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# Where Have All the "Creative Talents" Gone? Employment Dynamics of US Inventors

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# Where Have All the "Creative Talents" Gone? Employment Dynamics of US Inventors*

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**Abstract**

How are inventors allocated in the US economy and does that allocation affect innovative capacity? To answer these questions, we first build a model of creative destruction where an inventor with a new idea has the possibility to work for an entrant or incumbent firm. If the inventor works for the entrant the innovation is implemented and the entrant displaces the incumbent firm. Strategic considerations encourage the incumbent to hire the inventor, offering higher wages, and then not implement the inventor's idea. To test this prediction, we combine data on the employment history of over 760 thousand U.S. inventors with information on jobs from the Longitudinal Employer-Household Dynamics (LEHD) Program at the U.S. Census Bureau. Our results show that (i) inventors are increasingly concentrated in large incumbents, less likely to work for young firms, and less likely to become entrepreneurs, and (ii) when an inventor is hired by an incumbent, compared to a young firm, their earnings increases by 12.6 percent and their innovative output declines by 6 to 11 percent. We also show that these patterns are robust and not driven by life cycle effects or occupational composition effects.

**JEL Codes:** O3, O4
**Keywords:** Inventors, innovation, R&D, firms, dynamism, reallocation

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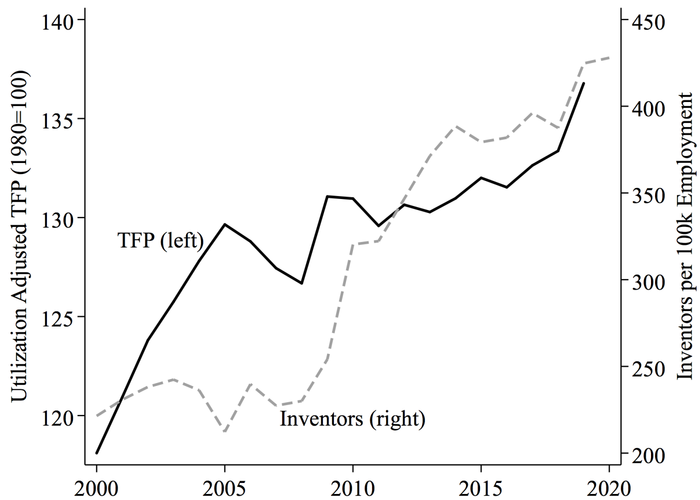
# 1 Introduction

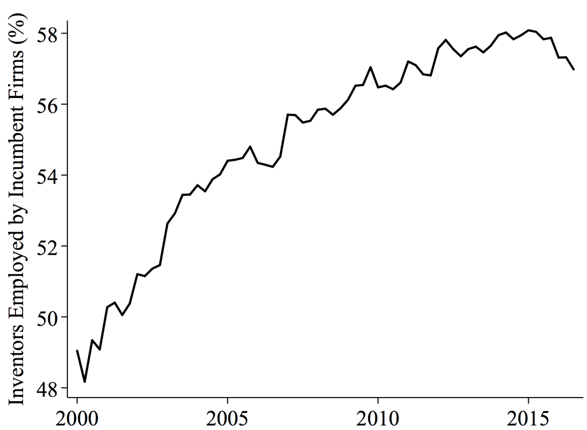
Societies allocate a significant fraction of their resources into R&D to generate economic growth through technological progress. Therefore many analyses of economic growth focus on a country's innovation inputs, either aggregate R&D spending as a share of GDP or the share of inventors in its workforce (e.g., Jones, 1995). In this paper we argue that it is not only the level of innovation inputs that matters for growth, but also the allocation of those investments. As Arrow (1962) has pointed out, incumbent monopolists suffer from the replacement effect, and may shift their efforts away from producing radical breakthroughs to defensive activities (Akcigit, Baslandze, and Lotti, 2022). As such, the social impact of an inventor may depend on the type of firm they work for.

Standard models of endogenous growth (Romer, 1990; Aghion and Howitt, 1992; Grossman and Helpman, 1991; Klette and Kortum, 2004; Akcigit, 2017) predict that economic growth should be proportional to the share of the workforce employed in the research sector. Figure 1 presents seemingly contradictory evidence on this point. Panel A shows utilization-adjusted total factor productivity (TFP) in the U.S. since 2000 (left axis) and a per capita measure of inventor labor (right axis). While there was a visible acceleration between 2000-2005, after 2005 we see a marked slow-down in TFP growth even as the share of inventors nearly doubled over the same period. In other words, innovation inputs are rising as technical progress slows. Equally striking is the shifting allocation of inventors across different-sized firms. Not only did the US economy allocate a bigger share of its employment into innovation, but its composition has also shifted towards the largest players in the economy. Panel B shows that the share of inventors employed by large, incumbent firms rose from 48 percent 2000 to about 57 percent in 2016. Akcigit and Goldschlag (2022) show a complementary fall in the share of inventors employed by young firms. The changing composition might be especially concerning if inventors at incumbents produce lower quality innovations, which appears to be the case in Panel C. Panel C shows that inventors at incumbents produce lower quality innovations, with fewer citations, fewer citations per application, fewer independent claims, and more self citations (e.g. more incremental). These striking figures give rise to an important question: How are inventors allocated in the U.S. economy and does that allocation affect innovative capacity?

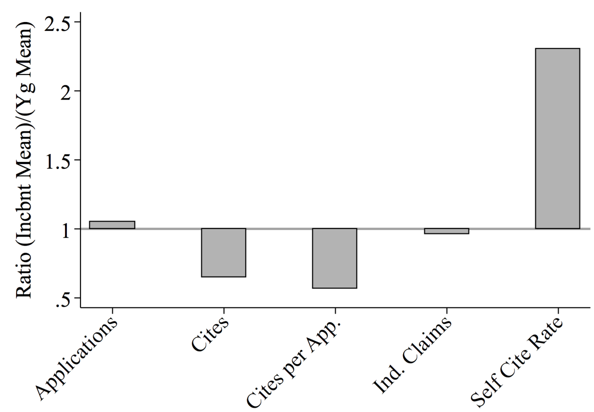
# Figure 1: Inventor Employment Dynamics




(a) TFP & Inventors




(b) Inventors at Incumbent Firms




(c) Inventor Productivity, Young & Incumbent Firms

Source: Fernald and Jones (2014), Inventor Employment History, BDS, author's calculations
Notes: Panel A shows utilization adjusted TFP (left axis) indexted to 1980 and the count of unique inventors per 100 thousand employment (right axis). Panel B shows the percent of inventors employed at incumbent firms, which are defined as those $>$ 20 years old and $>$ 1000 employees. Panel C shows the ratio of inventive productivity measures for inventors at incumbent firms relative to young firms, which are defined as firms aged $\leq$ 5 years old. Applications is the count of applications that are eventually granted, cites is the count of citations received, cites per app. is the count of citations divided by the count of applications, ind. claims is the count of independent claims per granted application (Marco, Sarnoff, and deGrazia, 2019), and the self cite rate is the share of citations made to patents with the same assignee.

To answer these questions, we first build a tractable creative destruction model that develops intuitions about the strategic incentives incumbent firms face and how they might use the innovation input market to limit competition. In particular, we allow for an incumbent to hire an inventor who otherwise would create an innovation inside an entrant firm and displace the incumbent. Since the incumbent monopolist already has a product that it sells to the market, without strategic considerations, it does not have any incentive to produce an innovation that would replace the already successful product that it sells. However, strategic considerations make the incumbent firm hire the inventor, offering higher wages, and under certain circumstances, choosing not to implement the inventor's idea. The model implies that inventors hired by incumbent firms will earn more but produce fewer innovations compared to inventors hired by entrants.

Our empirical analysis tests the models implications using data on the employment history of over 760 thousand U.S. inventors. We combine data on individual inventors of patents granted by the U.S. Patent and Trademark Office with information on jobs from the Longitudinal Employer-Household Dynamics (LEHD) Program at the U.S. Census Bureau. LEHD contains quarterly employee-employer relationships drawn from administrative state-level unemployment insurance records.

Our results show that (i) inventors are increasingly concentrated in large incumbents, less likely to work for young firms, and less likely to become entrepreneurs, (ii) in the cross section, inventors working for incumbent firms earn more and produce less impactful innovations than inventors at young firms, and (iii) when an inventor is hired by an incumbent, compared to a young firm, their earnings increases by 12.6 percent and their innovative output declines by 6 to 11 percent. We also show that these patterns are robust and not driven by promotion to managerial positions in large incumbents, for instance.

## Related Literature

Our paper is related to a number of literatures on firms, inventors, and innovation. First, a growing literature has documented that factor reallocation among competing firms is an important source of productivity growth (e.g., Foster, Haltiwanger, and Krizan, 2001, 2006; Acemoglu, Akcigit, Alp, Bloom, and Kerr, 2018). Firms that experience a positive shock, such as the arrival of a new innovation, expand, increasing aggregate productivity. Responsiveness to shocks, however, may depend on market conditions. Indeed, in recent decades the dispersion of firm-level shocks has risen as firm responsiveness to those shocks as weakened Decker, Haltiwanger, Jarmin, and Miranda (2020). Moreover, models of reallocation typically assume that reallocation, if it occurs, is productivity enhancing. Our work shows that the reallocation of inventor labor may reduce productivity growth when it is the result of strategic behavior of incumbents. We also show how those strategic channels dampen reallocation and limit the replacement of incumbent firms.

