper by Kogan et al. (2022) suggests that worker skills are likely to be technology-specific. After linking patents to occupations, they show that patents on labor-displacement technologies reduce the wages of workers, with a particularly pronounced effect on high-wage workers in each occupation. This finding implies that the obsolescence cost of worker skills influences firm decisions on technology upgrades, potentially hindering them from choosing more productive technologies in the long run.

3 Model

The model aims to replicate the empirical results of this paper and extend the results to derive macroeconomic implications on the composition of long-run growth. The model features search and matching labor market frictions that differentiate gross worker turnover from net job turnover and the technology upgrade choice of

firms to endogenize the long-run growth. The calibrated model replicates the effect of an exogenous increase in EE transition rates on disruptive innovation, especially for old incumbents.

The economy consists of workers and firms operating in a fictional labor market. Unit mass of workers are either nonemployed or employed. Nonemployed workers are matched with firms at an exogenous Poisson rate p^N, whereas employed workers are contacted by other firms at an exogenous Poisson rate p^E. Employed workers are either skilled or unskilled at their current workplaces. Skilled workers are more productive than unskilled workers by a factor of $1/\nu > 1$ under the current technology.

Firms hire workers and produce homogeneous goods with their current idiosyncratic technology level z. On top of the idiosyncratic productivity, the aggregate average productivity of the entire economy has a spillover effect on the yield of incumbent firms. Specifically, a firm produces additional $y_0\bar{z}_t$ units of final goods per worker, where $\bar{z}_t$ is the cross-sectional average z at time t. Thus, a firm with n skilled and l unskilled workers produces $z \times (n + \nu l) + y_0\bar{z}_t \times (n + l)$ per unit of time. The parameter y_0 governs the degree of this static productivity spillover.

Firms choose the speed of technology upgrades $g \geq 0$. If a firm with z chooses g, the change in z is characterized by the following equation.

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

where W_t follows the standard Wiener process, and σ governs the magnitude of the productivity shock. In this equation, the existing technology of others, $\bar{z}_t$, has a dynamic spillover effect on the efficiency of technology upgrades and on the magnitude of productivity shock.

Technology upgrades incur two types of costs to the firm. First, the firm has to pay $(n + l)\bar{z}_t c(g)$ per unit of time to upgrade the technology. This cost is also linear in employment and convex in the speed of innovation. Second, worker skills under the existing technology become obsolescent, and some skilled workers become unskilled under the new technology. This down-skilling happens stochastically at a Poisson rate $d(g)$ to each skilled worker. This down-skilling probability is also

increasing and convex in g.

Entrant firms post vacancies, draw productivity from probability density $\bar{f}_{0,t}(z)$ upon matching, and start with zero skilled workers. The number of vacancies posted by entrants is denoted by v_0. Existing technology has a positive spillover effect on the productivity of entrants.

$$\bar{f}_{0,t}(z) = \bar{f}_0\left(\frac{z}{\bar{z}_t}\right)$$

In this equation, $\bar{f}_0$ is a time-invariant function. Thus, as $\bar{z}_t$ increases over time, entrants draw from a distribution with higher expected productivity.

Firms exit in two cases. First, they have an exogenous exit rate of $\bar{\delta}$. Second, they exit if their productivity is so low that they cannot continue matches with any worker. If incumbent matches with unskilled workers do not generate a positive surplus but the matches with skilled workers yield a positive surplus, the firm separates only with unskilled workers until the point match surplus with unskilled workers is nonnegative or the firm has only skilled workers.

Matching is random, and match rates of firms are proportional to the employment size of the firm. The match protocol follows Cahuc et al. (2006). A firm that hires a worker who was nonemployed before gives $\gamma > 0$ fraction of the match surplus to the worker. When an employed worker is matched to a new firm, the new firm and the current firm of the employed worker bid against each other to attract the worker. The worker moves to the new firm if and only if the match surplus is larger at the new firm. The worker receives the match surplus of the firm that lost the bid plus γ fraction of the additional match surplus in the form of a bargaining weight committed by the winning firm. This bargaining weight stays constant over the tenure of the job as long as the worker is not matched to a firm that gives a higher surplus to the worker.

Matches end if workers and firms separate exogenously at a Poisson rate χ or firms exit the market exogenously at a Poisson rate $\bar{\delta}$. Matches also separate endogenously if the match does not yield a positive surplus to both firms and 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 is negative. This assumption also makes firms choose g and v which maximize the collective match surplus of all the matches at the firm. Because of this property, it suffices to determine the joint match value to characterize the equilibrium and determine worker flows. The wage is renegotiated every period to distribute the match surplus according to the bargaining weight decided from the employer auction.

The model features all values of firms and workers homogeneity of degree one with respect to the size of the firm, conditional on the composition of workers within each firm. As in Coles and Mortensen (2016), this feature successfully reduces the dimension of the state variable at the match level and improves the tractability of the model.

3.1 Values

The state of a match is represented by a vector (n, l, z). Let $\bar{\mathfrak{M}}_t(n, l, z)$ denote the total value of all the matches that belong to a firm with (n, l, z). With revenue, costs, and matching technology linear in employment, it can be shown that the match value is also linear in employment and that the state variable can be reduced to (ω, z), where $\omega = n/(n + l)$ is the fraction of skilled workers within the firm.

$$\bar{\mathfrak{M}}_t(n, l, z) = (n + l)\, \mathfrak{M}_t\left(\omega, z\right).$$

Then, $\partial_n \bar{\mathfrak{M}}_t = \mathfrak{M}_t + \partial_\omega \mathfrak{M}_t\left(1 - \omega\right)$, and $\partial_l \bar{\mathfrak{M}}_t = \mathfrak{M}_t - \partial_\omega \mathfrak{M}_t \omega$.

We focus on the Balanced Growth Path (BGP) where the average productivity $\bar{z}_t$ grows at a constant rate μ over time. In this case, the gross match value can be further simplified as $\mathfrak{M}_t(\omega, z) = \bar{z}_t M(\omega, z/\bar{z}_t)$. Likewise, the value of nonemployment, $\mathfrak{U}_t$, can be expressed as $\bar{z}_t U$. Define $x = z/\bar{z}_t$ as the relative productivity. Then, $dx = (g - \mu x)dt + \sigma dW_t$.

The HJB equation that characterizes the match value per worker is expressed as

in the following equation.

$$
\begin{aligned}
(r+\bar{\delta}-\mu)M(\omega,x) = \max_{g}\Bigg\{ & y_0 + x\left\{\omega+\nu(1-\omega)\right\} - c(g) + \bar{\delta}U \\
& + \chi\omega\left(U - MV_n(\omega,x)\right) + \chi\left(1-\omega\right)\left(U - MV_l(\omega,x)\right) \\
& + p^E\omega\gamma \underbrace{\mathbb{E}_O\left[\max\left\{MV_l(\omega',x') - MV_n(\omega,x), 0\right\}\right]}_{\text{prospective surplus from EE transition (skilled)}} \\
& + p^E(1-\omega)\gamma \underbrace{\mathbb{E}_O\left[\max\left\{MV_l(\omega',x') - MV_n(\omega,x), 0\right\}\right]}_{\text{prospective surplus from EE transition (unskilled)}} \\
& + (g-\mu x)\partial_x M(\omega,x) + \frac{\sigma^2}{2}\partial_{x^2}M(\omega,x) \\
& + q^U\left(1-\gamma\right) \quad \underbrace{\left(MV_l(\omega,x) - U\right)}_{\text{prospective surplus from NE hire}} \\
& + q^E\left(1-\gamma\right) \underbrace{\left[\int \max\left\{MV_l(\omega,x) - MV_n(\omega',x'), 0\right\} d\bar{F}^n(\omega',x')\right]}_{\text{prospective surplus from EE hire (skilled)}} \\
& + q^E\left(1-\gamma\right) \underbrace{\left[\int \max\left\{MV_l(\omega,x) - MV_n(\omega',x'), 0\right\} d\bar{F}^l(\omega',x')\right]}_{\text{prospective surplus from EE hire (unskilled)}} \\
& + \underbrace{\psi(1-\omega)\partial_\omega M(\omega,x)}_{\text{upskilling from old tech.}} - \underbrace{d(g)\omega\partial_\omega M(\omega,x)}_{\text{down-skilling from new tech.}} \Bigg\}.
\end{aligned}
$$

In this equation, r is the interest rate, q^N (q^E) is the firms' match rate to meet a nonemployed (employed) worker, and $\bar{F}^n(\omega,x)$ ($\bar{F}^l(\omega,x)$) is the probability distribution of skilled (unskilled) workers conditional on employment. $\mathbb{E}_O$ is the expectation operator with respect to the offer distribution of vacancies, O. In all the following equations, ∂_y is the partial derivative operator with respect to a variable y. $MV_n(\omega,x) := M(\omega,x) + \partial_\omega M(\omega,x)\left(1-\omega\right)$ is the marginal match value of a skilled worker, and $MV_l(\omega,x) := M(\omega,x) - \partial_\omega M(\omega,x)\omega$ is the marginal match value of an unskilled worker.

The boundary condition for the match value is given by

$$MV_l(\omega, x) \equiv M(\omega, x) - \partial_\omega M(\omega, x)\omega \geq U, \tag{4}$$

$$MV_n(\omega, x) \equiv M(\omega, x) + \partial_\omega M(\omega, x)(1-\omega) \geq U. \tag{5}$$

Since $\partial_\omega M(\omega, x) > 0$, the boundary condition (5) binds whenever the condition (4) binds. In other words, unskilled workers separate always before skilled workers.

3.2 Distribution

On the BGP, if both unskilled and skilled workers do not separate, the density of employed workers, $f(\omega, x)$, is characterized by the following equation.

$$\begin{aligned} 0 = &-\partial_\omega \left[\dot{\omega}\left(\omega, x\right) f\left(\omega, x\right)\right] - \partial_x \left[\dot{x}\left(\omega, x\right) f\left(\omega, x\right)\right] + \partial_x^2 \left[\frac{\sigma^2}{2} f\left(\omega, x\right)\right] \\ &- \left(\chi + \bar{\delta}\right) f\left(\omega, x\right) - p^E i(\omega, x) + p^U \bar{o}\left(\omega, x\right) u + q^E j(\omega, x) \end{aligned} \tag{6}$$

If a value for the share of skilled workers, ω', implies separation of unskilled workers at given x, the matches are dissolved selectively to unskilled workers until the match value of unskilled workers exceeds the nonemployment value.

In Equation (6), $p^E i(\omega, x)$ is the flow of workers poached out of a match with (ω, x), and $q^E j(\omega, x)$ is the flow of workers poached into a match with (ω, x). They are given by the following equations.

$$\begin{aligned} i\left(\omega, x\right) = &\int_{\forall\omega', \forall x'} \bar{o}\left(\omega', x'\right) \mathbf{1}\left[MV_l\left(\omega', x'\right) \geq MV_n\left(\omega, x\right)\right] f^n\left(\omega, x\right) d\left(\omega', x'\right) \\ &+ \int_{\forall\omega', \forall x'} \bar{o}\left(\omega', x'\right) \mathbf{1}\left[MV_l\left(\omega', x'\right) > MV_l\left(\omega, x\right)\right] f^l\left(\omega, x\right) d\left(\omega', x'\right) \\ j\left(\omega, x\right) = &\int_{\forall\omega', \forall x'} \bar{f}^n\left(\omega', x'\right) \mathbf{1}\left[MV_l\left(\omega, x\right) > MV_n\left(\omega', x'\right)\right] o\left(\omega, x\right) d\left(\omega', x'\right) \\ &+ \int_{\forall\omega', \forall x'} \bar{f}^l\left(\omega', x'\right) \mathbf{1}\left[MV_l\left(\omega, x\right) > MV_l\left(\omega', x'\right)\right] o\left(\omega, x\right) d\left(\omega', x'\right). \end{aligned}$$

In this equation, $f^n(\omega, x) = \omega f(\omega, x)$ is the density of skilled workers, $f^l(\omega, x) =$

$(1-\omega)f(\omega,x)$ the density of unskilled workers, $\bar{f}^n(\omega,x) = f^n(\omega,x)/F$ is the distribution of skilled workers conditional on employment, and $\bar{f}^l(\omega,x) = f^l(\omega,x)$ is the distribution of unskilled workers conditional on employment. $F(\omega,x) := \iint_{s\leq\omega,t\leq x} f(s,t)d(s,t)$, and $F = F(1,\infty)$ is the mass of employed workers. $\bar{o}(\omega,x) = o(\omega,x)/\mathbf{O}$ is the probability density of offers to workers, where $\mathbf{O} = \iint o(\omega,t)d(\omega,t)$ is the mass of offers relative to the workers. The offer density $o(\omega,x)$ is given by the following equation.

$$o(\omega,x) = \begin{cases} v_0\bar{f}_0(x) + f(\omega,x) & \text{if } \omega = 0 \\ f(\omega,x) & \text{if } \omega > 0. \end{cases}$$

In this equation, v_0 is the exogenous flow rate of entrants.

