Born Different: Entrepreneurship through Inventor Mobility, Innovation, and Growth*

Salomé Baslandze   Ia Vardishvili

December 30, 2025

Abstract

Large productivity differences across firms reflect substantial ex-ante heterogeneity at entry, yet the origins of this heterogeneity remain poorly understood. This paper shows that *innovating spinouts*—firms formed by inventors leaving incumbent innovators—are a key endogenous source of high-growth entrepreneurship and aggregate productivity growth. Using inventor mobility in patent data, we document that spinouts systematically outperform other entrants throughout their life cycle, their performance is strongly linked to parent-firm technological strength, and their formation temporarily depresses parent-firm innovation. We develop a Schumpeterian growth model that endogenizes spinout formation and the fundamental tradeoff between knowledge diffusion, creative destruction, and appropriability. Closely disciplined by rich micro-level data, the model implies that spinouts account for a disproportionate share of high-growth firms and nearly forty percent of aggregate productivity growth, but that inventor departures also impose sizable costs on incumbents, generating a fundamental policy tradeoff. Policy counterfactuals show that relaxing non-compete restrictions raises aggregate growth and welfare and amplifies the effectiveness of entry subsidies.

Keywords: Innovation, growth, firm dynamics, spinouts, entrepreneurship, non-compete laws.

JEL Classifications: O30, O43.

*Baslandze: Federal Reserve Bank of Atlanta and CEPR (baslandze.salome@gmail.com). Vardishvili: Auburn University (izv0013@auburn.edu). We thank Ufuk Akcigit, Harun Alp, Rüdiger Bachmann, Jeremy Greenwood, David Lagakos, Pau Roldan-Blanco (discussant), Felipe Saffie, Ben Pugsley, and conference and seminar participants at the University of Pennsylvania, University of Barcelona, Atlanta Fed, SEA, SED, Konstanz Seminar on Monetary Theory and Monetary Policy, and I-85 Macroeconomics Workshop for useful comments and suggestions. The views expressed here are those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of Atlanta and the Federal Reserve System. The paper circulated earlier under the title "Entrepreneurship through Spinouts, Innovation and Growth."

1 Introduction

Large and persistent productivity differences across firms are a defining feature of modern economies, with a small set of high-growth firms accounting for a disproportionate share of innovation and aggregate productivity growth (Bartelsman and Doms, 2000; Haltiwanger, Hurst, Miranda and Schoar, 2017). Recent evidence shows that these differences arise at birth, reflecting substantial ex-ante heterogeneity in firms' growth trajectories (Sterk, Sedláček and Pugsley, 2021). Despite its importance, much of the growth and firm-dynamics literature takes this heterogeneity as given, leaving its origins, persistence, and implications for innovation and aggregate productivity poorly understood. This paper studies *innovating spinouts*—firms arising from inventors leaving incumbent innovators—and shows that they are a central endogenous source of ex-ante heterogeneity and aggregate growth.

The transformative role of spinouts in generating high-productivity entrants and reshaping entire industries is well documented in case studies and industry histories (Klepper, 2002; Klepper and Sleeper, 2005; Franco and Filson, 2006). Prominent examples include the semiconductor family tree originating at Bell Labs and Fairchild Semiconductor (Figure 1) and, more recently, firms such as Zoom Communications. Yet, spinout formation generates a fundamental tension: employee departures reduce appropriability and may weaken incumbent innovation incentives.[1] This tension lies at the center of ongoing policy debates over employee mobility, particularly non-compete enforcement.[2] Using rich inventor–firm data and a quantitative Schumpeterian growth model closely disciplined by micro-level evidence, this paper provides a systematic, economy-wide analysis of how spinout-driven entrepreneurship shapes firm heterogeneity and aggregate growth, quantifies the associated innovation costs borne by incumbents, and—within this unified framework—evaluates the aggregate consequences of employee-mobility policies.

We begin by constructing comprehensive data to study innovating spinouts across the U.S. economy. We merge the NBER–USPTO patent data covering the universe of U.S. patenting firms with disambiguated inventor identities from the Harvard Patent Network Dataverse, which allows us to track individual inventors as they move across firms. We classify a firm as a spinout if at least one inventor listed on the firm's first patent application previously invented at another firm. This definition captures patenting firms—those most relevant for innovation-driven growth—and identifies the early technical contributors who shape a startup's trajectory, whether or not they hold formal ownership.[3] Spinouts represent a sizable share of entry: 28% of patenting firms (18,012 firms). We validate our methodology by showing that it successfully identifies the spinout cases documented using industry reports in Franco and Filson (2006) and reproduces the key empirical patterns found in industry-level studies.