Second, a large literature has debated the relative contribution of small, young, and large firms to innovation.[1] Akcigit and Kerr (2018), for example, show that lower quality innovations scale more quickly with firm size. Complementary evidence stresses the importance of the strategic behavior of incumbents. Argente, Baslandze, Hanley, and Moreira (2020) show that not only are the patents of large firms less innovative, but they are often used to deter competition. In the extreme, incumbents may acquire entrants to avoid competition and stifle innovation (Cunningham, Ederer, and Ma, 2021). We contribute to this literature by demonstrating how differences in innovation incentives across firm types, and the strategic behavior of incumbents, affects how innovation inputs are utilized. Our theoretical framework and empirical evidence is highly complimentary to the work of Cunningham, Ederer, and Ma (2021), who demonstrate the "killer acquisiton" phenomenon both theoretically and empirically. Where they focus on firm-level poaching, our focus is on inventors, employment dynamics, and earnings.

Third, a large literature has documented that capital or labor misallocation can lead to sizable productivity losses (e.g., Hopenhayn and Rogerson, 1993; Hsieh and Klenow, 2009; Hsieh, Hurst, Jones, and Klenow, 2019). In these papers, misallocation is discussed in terms of static, cross sectional misallocation of factor inputs. From a dynamic perspective focused on the supply of inventors, a related literature finds misallocation of talent due to financial frictions, socioeconomic background, and R&D and education policies.[2] Our findings speak to both of these literatures by showing how the effects of misallocation in who becomes an inventor are mediated by how inventors are utilized by firms.

Finally, various recent papers have argued that the U.S. economy has exhibited declining business dynamism. Decker, Haltiwanger, Jarmin, and Miranda (2014) show that the entry rate of firms and establishments has declined over the past several decades. Karabarbounis and Neiman (2014) document the decline in labor share during the same period, while Autor, Dorn, Katz, Patterson, and Van Reenen (2020) argue that market concentration has increased and this increase has been strongly correlated with the de-

[1]See Akcigit and Kerr (2018) for an overview of this literature.

[2]See Celik (2022), Aghion, Akcigit, Hyytinen, and Toivanen (2017), Bell, Chetty, Jaravel, Petkova, and Van Reenen (2019), Akcigit, Grigsby, and Nicholas (2017), Akcigit, Pearce, and Prato (2020).

cline in labor share at the sectoral level. Akcigit and Ates (2022) provide a quantitative investigation and argue that the decline in knowledge diffusion from market leaders to followers could be an important driver of declining business dynamism. In this paper, we show the rising in concentration of inventors within large incumbents, combined with the strategic hiring of inventors, could lead to a decline in overall dynamism in the U.S. economy.

# 2 Model

To motivate and provide a framework for interpreting our empirical analyses, we present a simple model in which incumbents face displacement by innovating entrants. Entrants employ an inventor whose idea can be implemented, at a cost, increasing product quality and capturing the market. Under certain assumptions, incumbents will have an incentive to strategically hire, or poach, the entrant's inventor and not implement the quality-improving innovation. This occurs if implementing the innovation is sufficiently costly relative to the size of the innovative step, making it more profitable for the incumbent to share monopoly rents with the inventor, via higher wages, and avoid displacement by the entrant. In this environment, we expect to see higher wages and less innovative output associated with inventors hired by incumbents relative to inventors hired by entrants.

### Production Environment

Individuals consume a unique final good $Y_t$, which is also used for R&D as discussed below. A measure $L$ units of labor is supplied inelastically by the household. The final good at time $t$ is produced by labor and a continuum of intermediate goods $j \in [0,1]$ with the production technology as follows,

$$Y_t = \frac{L_t^{\beta}}{1-\beta} \int_0^1 q_{jt}^{\beta} k_{jt}^{1-\beta} djt. \tag{1}$$

Henceforth, we will omit the time subscript where doing so does not cause confusion. Producing each unit of $k_j$ has a marginal cost of $\eta > 0$ in terms of the final good. Final good is produced in a perfectly competitive market whereas intermediate goods will be produced by monopolists. Maximization behavior of the final goods producer yields demand for each intermediate good as follows,

$$p_j = L^{\beta} q_j^{\beta} k_j^{-\beta}. \tag{2}$$

This implies that the monopoly profit maximization in sector $j$ can be expressed as follows,

$$\pi_j = \max_{k_j, p_j} \{p_j k_j - \eta k_j\} \quad \textit{Subject to Equation (2)}$$

Hence the equilibrium would be,

$$k_j^* = \left[\frac{1-\beta}{\eta}\right]^{\frac{1}{\beta}} Lq_j \text{ and } p_j^* = \frac{\eta}{1-\beta}.$$

We normalize $\eta = 1 - \beta$ and $L = 1$. Then the equilibrium profit becomes,

$$\pi_j^* = \beta q_j.$$

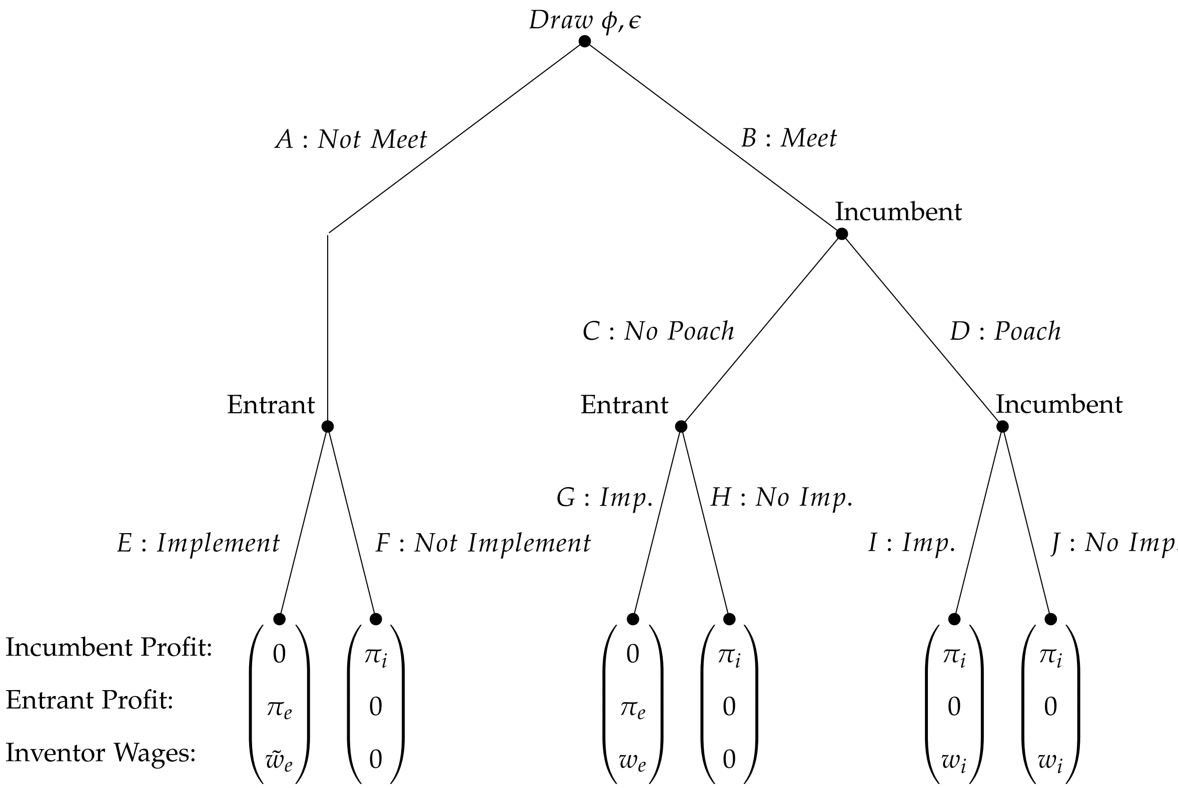
## Innovation Environment

Each monopolist, operating in a given sector, lives for only one period and passes the firm to their offspring. We assume incumbent monopolists maximize their one-period return.[3] Each sector has one potential entrant that employs an inventor. Each inventor has an idea that can be implemented at some cost. In some cases, the incumbent is presented with the opportunity to poach the inventor. Search and matching frictions limit how often the incumbent is able to hire the entrant's inventor. Tightness of the inventor labor market for each sector is fixed, as there is only one inventor, so the incumbent's ability to poach resolves to a simple probability of meeting the inventor. If the entrant implements the inventor's idea, product quality increases and the entrant displaces the incumbent (i.e. creative destruction occurs). When displacing the incumbent, the entrant receives post-innovation profits with upgraded quality net of implementation costs and the incumbent exits. Alternatively, if the incumbent poaches the inventor, the incumbent must then choose whether to implement the idea or not. If the value of monopoly rents associated with the previous technology dominates the value of implementing the new idea, net of implementation costs, the incumbent will act strategically, poaching the inventor, and not implement the innovation.

More formally, the sequence of events can be described by the game-tree presented in Figure 2, which we describe in greater detail below.

[3] This relatively simple environment allows us to capture the salient strategic interactions without significant loss of generality.