The mass of employed workers, F, is given by

$$\left(\chi+\bar{\delta}\right)F + \int_{\omega\in[0,1]} \frac{\sigma^2}{2}\left[\partial_x f(\omega,x)\right]_{x=\underline{x}^l(\omega)} d\omega = p^U(1-F),$$

The density of unskilled and unskilled workers among employed workers is given by $\omega F(\omega,x)/F = \bar{F}^n(\omega,x)$ and $(1-\omega)F(\omega,x)/F = \bar{F}^l(\omega,x)$. $\underline{x}^l(\omega) := \inf_x\{MV_l(\omega,x) \geq U\}$ is the cutoff productivity for the continuation of the match with unskilled workers. The equation implies that the number of workers hired out of nonemployment is the same as those separated into nonemployment exogenously or endogenously.

The growth rate, μ, is derived in the following equation. The equation decomposes the long-run growth rate into three margins: i) within-job technology upgrades, ii) diffusion of better technologies through EN and NE transitions, and iii) diffusion of better technologies EE transitions. Firms with better technologies hire more workers from nonemployment and poach more workers from firms with worse technologies. Thus, worker turnover directly contributes to productivity growth through the diffusion of better technologies. Since $\bar{x} = 1$, we have the fol-

lowing equation.

$$\mu = \underbrace{\iint g(\omega,x)f(\omega,x)d\omega dx}_{\text{Within-job upgrade}} + \underbrace{p^U\mathbb{E}_o[x] - \left(\chi+\bar{\delta}\right) - \chi\tilde{x}}_{\text{Diffusion (EN-NE)}} \tag{7}$$
$$+ \underbrace{p^E \iint\iint \left(x-x'\right)\bar{o}(\omega,x)\mathbf{1}^n\left[\cdot\right] f^n\left(\omega',x'\right) d\left(\omega',x'\right) dxd\omega}_{\text{Diffusion (EE: skilled)}}$$
$$+ \underbrace{p^E \iint\iint \left(x-x'\right)\bar{o}(\omega,x)\mathbf{1}^l\left[\cdot\right] f^l\left(\omega',x'\right) d\left(\omega',x'\right) dxd\omega}_{\text{Diffusion (EE: unskilled)}}.$$

In this equation, $\tilde{x}$ is the average relative productivity of matches that separate endogenously. $\mathbf{1}^n[\cdot]$ and $\mathbf{1}^l[\cdot]$ are the indicators of an EE transition from a firm with (ω,x) to another firm with (ω',x') to skilled and unskilled workers, respectively.

Lastly, the endogenous match rates to the firms are consistent with the exogenous match rates to the workers.

$$p^N(1-F) = q^N(v_0+F),$$
$$p^E F = q^E(v_0+F).$$

4 Quantification

For quantification, the probability density function of the productivity of the entrants, $\bar{f}_0(x)$, is parameterized as the normal distribution with mean μ_0 and standard deviation σ_0. $\mu_0 < 1$ implies that the entrants are on average less productive than the incumbent firms.

Also, we assume the following parametric forms for the cost functions.

$$c(g) = \frac{\varepsilon_g}{\varepsilon_g+1}\kappa_g g^{\frac{\varepsilon_g+1}{\varepsilon_g}}$$
$$d(g) = \frac{\varepsilon_g}{\varepsilon_g+1}\delta g^{\frac{\varepsilon_g+1}{\varepsilon_g}}.$$

For analytical simplicity, we assume that the monetary cost elasticity of technology upgrades, $\frac{\varepsilon_g+1}{\varepsilon_g}$, is the same as the down-skilling cost elasticity.

Then, the first-order conditions with respect to v and g imply the following equations.

$$g(\omega, x) = \left(\frac{\partial_x M(\omega, x)}{\kappa_g + \delta\omega\partial_\omega M(\omega, x)} \right)^{\varepsilon_g}. \tag{8}$$

Equation (8) shows that the value of existing skills, $\partial_\omega M(\omega, x)$, works as a wedge to increase the cost of innovation and lower the speed of technology upgrades. New technologies make skills accumulated under existing technologies obsolete. This cost is higher when the firms have a higher share of workers with skills, which is correlated positively with the firm age and match tenure.

4.1 Calibration

Table 1 shows the values of calibrated parameters along with the targeted moments. Panel A shows the values of moments targeted without solving the model numerically. The Euler equation of the representative household in Appendix B.1 implies that $r = \rho + \mu$. With a 2% annual growth rate targeted and 6% as the annual risk-free interest rate, ρ is calibrated at an annual 4%. The monthly NE rate of nonemployed workers, $p^N + \tilde{p}^N$, is calibrated to be 17% per month. The monthly NE rate consists of a job-search probability of nonemployed workers that increases employment, p^N, and a random switch probability between employed and nonemployed workers, $\tilde{p}^N$, which is described below.

Panel B of Table 1 shows the values of parameters calibrated after solving the model. First, we set the monetary cost parameter of the technology upgrade, κ_g, to match the annual growth rate of 2%. Then, the elasticity of technology upgrade, ε_g, is chosen to match the net EE hire rate of old firms. The net EE hire rate is calculated as the gross EE hire rate subtracted by the EE separation rate of workers hired at old firms between the ages of ten and twenty. This target captures the idea that young firms are less productive but grow faster than old firms. If young firms grow faster, the productivity gap between young and old firms becomes wider. With the large

Table 1: Calibration Results

Symbol	Parameter	Value	Target	Data	Model
A. External Calibration					
ρ	Discount Rate	4%	Interest Rate	6%	6.0%
$p^N + \tilde{p}^N$	NE Rate	17.0%	-	18.7%	18.7%
B. Internal Calibration					
κ_g	Upgrade Cost Shifter	7.47e+03	Growth Rate	2.00%	2.02%
ε_g	Upgrade Elasticity	1.27	Net EE Hire (Old)	-0.05%	-0.10%
ψ	Upskilling Rate	2.30%	Net EE Hire (Middle)	-0.12%	-0.06%
δ	Downskilling Cost	3.43e+03	Net EE Hire (Young)	0.33%	0.24%
q^N	Match Rate (Unemployed)	0.65%	Employment Share (Old)	43.5%	36.3%
q^E	Match Rate (Employed)	0.30%	Within Contribution	86.5%	81.2%
y_0	Productivity Spillover	0.36	Wage (Long)	1.136	1.135
γ	Surplus Share (Worker)	0.29	Wage (Middle)	1.098	1.092
ν	Skill (Unskilled)	2.30%	Wage (Short)	1.022	1.034
b	Unempl. Benefit	0.29	Replacement Rate	28.6%	28.4%
v_0	Vacancy Flow (Entrants)	0.50%	Employment Share (Start-up)	11.4%	15.1%
μ_0	Mean Productivity (Entrant)	0.95	Hire/Employment (Start-up)	9.9%	12.5%
σ_0	Std. Productivity (Entrant)	1.33e-01	EE Rate (Long)	1.1%	1.4%
σ	Productivity Shock	0.20%	EE Rate (Medium)	1.6%	1.5%
C_E	Random EE Reduction	1.25%	EE Rate (Short)	2.0%	2.4%
$\tilde{p}_0^E$	Initial Random EE Rate	7.55%	EE Rate (New)	4.2%	4.0%
χ	Exog. Separation	1.00%	EN Rate (Long)	1.20%	0.99%
C_U	Random EN Reduction	0.03%	EN Rate (Medium)	1.4%	1.0%
$\tilde{\chi}_0$	Initial Random EU Rate	9.8%	EN Rate (Short)	2.2%	2.5%
-	-		EN Rate (New)	4.94%	4.87%

Notes: This table describes calibration targets in the data and model and the resulting calibrated parameters. Discount, interest, and growth rates are annual. All the other rates are monthly. Start-ups are firms under the age of two. Young, Old, and Middle are firms under the age of five, over ten (but under twenty), and between five and ten, respectively. New and Short are job matches with tenures shorter than two years and between two and five years, respectively. Medium and Old are job matches with tenures between five and ten years and older than ten years, respectively. Within Contribution is the contribution of within-job technology upgrades to the growth rate on the BGP as shown in Equation (7). Average wages of long-, middle-, and short-tenure matches are measured relative to the average wage of new matches.

productivity difference between young and old firms, employed workers are more likely to work in old firms when contacted on the job.

The upskilling rate and the downskilling cost parameters, ψ and δ, govern how firm age is associated with the share of skilled workers, which are related to the technology upgrade rates over the firm age profile. These parameters are also cali-

brated to match the net EE hire rates implied by the productivity difference between firms of different ages. The net EE hire rates are calculated from the J2J database of the U.S. Census Bureau.

The contact rate of incumbent matches to nonemployed workers, q^N, is calibrated to match the share of firms between the ages of ten and twenty. Since all nonemployed workers work with contacted firms, higher q^N implies a higher share of young firms with low productivity and, equivalently, a lower share of old firms with high productivity. The employment share of old firms between ten and twenty is calculated from the Business Dynamics Statistics (BDS) of the Census Bureau. This statistic informs us of the productivity difference between firm age groups and thus is used to calibrate the cost parameters of technology upgrades. We exclude firms older than twenty from the calibration target since their employment is disproportionately affected by workers near their retirement ages.

We target the contribution of within-job technology upgrade to growth at 86.5% to calibrate q^E, the contact rate of incumbent matches to employed workers. The accounting formula of Baily et al. (1992) decomposes the productivity growth of the manufacturing sector (ΔA_t) into four margins in the following equation.

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

In the Baily-Campbell-Hulten decomposition, s_{it} is the share of plant i in year t, Δa_{it} is the change in plant-level productivity, Δs_{it} is the change in share, $\mathbf{C}_t$ is the set of plants that continue to operate, $\mathbf{E}_t$ is the set of entrants, and $\mathbf{X}_t$ is the set of plants that exit. Baily et al. (1992) find that 86.5% of growth comes from the within-plant productivity growth with fixed shares in 1982-1987. With declines in job turnover rates over time, the contribution of within-job productivity growth targeted at 86.5% is likely a lower bound.

A more traditional way to calibrate the match rate of employer workers is to

match the EE transition rate (Petrongolo and Pissarides, 2001). However, recent papers emphasize the importance of amenities and non-monetary motives for on-the-job moves (Sorkin, 2018; Bagga et al., 2023), which do not contribute to the diffusion of better technologies and long-run growth. In the model, on-the-job search makes a long-run growth because worker transition from worse to better technologies increases the average technology level of the economy. Thus, we match the contribution of within-employer productivity growth to calibrate the search efficiency of employed workers.

At the same time, Hall and Kudlyak (2019) and Gregory et al. (2021) point out the importance of worker-level heterogeneity to determine the worker flows across employment and nonemployment. They find that the labor market transitions are better approximated with groups of workers with heterogeneous job-finding and job-separation rates. Then, EN rates that decrease over the job tenure can be interpreted as selection over worker types.

Still, job tenure gives information on skill accumulation and the bargaining position of workers within jobs without direct observations of match-level productivity. The tenure profile of wage signals the magnitude of human capital accumulation and advances of bargaining position, despite non-monetary motives behind on-the-job matches and selection of worker types over tenure. The calibration aims to match the tenure profile of wages with some assumptions of non-monetary incentives for EE and EN transitions.

To tackle this challenge, we assume random tenure-specific EE and EN shocks that are entirely orthogonal to the economic motives. Specifically, an incumbent match randomly meets another match with the same match-level state variables, the skill level of workers, the productivity, the share of skilled workers within the firm, and the committed match surplus. These two matches then swap the worker and continue to operate. This event happens at a tenure-specific rate, $\tilde{p}^E(t)$, where t is the job tenure. Although not very realistic, this random shock implies that the frequency of the random EE shock does not affect economic outcomes such as technology upgrade rates and wages. The shock only affects how wages are distributed

over the match tenure. We consider the following form for $\tilde{p}^E(t)$.

$$\tilde{p}^E(t) = \frac{\tilde{p}_0^E exp(-C_E t) + \tilde{p}_1^E exp(C_E t)}{exp(-C_E t) + exp(C_E t)}$$

If $\tilde{p}_0^E > \tilde{p}_1^E$, then the random EE shock is less frequent for matches with long tenure. The parameter C_E governs the degree to which the random EE shock becomes less frequent over tenure.