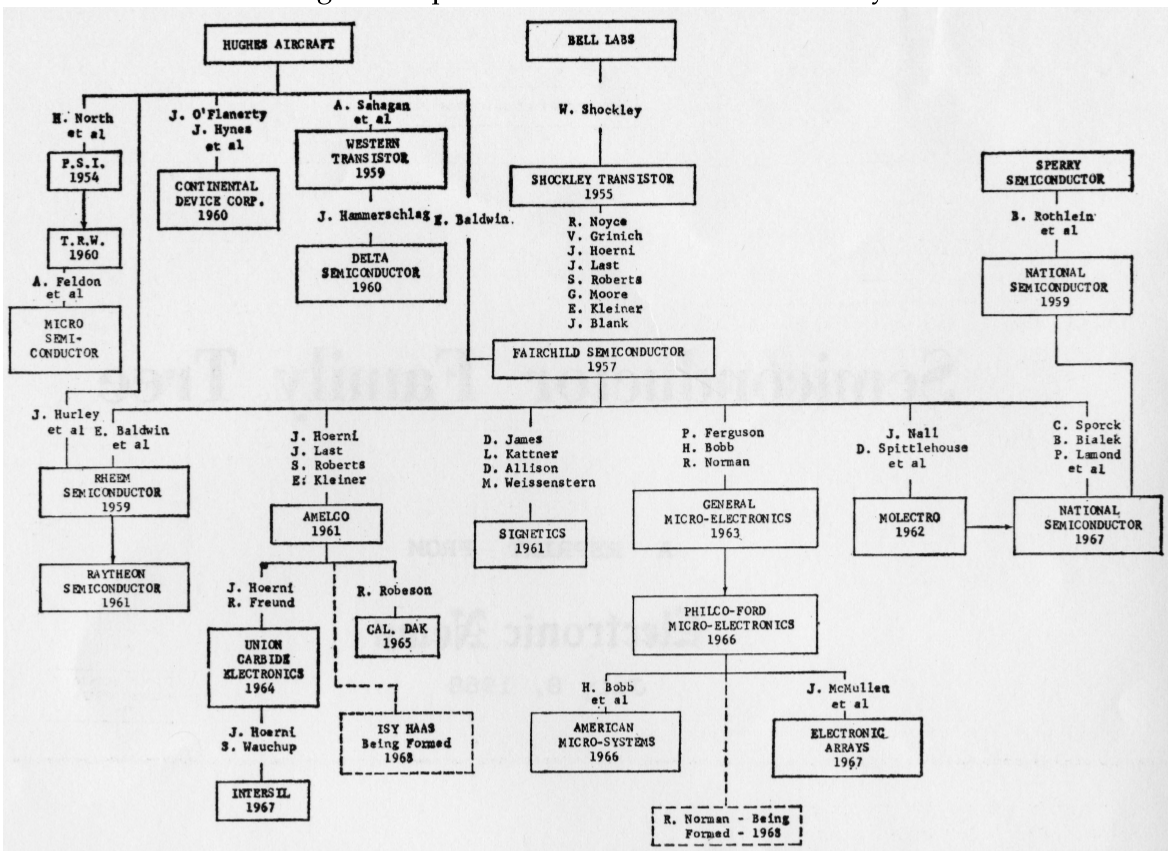
We document three empirical regularities regarding the characteristics of innovating spinouts, their

[1]See Pakes and Nitzan (1983) and Anton and Yao (1995) for the first theoretical exploration of this tension. Intel general counsel Roger Borovoy captured it succinctly: "Don't let your employees do to you what you did to your former boss." Intel itself is a spinout from Fairchild Semiconductor.

[2]Recent proposals range from strengthening non-compete enforcement (e.g., Bill S.998, 2017–2018) to banning it altogether (S.2614, Workforce Mobility Act of 2019). President Biden's Executive Order 14036 (2021) also targeted non-competes, and the Federal Trade Commission issued its 2024 Final Rule banning non-compete clauses for most workers.

[3]See Choi, Goldschlag, Haltiwanger and Kim (2019) for the importance of "early teams" for startup performance.

Figure 1: Spinouts in Semiconductor Industry



Source: "Semiconductor Family Tree", *Electronic News*, July 8, 1968.

consequences for parent firms, and the institutional factors that potentially shape their formation. *First*, spinout entrants systematically outperform regular entrants throughout their life cycle: they file more and higher-quality patents, exhibit higher survival rates, grow faster, and are more R&D-intensive. Moreover, among spinouts, those originating from parents with greater technological leadership produce innovations of even higher quality. *Second*, using a dynamic event-study design that compares parents whose inventors depart to form spinouts with parents whose inventors move to other incumbent firms, we show that spinout formation leads to a temporary decline in parent innovation and technological leadership. *Third*, using state-level variation in non-compete enforceability, we document that stricter non-compete laws, which hinder employee mobility and entrepreneurship, are associated with reduced spinout formation.

This empirical evidence highlights a fundamental tension inherent in inventor mobility and spinout formation, a tradeoff that is closely related to policy debates on labor mobility, competition, and innovation incentives. On the one hand, spinouts generate high-quality firms with superior performance; on the other hand, inventor departures reduce incumbents' appropriability and may weaken incentives for future innovation. To quantify these trade-offs and assess their implications for growth, welfare, and policy—including mobility restrictions and directed entry subsidies—we develop a Schumpeterian growth model with endogenous firm entry and exit, in which spinouts arise through inventor mobility. Relative to standard innovation-driven firm dynamics models (Acemoglu, Akcigit, Alp, Bloom and Kerr, 2018; Peters, 2020), the framework introduces two key departures: it features endogenous occupational choice of skilled workers between entrepreneurship and R&D employment, and it endogenizes the distribution of firm quality types through spinout formation. The economy is populated by skilled workers who endogenously choose among three occupations: they can operate firms as entrepreneurs, work for incumbent firms as R&D managers (inventors), or remain outside while contemplating either path. Firms are run by entrepreneurs and are heterogeneous in their innovation capacity. Upon entry, each firm draws a permanent innovation quality type that governs its R&D efficiency: high-type firms convert R&D resources into innovation more effectively than low-type firms. Over time, firms invest in innovation to improve their technological lead and climb the quality ladder.