Figure 2: Innovation Environment Game Tree




Notes: $\phi$ is the cost of implementing the inventor's idea. $\epsilon$ is the probability the incumbent meets the entrant's inventor in the labor market. $\pi_i$ and $\pi_e$ are the incumbent and entrant profits, respectively. $\tilde{w}_e$ is inventor wages in the case of no meeting with the incumbent. $w_e$ and $w_i$ are inventor wages at the entrant and incumbent respectively.

**Entrant Innovation.** The cost of implementing the inventor's idea is $\phi > 0$. When the inventor's idea is implemented, quality increases from $q_j$ to $(1+\lambda)q_j$ and the entrant displaces the incumbent. If this occurs, the entrant gets post-innovation profits, with upgraded quality, net of implementation costs, $\beta q_j(1+\lambda) - \phi$ and the incumbent exits and receives zero. We assume that the implementation cost lies between the incremental value of the innovation ($\beta q_j \lambda$) and the post innovation revenues $\beta q_j(1+\lambda)$, as in Inequality 3.

$$\beta q_j(1+\lambda) > \phi > \beta q_j \lambda \tag{3}$$

The remaining possibilities are that $\phi > \beta q_j(1+\lambda) > \beta q_j \lambda$ or $\beta q_j(1+\lambda) > \beta q_j \lambda > \phi$. The former corresponds to no ideas being implemented because they are too costly for both the entrant and incumbent. In the latter case, all ideas will be implemented without strategic considerations because it is always profitable to do so. With Inequality 3, we focus on the most interesting and empirically relevant case.

With probability $\epsilon \in (0,1)$ the incumbent meets the entrant's inventor and has the opportunity to poach. If no meeting occurs, the inventor remains at the entrant and bargains over wages with no outside options. We will solve the no meeting and meeting cases in turn.

**Incumbent does not meet inventor (branch $A$).** With probability $1-\epsilon$ there is no meeting between the incumbent and inventor. In this case the inventor remains at the entrant. Since the cost of implementation is less than the entrant's post-entry return ($\beta q_j(1+\lambda) > \phi$), the entrant will implement the idea and displace the incumbent, following branch $AE$ of Figure 2. We assume Nash bargaining between the entrant and inventor, with the entrant's bargaining power represented by $\gamma \in (0,1)$. Since the entrant and inventor's outside options are zero (branch $AE$ vs $AF$), the Nash bargaining can be expressed as the following maximization problem.

$$\max_{\tilde{w}_e}(\pi_e - \tilde{w}_e)^{\gamma}\tilde{w}_e^{1-\gamma}$$

The inventor's wages in the case of no meeting with the incumbent is $\tilde{w}_e$ and the entrant's profit is $\pi_e$. Through first-order conditions, we find that the inventor's equilibrium wages are a fraction of the entrant's profits equal to their bargaining power $(1-\gamma)$,

$$\tilde{w}_e^* = (1-\gamma)\pi_e$$

**Incumbent meets inventor (branch $B$).** If the incumbent meets the inventor it must choose whether or not to poach the inventor. Not poaching the inventor resolves equivalently to not meeting the inventor, described above ($A$ and $BC$ of Figure 2).

The threat of entry creates interesting strategic considerations. Conditional on having poached the inventor, the incumbent's innovation decision (branch $BD$) takes the following form:

$$\max\left\{\underbrace{0}_{Value\ of\ not\ implementing},\ \underbrace{\beta q_j\lambda - \phi}_{Value\ of\ implementing}\right\}$$

The value of not implementing the idea is profits from the existing technology ($\beta q_j > 0$). The value of implementing the idea is post innovation profits net of implementation costs and net of profits associated with the existing technology. Given the assumptions on $\phi$ in Inequality 3, the value of innovation will be negative, and thus the incumbent chooses not to implement the inventor's idea, following *BDJ* of Figure 2.

In order to poach the inventor the incumbent must offer wages sufficient to induce the inventor to switch. As with in the no meeting case, we assume that wages are determined through Nash bargaining with the firm's bargaining power being $\gamma$. When bargaining, the inventor's outside option is to work for the other firm in the sector. Conditional on meeting the inventor, the bargaining between the incumbent and the inventor takes the following form:

$$\max_{w_i}(\pi_i - w_i)^\gamma (w_i - w_e)^{1-\gamma}$$

Subscripts $i$ and $e$ designate incumbent and entrant values respectively. The incumbent's surplus is profit from the existing technology ($\pi_i = \beta q_j$) net of inventor wages paid by the incumbent ($w_i$). The inventor's bargaining surplus is the wage at the incumbent ($w_i$) net of the outside option of wages at the entrant ($w_e$). A similar, symmetric bargaining problem occurs between the entrant and inventor:

$$\max_{w_e}(\pi_e - w_e)^\gamma (w_e - w_i)^{1-\gamma}$$

Now we conjecture, and verify, that $w_i^* > w_e^*$. If incumbent wages are greater than entrant wages, the entrant bargaining problem is maximized when $w_e^* = \pi_e$. Intuitively, if the incumbent offers higher wages, the inventor can always do better by working for the incumbent. Since the entrant's outside option is not entering and receiving zero, the entrant is willing to set the inventor's wages equal to its profit. Solving the incumbent bargaining problem, given entrant wages are equal to entrant profit, the inventor's equilibrium wages at the incumbent can be written as follows:

$$w_i^* = (1-\gamma)\pi_i + \gamma\pi_e$$

Our assumption in Inequality 3 implies that $\pi_i > \pi_e$ since $\pi_i = \beta q_j$ and $\pi_e = \beta q_j + (\beta q_j \lambda - \phi)$ and $\phi > \beta q_j \lambda$. As $\pi_i > \pi_e$ and $w_i^* > w_e^*$, our conjecture is verified. Note that since entrant wages are equal to entrant profits the model also captures the dynamics of inventor entrepreneurship. If the inventor owns the entrant, rather than being employed by it, the inventor's return remains equal to post-entry profits and strategic interaction with the incumbent remains unchanged.

The model yields the following predictions. When an incumbent producing using an older technology has a cost advantage over an innovative entrant, the model predicts:

**Prediction 1:** The incumbent will poach the inventor and not implement the inventor's idea, reducing aggregate innovative activity.

**Prediction 2:** The incumbent will poach inventor entrepreneurs and not implement the inventor's idea, reducing aggregate innovative activity.

**Prediction 3:** The incumbent will offer higher wages than the entrant in order to poach the inventor from the entrant.

# 3 Empirical Evidence

This section describes the empirical results on inventor productivity and firm characteristics.

## Data

**Patent Data.** We use data from the U.S. Patent and Trademark Office on patents granted between 2000 to 2019. We use this data to identify inventors of granted patents and characterize their inventive output each period. Name and location information from patent documents are used in the matching procedures described below. Those matching algorithms also rely on the name and location of patent assignees, the firm to which the patent was associated with at the time of grant. Information on the date of each patent grant, and the associated application was submitted, are used to create counts of patents associated with each inventor each period. Additionally, we use data on citations to citation weight patents counts and count self citations. We also utilize claim counts, as well as the categorization of claims as either independent or dependent, developed by Marco, Sarnoff, and deGrazia (2019).

**Data Linking.** We use linkages between inventor records (patent, inventor sequence combinations) and the Census Bureau's disambiguated, anonymized, person-level identifiers, known as Protected Identification Keys (PIKs), developed by Akcigit and Goldschlag (2022). The match proceeds in several steps. First, the Person Validation System (PVS) is used to match inventor name and location information to PIKs (Wagner and Lane, 2014). The PVS typically relies on detailed personally identifiable information such as date of birth, street address, and/or social security number. Since the patent data contains only name, city, and state, the PVS system generates a large number of false positives. To address this, we rely on the the simultaneous consideration of inventor-PIK and assignee-firm linkages as described in Graham, Grim, Islam, Marco, and Miranda

(2018) and Dreisigmeyer, Goldschlag, Krylova, Ouyang, and Perlman (2018). We augment those matches with unique PVS matches and additional inventor records captured by the disambiguated inventor identifiers in the PatentsView patent database.

Ultimately, we observe the employment histories of approximately 760 thousand inventors associated with 3.6 million patents granted between 2000 and 2016.

**Administrative and Survey Data.** Our frame of inventor jobs is developed using data from the LEHD Program at the U.S. Census Bureau. LEHD contains quarterly job-level observations drawn from administrative state-level unemployment insurance records. Not all states are covered by these data and those that are covered are not observed in every year. We restrict to 45 states with employment data starting in 2004 or earlier. Our job-level panel includes only dominant (highest earnings), beginning-of-quarter jobs from 2000Q1 to 2016Q3.[4] Our final sample contains nearly 35 million quarterly job observations.

We augment LEHD employer information with firm characteristics including firm size and firm age from the Longitudinal Business Database (LBD) (Haltiwanger, Hyatt, McEntarfer, Sousa, and Tibbets, 2014). In addition to firm age and firm size, we also use linkages between the LEHD and LBD to identify entrepreneurs. Finally, we collect information on occupation from the American Community Survey (ACS). Despite being relatively rare—the ACS sample ranges from 800 thousand to 3.5 million housing units during our sample period—we are able to attach occupation information to over 100 thousand of our inventor-job observations.