We also allow random shocks for EN and NE transitions. Like the random EE transitions, an incumbent match meets an unemployed worker and switches their positions at a tenure-specific rate, $\tilde{\chi}(t)$. After this event, the match-level state variable of the previously nonemployed worker is the same as that of the previously employed worker. The previously employed worker is paid with severance pay equal to her share of the match surplus, and the fund is sourced from the previously nonemployed worker. In this case, the frequency of the random EN shock affects none of the economic decisions. This EN random shock is parameterized similarly to the random EE shock.

$$\tilde{\chi}(t) = \frac{\tilde{\chi}_0 exp(-C_U t)}{exp(-C_U t) + exp(C_U t)}$$

Thus, it is assumed that this random shock does not affect matches with long tenure. Then, the separation probability of matches with long-tenure informs us with the rate that jobs end without successive workers, χ. In this case, the monthly NE probability captures both random and non-random job-finding behavior, $\tilde{p}^N$, and p^N. The random NE probability is given by the following formula.

$$n\tilde{p}^N = \int_{t \geq 0} \tilde{\chi}(t)\tilde{f}(t)dt.$$

n is the mass of nonemployed workers, and $\tilde{f}(t)$ is the density of workers with tenure equal to t in the stationary equilibrium. $p^N + \tilde{p}^N$ determines the NE transition rates. The EN and EE separation rates over match tenure bins, calculated from the Job Tenure and Occupational Mobility Supplement (JTOM supplement) of CPS, are targeted to calibrate the random shock parameters, $\tilde{p}_0^E$, $\tilde{p}_1^E$, C_E, $\tilde{\chi}_0$, C_U, and the job-

ending rate, χ. We use four bins for the tenure of matches: new (tenure $<$ 2 years), short (tenure $\geq$ 2 years, $<$ 5 years), medium (tenure $\geq$ 5 years, $<$ 10 years), and long (tenure $\geq$ 10 years).

The tenure profile of worker wages is targeted to match the static productivity spillover parameter, y_0, the skill differences between skilled and unskilled workers, ν, and the worker share of excessive surplus in the employer auction, γ. The lower value of y_0 and higher values of ν and γ imply a steeper slope for the tenure profile of worker wages. The wage schedule of job tenure is calculated from the March supplement (ASEC) of CPS merged with the JTOM supplement. We use only male workers between the ages of 25 and 54. The raw wage is the weekly earnings, the yearly labor earnings divided by the number of weeks worked. The wage is taken logs and then residualized with age, squared age, race, education, and year, industry, and occupation fixed effects. The model-implied wage function is described in B.2. Nonemployment benefit rate b is calibrated to match the average replacement rate at 28.6% as in Hall and Milgrom (2008).

The employment share of entrants from the BDS informs the model of the vacancies posted by entrants relative to the incumbents, v_0. The average productivity of entrants relative to the average, μ_0, is set to match the monthly hires made by start-ups relative to their employment size. With lower productivity, entrants are less likely to retain their workers with more EE separations. Thus, the number of hires entrants make is higher than their employment size. The dispersion of the entrants' productivity, σ_0, and the magnitude of productivity shock to incumbents, σ, are calibrated to target the EE separation rates of matches with long and medium tenures.

The last two columns of Table 1 compare the values of targeted moments from the data to the counterparts from the model. The calibrated model can match the targeted moments closely.

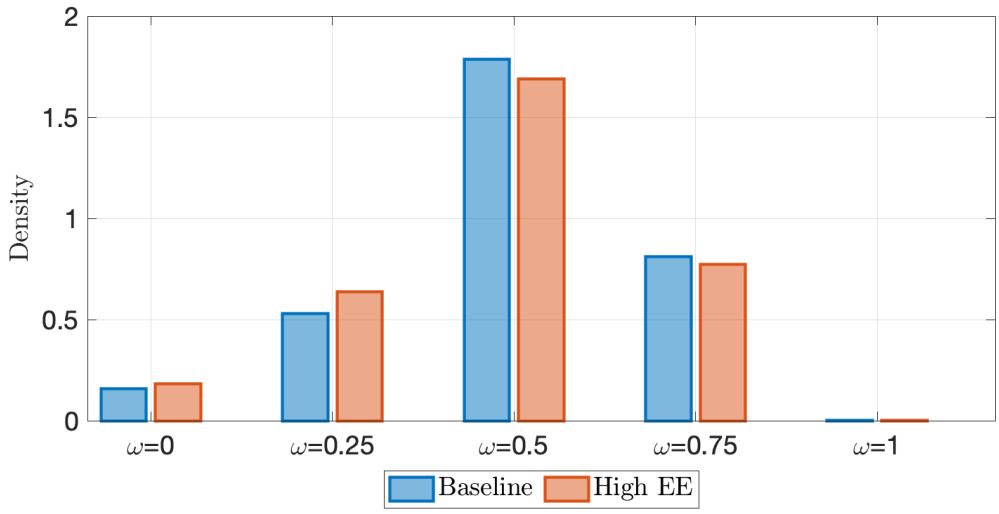


Figure 7: Counterfactual Worker Distribution over ω

Notes: This graph compares the composition of steady-state growth in Equation (7) on the counterfactual BGP equilibrium to the baseline case. The first column denotes the case where v_0, p^E and p^U is increased.

5 Model Fit

In this section, the calibrated model is used to replicate the effect of low NC enforceability in Section 2.2. The low NC enforceability is interpreted as an exogenous shift in the match rate of employed workers because NC contracts ban employees from moving within a group of related employers. The match rate of employed workers, p^E, is increased by 50% from the baseline case. The entry rate, v_0, is fixed at the baseline value throughout the exercise. Appendix A.3 indicates that the job creation share of entrant firms does not increase but somewhat decreases after the institutional change.

5.1 Balanced Growth Path

Figure 7 shows the distribution of workers across skill intensity. With higher p^E, skilled workers move to better employers and start as unskilled more frequently. Thus, the stationary distribution of workers features lower shares of skilled workers

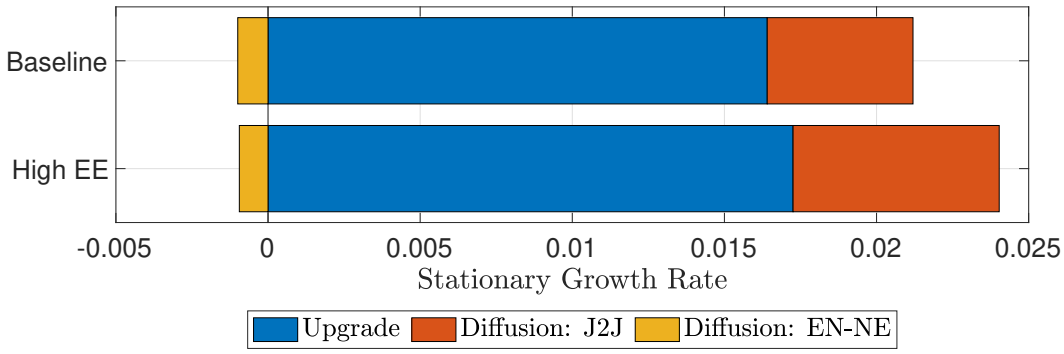


Figure 8: Counterfactual Steady-State Growth Decomposition

Notes: This graph compares the composition of steady-state growth in Equation (7) on the BGP equilibrium with 20% higher match rate of employed workers (p^E) to the baseline case.

within firms. The largest change comes from the shares of workers with $\omega = 0.25$ and $\omega = 0.5$. The expected share of skilled workers exceeds 0.5 when a firm operates over six years. Thus, the change in p^E disproportionately affects the technology upgrade choices of these firms.

Figure 8 shows the growth decomposition result from Equation (7). With higher match rates of employed workers, the diffusion of better technologies is faster automatically. On top of that, a higher EE transition rate changes within-job productivity growth in two channels. First, it lowers the fraction of workers skilled under existing technologies, reducing the opportunity cost of new technologies. Second, with faster worker transition, returns to technology upgrade increases for ω and x fixed. Returns to technology upgrades consist of the productivity increase in current matches and prospective match surplus from future hires. This prospective match surplus increases with a higher match rate to employed workers.

Thus, within-job technology upgrades significantly contribute to faster long-run growth, as shown in Figure 8. Overall, the long-run growth rate on the BGP rises by 0.3 percentage points. The diffusion of better technologies through EE and EN-NE transitions account for 66% and -6% of the increase in stationary growth rates, respectively. The within-job technology upgrade margin also accounts for a substantial share of changes in growth rates, 40%.

Figure 9 shows the average productivity and the employment share of skilled

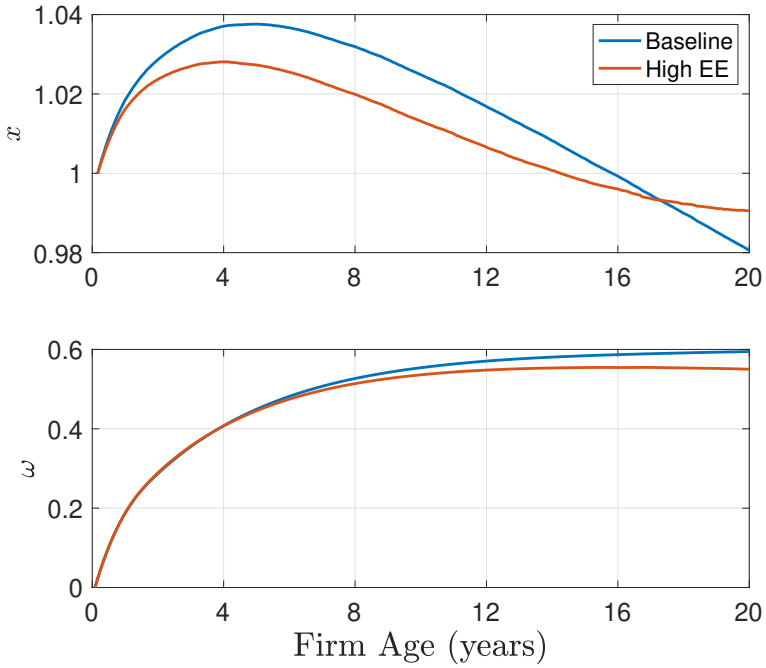


Figure 9: Counterfactual Firm Age Characteristics

Notes: This graph compares the average productivity, x, and average skill intensity, ω, over firm ages on the BGP equilibrium with a 20% higher match rate of employed workers (p^E) to the baseline case. These series are calculated with a simulated panel of 10,000 firms.

workers conditional on firm age, weighted by employment. In the lower panel of Figure 9, higher match rates of employed workers disproportionately lower the share of skilled workers for firms over the age of eight and raise their technology upgrade rates. Thus, the relative productivity of firms over the age of ten decreases more slowly, and the relative growth of young firms under the age of three becomes less pronounced in the upper panel.

Despite a smaller average productivity difference between young and old firms, the share of young firms slightly increases with more EE transitions from old and unproductive to young and productive firms in Figure 10.

5.2 Transition Path

Figure 11 describes the changes in output over the transition path from the baseline BGP at $t < 0$ to the new BGP with a match rate of employed workers, p^E,

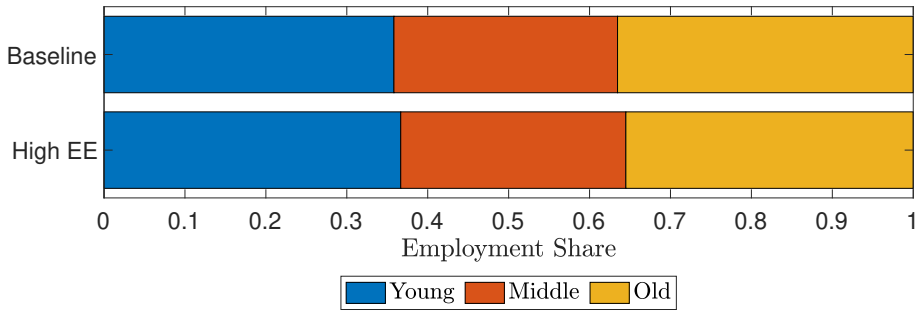


Figure 10: Counterfactual Employment Share over Firm Age

Notes: This graph compares the employment shares of young (age$\leq$ 5), middle (age $>$ 5 & $\leq$ 10), and old (age $>$ 10 & $\leq$ 20) firms on the BGP equilibrium with a 20% higher match rate of employed workers (p^E) to the baseline case. These series are calculated with a simulated panel of 10,000 firms.

permanently and unexpectedly increased by 20% at $t = 0$. The economy grows faster than the baseline case due to faster within-job technology upgrades and EE transitions. The contribution of EN-NE transition on output growth relative to the baseline economy is small. Because the reduction in worker skill reduces output, the output growth during the first few years after the shock is not pronounced. Nonetheless, with faster technology upgrades and EE transitions, skill depreciates but more slowly than productivity grows within jobs. Thus, the output path is always located above the baseline benchmark.