At the core of the model is an endogenous entry mechanism that determines both the volume and composition of entrants driving creative destruction. Skilled workers can enter entrepreneurship either directly, as regular entrants without prior R&D experience, or through spinouts arising from inventor mobility from incumbent firms. While supplying innovation effort to the parent firm, R&D managers simultaneously choose a separation effort that may lead to the creation of a new firm. A successful separation generates a spinout entrant whose probability of drawing a high type grows with the technological lead of the parent firm; this knowledge diffusion channel captures the parent-spinout quality link documented in the data. At the same time, the parent firm incurs a temporary loss in innovation efficiency following the manager's departure, in line with the empirical evidence. Finally, the separating manager pays a fixed cost, reflecting barriers from non-compete enforcement. Through this mechanism, spinout entry dynamics and mobility policies endogenously shape the distribution of firm types and innovation incentives in the economy.

We discipline the model using rich firm–inventor data that allow us to map the model's core objects—firm type, technological lead, innovation, entry, exit, and inventor mobility—directly to their empirical counterparts. The calibrated model closely matches key targeted moments: high-type firms are about 3.8 times more innovative than low-type firms; regular entrants account for roughly 10.7% of new firms, while spinouts represent 4.2%; and despite being fewer, spinouts are substantially higher quality, with about 36% entering as high-type firms compared with 19.8% among regular entrants. The model also replicates the dynamic costs of spinout formation for incumbents, generating a decline in parent-firm innovation of roughly 13 percentage points at the time of inventor departure and a gradual recovery over about five years. Beyond these targeted moments, the model successfully matches a wide range of untargeted moments: it reproduces the stationary distribution of firms across technological gaps, the overall and entrant shares of high-type firms, and the heterogeneous innovation, separation, and survival patterns observed in the data. Together, these results show that the model is tightly disciplined by the data and captures the key lifecycle and selection forces underlying firm heterogeneity and spinout-driven growth, providing a solid foundation for quantitative analysis.

Our first quantitative findings highlight the important role of spinouts in shaping firm heterogeneity and aggregate productivity growth. In the model, only 40 percent of active firms are high-type, yet they account for nearly three-quarters of innovation-driven growth–reiterating the importance of a small set of firms in generating large growth contributions (Haltiwanger et al., 2017; Bartelsman and Doms, 2000). Critically, 42 percent of these high-type incumbents originated as spinouts, leading spinouts to account for 37 percent of aggregate productivity growth even though regular entrants are nearly three times as numerous at birth. These findings highlight that entrepreneurship via inventor mobility is an important and micro-founded source of the ex-ante firm heterogeneity emphasized by Sterk et al. (2021).

Next, using model counterfactuals, we show that spinout formation acts as an underpinning force behind aggregate growth and reallocation toward high-growth firms, despite a fundamental trade-off between knowledge diffusion, creative destruction, and appropriability. In the model, the creation of spinouts affects the aggregate economy through three main channels: a *direct-entry* effect that intensifies creative destruction; a *type-composition* effect through which disproportionately high-type spinout entry shifts the firm distribution toward higher-growth entrepreneurs; and a negative *incumbent-innovation* effect, as spinout departures reduce parent-firm efficiency and dampen incumbents' ex-ante R&D incentives.[4] We show that shutting down spinout formation entirely reduces aggregate growth by 0.33 percentage points and welfare by 2 percent in consumption-equivalent variation, indicating that the direct-entry and type-composition channels play a quantitatively important role in sustaining growth. At the same time, we find that the negative impact of spinouts on incumbent innovation—a key concern in policy debates—is economically significant: removing the harm spinouts impose on parent firms raises aggregate growth by 0.22 percentage points and welfare by 2.4 percent.

Finally, we use the model to evaluate mobility and entry policies. Non-compete laws—a key restriction on inventor mobility—vary widely across U.S. states, ranging from no enforcement in California to broad enforcement in states such as Florida.[5] Our quantitative policy experiments show that these restrictions on inventor mobility impose significant aggregate costs. In an economy calibrated to average U.S. enforcement, eliminating non-compete laws raises aggregate growth by 0.10 percentage points and welfare by 1.44 percent, with substantially larger gains—up to 0.28 percentage points in growth and 2.57 percent in welfare—– when non-compete stringency matches that of the strictest jurisdictions, such as Florida or Washington, DC. These results arise because greater spinout activity increases creative destruction and reallocates activity toward higher-growth entrepreneurs, which in equilibrium more than offsets the negative incentive effects on individual incumbents.

The importance of heterogeneity at entry also raises the question of whether targeted entry subsidies can more effectively promote high-growth entrepreneurship and innovation. We find that subsidies directed at spinouts deliver the largest growth gains, whereas subsidies targeted at regular entrants generate the strongest welfare improvements. Across all policies, non-compete enforcement substantially weakens effectiveness by limiting the formation of high-type innovators, whereas remov-

[4] A fourth mechanism—the *pro-competitive effect*, through which higher entry pushes industries toward younger and closer competitors—also operates in the model but plays only a minor quantitative role in our results.

[5] State-level enforceability classifications follow Garmaise (2011) and Starr (2019). Non-compete agreements have become increasingly widespread: recent estimates suggest that 28-47% of private-sector workers are subject to them (Colvin and Shierholz, 2019), with high-skill and technical workers even more likely to face such restrictions. Interviews with patent holders further show that non-competes play a meaningful role in shaping the career paths of technical professionals (Marx, 2011).

ing these restrictions amplifies the impact of any subsidy scheme. Overall, the results highlight that both inventor mobility and pre-entry heterogeneity are central for policy design, and that growth- and welfare-maximizing interventions need not coincide.