## Measures

**Inventive Productivity.** Once inventor records are disambiguated and linked to PIKs, we are able to assign time-varying inventive productivity measures drawn from patent data. We count the number of granted patent applications ($Apps$) and applications weighted by the number of citations received in the first five years after the patent was granted ($Cites$). Windowing citation counts in this way limits truncation effects due to older patents having more time to accrue citations. We also compute the number of citations received per application in the period ($Cites\ Per\ App$). We differentiate between citations made and citations received, identifying self-citations as those where the citing and cited patent have the same assignee. We use the count of citations made and self citations

[4] A beginning-of-quarter job is defined as a job for which the individual has positive earnings in both $t$ and $t-1$. A dominant beginning-of-quarter job is the highest earning beginning-of-quarter job for the individual within a given quarter. Some states enter the data after 2000Q1.

made to compute the share of self citations ($Self\ Cite\ Rate$). Patents that primarily cite other patents owned by the same firm are more incremental in nature (Akcigit and Kerr, 2018). Finally, we measure the scope of patents by computing the share of claims that are classified as independent ($Independent\ Claims$) using data developed by Marco, Sarnoff, and deGrazia (2019).

**Employment Outcomes.** For each quarter in our Inventor Employment History database we measure the natural log of real full-quarter earnings ($ln(Earnings)$).[5] Hire and separation events are identified using the sequence of employers observed in an individual's employment history.[6] Following Choi, Goldschlag, Haltiwanger, and Kim (2021), we identify entrepreneurs as individuals that receives earnings from a startup "on day one" and are among the top earning workers at the firm in the first year.[7]

To better approximate the intuitions of the model, we classify employers based on size and age as either a young or incumbent firm. Young firms are those less than age six. Incumbents are older larger firms that are at least 21 years old and have at least 1,000 employees. This dichotomy sharpens the contrast in the types of firms that employ inventors.

## Results

In our Inventor Employment History database roughly 12 percent of inventors are female, 27 percent were born outside of the US, and approximately 9 percent are observed starting at least one business during our sample period. Over 60 percent of the inventor-quarter observations are of inventors aged 36 to 55, making our inventor sample older, on average, than the US workforce. In 2010, approximately 46 percent of the US labor force was between the ages of 35 and 54.[8] Approximately 55 percent of inventor jobs are at incumbent firms while about 10 percent are at young firms. Comparing this to data from the Census Bureau's Business Dynamics Statistics, approximately 38 percent of all employment during this period was associated with incumbent firms and 12 percent in young firms.[9] The hire and separation rates we observe for inventors are about 4.6

[5]Full quarter earnings is only observed when a job has positive earnings in both the previous and subsequent quarters. This reduces the likelihood that an earnings measure represents only partial quarter employment. Earnings is normalized to 2012q1 dollars and demeaned within 6-digit NAICS and quarter.

[6]Stable hire and separations are defined analogously to those measured in the Quarterly Workforce Indicators (QWI).

[7]Entrepreneurship outcomes are only available in our data through 2015.

[8]See the Bureau of Labor Statistics Current Population Survey Employment status of the civilian noninstitutional population by age, sex, and race tables for details https://www.bls.gov/cps/aa2010/aat3.txt.

[9]See the Business Dynamics Statistics tables for details https://www.census.gov/data/datasets/time-series/econ/bds/bds-datasets.html.

percent and 4.4 percent, respectively.[10]

We find interesting time series patterns for several of our employment dynamics measures. As shown in Figure 1, the share of inventors employed by incumbents rose by 17%, or 8 percentage points, from 48.9 percent in 2000 to 57.3 percent in 2016. Also, as shown by Akcigit and Goldschlag (2022), hire and separation rates for inventors are declining over this period. The hire and separation rates of inventors fell by roughly 40% between 2000 and 2016, from about 7 percent to less than 4 percent. Meanwhile, workers in similar industries saw hire and separation rates that were fairly stable at 6 to 6.5 percent, suggestive of declining employment dynamism among inventors.

The entrepreneurship rate among inventors also fell over this period. Panel A of Figure 3 shows the change in the likelihood that an inventor starts a new business each year, relative to 2000, after controlling for individual fixed effects. Entrepreneurship among inventors is relatively rare. Though about 9 percent of inventors are ever observed as entrepreneurs, only 0.639 percent founded firms in 2000. Since 2000, the inventor entrepreneurship rate fell by roughly 44%, or nearly 0.3 percentage points. This is especially concerning since firms founded by inventors have a much steeper life cycle curve. Panel B of Figure 3 shows the change in firm size over the firm's life cycle for inventor founded and non-inventor founded firms, relative to its size at birth, after controlling for industry-year effects. Conditional on survival, by age five inventor founded firms grow by nearly 70 percent while non-inventor founded firms grow by 41 percent.[11] Not only do inventor founded firms experience higher growth rates, they are also larger at birth. On average, inventor founded firms have 8.1 employees and non-inventor founded firms have 5.7 employees.[12] The results in Figure 3 suggest that the high growth young firms generated by inventors are becoming more rare over time.

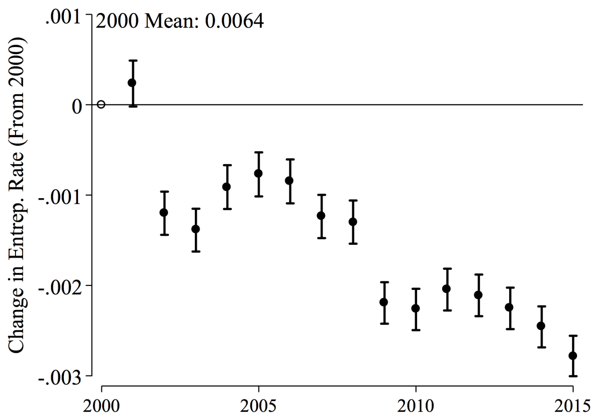
Though many measures of employment dynamics and entrepreneurship in the U.S. economy fell over this period, one might have expected those trends to be different among the high human capital inventive workforce. Instead, we find that inventors are increasingly less likely to change jobs, less likely to start a business, and increasingly concentrated among older, larger incumbent firms. In the cross section, we find that inventors employed by incumbents produce patents that have fewer citations, fewer independent claims, and more self citations (Panel C of Figure 1). Moreover, inventors

[10] See Akcigit and Goldschlag (2022) for additional descriptive analyses of the Inventor Employment History database.

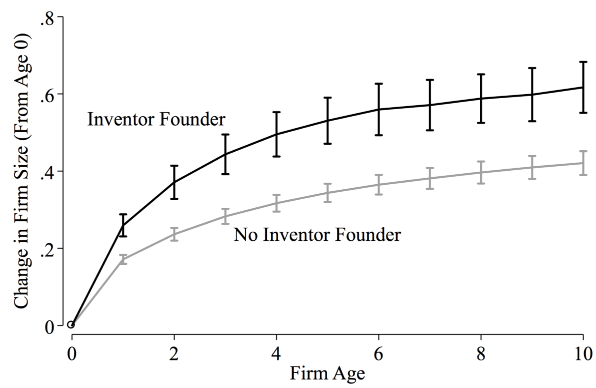
[11] Elasticities for $ln(FirmSize)$ are interpreted using the $e^{\beta_a}$, where $\beta_a$ is defined as in the equation in the Figure notes.

[12] Standard errors for these means are (32.5) and (24.1), respectively.

# Figure 3: Inventor Entrepreneurship




(a) Declining Inventor Entrepreneurship




(b) Inventor Firm Performance

Source: Inventor Employment History, author's calculations
Notes: Panel A reports estimates of $\beta_k$s from the following equation,
$Entrep_{i,t} = \alpha + \sum_{k=2001}^{2015} \beta_k D_t^k + \psi_i + \epsilon_{i,t}$. For inventor $i$ in year $t$, $Entrep_{i,t}$ equals 1 if the inventor started a business in that year and zero otherwise, $D_t$ are year effects, and $\psi_i$ are person fixed effects. The mean of $Entrep_{i,t}$ in 2000 is 0.0064. Panel B shows estimates of $\beta_a$s from the following equation,
$ln(FirmSize_{f,t}) = \alpha + \sum_{a=1}^{10} \beta_a FirmAge_{f,t} + \delta_{f,t} + \epsilon_{f,t}$. For firm $f$ in year $t$, $ln(FirmSize_{f,t})$ is the log of firm employment in year $t$, $FirmAge_{f,t}$ is the firm's age in year $t$, and $\delta_{f,t}$ are industry-year fixed effects.

employed by incumbents have 13% higher earnings than inventors at young firms.[13]

The shift of inventors away from young firms towards incumbents, taken together with the fact that inventors employed by incumbents have slightly more but lower quality patents, may lead to an aggregate decline in quality-adjusted innovative output. To put the shifting composition into context, and setting aside causality and general equilibrium forces, a back-of-the-envelope calculation suggests that the shifting composition could yield, ceteris paribus, a 0.6% increase in applications and a 5.3% decrease in citations.[14] This finding is consistent with the strategic use of patents described by Argente,

[13]Additional summary statistics on the Inventor Employment History database can be found in the Online Appendix

[14]The share of inventors at young firms was 14 and 7.5 percent in 2000 and 2016, respectively. The share at incumbents was 48 and 57 percent. Normalizing these shares to exclude the omitted group (middle age and small old firms), the incumbent share rose from 77.4 to 88.4 percent. The average applications at incumbents and young firms is 0.919 and 0.0872, respectively. Average citation weighted application count is 0.537 and 0.828 for incumbent and young, respectively (see Online Appendix Table A1). This implies a shift in applications of 0.568 percent ($100 * \frac{((0.884*0.919)+(0.116*0.0872))-((0.774*0.919)+(0.226*0.0872))}{(0.774*0.919)+(0.226*0.0872)}$) and a 5.3 percent decrease in citations ($100 * \frac{((0.884*0.537)+(0.116*0.828))-((0.774*0.537)+(0.226*0.828))}{(0.774*0.537)+(0.226*0.828)}$).