The welfare of the representative household, as defined in Appendix B.1, increases with this MIT shock on the match rate of employed workers. The new consumption path is equivalent to a 3.58% permanent increase in consumption of the baseline economy. The within-job technology upgrade and the diffusion through the EE transition make welfare gains equivalent to 1.45% and 2.34% increases in baseline consumption, respectively. Thus, the within-job technology upgrade margin contributes to a substantial welfare change over the transition path, as well as the change in growth rates on the BGP.

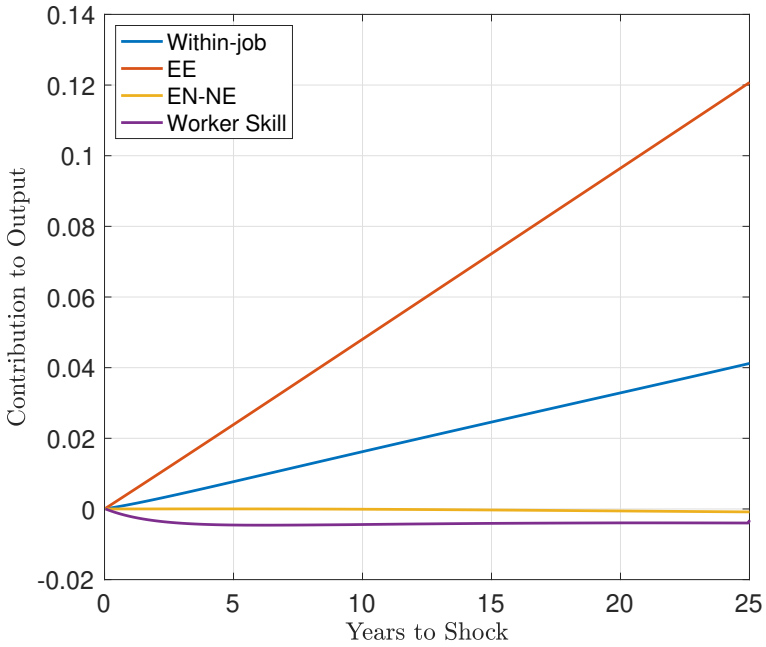


Figure 11: Change in Log Output and Components

Notes: This graph shows changes in output over transition path after an unexpected and permanent increase in match rates of employed workers (p^E) by 20% at $t = 0$ relative to the baseline BGP.

6 Model Application: Aging Population, Declines in Business Dynamism, and Growth

We use the model to evaluate the effects of the two most notable trends in the labor market, the aging population and the declines in start-up rates, on long-run growth. Young workers are naturally untied to any job-specific skills and thus favor upgrades to new technologies. Therefore, the aging workforce makes the economy more stuck in existing technologies and slows down long-run growth. Young workers are also less likely to move to new jobs and separate from their current jobs (Engbom, 2019). Thus, we replicate the aging population with lower exogenous separation rates, χ, and on-the-job match rate, p^E. These changes naturally lower the share of skilled workers through EN and NE transitions. On the other hand, start-ups have zero skilled workers and thus invest more to upgrade their technologies. Thus, with fewer start-ups, the economy tries new technologies less frequently. We replicate this composition change on the employer side by changing v_0.

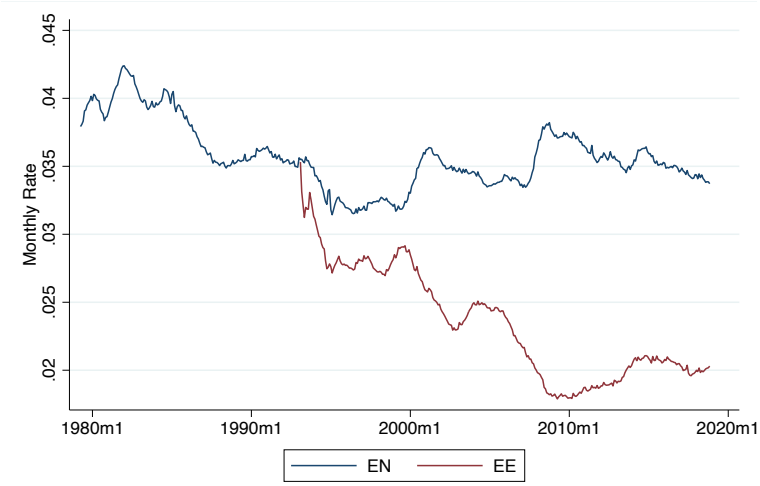


Figure 12: EN and NE Rates over Time

Notes: This graph shows a historical series of the monthly EN and NE rates calculated using the CPS microdata. EN rates are measured as the share of workers not employed in month $t+1$ among the employed in month t. EE rates are the share of workers that switched to a new employer in month $t+1$ among the employed in month t. Samples include workers between 20 and 65.

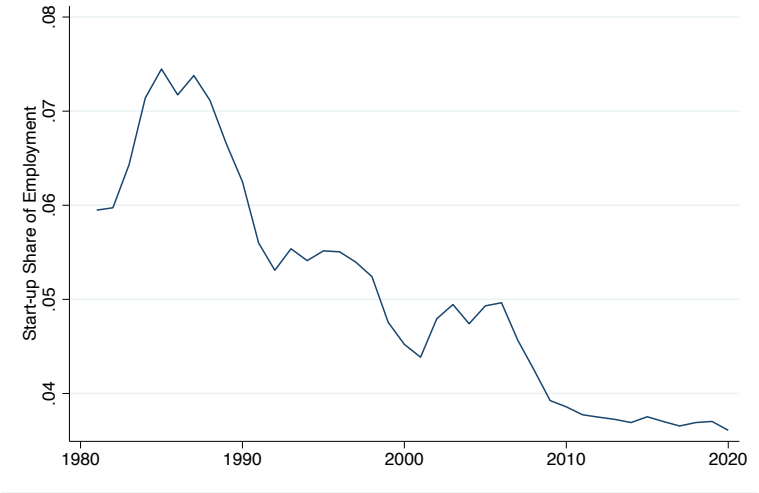


Figure 13: Start-up Employment Share over Time

Notes: This graph shows a historical series of employment shares of start-ups calculated using the BDS. Start-ups are firms under the age of two.

Figure 12 shows historical trends in EN and EE transition rates measured from the CPS microdata.[7] EN rates dropped sharply from 4% to 3.5% between the 1980s and 2010s. EE rates are also decreased from 3% to 2.2% from the 1990s to the 2010s. Thus, the aging population is simulated as an exogenous reduction in χ and p^E by 12.5% and 25%, respectively. Since the baseline parameters target moments from the 2010s. We increase χ and p^E by 14% and 33%.

At the same time, the employment share of start-ups also decreased sharply in the United States, as in Figure 13. In the 1980s, start-ups under the age of two accounted for 6 to 7% of total employment. This share decreased to below 4% in the late 2010s. In the context of the model, this change is interpreted as a 33% reduction in vacancies posted by start-ups.

We first compute the equilibrium with all the three parameters χ, p^E, and v_0, changed from the baseline case. Then, to decompose the effects of the aging population and low start-up rates, we consider a case where only χ and p^E are increased and another case where only v_0 is changed. To exclude welfare changes associated with employment rates and gross labor supply, the match rate of nonemployed workers, p^N, is adjusted so that the employment rate stays the same in each case.

Table 2 shows the growth rate decomposition and employment shares of firm age groups in the counterfactual and the baseline equilibria. The counterfactual BGP before the aging population and declines in start-up rates has a growth rate similar to that of the baseline BGP. However, the composition of the stationary productivity growth is different. The counterfactual BGP features more productivity growth stemming from the diffusion of better technologies through EE transitions, whereas the baseline equilibrium growth results more from within-job productivity changes.

The aging population slows down growth through slower diffusion of new technologies but has a mixed effect on within-job technology upgrades. The aging popu-

[7] EN transition rates are measured by the share of unemployed or non-participating workers in month $t+1$ among those employed in month t. EE transition rates are measured by the share of workers switched to a new employer among those employed in month t. Samples are workers between the ages of 20 and 65. The series is seasonally adjusted by taking moving averages over 12 months.

Table 2: Changes on the BGP

Population Start-up Rate	Young High	Young Low	Old High	Old Low
Growth Rate Decomposition				
Within-job Upgrade	1.39%	1.64%	1.44%	1.64%
EE Transition	0.72%	0.78%	0.46%	0.48%
EN-NE Transition	-0.09%	-0.12%	-0.12%	-0.10%
Growth Rate	2.04%	2.30%	1.78%	2.02%
Employment Share				
Young	42.8%	39.3%	39.2%	35.8%
Middle	28.2%	28.1%	27.9%	27.6%
Old	29.0%	32.6%	32.8%	36.5%

Notes: This table shows the composition of growth rate and employment shares of firm age groups across the counterfactual and the baseline BGPs. The growth rate is decomposed as in Equation (7). The first column sets the separation and match rate of employed workers and the vacancy share of entrants higher than the baseline case. The second column changes only the vacancy share of entrants, and the third column changes only the separation and match rates of employed workers.

lation implies fewer hires of nonemployed workers, and low probabilities of future hires reduce the returns to technology upgrades. Furthermore, the aging population implies a higher share of skilled workers, and this composition change further lowers the average within-job technology upgrade rate. However, the duration of existing matches is longer because older workers tend to move less between firms. Thus, the aging population has an ambiguous effect on the within-job technology upgrade margin. In the end, the effect of slower EE diffusion is quantitatively dominant and determines the net effect of the aging population on growth.

Low start-up rates, with fixed match rates of employed and nonemployed workers, increase the match rate of incumbent firms. Thus, the returns to technology upgrades increase for incumbent firms. Moreover, low start-up rates mildly accelerate growth through diffusion because productive incumbent producers make more EE transitions with lower start-up rates.[8] Thus, a decrease in start-up rates substantially raises the growth rate on the BGP.

[8]We assume a constant p^E in this case. Thus, more matches of start-ups to employed workers crowd out matches of incumbents to employed workers.

Table 3: Changes on Transition Path

Population Start-up Rate	Young Low	Old High	Old Low
Δ Output ($\leq$ 5 years)	0.20%	-0.11%	0.08%
Δ Output (5 to 10 years)	1.49%	-0.60%	0.35%
Δ Output (10 to 20 years)	4.37%	-1.51%	1.03%
CEV	4.74%	-1.51%	1.27%
Within-job Upgrade	3.43%	0.46%	3.66%
EE diffusion	1.06%	-2.81%	-2.78%
EN-NE diffusion	0.73%	0.50%	0.42%
Worker Skill	-0.52%	0.37%	0.07%

Notes: This table summarizes changes in output and welfare over transition path after an unexpected and permanent increase in $t = 0$. The last column sets the separation and match rate of employed workers lower than the benchmark BGP without aging population and reduction in start-up rates. The first column changes only vacancy share of entrants, and the second column changes only the separation and match rates of employed workers.

Table 3 summarizes the changes in output and welfare over the transition path in the three scenarios. During the first five years after the shock, low start-up rates increase output because incumbents upgrade their technologies at an accelerated rate. More frequent introduction of new technologies implies faster obsolescence of worker skills, but the productivity effect dominates. The productivity growth accumulates over time, and the output increase relative to the benchmark becomes larger after the next five and ten years. As a result, the welfare increases with low start-up rates, and the increase is equivalent to a 4.74% permanent increase in consumption on the benchmark BGP. Within-job technology upgrades account for the most significant increase in welfare.

On the other hand, welfare deteriorates after the aging population shock. Faster within-job technology upgrades and fewer EN-NE transitions increase the welfare of the households. However, the increment is insufficient to cancel out the reduction in welfare after a decrease in EE transitions. Indeed, the counterfactual output path after the aging population shock always stays below the benchmark BGP. The two shocks combined increase the output on the transition path relative to the benchmark case with faster worker turnover and high start-up rates. However, the effect

is small in magnitude because the aging population and lower start-up rates cancel out each other.

7 Conclusion

Despite empirical evidence highlighting the role of incumbent innovation on long-run growth, few works have been done to structurally analyze how incumbent innovation interacts with economic conditions. This paper shows that faster worker turnover promotes disruptive innovation made by incumbents and accelerates long-run growth. Faster turnover not only increases returns to innovation but also reduces the opportunity costs of innovation.

Empirically, MSAs with faster worker turnover have faster productivity growth and more disruptive innovations. Furthermore, institutional changes that facilitate EE transitions make innovations more disruptive. Motivated by these general equilibrium responses, this paper develops an endogenous growth model that features technology upgrade choices and skill accumulation in a frictional labor market. If worker skills are specific to both jobs and technologies, worker turnover reduces skills accumulated under the existing technologies and, thereby, opportunity costs of new technologies. This model assumption is consistent with micro evidence on the scope of worker skills.