Related Literature This paper contributes to several literatures by combining rich inventor–firm patent data with a unified quantitative general-equilibrium framework linking spinout formation to ex-ante firm heterogeneity, innovation dynamics, and aggregate growth.

First, we relate to the literature emphasizing firm heterogeneity in shaping innovation and productivity growth. Firm-level productivity differences are large, persistent, and highly skewed, with a small set of high-performing firms accounting for a disproportionate share of innovation and growth (Dunne, Roberts and Samuelson, 1988; Abbring and Campbell, 2005; Sterk, Sedláček and Pugsley, 2021; Guzman and Stern, 2020). Importantly, recent evidence shows that this skewness largely reflects heterogeneity present at entry rather than gradual post-entry divergence (Abbring and Campbell, 2005; Sterk, Sedláček and Pugsley, 2021; Guzman and Stern, 2020). Despite this evidence, most existing models—from canonical firm-dynamics frameworks to modern general-equilibrium models of innovation and growth—either abstract from persistent type heterogeneity or take entrant heterogeneity as exogenous, offering limited insight into the mechanisms that generate high-growth firms in the first place (Hopenhayn, 1992; Hopenhayn and Rogerson, 1993; Aghion and Howitt, 1992; Klette and Kortum, 2004; Lentz and Mortensen, 2008; Acemoglu and Akcigit, 2012; Acemoglu, Akcigit, Alp, Bloom and Kerr, 2018; Peters, 2020).

We contribute by identifying innovating spinouts as a central endogenous source of entry heterogeneity with first-order implications for innovation and growth. We extend general-equilibrium models of innovation, firm dynamics, and growth by introducing inventors' occupational choice and spinout formation, through which entrant heterogeneity arises as spinout entrants are endowed at entry with initial quality linked to their incumbent parent firms. As a result, the composition of entrants is determined endogenously in equilibrium, with inventor mobility providing a microfoundation for the knowledge diffusion mechanisms that improve the productivity distribution in related models (Perla and Tonetti, 2014; Lucas and Moll, 2014; Benhabib, Perla and Tonetti, 2021).

Early theoretical work on employee entrepreneurship begins with Pakes and Nitzan (1983) and Anton and Yao (1995), who analyze optimal contracting when researchers can leave to commercialize ideas. Chatterjee and Rossi-Hansberg (2012) study spinoff creation and scale-independent growth. Closest to our work are Franco and Filson (2006), who examines employee imitation and spinout-driven industry dynamics, and Franco and Mitchell (2008), who analyze how mobility restrictions shape regional outcomes such as the Route 128–Silicon Valley divergence. These contributions provide important insights but rely on stylized or partial-equilibrium settings not suited for quantitative analysis. A related study by Sohail (2021) documents spinout patterns using Mexican data and analyzes macro implications of the link between employer size and spinout dynamics. We contribute by embedding spinout formation into a general-equilibrium Schumpeterian growth framework that endogenizes both the quality composition of entrants and the innovation costs borne by parent firms–allowing us to quantify the offsetting forces emphasized in policy debates.

Our empirical analysis complements a body of industry-level evidence on spinout formation. Studies spanning automobiles, lasers, disk drives, medical devices, and other sectors establish that spinouts account for a substantial share of entry, outperform regular entrants, exhibit lower failure rates, and tend to originate from industry leaders (see, among others, Klepper (2002), Agarwal et al. (2004), Klepper and Sleeper (2005), Franco and Filson (2006), Chatterji (2009), and Campbell et al. (2012)). Using economy-wide inventor–firm matched data, we show that these regularities extend broadly across innovating firms, provide new evidence on the innovation costs borne by parent firms, and use these moments to discipline our quantitative framework.

Finally, we contribute to the literature on non-compete enforcement. Empirical work documents that stricter enforcement reduces labor mobility (Fallick et al., 2006; Marx et al., 2009; Garmaise, 2011; Starr et al., 2018) and firm entry, including spinout formation (Samila and Sorenson, 2011; Jeffers, 2019), while increasing firm investment in knowledge-intensive industries (Conti, 2014; Jeffers, 2019; Barnett and Sichelman, 2020). This evidence highlights a tradeoff between mobility-driven entry and incumbent investment incentives but cannot resolve whether restricting mobility raises or lowers aggregate welfare—hence the diverse views among scholars and policymakers (Saxenian, 1994; Gilson, 1999; Barnett and Sichelman, 2020). We provide a quantitative assessment of this tradeoff in a general-equilibrium framework linking non-compete enforcement to spinout formation, incumbent innovation, and aggregate growth. Related structural work on non-compete enforcement by Shi (2021) focuses on executive mobility through job-to-job transitions and wage contracting. Our analysis focuses on the entrepreneurial aspect of inventor mobility, a margin that we find plays a central role in shaping innovation dynamics, firm heterogeneity, and aggregate growth. Together, these perspectives highlight distinct but complementary channels through which mobility restrictions operate, and both are essential for a comprehensive evaluation of the aggregate and welfare effects of non-competes.

2 Empirical Analysis

To identify and characterize innovating spinout firms, we construct a new micro-level dataset that links patent records to firms and inventors, allowing us to trace inventor mobility, spinout formation, and their performance. The empirical analysis serves two main purposes. First, it documents key empirical regularities on spinout performance over the life cycle, parent-firm innovation following spinout separation, and the relationship between spinout formation and non-compete enforceability. Second, these empirical patterns discipline both the structure and calibration of the quantitative model developed in the next section, guiding key assumptions and parameter choices.