Baslandze, Hanley, and Moreira (2020).

Rather than different types of firms doing fundamentally different types of innovation, these patterns may reflect a broader shift in the age composition of the inventor workforce. Indeed, Akcigit and Goldschlag (2022) document an aging of the inventor population. If older inventors have lower output (e.g. Jones (2010)), higher earnings, and are more likely to work for incumbents, then these differences may simply reflect inventor life cycle and age composition effects.

In order to more precisely estimate the difference in inventor output and earnings between inventors at young and incumbent firms, we propose a matching exercise and event study framework. Specifically, we identify similar inventors hired by incumbents and young firms and measure how their outcomes differ after the hire. We identify inventors hired by incumbents and young firms each period and create an annual panel of earnings and inventive output measures before and after the hire ($t-4$ to $t+4$ with $t=0$ being the year of the hire event).[15] To find "pairs" of very similar hire events, we classify inventors into deciles of the distribution of inventive output or earnings in each year prior to the hire ($t-1$ to $t-4$ with $t=0$ being the year of the hire event). For each outcome measure, we match on these decile bins, sector, and hire quarter. When more than one potential match exists, we select a single match that is closest in age and pre-hire inventive productivity or earnings.[16] By incorporating age in our matching algorithms we ensure that differences in earnings and inventive output do not simply reflect differences in the inventor's life cycle. Our matching strategy generates very similar pre-hire outcomes (see bottom panel of Table 1).

With the sample of matched incumbent and young firm hires, we measure the difference in post-hire outcomes between the two groups by estimating the following equation. For inventor $i$, in year relative to the hire $t$, and hire event $e$ we estimate,

[15] For the event study we aggregate from the quarterly observations in our inventor jobs panel to the annual level by summing applications and citation weighted applications and taking the mean of full quarter earnings, self citation rate, independent claim share, and citations per application. Individuals with no applications in a given year will appear with zero applications while those with no full quarter earnings will be have a missing earnings value for the year (and are therefore dropped).

[16] Specifically, we minimize the normalized euclidean distance between age and inventor output or earnings in each year $t-1$ to $t-4$. The match that is closest in age and pre-hire outcomes will be selected. A given young hire event cannot be matched to more than one incumbent hire event and vice versa. However, if an inventor experiences more than one hire event over time, they may enter the regression analysis with either multiple hire events for a given firm type (e.g. incumbent) or different firm types. For additional details and match balance statistics, see Online Appendix.

$$Y_{ite} = \alpha + \sum_{j=-4}^{4} \lambda_j d[j]_{ite} + \beta_1 Incumbent_{ie} + \sum_{j=-4}^{4} \eta_j d[j]_{ite} \times Incumbent_{ie} \\ + \beta_2 Age_{ite} + \delta_j + \gamma_k + \psi_i + \epsilon_{ite} \quad (4)$$

$Incumbent_{ie}$ is equal to one if the hire event occurred at a incumbent firm, zero if it occurred at a young firm. $\delta_j$, $\gamma_k$, and $\psi_i$ are sector, hire year, and person fixed effects respectively. Person-level fixed effects will control for time invariant characteristics of individual inventors. $Age_{ite}$ is the inventor age. $\lambda_j$s capture year relative to hire effects. Our focus will be estimates of the $\eta_j$s, which capture the difference in outcome $Y$ between inventors hired by incumbents to similar inventors hired by young firms in each period before and after the hire event.

Figure 4 shows the results of the hire event study for earnings and applications. Our matching, by construction, eliminated pre-event differences between the incumbent and young firm hire samples. Estimates of $\eta_j$ for $t-4$ to $t-2$ are insignificant for both earnings and applications. In the year of the hire ($t = 0$) we see incumbents have 15 percent higher earnings than young firm hires.[17] This stabilizes to roughly 11 percent four years after the hire event. At the same time, incumbent hires see a 0.023 lower application count which falls to a 0.052 gap four years after the hire event. A decline in applications of 0.052 represents approximately 8 percent of the pre-hire mean application count (see bottom panel of Table 1).

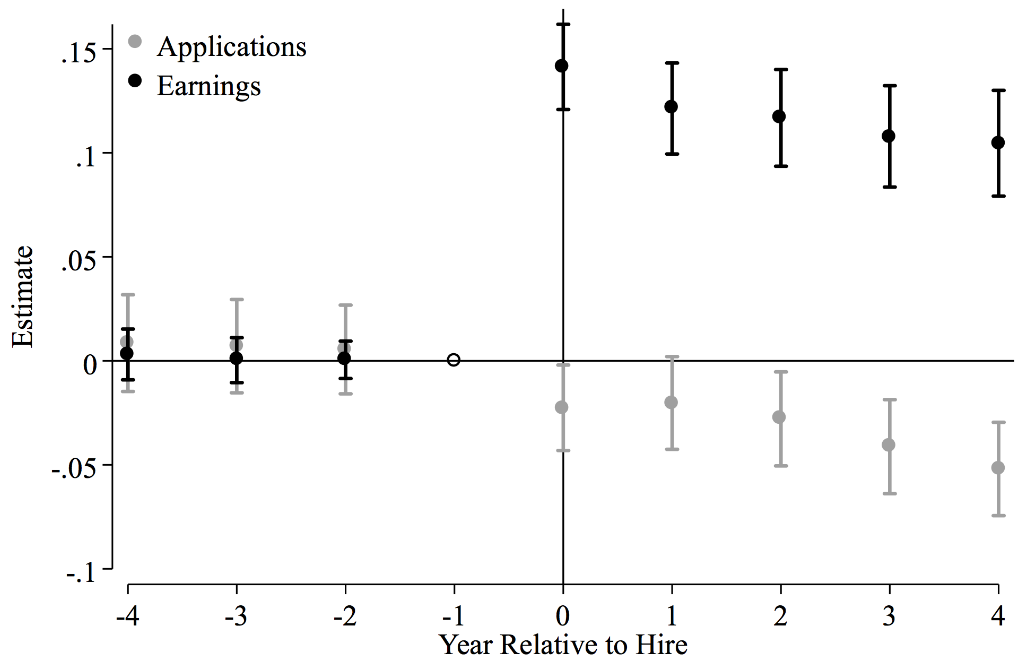
As noted previously, we consider several different measures of inventive output. To explore these alternative measures, we collapse the time dimension of our event study into a difference-in-differences framework with a $Post_{ite}$ binary that is equal to one if $t \geq 0$ and zero otherwise. The estimation equation becomes the following.

$$Y_{ite} = \alpha + \ + v_1 Post_{ite} + v_2 Incumbent_{ie} + v_3 Post_{ite} \times Incumbent_{ie} \\ + \beta_4 Age_{ite} + \delta_j + \gamma_k + \psi_i + \epsilon_{ite} \quad (5)$$

The difference-in-differences estimates for these additional outcomes are presented in Table 1. The table shows the estimates for $v_1$ and $v_3$ and the associated pre-hire means in the bottom panel. The first two columns show the estimates for applications and earnings. We find 0.036 lower applications for incumbent hires in the post period, roughly 6 percent of the pre-hire mean for those hired by incumbents. For earnings, we

[17] Elasticities for $ln(Earnings)$ are interpreted using the $e^{\eta_j}$.

Figure 4: Young and Incumbent Inventor Hires




Source: Inventor Employment History, Founding Team Database
Notes: Shown are event study estimates for years relative to the hire event of the difference in an inventor's outcome, patent quality (citations per application) and log earnings, between inventors hired by an incumbent firm and those hired by a young firm. We match inventor hire events at young firms (those age $\leq 5$) and incumbent firms (firms at least 21 years old and with at least 1,000 employees). Matching is performed on hire period and pre-hire period characteristics. Shown are estimates of $\eta_j$ from Equation 4.

find 12.6 percent higher post-hire earnings for inventors hired by incumbents relative to young firm hires. Across the other measures, incumbent hires have 11.9 percent lower citations, 11.3 percent lower citations per application, 5.4 percent lower independent claim share, and 37.7 percent higher self citation rates, all relative to pre-hire incumbent means.

The estimates shown in Table 1, though not casual, are in agreement with the cross sectional differences in earnings and inventive output referenced earlier and are consistent with the predictions of the model. Taken together these estimates suggests inventors employed by and those hired by incumbents, relative to those at young firms, have higher earnings and lower inventive output, fewer applications, fewer citations and citations per application, patents with more limited scope, and a higher self citation rate.