The quantitative result in this paper suggests that incumbents' within-job innovation is essential in shaping the aggregate responses of productivity growth to economic changes. Compared to the declines in worker turnover rates after the late 20th century, the growth rate decreased only slightly, implying that the contribution of within-job productivity growth became more important than before. This empirical pattern calls for continuing research on the determinants of within-job innovation made by incumbents. This paper proposes labor market conditions as one of the determinants.

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A Data Appendix

A.1 Correlation between Worker Turnover and Growth

We use the local projection method in Jordà (2005) to estimate the dynamic correlation of worker turnover rates with labor productivity and patenting activities. Specifically, the following equation is estimated using the OLS for each $h \in 1, \ldots, 7$.

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

β_h estimates the correlation of a change in $r_{i,t}$ in MSA i at time t with a change in y at time $t+h$. The correlation controls for the MSA and year fixed effects, and some controls at time t and $t+h$. The control variables at time t, $X_{i,t}$, include lagged log labor productivity, the share of manufacturing employment, and the job creation share of entrants.[9] Other controls at time $t+h$, $X_{i,t+h}$, include unemployment rate, GDP growth between $t+h$ and $t+h-1$, and lagged log labor productivity. These variables are included to control cyclical components that result in a correlation between turnover, productivity, innovation, and the heterogeneity of MSAs in terms of industry and firm age composition.

Figures A.1-A.4 show the estimation results for log labor productivity, the number of patents per worker, the number of citations per worker, and the number of citations per patent. In Figure A.1, a 1 percentage point increase in EE and NE hire rates in an MSA decreases labor productivity by 3%. As time passes, however, the sign of the correlation flips, and, in the fifth year after an increase in $r_{i,t}$, the regression estimates become positive. The correlation with productivity growth is, thus, positive in the first and the second years.

The response in the number of patents per thousand workers, however, is overall small and insignificant except in the sixth and the seventh year (See Figure A.2). Contrary to the raw number of patents, the number of citations per patent, which usually measures how disruptive or creative a patent is (Acemoglu et al., 2022), significantly increases until the second year. Moreover, the short-term correlation is sizeable. A 1 percentage point increase in EE hire rates is translated into 0.4 more

[9] Entrants are firms that entered the labor market in the current year or the year before in the BDS.

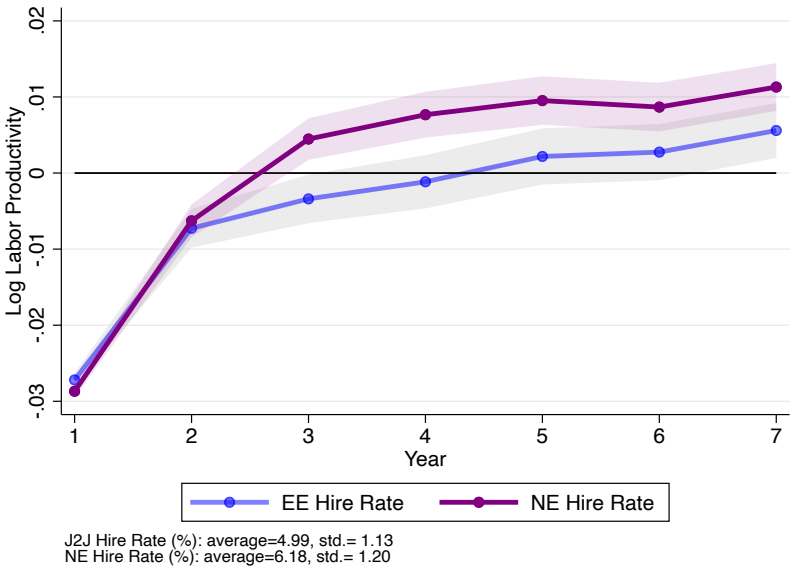


Figure A.1: Local Projection of Turnover Rates on Labor Productivity

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

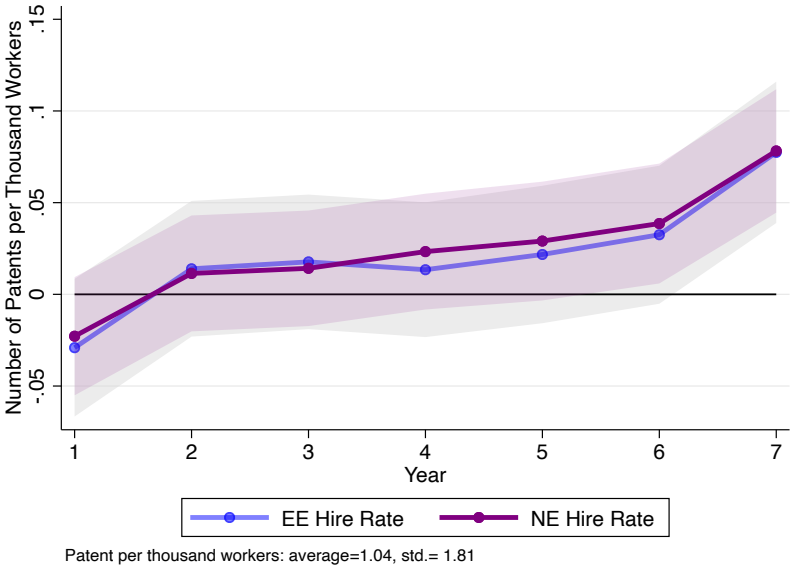


Figure A.2: Local Projection of Turnover Rates on Patents

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

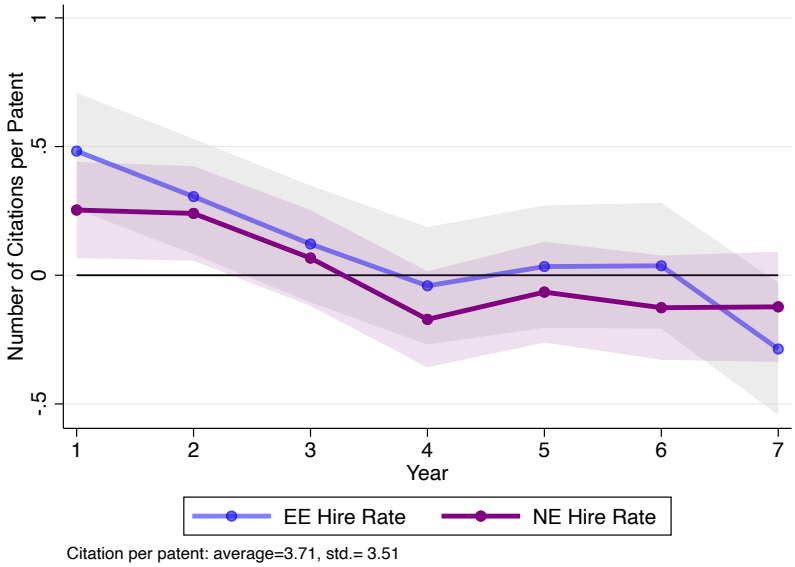


Figure A.3: Local Projection of Turnover Rates on Patent Impact

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

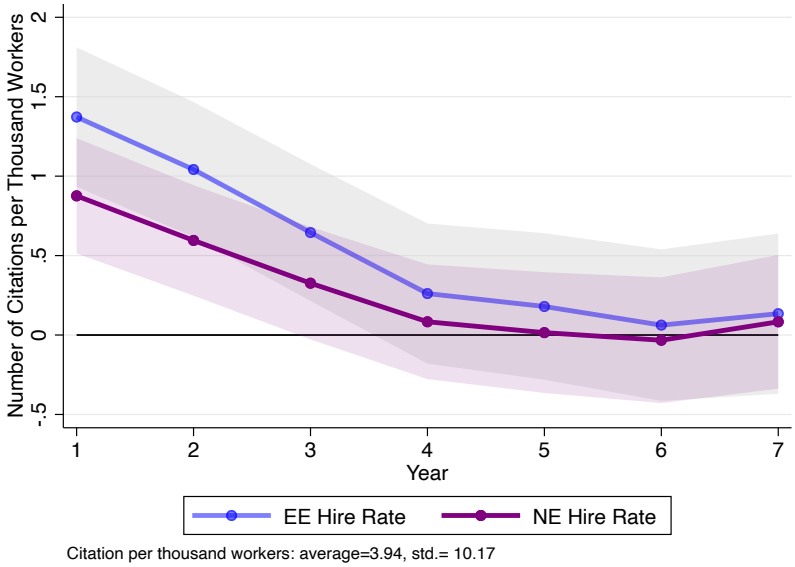


Figure A.4: Local Projection of Turnover Rates on Citations

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

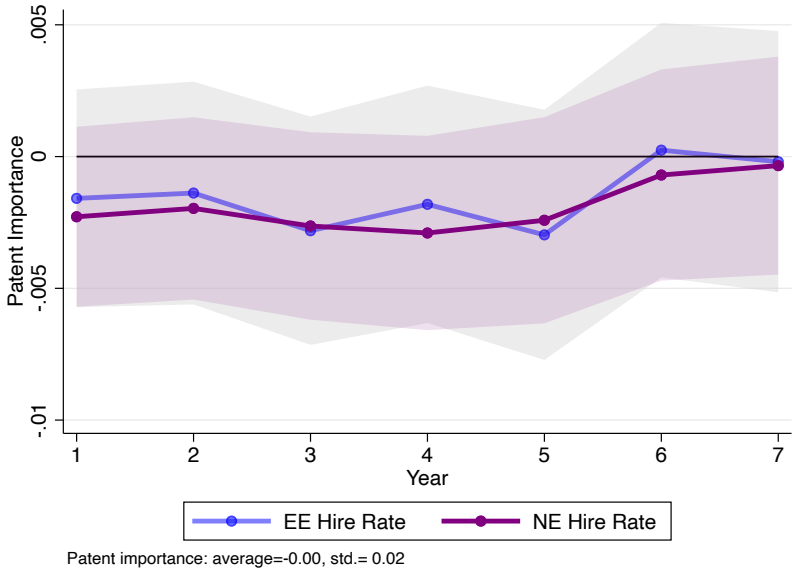


Figure A.5: Local Projection of Turnover Rates on Citations

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

citations per worker, 11% of the standard deviation of the entire sample. Results are quantitatively smaller but qualitatively similar for NE hire rates.

Consequently, the number of citations per thousand workers increases with higher EE and NE hire rates. A 1-percentage point increase in EE hire rates is associated with 1.5 more citations per thousand workers, 15% of the standard deviation. This effect also stays significantly positive until the third year after an increase in EE hire rates. Results are again smaller but hold similarly for NE hire rates. Unlike in Section 2, patent importance does not exhibit a significant correlation with changes in local EE and NE hire rates.

A.1.1 Robustness of LP Correlations

The estimates of local projection do not change after controlling job creation and job destruction rates. Figures A.6-A.9 show the local projection results when the net labor turnover rates (job creation and destruction rates) enter the local projection regression as controls. The coefficient estimates barely change after controlling for net turnover rates compared to the baseline case in Appendix A.1.

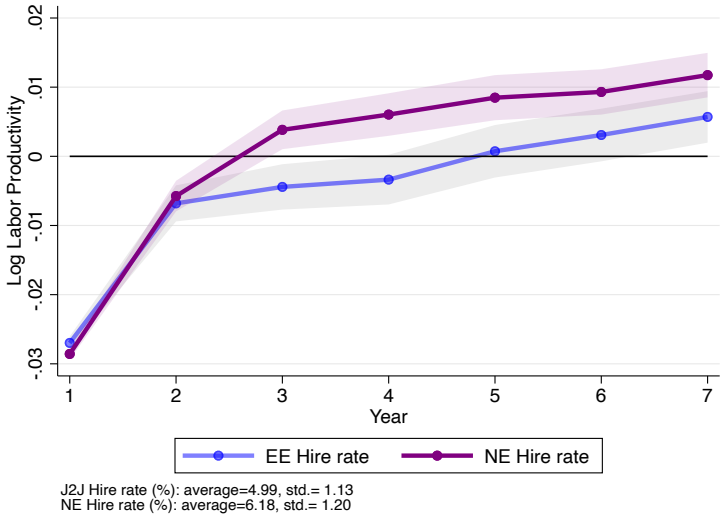


Figure A.6: Robustness: Local Projection of Turnover Rates on Labor Productivity

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.1. Shaded areas represent the 95% confidence interval of the estimates.