We begin by describing the data sources and our spinout identification strategy, and then present three sets of empirical facts that underpin the model.

2.1 Data and Identification of Spinouts

2.1.1 Data Sources

NBER-USPTO Patent Data (PD). The core of the empirical analysis relies on the U.S. Patent and Trademark Office (USPTO) dataset drawn from the NBER Patent Data Project (Hall et al., 2001). The NBER data contains all USPTO granted patents for the 1976-2006 period. We use detailed information on 1,841,499 patents assigned to 1,457,121 U.S. entities (assignees). For each patent, we use the following patent characteristics: patent's technology classification, patent claims, and the number of forward patent citations received – a widely-used metric of the economic and technological significance of a patent (Trajtenberg, 1990; Harhoff et al., 1999; Kogan et al., 2017), as well as information on the assignees that file a patent. For the analysis, we focus on patents of the U.S. corporate assignees.[6] For each patenting firm, we use its location (state) and define its technology classification based on the most common technology classification of the patents this firm files.

Disambiguated Inventors Data (DID). The second source of data on the U.S. patent inventors comes from the Harvard Patent Network Dataverse (HPND) project (Lai et al., 2011). Each patent application, in addition to listing patent assignees, also lists the names of all individual inventors of the patent. The HPND project disambiguates inventor names to provide unique identifiers for each inventor in the USPTO data. As a result, by matching PD and DID datasets, we obtain the matched firm-inventor dataset from 1976 to 2006 for nearly a million innovating firms in the U.S. and more than 650 thousand unique inventors working in those firms. The advantage of this data match is that it allows us to measure a firm's innovation output quality and track individual inventors over time across different firms.

Compustat North American Fundamentals. To measure other firm-level outcome variables, such as sales, total employment, assets, and R&D expenditures, we link the matched dataset to financial data for publicly listed firms from Compustat North American Fundamentals (Annual). As a result, the empirical section consistently refers to two data samples: "Patent Data" comprises all patenting firms in our dataset, and "Compustat + Patent Data" is the subsample of firms matched to Compustat.

2.1.2 Sample and the Identification of Spinout Firms

Using our sample of innovating firms, we first define entry and exit. Firms are classified as entrants based on the year of their first patent application, and their exit year is defined as the grant year of their last patent in the data. Although these dates may not exactly coincide with a firm's literal birth or death in the economy, they provide consistent proxies for a firm's entry into and exit from *innovation*—the relevant concept for our analysis. The first patenting year captures a firm's transition into the innovation stage, mirroring entry in the model, while the last patent captures its exit from active innovation, consistent with the model's notion of firm exit.[7]

[6] As a result of the extensive firm name cleaning and tracking firm reorganizations, PD provides unique company identifiers for each corporate assignee.

[7] Comparisons with case studies in Franco and Filson (2006), discussed below, indicate that entry into patenting lags firms' true founding dates by approximately 1.3 years on average.

To identify spinouts, we track inventor mobility across firms using their patenting histories. A firm is classified as a *spinout entrant* if at least one inventor on a patent application in the firm's entry year previously patented at another firm.[8] To reduce measurement error, we drop cases where the gap between an inventor's last patent at the prior firm and the first patent at the entrant exceeds five years, and we exclude moves associated with mergers or acquisitions (identified using the "Dynass" file in the PD database). Entrants that do not meet these criteria are classified as *regular entrants*.

The following example illustrates the spinout classification. Computer Memories Inc., a California-based hard-disk manufacturer active in the 1980s, has seven granted patents in our data. Ara W. Nazarian appears as an inventor on two of its 1983 patent filings (*US*4578625 and *US*4685007). In 1986, Nazarian filed *US*4786995 under Peripheral Technology Inc., which is also that firm's first patent. We therefore classify Peripheral Technology Inc. as a spinout entrant.[9]

Our main sample focuses on entrants born between 1981 and 1999, a window chosen to minimize truncation concerns. Because the dataset includes only patents granted from 1976 onward, we begin identifying entrants in 1981 to limit left-truncation. Likewise, since the data end in 2006 due to application–grant lags, we restrict entrant identification to 1999 to mitigate right-truncation. This 1981–1999 window provides sufficient time to observe entrants' subsequent innovation, performance, and potential exit. Firms with patent applications before 1981 are classified as *incumbents*—or as firms with an unknown origin—and appear as such in our sample starting in 1981.

2.1.3 Descriptive Summary Statistics

Table 1 reports summary statistics for the patent data. Panel A covers all innovating firms. We observe 63,561 firms born between 1981 and 1999 ("entrants") and 11,408 firms operating before 1981 ("incumbents"). Entrants have an average longevity of 3.9 years, with 6 patents and 107 citation-weighted patents on average.[10] Incumbents, by contrast, survive 14.9 years on average and file 67 patents and 946 citation-adjusted patents.

Among entrants, 18,012 (28.3%) are classified as spinouts and 45,549 as regular entrants. Spinouts survive longer (4.3 vs. 3.4 years) and exhibit substantially higher innovation output, averaging 11 patents and 204 citation-adjusted patents per firm, compared with 4 patents and 69 citation-adjusted patents for regular entrants.