Table 1: Young and Incumbent Hires: Alternative Outcomes

| | Apps | $ln(Earnings)$ | Citations | Citations per App | Independent Claims | Self Cite Rate |
|---|---|---|---|---|---|---|
| Post | -0.1289*** | -0.03429*** | -0.8955*** | -0.2611*** | -0.07455*** | -0.01234*** |
| | (0.006064) | (0.007612) | (0.2094) | (0.02871) | (0.002297) | (0.001006) |
| Post x Incumbent | -0.03585*** | 0.1184*** | -0.6861*** | -0.1145*** | -0.01581*** | 0.02278*** |
| | (0.007011) | (0.009772) | (0.2069) | (0.02439) | (0.002392) | (0.001358) |
| $R^2$ | 0.311 | 0.8106 | 0.2531 | 0.1845 | 0.1818 | 0.4716 |
| N | 781,000 | 143,000 | 371,000 | 370,000 | 660,000 | 213,000 |
| *Pre-Hire Means* | | | | | | |
| Incumbent Hires | 0.6017 | 10.29 | 5.758 | 1.009 | 0.2925 | 0.06035 |
| | (1.34) | (1.045) | (33.01) | (4.246) | (0.5645) | (0.132) |
| Young Hires | 0.6068 | 10.29 | 5.933 | 1.039 | 0.2947 | 0.0601 |
| | (1.429) | (1.051) | (33.27) | (4.338) | (0.5795) | (0.1309) |

Source: Inventor Employment History, author's calculation
Notes: Difference-in-Differences estimates for the hire event for each outcome $Y_{i,t,e}$, between inventors hired by an incumbent firm and those hired by a young firm. Estimates are of $v_1$ and $v_3$ from Equation 5. Standard errors are shown in parentheses. Observation counts vary by measure because outcome relies a separate match, minimizing the difference in pre-match values of the given measure. Incumbent binary included but not reported. Observation counts have been rounded to avoid the disclosure of confidential information.

## Robustness

In this section we demonstrate the robustness of our estimates to several concerns about measurement and mechanisms.

**Mechanical Self Citation Rate Effects.** One potential concern with the self citation rate estimates is that since incumbents have larger patent portfolios inventors hired by incumbents mechanically exhibit higher self citation rates because incumbent firms account for a larger share of patents at risk of receiving a citation. To determine the extent to which this mechanical effect accounts for our estimates, we create a simulated self citation rate by randomly generating self citations in proportion to the assignee's share of the technology groups (Cooperative Patent Classification (CPC) codes) cited by the patent. When an assignee accounts for a larger share of the corpus of patents within a given technology code, the patent is more likely to generate self citations. We then estimate Equation 5 with this simulated self citation rate and find estimates that are an order of magnitude lower. The estimate for $Post \times Incumbent$ is 0.002107 compared to

0.02278 found in Table 1.[18] This suggests that the result that incumbent hires are more likely to generate self citations is not entirely mechanical.

**Occupational Differences.** One potential explanation for the event study patterns are differences in the types of jobs inventors are doing at incumbents versus young firms. If inventors are more likely to be managers at incumbent firms, or become managers when they are hired by incumbents, we might expect divergent patterns in earnings and innovative output. We explore this possibility by using occupation information matched to our full inventor jobs panel (not limited to the hire match samples). In the ACS-matched sample, 49.8% of inventors are in technical occupations occupations while 26% are in managerial occupations.[19] Looking at the occupational composition of inventors at incumbents versus young firms, we find inventors at young firms are more likely to be managers and less likely to be in technical occupations than inventors at incumbent firms. Among inventors employed by incumbents, 57% are in technical occupations. That number is 44% for young firms. In contrast, the percent of inventors employed by incumbents that are managers is 23%, but this figure is 31% at young firms. These patterns are intuitive if we think inventors at young firms tend to be key employees or founders that bring both innovative and managerial skills to the firm. In either case, these shares suggest that the diverging earnings and output measures we find are not driven by differences in occupation.

**Age and Life Cycle Effects.** Despite the fact that our matching algorithms generate a balanced age composition among both incumbent and young firm hires, it may still be the case that the estimated effects are primarily driven by differences among older inventors. To explore this possibility, we fully interact our difference-in-differences specification (Equation 5) with a binary, $OlderInventor_{ie}$, equal to one if the inventor is greater than the median age among our hire-event inventors and zero otherwise. The triple interaction of $Post_{ite} \times Incumbent_{ie} \times OlderInventor_{ie}$ captures the difference in the post-hire outcomes between younger and older inventors. We find the triple interaction insignificant for all of our inventive output measures and negative and significant for earnings. The earnings estimates are intuitive since earnings life cycle effects will tend to result in older inventors having higher earnings, lessening the incumbent earnings premium.[20]

[18] The standard error for the simulated self citation rate $Post \times Incumbent$ estimate is (0.0003031). See the Online Appendix for additional estimation details.

[19] Within technical occupations we include Computer and Mathematical, Architecture and Engineering, or Life, Physical, and Social Science occupations, which correspond to ACS occupation codes 1000 to 1965. In management occupation we include Management, Business Operations, or Financial Specialists, which correspond to ACS occupation codes $\leq 950$.

[20] See Online Appendix for estimation output.

**Adjustment Costs at Incumbents.** Another potential explanation consistent with out findings is that the post-hire costs of integrating into incumbent firms is more significant than for young firms. Incumbents may be less flexible to do additional layers of bureaucracy (Williamson, 1984). Incumbent firms may also have established R&D projects that new inventor hires must integrate with. To test this possibility, we define a new measure that captures whether an inventor has a patent application in a technology class that is new to the inventor in a given year. The measure, $NewCPC_{it}$, is equal to 1 if an inventor has a patent application at time $t$ in a major CPC class that the inventor has no prior applications in and zero otherwise. Estimation results suggest that incumbent hires are actually less likely to submit patent applications in a new-to-the-inventor CPC class than young firm hires.[21]

**Hire Events in Great Recession.** The structure of our hire event study requires information on earnings and patenting activity observed before and after the hire event. In addition, citation-based outcomes are observed only through 2014 because all patents are allowed five years after grant to accrue citations. All of these restrictions taken together mean that our hire events occur only in the years 2005 to 2012, which straddles the great recession. To ensure our results are not primarily driven by the great recession years we estimate our difference-in-differences specification with hire events occurring in 2005 and 2006. We again find negative effects for citations per application and positive effects for earnings. The earnings estimates for Post $\times$ Incumbent is a bit larger (0.1803), and the citation estimate is more negative as well (-1.864).[22]

# 4 Conclusion

Talent is the most important ingredient for innovation and the allocation of talent across firms has a first-order impact on the innovative capacity of an economy. In this paper, we develop a theory of creative destruction that focuses on the allocation of inventors across firms. Our model describes the strategic incentives faced by incumbents. To avoid displacement by the entrant, incumbent firms will poach inventors and shelve their innovations.

On the empirical side, our paper uses novel data on the employment history of over 760 thousand inventors, to investigate the model's predictions. We show empirically that (i) inventors are increasingly concentrated in large incumbents, less likely to work for

[21]See Online Appendix for estimation output.

[22]The standard errors for these estimates are 0.02457 for earnings and 0.5934 for citations.

young firms, and less likely to become entrepreneurs, (ii) when an inventor is hired by an incumbent, compared to a young firm, their earnings increases by 12.6 percent and their innovative output declines by 6 to 11 percent.

These findings have very important policy implications. First, looking to country-level aggregates of innovation inputs (e.g. R&D spending or inventors per capita) may be misleading and fail to provide a complete picture of a country's innovative capacity. While having a higher share of inventors is desirable, the composition of those inventors across firm types is also important. Second, not all factor reallocation is necessarily good. Our analysis has documented that inventor reallocation toward large incumbents, at least the way it happened in recent decades, might be lowering the growth capacity of the country. Finally, policies that encourage more incumbent innovation might occur at the expense of entrant innovations, which are higher quality on average.

These important findings point to several interesting, policy-relevant questions. For instance, what role do non-compete agreements play in explaining when inventors work for incumbents or young firms? Those policies may play an important role in generating spin-offs and inventor entrepreneurship. In addition, what role do financial frictions play in explaining inventor's choice to work for incumbents? If an inventor faces credit constraints, that may weaken incentives to work for an entrant or start a new firm. We hope that the data developed by Akcigit and Goldschlag (2022) will spur further research on these topics and shed light on the "black box" of inventor employment dynamics in the US.

# References


Acemoglu, D., U. Akcigit, H. Alp, N. Bloom, and W. Kerr (2018) "Innovation, Reallocation, and Growth," *American Economic Review*, 108(11), 3450–91.

Aghion, P., U. Akcigit, A. Hyytinen, and O. Toivanen (2017) "The Social Origins of Inventors," National Bureau of Economic Research Working Paper 24110.

Aghion, P., and P. Howitt (1992) "A Model of Growth through Creative Destruction," *Econometrica*, 60(2), 323–351.

Akcigit, U. (2017) "Economic Growth: The Past, the Present, and the Future," *Journal of Political Economy*, 125(6), 1736–1747.

Akcigit, U., and S. T. Ates (2022) "What Happened to US Business Dynamism?," *Journal of Political Economy*, forthcoming.

Akcigit, U., S. Baslandze, and F. Lotti (2022) "Connecting to Power: Political Connections, Innovation, and Firm Dynamics," *Econometrica*, forthcoming.