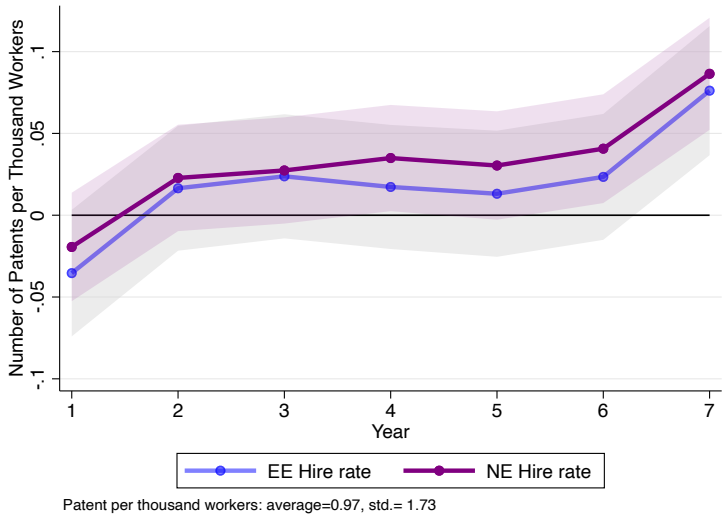


Figure A.7: Robustness: Local Projection of Turnover Rates on Patents

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.1. Shaded areas represent the 95% confidence interval of the estimates.

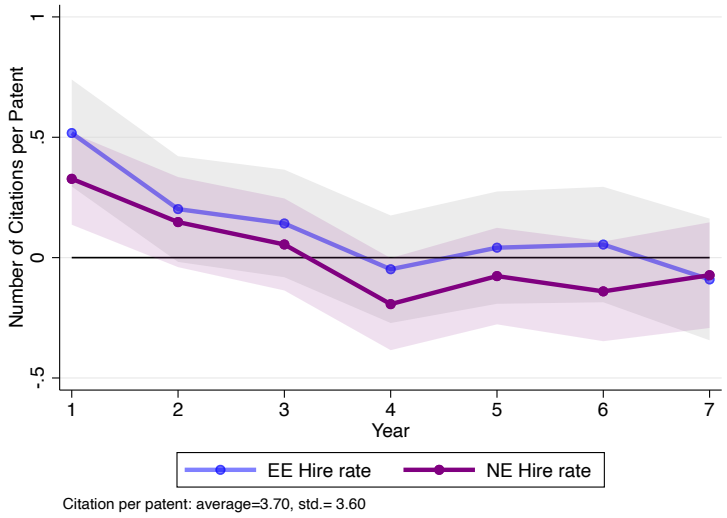


Figure A.8: Robustness: Local Projection of Turnover Rates on Patent Impact

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.1. Shaded areas represent the 95% confidence interval of the estimates.

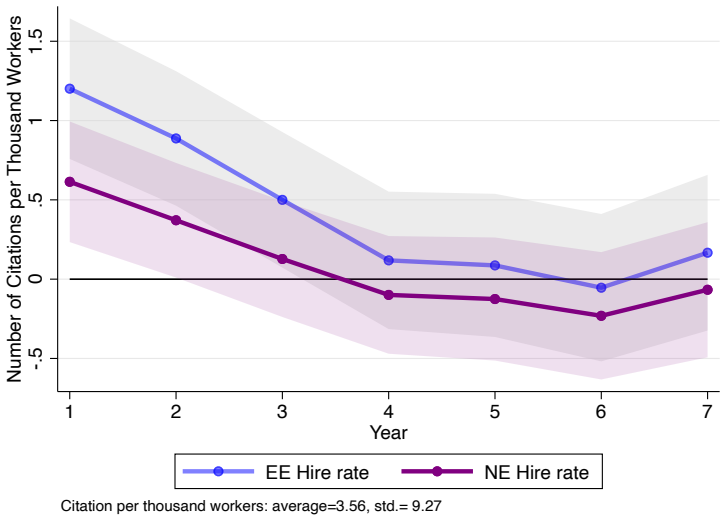


Figure A.9: Robustness: Local Projection of Turnover Rates on Citations

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.1. Shaded areas represent the 95% confidence interval of the estimates.

A.2 Other NC Changes

This appendix shows the effects of state-level institutional changes that increased the enforceability of NC contracts from Jeffers (2024). As predicted by Jeffers (2024), higher enforceability of NC contracts at the state level does not necessarily imply more binding NC contracts if workers prefer to work in sectors that do not require NC clauses. Indeed, Figure A.10 shows that the EE hire rates in MSAs of states with higher enforceability of NC contracts experience marginally higher, not lower, EE hire rates.

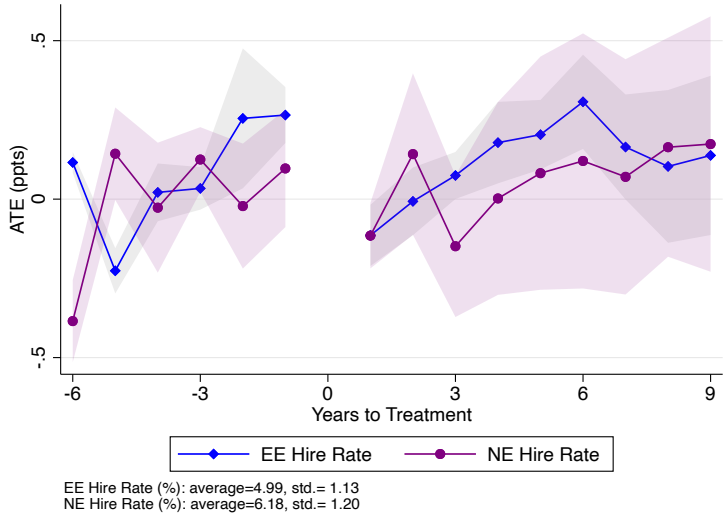


Figure A.10: Effect of Higher NC Enforceability on Gross Turnover

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.

Consistent with the results in Section 2.2, the number of patents in these states does not significantly increase (See Figure A.11). Additionally, citations per patent increase significantly four years after institutional changes. Although insignificant, citations per thousand workers marginally increase after the change. Similarly, the importance of local patents rises after court rulings that change the enforceability of patents.

In Figure A.14 response of labor productivity is mostly insignificant after treatments, and the point estimates are negative. This result is consistent with the higher

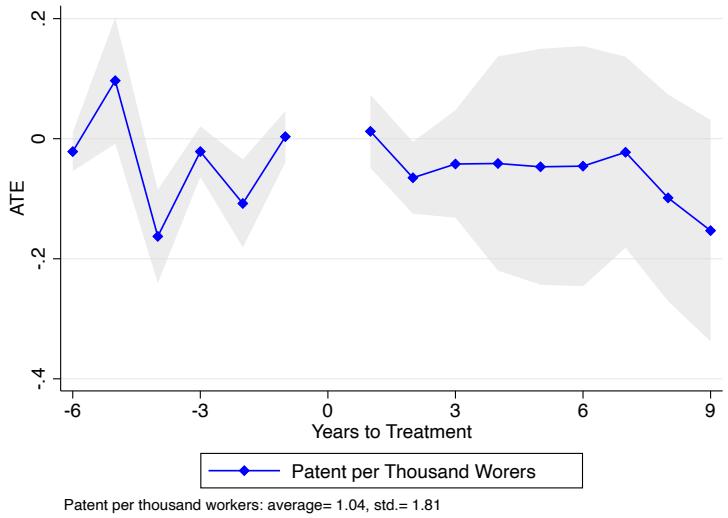


Figure A.11: Effect of Higher NC Enforceability on Patents

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.

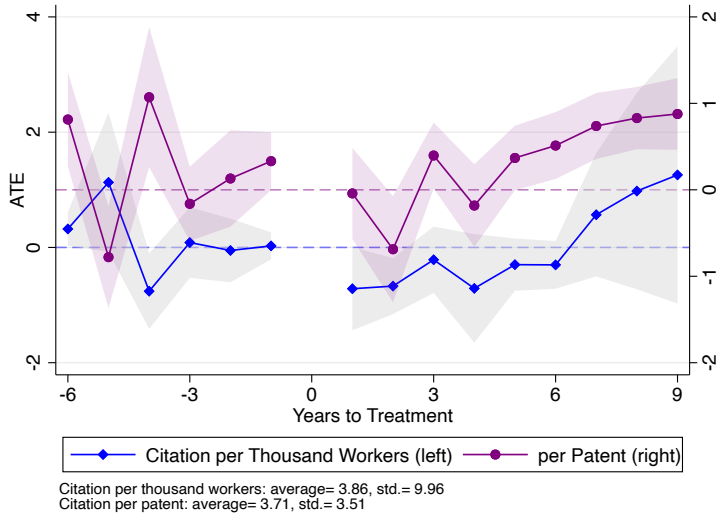


Figure A.12: Effect of Higher NC Enforceability on Citations

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.

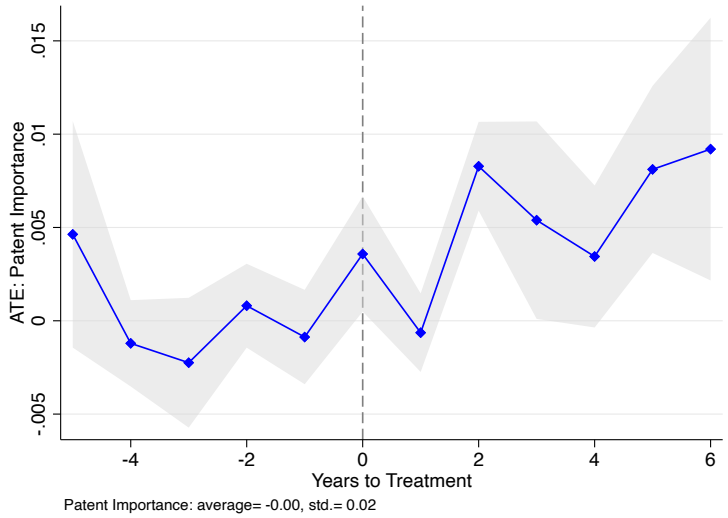


Figure A.13: Effect of Higher NC Enforceability on Patent Importance

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.

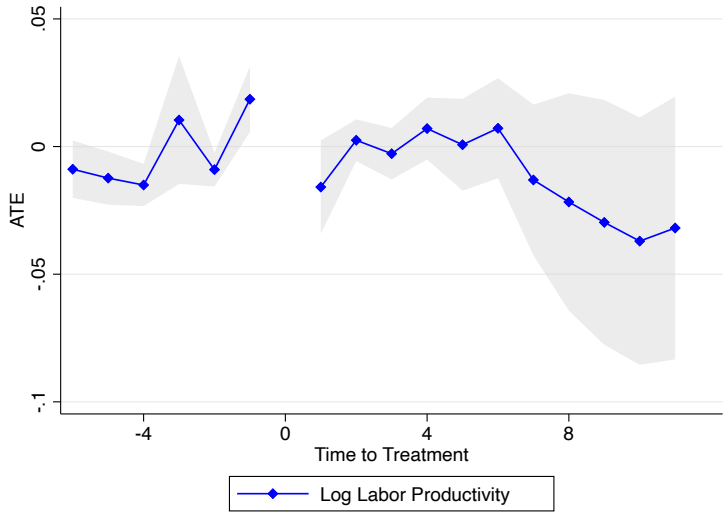


Figure A.14: Effect of Higher NC Enforceability on Labor Productivity

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.

enforceability of NC contracts, forcing workers to choose less productive and less restrictive jobs. This reallocation of workers may mitigate the growth effect of disruptive innovations.

A.3 Entrants vs. Incumbents

The MSA-level responses to the institutional changes of the NC agreement are from incumbents rather than entrants. First, all equations in Section 2.2 control for the job creation shares of entrants in BDS. Moreover, job creation share of entering firms in the BDS does not increase after the enforceability changes but somewhat decreases (See Figure A.15). Lastly, when incumbent patents are defined as patents granted to assignees who appear in the USPTO data more than two years before the grant year, the results on patents, citations, and importance remain almost the same in Figures A.16-A.18. The reason why the results stay quantitatively the same is because incumbents make most patents. Between 2000 and 2019, 91.5% of patents are granted to incumbents.

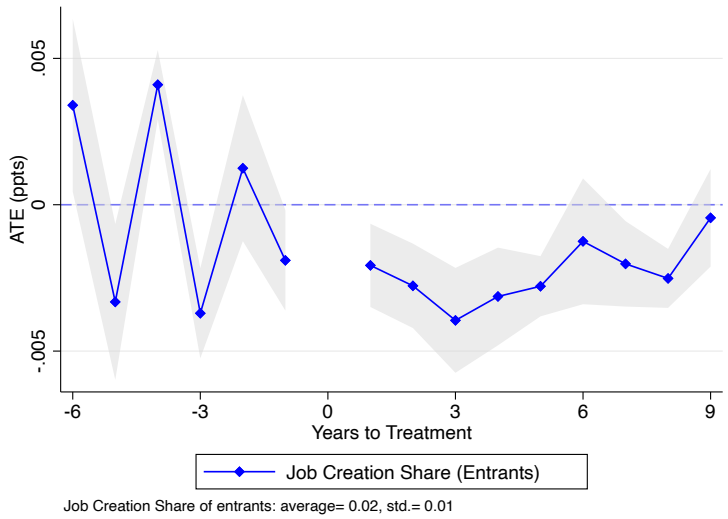


Figure A.15: Effect of Lower NC Enforceability on Job Creation of Entrants

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.