Despite being only 28.3% of entrants—2.5 times fewer than regular entrants—spinouts account for a disproportionate share of entrant innovation. Over 1981–2006, they generate 52.8% of entrant patents (16.7% of all patents) and 54% of entrant citation-adjusted patents (20% of all citation-adjusted patents). These patterns already signal the superior innovation performance of spinouts relative to regular entrants.

Panel B focuses on firms that match to Compustat, yielding 1,539 entrant and 2,880 incumbent firms.

[8] An alternative definition—using inventor backgrounds from the first two post-entry years—yields similar results.

[9] Consistent with this classification, Franco and Filson (2006) document that Peripheral Technology Inc. was founded by former employees of other firms in the hard disk industry. They report entry in 1985 and exit via acquisition two years later. In our data, the firm enters in 1986 and exits in 1988, the year of its last patent was granted. Notably, Computer Memories Inc. announced its exit from the hard disk industry in 1986—the same year it files its last patent.

[10] We use truncation-adjusted citations following Hall et al. (2001).

Table 1: Summary Statistics

	Spinout Entrants	Regular Entrants	Incumbents
- Panel A. Patent Data-			
Number of firms	18012	45549	11408
Years in sample	4.3	3.4	14.9
Number of spinouts spawned	0.3	0.1	0.9
Number of parents	1.2	–	–
Lifetime number of patents	11	4	67
Lifetime number of cit-weighted	204	69	946
- Panel B. Patent + Compustat data-			
Number of firms	803	736	2880
Years in sample	9.8	9.0	17.3
Number of spinouts spawned	0.8	0.6	2.3
Number of parents	1.4	–	–
Lifetime number of patents	103	62	225
Lifetime number of cit-weighted	1978	1282	3300
Sales (yearly)	859	696	2192
Sales growth (yearly)	0.22	0.19	0.05
Employees (yearly)	3.5	2.7	11.1
Assets (yearly)	1048	1046	3277
R&D Expenditure (yearly)	42	27	32

Note: The table presents summary statistics for spinout entrants, regular entrants, and incumbent firms in 1981-2006 along various dimensions. The entrants are identified in the period 1981-1999, while incumbents are defined as firms filing at least one patent before 1981. The first panel presents statistics for all the innovating firms in the data, while the second panel presents statistics for firms matched to Compustat.

Among entrants, 803 are spinouts and 736 are regular entrants. Because Compustat includes only publicly listed (and thus larger, positively selected) firms, the fact that 5.2% of spinouts—but only 1.9% of regular entrants—appear in this sample reinforces their relative strength. Even within this positively selected group, spinout entrants continue to outperform regular entrants across innovation, financial, and operational metrics: they are larger in assets, sales, and employment and devote more resources to R&D.

2.1.4 Discussion and Validation Exercises

Before presenting the empirical results, we discuss the main features of our innovating spinout identification strategy, its relevance for our analysis, and our validation exercises.

First, our study centers on the universe of *innovating* firms that appear in patent data, reflecting our focus on innovation as the central engine of technological progress and growth. In this context, patents remain the most systematic and scalable measure of innovation, robustly linked to firm-level and aggregate growth (Griliches, 1981; Hall et al., 2007; Kogan et al., 2017; Argente et al., 2020). We also verify in Appendix Table A2 that even among the highly selected sample of publicly listed firms in Compustat, firms that engage in patenting activity significantly outperform non-patenting firms across all productivity and growth dimensions.

Next, our focus on spinouts identified via *inventor mobility* naturally excludes spinouts formed without inventor participation. This classification choice may group some such non-inventor spinouts together with regular entrants in our empirical analysis. Nevertheless, we find that, on average, inventor spinouts substantially outperform this combined comparison group, suggesting that inventor mobility captures a critical dimension of high-performing spinouts. Complementary evidence from Islam and Zein (2020) demonstrates that firms led by inventor-CEOs significantly outperform those led by non-inventors. Together, these findings indicate that our inventor-based classification successfully isolates the subset of spinouts most central to innovation-driven growth and most relevant for understanding ex-ante heterogeneity in firm performance.

Finally, our inventor-mobility–based definition of spinouts is broader than the conventional ownership-based definition and more generally captures a firm's early *founding team* of inventors. Despite this difference, as we show below, our approach closely tracks standard ownership-based spinout classifications. Viewed more broadly, this definition aligns with the perspective in Choi, Goldschlag, Haltiwanger and Kim (2019), who emphasize that a startup's long-run performance is shaped by the broader founding team rather than solely by formal business founders. Our findings highlight inventors as founding-team members who are especially central to a new firm's technological direction and performance.

We validate our spinout identification using two approaches. First, we compare our definition of spinouts with the traditional definition found in the literature. The influential work of Franco and Filson (2006) analyzes the rigid disk drive industry using detailed industry reports and identifies 40 spinout entrants between 1977 and 1993. We classify these entrants using our methodology and report the detailed comparisons of the classifications in Appendix Table A1. Of the 40 spinouts in their sample, 25 appear in our data—that is, they have patents during the period covered by our sample.[11] Among these 25 innovating spinouts, 21 (84%) are also identified as spinouts via inventor mobility. This high concordance provides strong validation that inventor mobility closely captures the entry of innovative spinouts.