Akcigit, U., and N. Goldschlag (2022) "Measuring the Characteristics and Employment Dynamics of U.S. Inventors," Discussion paper, Center for Economic Studies CES-WP-2022-43.

Akcigit, U., J. Grigsby, and T. Nicholas (2017) "The Rise of American Ingenuity: Innovation and Inventors of the Golden Age," National Bureau of Economic Research Working Paper 23137.

Akcigit, U., and R. W. Kerr (2018) "Growth through Heterogeneous Innovations," *Journal of Political Economy*, 126(4), 1374–1443.

Akcigit, U., J. G. Pearce, and M. Prato (2020) "Tapping into talent: Coupling education and innovation policies for economic growth," National Bureau of Economic Research Working Paper 27862.

Argente, D., S. Baslandze, D. Hanley, and S. Moreira (2020) "Patents to Products: Product Innovation and Firm Dynamics," CEPR Discussion Paper No. DP14692.

Arrow, K. J. (1962) "Economic Welfare and the Allocation of Resources for Invention," in *The Rate and Direction of Inventive Activity: Economic and Social Factors*, ed. by R. R. Nelson, pp. 609–626. Princeton: Princeton University Press.

Autor, D., D. Dorn, L. F. Katz, C. Patterson, and J. Van Reenen (2020) "The Fall of the Labor Share and the Rise of Superstar Firms," *Quarterly Journal of Economics*, 135(2), 645–709.

Bell, A., R. Chetty, X. Jaravel, N. Petkova, and J. Van Reenen (2019) "Who Becomes an Inventor in America? The Importance of Exposure to Innovation," *Quarterly Journal of Economics*, 134(2), 647–713.

Celik, M. A. (2022) "Does the Cream Always Rise to the Top? The Misallocation of Talent in Innovation," *Journal of Monetary Economics*, forthcoming.

Choi, J., N. Goldschlag, J. C. Haltiwanger, and J. D. Kim (2021) "Founding Teams and Startup Performance," National Bureau of Economic Research Working Paper 28417.

Cunningham, C., F. Ederer, and S. Ma (2021) "Killer Acquisitions," *Journal of Political Economy*, 129(3), 649–702.

Decker, R., J. Haltiwanger, R. Jarmin, and J. Miranda (2014) "The Role of Entrepreneurship in U.S. Job Creation and Economic Dynamism," *Journal of Economic Perspectives*, 28(3), 3–24.

Decker, R. A., J. Haltiwanger, R. S. Jarmin, and J. Miranda (2020) "Changing Business Dynamism and Productivity: Shocks versus Responsiveness," *American Economic Review*, 110(12), 3952–3990.

Dreisigmeyer, D., N. Goldschlag, M. Krylova, W. Ouyang, and E. Perlman (2018) "Building a Better Bridge: Improving Patent Assignee-Firm Links," Discussion paper, Center for Economic Studies CES-TN-2018-01.

Fernald, J. G., and C. I. Jones (2014) "The Future of US Economic Growth," *American Economic Review*, 104(5), 44–49.

Foster, L., J. Haltiwanger, and C. J. Krizan (2006) "Market Selection, Reallocation, and Restructuring in the US Retail Trade Sector in the 1990s," *Review of Economics and Statistics*, 88(4), 748–758.

Foster, L., J. C. Haltiwanger, and C. J. Krizan (2001) "Aggregate Productivity Growth: Lessons from Microeconomic Evidence," in *New Developments in Productivity Analysis*, pp. 303–372. University of Chicago Press.

Graham, S. J., C. Grim, T. Islam, A. C. Marco, and J. Miranda (2018) "Business Dynamics of Innovating Firms: Linking US Patents with Administrative Data on Workers and Firms," *Journal of Economics & Management Strategy*, 27(3), 372–402.

Grossman, G. M., and E. Helpman (1991) "Quality Ladders in the Theory of Growth," *Review of Economic Studies*, 58(1), 43–61.

Haltiwanger, J., H. R. Hyatt, E. McEntarfer, L. Sousa, and S. Tibbets (2014) "Firm Age and Size in the Longitudinal Employer-household Dynamics Data," Discussion paper, Center for Economic Studies CES-WP-14-16.

Hopenhayn, H., and R. Rogerson (1993) "Job turnover and policy evaluation: A general equilibrium analysis," *Journal of political Economy*, 101(5), 915–938.

Hsieh, C.-T., E. Hurst, C. I. Jones, and P. J. Klenow (2019) "The Allocation of Talent and US Economic Growth," *Econometrica*, 87(5), 1439–1474.

Hsieh, C.-T., and P. J. Klenow (2009) “Misallocation and manufacturing TFP in China and India,” *Quarterly Journal of Economics*, 124(4), 1403–1448.

Jones, B. F. (2010) “Age and Great Invention,” *Review of Economics and Statistics*, 92(1), 1–14.

Jones, C. I. (1995) “R & D-based Models of Economic Growth,” *Journal of Political Economy*, 103(4), 759–784.

Karabarbounis, L., and B. Neiman (2014) “The Global Decline of the Labor Share,” *Quarterly Journal of Economics*, 129(1), 61–103.

Klette, T. J., and S. Kortum (2004) “Innovating Firms and Aggregate Innovation,” *Journal of Political Economy*, 112(5), 986–1018.

Marco, A. C., J. D. Sarnoff, and C. deGrazia (2019) “Patent Claims and Patent Scope,” *Research Policy*, 48(9), 103790.

Romer, P. M. (1990) “Endogenous technological change,” *Journal of political Economy*, 98(5, Part 2), S71–S102.

Wagner, D., and M. Lane (2014) “The person identification validation system (PVS): applying the Center for Administrative Records Research and ApplicationsâĂŹ(CARRA) record linkage software,” Discussion paper, Center for Economic Studies, US Census Bureau, WP-2014-01.

Williamson, O. E. (1984) “The Incentive Limits of Firms: A Comparative Institutional Assessment of Bureaucracy,” *Weltwirtschaftliches Archiv*, 120(4), 736–763.

# Online Appendix

## A.1 Inventor History Summary Statistics

Table A1 provides summary statistics for our Inventor Employment History database. The Panel A provides characteristics and employment dynamics measures and the bottom two panels (B and C) summarize our earnings and inventive outcome measures for inventor jobs at incumbent and young firms respectively. Observation counts are reported in thousands. The observation counts for the first three rows are the count of unique inventors. In the remaining rows, observation counts represent the number of quarterly job observations. For example, for Female in Table A1, there are 760 thousand inventors, 11.7 percent of which are female. In contrast, for Age $\leq$25, there are nearly 34.7 million job observations, 3.4 percent of which cover inventors inventors age less than or equal to 25 years old.

Table A1: Summary Statistics

| | Mean | Std. Dev | N (000s) |
|---|---|---|---|
| *Panel A: Characteristics and Dynamics* | | | |
| Female | 0.1168 | 0.3212 | 760 |
| Foreign Born | 0.2686 | 0.4432 | 760 |
| Ever Entrepreneur | 0.0896 | 0.2856 | 759 |
| Age $\leq 25$ | 0.03352 | 0.18 | 34,690 |
| Age 26-35 | 0.2051 | 0.4038 | 34,690 |
| Age 36-45 | 0.3359 | 0.4723 | 34,690 |
| Age 46-55 | 0.2994 | 0.458 | 34,690 |
| Age $\geq 56$ | 0.126 | 0.3319 | 34,690 |
| Incumbent Employer | 0.551 | 0.4974 | 34,690 |
| Young Employer | 0.1027 | 0.3036 | 34,690 |
| Hires | 0.04558 | 0.2086 | 34,570 |
| Separations | 0.04442 | 0.206 | 34,570 |
| *Panel B: Incumbent Employer* | | | |
| ln(Earnings) | 10.33 | 0.659 | 18,320 |
| Apps | 0.09188 | 0.5301 | 19,110 |
| Cites | 0.5371 | 22.29 | 15,920 |
| Ind Claim per App | 0.1575 | 0.7996 | 17,110 |
| Cite per App | 4.852 | 15.44 | 1,103 |
| Self Cite Rate | 0.1429 | 0.193 | 1,176 |
| *Panel C: Young Employer* | | | |
| ln(Earnings) | 10.2 | 0.8675 | 3,262 |
| Apps | 0.08717 | 0.4543 | 3,563 |
| Cites | 0.8275 | 10.09 | 3,145 |
| Ind Claim per App | 0.1634 | 0.9009 | 3,300 |
| Cite per App | 8.511 | 19.91 | 202 |
| Self Cite Rate | 0.06212 | 0.1289 | 213 |

Source: Inventor Employment History, Founding Team Database
Notes: Observation counts have been rounded to avoid the disclosure of confidential information.

## Hire Event Matching

This analysis measures the impact on an inventor's earnings and inventive output of being hired by an incumbent firm *relative to* being hired by a young firm. To do this, we identify all hire events for inventors in which the hiring firm is either an incumbent or a young firm. With those hire events we construct a balanced panel of annual observations before and after the hire. The panel contains 9 years, 4 years before the event, $t = 0$ is hire event quarter and the following 3 quarters, and then 4 years following the hire year. We track measures of inventive productivity (apps, citations, etc.) and earnings aggregated to the annual level for each year (lead and lag) relative to the hire event. We aggregate to annual measures of earnings and inventive productivity by summing applications and citation weighted applications and taking the mean of full quarter earnings, self citation rate, independent claim share, and citations per application. Individuals with no applications in a given year will appear with zero applications while those with no full quarter earnings will be have a missing earnings value for the year (and are therefore dropped). Note that if an inventor has multiple back-to-back hire events, the relative year measures will overlap for the different inventor-hire event combinations.