Figure A.19 shows the treatment effect estimates of different innovator age groups. Innovator age is defined by the difference between the first appearance of the assignee in the patent data and the year the patent is assigned. The result shows that the effect of NC enforceability changes is quantitatively stronger for old innovators, although the effect on young innovators is also significant with a smaller

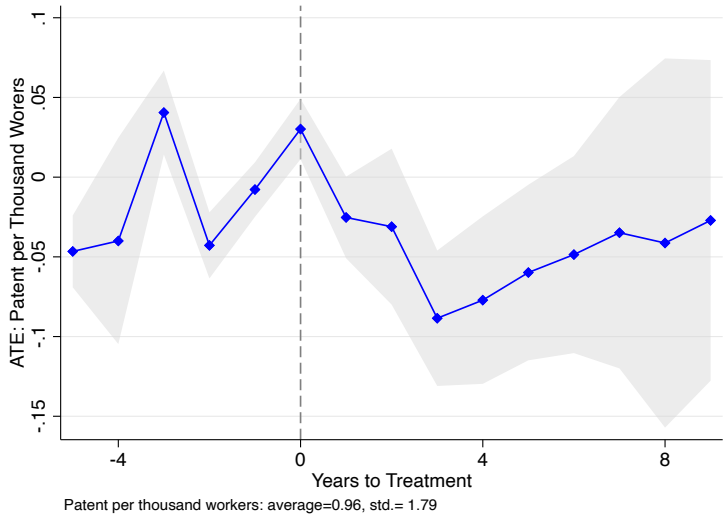


Figure A.16: Effect of Lower NC Enforceability on Incumbent Patents

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.

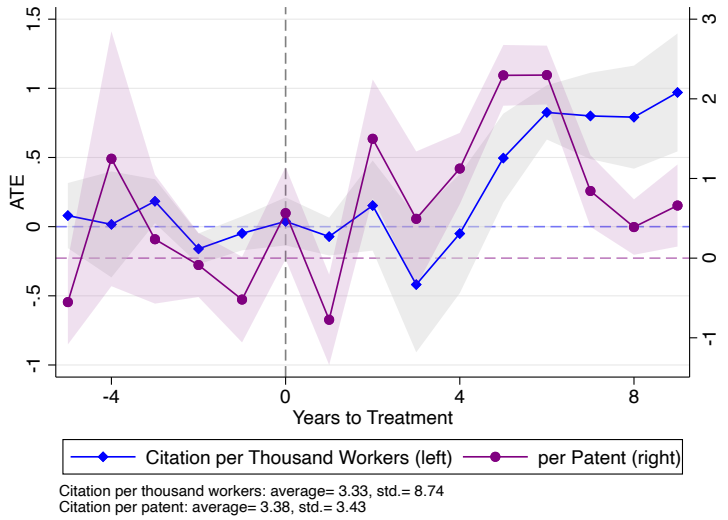


Figure A.17: Effect of Lower NC Enforceability on Incumbent Citations and Impacts

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.

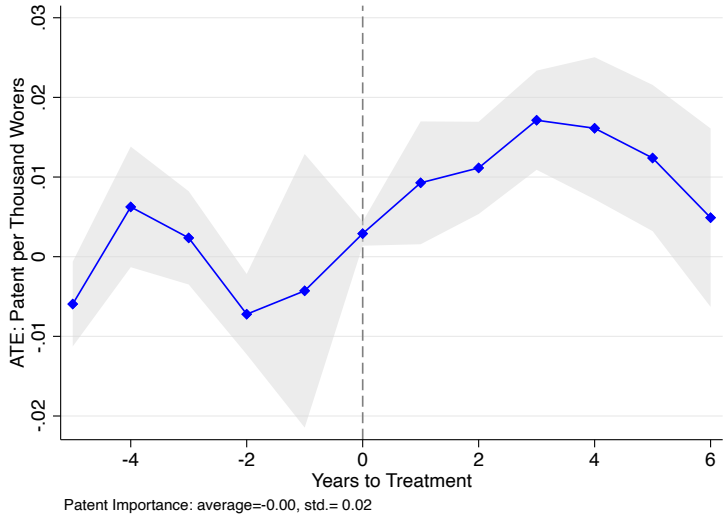


Figure A.18: Effect of Lower NC Enforceability on Incumbent Patent Importance

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.

magnitude. The effects on patent importance are largely consistent with the citation results in Figure A.20.

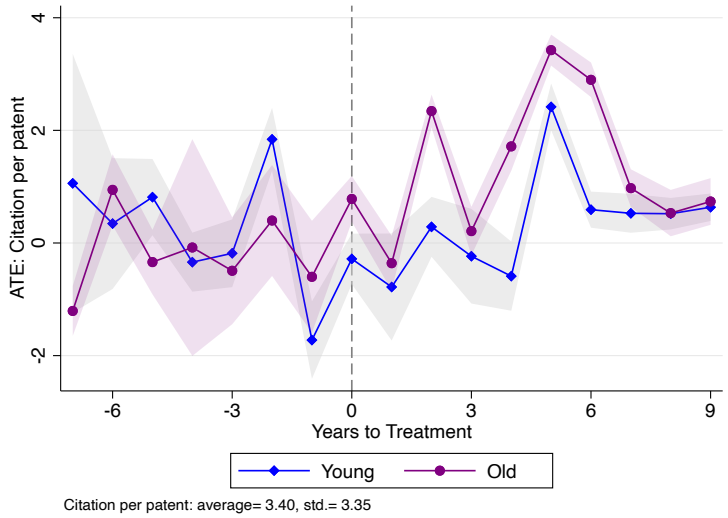


Figure A.19: Effect of Lower NC Enforceability on Citations per Patent by Age

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.

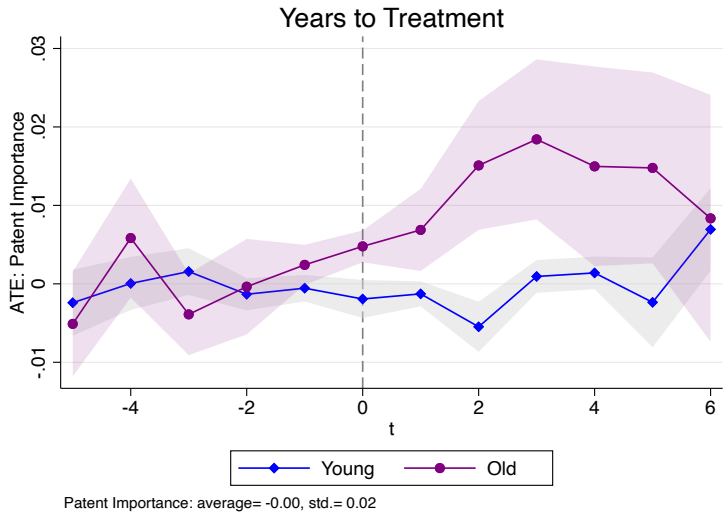


Figure A.20: Effect of Lower NC Enforceability on Patent Importance by Age

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.

A.4 Net vs. Gross

Gross worker turnover, not net job turnover across establishments, is not likely to drive the patent and citation results in Section 2.2. In Figure A.21, job creation and destruction results do not respond to the enforceability changes.

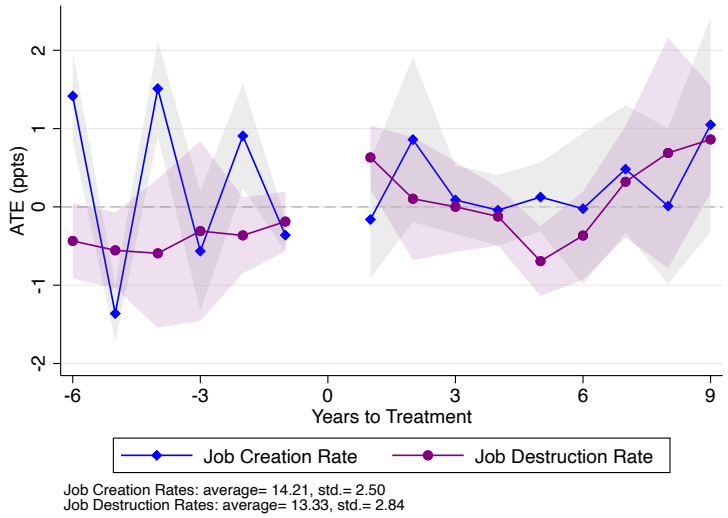


Figure A.21: Effect of Lower NC Enforceability on Net Labor Turnover

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.

A.5 Inventor Mobility

Existing literature often emphasizes the role of inventor mobility in promoting innovation. In this appendix, we show that inventor mobility is not likely to derive the citation result of NC enforceability because inventor mobility did not increase in response to the institutional changes in NC contracts.

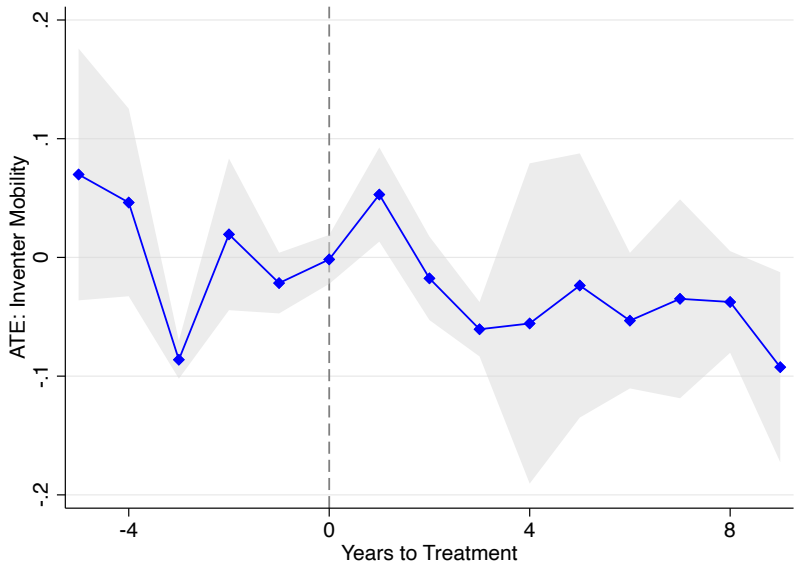


Figure A.22: Effect of Lower NC Enforceability on Inventor Mobility

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.

Figure A.22 shows the regression results. For inventors that appear in the patent application data in a given year and MSA, inventor mobility is defined as the share of inventors with multiple assignees in the year or that switched from an assignee to anther between current year and the year before. Inventor mobility does not change systematically after the changes in enforceability. If anything, inventor mobility somewhat decreases after the institutional changes.

B Model Appendix

B.1 Representative Household

The representative household maximizes the following lifetime utility after it gathers all earnings from wages and profits.

$$\max_{C_t, B_t} \int_0^\infty e^{-\rho t} \log C_t dt \quad \text{subject to}$$
$$rB_t + \int_0^1 \left(W_{i,t} + \Pi_{i,t}\right) di = C_t + \dot{B}_t$$

In the equation, C_t is the aggregate consumption and B_t is the real bond holding. $W_{i,t}$ is the wage of worker i at time t and is zero if the worker is nonemployed. $\Pi_{i,t}$ is the firm profit of the match associated with worker i, and r is the real interest rate. The Euler equation is given by

$$\frac{\dot{C}_t}{C_t} = r - \rho$$

In equilibrium $C_t = Y_t$ and $B_t = 0$. Thus, on the BGP, $\dot{C}_t/C_t = \dot{Y}_t/Y_t = \mu$. This implies that on the BGP $r = \rho + \mu$.