Our second validation approach compares key moments in our data with established empirical regularities from the broader spinout literature. A body of empirical studies across industries—including automobiles, disk drives, lasers, medical devices, legal services, and biotech (e.g., Klepper, 2002; Agarwal et al., 2004; Klepper and Sleeper, 2005; Franco and Filson, 2006; Chatterji, 2009; Klepper and Thompson, 2010; Campbell et al., 2012)—documents several robust facts: spinouts account for a sizable share of entry (typically 17–26%), they outperform other entrants and often become industry leaders, and they inherit knowledge from parent firms in ways that shape their comparative advantage. The moments in our data closely mirror these patterns. In particular, the share of spinout entrants in our sample—28%—is close to the documented range, and we likewise find that innovating spinouts exhibit superior performance and clear evidence of knowledge inheritance, as shown in the next section.

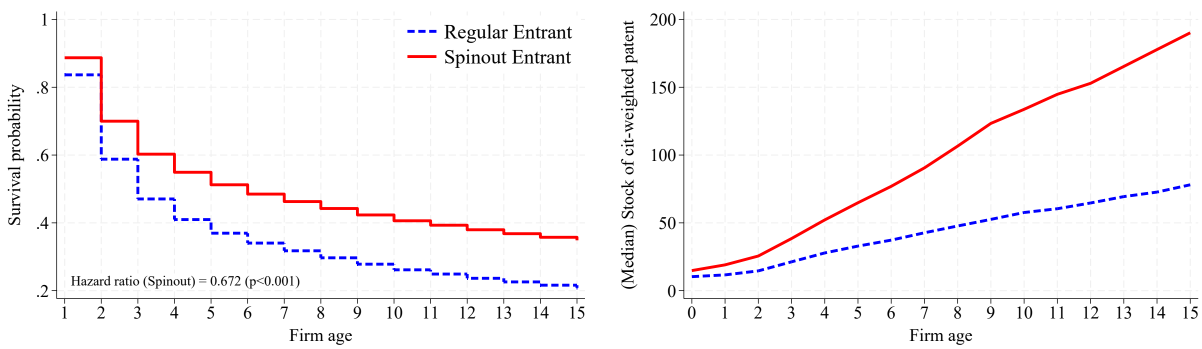
In sum, combining a comprehensive dataset on patenting firms with an inventor-mobility–based definition of spinouts allows us to zoom in on the firms most relevant for innovation-led growth and to construct granular measures of technological capability that are not systematically available from other sources.

[11] These patenting spinouts also survive substantially longer—about 11 years on average—than non-patenting spinouts, which survive roughly 4 years, reinforcing the relevance of patent data for characterizing innovation-driven growth.

Figure 2: Lifecycle Dynamics of Spinouts and Regular Entrants

(a) Firm Survival

(b) Citation-Adjusted Patents



Notes: This figure compares survival and innovation outcomes for spinout and regular entrants. Panel (a) plots survival probabilities by firm age using a Cox proportional-hazards model. Entry (age 0) is defined by the year of the first patent application, and exit by the last patent's grant year. We examine entrants founded between 1981 and 2000 and treat firms whose last grant year occurs before 2000 as exiting, ensuring they are not censored from above. The estimated hazard ratio for spinout entrants is 0.67 (p-value < 0.001). Panel (b) reports the median cumulative number of citation-adjusted patents by age for each entrant type, highlighting the persistently greater innovative output of spinouts.

2.2 Empirical Facts on Innovating Spinouts

This section documents three empirical facts on innovating spinouts that motivate the analysis and inform the quantitative model that follows. First, spinout firms systematically outperform regular entrants along multiple dimensions over the life cycle. Among spinouts, those originating from more technologically advanced parent firms display higher innovative quality. Second, we document a tension between spinout formation and parent-firm innovation: following a spinout event, parent firms experience a decline in innovation activity. Finally, we show that stricter enforcement of non-compete agreements is associated with a lower likelihood of spinout formation.

Fact 1. Spinout entrants outperform regular entrants

The first fact highlights systematic differences in the outcomes of spinout and regular entrant firms. Figure 2 documents the lifecycle patterns of spinout and regular entrants using the patent data. Panel (a) shows that spinout entrants exhibit markedly higher survival rates. By age 15, approximately 36% of spinouts remain active, compared to only 20% of regular entrants. Consistent with this visual pattern, the hazard ratio for spinout firms is 0.67 (p-value < 0.001), implying a 33% lower risk of exit. Panel (b) reports the median stock of citation-adjusted patents by firm age, showing that spinouts consistently generate more innovative output throughout their lifecycle. By age 15, the median spinout has accumulated roughly 200 citation-adjusted patents, versus only 70 for the median regular entrant.

Table 2 further compares spinouts and regular entrants across a broad set of performance metrics. Panel A reports lifetime outcomes using the patent data. Conditional on entering in the same cohort, operating in the same technology class, and locating in the same state, spinout firms file 54% more patents over their lifetime ($\exp(0.432)$). They also generate more citation-weighted patents, more high-quality patents, and remain active in the patent data for longer. Panel B merges the patent data with Compustat to examine financial performance. Despite the positive selection into public

Table 2: Spinouts vs. Regular Entrants

Panel A. Patent Data

	(1) Log Patents	(2) Log Cit-Patents	(3) Log Top Patents	(4) Log Lifespan
Spinout entrant	0.432***	0.560***	0.149***	0.257***
	(0.010)	(0.013)	(0.005)	(0.009)
Cohort FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
State FE	✓	✓	✓	✓
Observations	63,554	60,617	63,554	63,554
Mean	0.751	3.112	0.198	0.781

Panel B. Compustat + Patent Data

	(1) Log Cit-Patents	(2) Log Sales	(3) Log Employment	(4) Log R&D
Spinout entrant	0.210***	0.202***	0.210***	0.364***
	(0.040)	(0.041)	(0.031)	(0.032)
Cohort FE	✓	✓	✓	✓
Age FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
State FE	✓	✓	✓	✓
Observations	7,108	13,594	12,930	12,729
Mean	4.096	4.359	-0.582	1.498