With this inventor-hire event-relative year panel we perform our matching, aiming to find incumbent and young hire event twins—young and incumbent hire events in which the inventors have very similar pre-hire inventive productivity or earnings. We perform a separate matching exercise for each of our outcome variables (applications, earnings, etc.). We create percentile bins (10 for patent measures and 50 for earnings) of the outcome variable by relative year prior to hire (e.g. separate bins for $t-4$, $t-3$, etc.). Call these percentile bins $p_{t-4}$, $p_{t-3}$, $p_{t-2}$, and $p_{t-1}$. Similarly, call the outcome measure in each relative year $y_{t-4}$, $y_{t-3}$, etc.

Records with a zero measure in the outcome variable are grouped together within a relative year, which yields 11 bins for cite measures and 51 for earnings. Inventor-hire event pairs are dropped if (1) all outcome measures are either missing or zero for all pre-event relative years. These "all zero" cases are events we know relatively little about–it is difficult to assess the quality of an inventor or their trajectory if we observe no inventive activity within our window around the hire event.

The matching iterates over each young firm hire event, block matching to all incumbent hire events by [year and quarter of hire, sector,$p_{t-4}$,$p_{t-3}$,$p_{t-2}$,$p_{t-1}$]. In many cases, this yields more than one potential match for a given young hire event. To resolve this, we calculate the euclidean distance, $dist_{i,j}$, between the outcomes in each prior year and age. For young hire event $i$ and incumbent hire event $j$, the distance is defined as follows.

$$dist_{i,j} = \sqrt{yDiff^2_{t-4,i,j} + ... + yDiff^2_{t-1,i,j} + ageDiff^2_{i,j}} \tag{6}$$

The difference in each prior year, $yDiff_{t-k,i,j}$, is noramalized to fall between 0 and 1, and is defined as follows.

$$yDiff_{t-k,i,j} = \frac{abs(y_{t-k,i} - y_{t-k,j}) - \min_{\forall j}(abs(y_{t-k,i} - y_{t-k,j}))}{\max_{\forall j}(abs(y_{t-k,i} - y_{t-k,j})) - \min_{\forall j}(abs(y_{t-k,i} - y_{t-k,j}))} \tag{7}$$

The normalized difference in age, $ageDiff_{i,j}$, is defined analogously to $yDiff_{t-k,i,j}$. The matching algorithm minimizes the $dist_{i,j}$, breaking ties randomly. We match without replacement—once an incumbent hire event has been matched to a young hire event it cannot match to any other young hire event.

Table A2 shows the mean and standard deviation of pre-hire outcomes and age for the matched young and incumbent hires along with a ttest for the difference in means. Some differences in age are statistically significant, but all are less than one year. None of the differences in pre-hire outcomes are statistically significantly different.

Table A2: Hire Event Match Balance

| Variable | Mean Young | Mean Incumbent | Diff |
|---|---|---|---|
| *Applications* | | | |
| Age | 40.3 | 40.26 | -0.04 |
| | (9.613) | (9.602) | (0.03262) |
| Apps | 0.6068 | 0.6017 | -0.0051 |
| | (1.429) | (1.34) | (0.004703) |
| *Citations* | | | |
| Age | 39.93 | 39.61 | -0.32 |
| | (9.543) | (9.309) | (0.04644) |
| Cites | 5.933 | 5.758 | -0.175 |
| | (33.27) | (33.01) | (0.1633) |
| *Independent Claim Share* | | | |
| Age | 40.26 | 40.22 | -0.04 |
| | (9.636) | (9.556) | (0.03499) |
| Ind Claim Share | 0.2947 | 0.2925 | -0.0022 |
| | (.5795) | (.5645) | (0.002086) |
| *Cites per Application* | | | |
| Age | 39.91 | 39.57 | -0.34 |
| | (9.551) | (9.285) | (0.04648) |
| Cites per App | 1.039 | 1.009 | -0.03 |
| | (4.338) | (4.246) | (0.02119) |
| *Self Cite Rate* | | | |
| Age | 38.61 | 37.98 | -0.63 |
| | (10.54) | (10.73) | (0.02219) |
| Self Cite Rate | 0.0601 | 0.06035 | 0.00025 |
| | (.1309) | (.132) | (0.0008218) |
| *ln(Earnings)* | | | |
| Age | 40.18 | 40.05 | -0.13 |
| | (9.48) | (9.505) | (0.07345) |
| ln(Earnings) | 10.29 | 10.29 | 0 |
| | (1.051) | (1.045) | (0.008108) |

Source: Inventor Employment History, Founding Team Database
Notes: Match balance statistics for pre-hire characteristics from hire event study. Standard errors are shown in parentheses.

## Simulated of Self Citation Rates

Table A3 shows estimation results of Equation 5 where $Y_{ite}$ is a simulated self citation rate in which, given the number of citations a patent makes to each CPC technology group, a patent cite's the assignee's existing patent corpus in proportion to it's share of all patents in that CPC group.

Table A3: Simulated Self Citation Rates

| | Self Cite Rate Simulated |
|---|---|
| Post | -0.001016*** |
| | (0.0002248) |
| Post x Incumbent | 0.002107*** |
| | (0.0003031) |
| $R^2$ | 0.3374 |
| N | 213,000 |

Source: Inventor Employment History, author's calculation
Notes: Estimates are of $v_1$ and $v_3$ from Equation 5. Standard errors are shown in parentheses. Incumbent binary included but not reported. Observation counts have been rounded to avoid the disclosure of confidential information.

## New to Inventor Major CPC

Table A4: New Major CPC

| | New CPC |
|---|---|
| Post | -0.2013*** |
| | (0.001729) |
| Post x Incumbent | -0.002968** |
| | (0.001037) |
| $R^2$ | 0.1499 |
| N | 548,000 |

Source: Inventor Employment History, author's calculation
Notes: Estimates are of $v_1$ and $v_3$ from Equation 5. Standard errors are shown in parentheses. Incumbent binary included but not reported. Observation counts have been rounded to avoid the disclosure of confidential information. New CPC is a binary equal to one if the inventor has an application in a major CPC technology group that the inventor is not previous observed with patent applications in that major CPC. This measure is left censored in 2000, the beginning of our data.

## Age and Life Cycle Effects

## Table A5: Age of Inventor Heterogeneous Effects

| | Apps | $ln(Earnings)$ | Citations | Citations | Independent | Self Cite Rate |
|---|---|---|---|---|---|---|
| Post | -0.0875*** | 0.1425*** | -0.7108** | -0.285*** | -0.06288*** | -0.01155*** |
| | (0.006729) | (0.005931) | (0.2374) | (0.03404) | (0.002914) | (0.001388) |
| Post × Incmbnt | -0.03515*** | 0.1311*** | -0.7268** | -0.112** | -0.01578*** | 0.02411*** |
| | (0.007388) | (0.006376) | (0.2307) | (0.0343) | (0.003255) | (0.001869) |
| Post × Incmbnt × GT Median Age | -0.002157 | -0.02288** | 0.07252 | -0.003854 | -0.0001692 | -0.002262 |
| | (0.01031) | (0.008913) | (0.3262) | (0.04415) | (0.004564) | (0.00257) |
| $R^2$ | 0.3794 | 0.8408 | 0.3308 | 0.2694 | 0.2657 | 0.6357 |
| N | 781,000 | 143,000 | 371,000 | 370,000 | 660,000 | 213,000 |

Source: Inventor Employment History, author's calculation
Notes: Estimates for $\nu_1$, $\nu_4$, and $\nu_6$ from the following equation.

$$\begin{aligned} Y_{ite} = \alpha + \; & +\nu_1 Post_{ite} + \nu_2 Incumbent_{ie} + \nu_3 GTMed_{it} \\ & +\nu_4 Post_{ite} \times Incumbent_{ie} + \nu_5 GTMed_{it} \times Post_{ite} \\ & +\nu_6 GTMed_{it} \times Post_{ite} \times Incumbent_{ie} + \\ & +\beta_4 Age_{ite} + \delta_j + \gamma_k + \psi_i + \epsilon_{ite} \end{aligned}$$

## Hire Events Before Great Recession

### Table A6: Hire Events Before Great Recession

| | Citations | $ln(Earnings)$ |
|---|---|---|
| Post | 0.4137 | -0.06049*** |
| | (0.4502) | (0.01711) |
| Post $\times$ Incmbnt | -1.864** | 0.1803*** |
| | (0.5934) | (0.02457) |
| | | |
| $R^2$ | 0.6801 | 0.9576 |
| N | 82,500 | 23,500 |

Source: Inventor Employment History, author's calculation
Notes: Estimates are of $v_1$ and $v_3$ from Equation 5 using only hires that occurred in 2005 and 2006. Standard errors are shown in parentheses. Incumbent binary included but not reported. Observation counts have been rounded to avoid the disclosure of confidential information.