B.2 Wage Function

The wage function ($w_j(s,\omega,x)$) is a function of the match-level state variables, $j = s, l$, the skill-level of the worker, s the bargaining weight of the worker, ω, the share of skilled worker in the firm, and x, the productivity of the firm. The wage is characterized by the following equation.

$$
\begin{aligned}
(r-\mu)\left(sS_l(\omega,x)+U\right) &= w_l(s,\omega,x) - \left(\chi+\bar{\delta}\right) sS^l(\omega,x) \\
&+ p^E\left[\int \max\left\{\min\left\{(1-\gamma)S_l(\omega',x')+\gamma S_l(\omega,x),(1-\gamma)S_l(\omega,x)+\gamma S_l(\omega,x)\right\}-sS_l(\omega,x),0\right\} d\bar{O}(\omega',x')\right] \\
&+ \psi s\left(S_n(\omega',x')-S_l(\omega,x)\right) \\
&+ s\dot{\omega}(\omega,x)\partial_\omega S_l(\omega,x) \\
&+ s(g(\omega,x)-\mu x)\partial_x S_l(\omega,x) + s\frac{\sigma^2}{2}\partial_x S_l(\omega,x) \\
(r-\mu)\left(sS_n(\omega,x)+U\right) &= w_n(s,\omega,x) - \left(\chi+\bar{\delta}\right) sS_n(s,\omega,x) \\
&+ p^E\left[\int \max\left\{\min\left\{(1-\gamma)S_l(\omega',x')+\gamma S_n(\omega,x),(1-\gamma)S_n(\omega,x)+\gamma S_l(\omega,x)\right\}-sS_n(\omega,x),0\right\} d\bar{O}(\omega',x')\right] \\
&+ sd(g)\left(S_l(s,\omega,x)-S_n(s,\omega,x)\right) \\
&+ s\dot{\omega}(\omega,x)\partial_\omega S_n(\omega,x) \\
&+ s(g(\omega,x)-\mu x)\partial_x S_n(s,\omega,x) + s\frac{\sigma^2}{2}\partial_x S_n(s,\omega,x)
\end{aligned}
$$

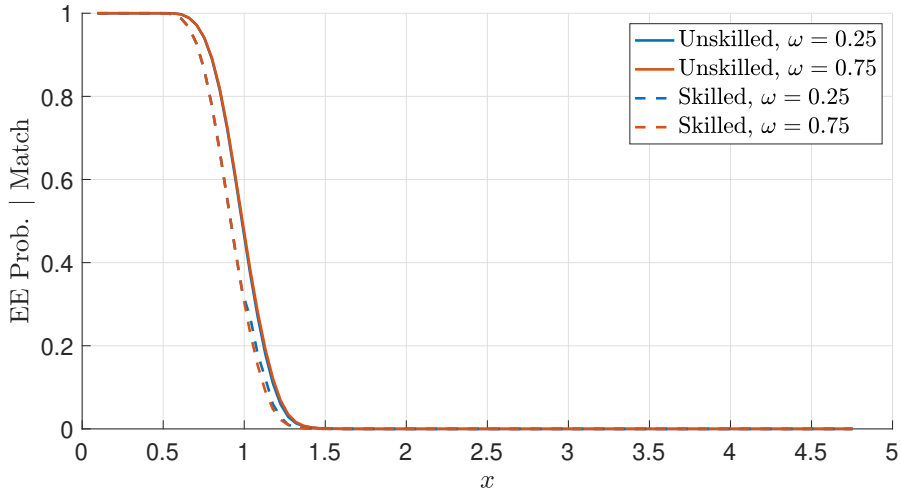
The left-hand side involves the worker surplus of the match, s fraction of the entire match surplus, added to the value of nonemployment. The right-hand side includes wage and expected returns to on-the-job search, up- or down-skilling, the changes in x and ω.

B.3 Quantitative Properties of the Model

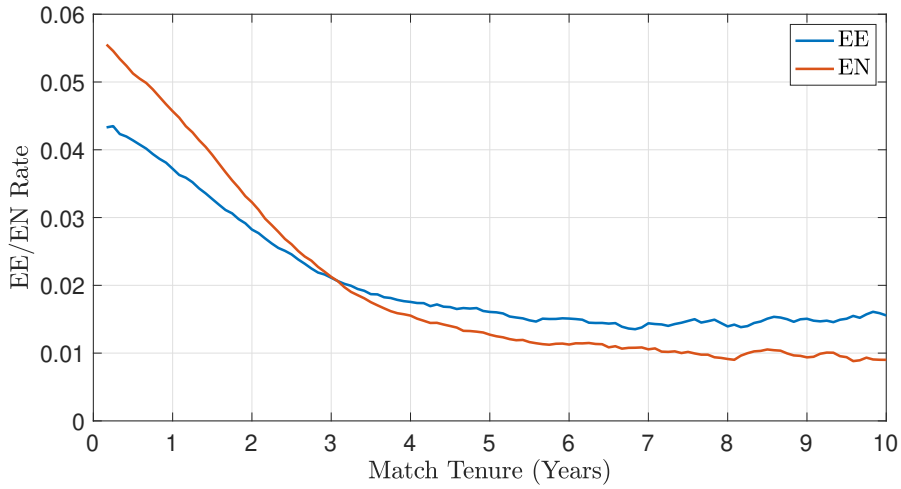
B.3.1 Baseline Economy

Figure B.1 shows the model-implied EE transition probability of unskilled and skilled workers over the relative productivity (x) and the skill intensity of the firm (ω), conditional on an on-the-job match. Skilled workers are less likely to move to a new employer than unskilled workers because worker skills are specific to the current employer. Also, workers in a firm with high productivity are less likely to move. Although not quantitatively significant, unskilled workers are more likely to move when they are working with a lower share of skilled workers. Staying with a lower share of skilled workers implies faster productivity growth but a lower probability of staying skilled in the firm with skill obsolescence after faster technology upgrades. Under the current version of calibration, the latter effect dominates, and the match surplus is lower for unskilled workers if ω is lower.

The lower panel of Figure B.1 shows the simulated profiles of EE and EN rates over the match tenure. Skill accumulation and continuous productivity growth over the match tenure increase the match surplus and decrease both EE and EN rates. Furthermore, the random EE and EN shocks are calibrated to be decreasing over the match tenure.



(a) x and ω



(b) Match Tenure

Figure B.1: Transition Rates over Match Characteristics

Notes: The transition rates include both random shocks and model-implied ones calculated by the on-the-job matching rates p^E multiplied by the probability of accepting an offer. The transition rates are calculated from a simulated panel of 10,000 workers over 50 years of burn-in and 20 years of simulation. The rates in the graph are the moving averages of simulated rates over 20 months.

Figure B.2 shows the optimal technology upgrade rates, $g(\omega, x)$, over skill intensity, ω, and relative productivity, x. Technology upgrade rates tend to increase when the density of workers is high and decrease when the density is low. This is because the returns to technology upgrades come from direct increases in the productivity

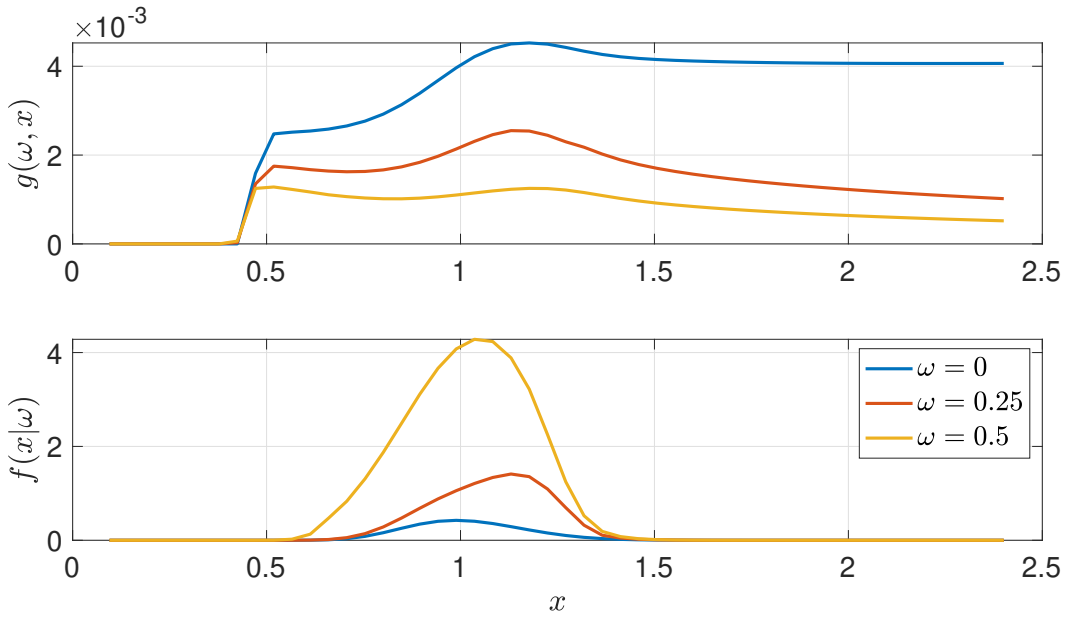


Figure B.2: Technology Upgrade Rates over Productivity and Skill Intensity

Notes: This graph shows technology upgrade rates and the distribution of productivity (x) conditional on selected values of skill intensity (ω).

of existing matches and advantages in future job poaching. High productivity implies that current matches are expected to survive longer and that future hires are more likely. This marginal return is particularly large if more workers have a match surplus similar to the surplus the firm offers.

Compared across different values of ω, technology upgrade rates tend to be higher for lower ω conditional on survival. This comes from the down-skilling cost of technology upgrades. However, because matches with low ω are less likely to survive, matches with high ω survive and have positive $g(\omega, x)$ when x is low and matches with low ω exit the market.

Figure B.3 depicts the average skill intensity, technology upgrade rates, relative productivity, and measured productivity over firm age. In the first panel, firm age is positively correlated with ω. Entrants enter only with unskilled workers and accumulate worker skills over time. More worker skills increase the down-skilling cost of technology upgrades, making the age profile of technology upgrade rates downward sloping.

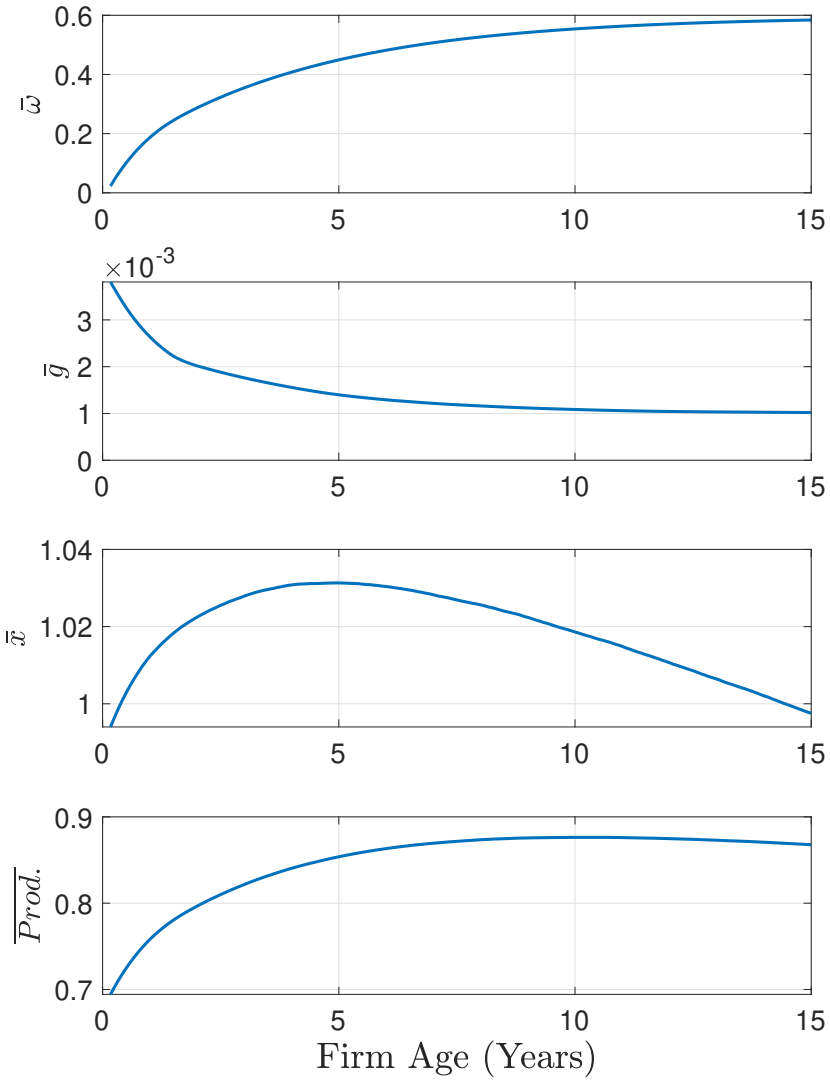


Figure B.3: Firm Characteristics over Firm Age

Notes: This graph shows the average skill intensity, $\bar{\omega}$, technology upgrade rates, $\bar{g}$, productivity, $\bar{x}$, and observed productivity, $\overline{Prod.}$, over firm age conditional on survival. The observed productivity of a firm with ω, x reflects the skill intensity, and thus $Prod. = x(\omega + \nu(1-\omega)$. The series are calculated with a simulated panel of 10,000 firms.

Older firms tend to be more productive because entrant workers enter with lower productivity than incumbent firms. Over time, though, entrants upgrade their technologies with higher rates and become more productive conditional on survival. The measured productivity, $x(\omega + \nu(1-\omega))$, increases over time more rapidly than the relative productivity because worker skills are accumulated over time.