	(5) Log R&D/Emp	(6) Cit-Patent/R&D	(7) Top Patent/R&D	(8) Sales growth
Spinout entrant	0.150***	1.677***	0.014***	0.023**
	(0.021)	(0.466)	(0.003)	(0.011)
Cohort FE	✓	✓	✓	✓
Age FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
State FE	✓	✓	✓	✓
Observations	11,499	12,729	12,729	11,996
Mean	2.112	5.241	0.027	0.108

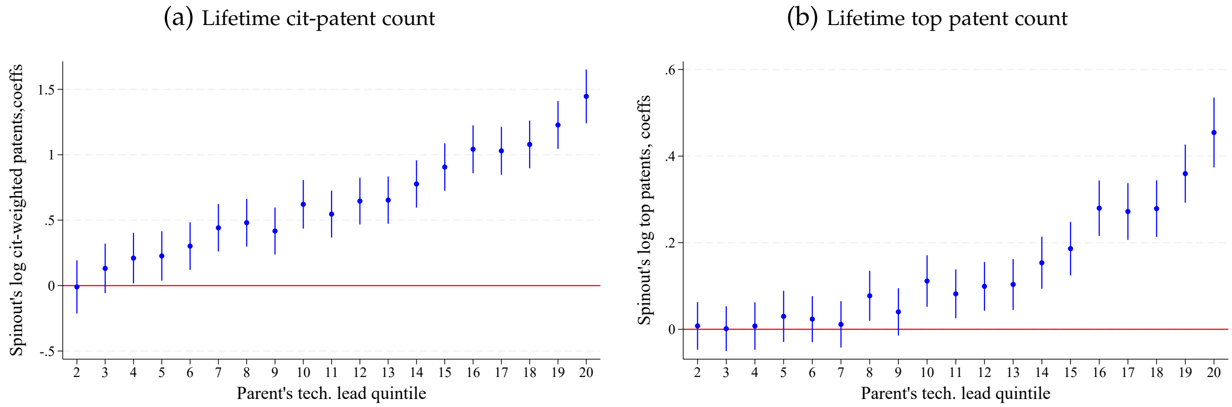
Notes: Each observation is an entrant firm founded between 1981 and 2000. *Spinout entrant* is an indicator equal to one for firms founded by inventors previously employed at incumbent patenting firms. Panel A includes all firms in the patent data; Panel B restricts to firms matched to Compustat. Patents, citation-adjusted patents, and top patents are lifetime totals. Top patents are defined as those with truncation-adjusted citations above the 90th percentile of patents filed in the same year and technology class. Lifespan measures the difference between the last and first years the firm appears in the patent data. Panel B variables are averages over all years the firm appears in Compustat. Sales growth is the mean annual growth rate. All regressions include cohort, technology-class (nclass), and state fixed effects. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

markets, Column (1) shows that spinout entrants continue to outperform regular entrants in citation-weighted patenting. Columns (2)–(4) indicate that spinouts are larger in sales and employment and invest more in R&D. Columns (5)–(7) show that they are more R&D-intensive and convert R&D into impactful patents more efficiently. Finally, Column (8) documents that spinouts grow faster, exhibiting an average sales growth rate 2.3 percentage points higher than regular entrants.

Overall, these patterns indicate that firms founded as spinouts of innovating incumbents are systematically more innovative and productive than firms without such origins. This heterogeneity in entry type can help account for part of the large and persistent ex-ante productivity differences observed across firms (Dunne et al., 1988; Sterk et al., 2021; Guzman and Stern, 2020).

We further examine heterogeneity among spinout firms and show that the parent's technological position is a strong predictor of spinout quality. Figure 3 compares spinouts spawned from parents with different technological leads. To construct parents' technological lead, we rank firms into 20

Figure 3: Parent's Technological Lead and Performance of Spinouts



Notes: The figures plot coefficients from regressions of spinout innovation outcomes on parents' technological lead, defined as 20 quantiles of the citation-weighted patent quality distribution within the parent's technology class over the preceding five years. Outcomes are (a) lifetime log citation-weighted patent counts and (b) lifetime log top-patent counts. Regressions control for the number of parents, parent's recent patent stock, technology class, state, and spinout cohort fixed effects. Shaded areas show 95% confidence intervals.

quantiles based on the distribution of their citation-weighted patent counts within their technology class over the previous five years. Panel (a) of Figure 3 plots estimated coefficients from regressions of a spinout's lifetime citation-weighted patent count on the parent's technological lead at the time of separation. Panel (b) shows analogous results for the lifetime number of top patents. All specifications control for the number of parents, the parent's recent patent stock, technology class, state, and spinout cohort fixed effects.

The pattern is pronounced: spinouts are substantially more innovative when their parents hold a larger technological lead. Because the regressions already condition on the quantity of parents' recent patents, the coefficients capture the additional effect of *quality*—that is, of being at the technology frontier rather than only being prolific. Appendix Table A3 shows that alternative parent patent quality measures are consistently strong correlates of spinout performance, whereas patent quantity plays a more limited role.[12] Several mechanisms may underlie this relationship. Inventors at technologically leading firms may be better positioned to identify high-quality ideas, recognize entrepreneurial opportunities, and learn how to successfully bring them to market (Chatterji, 2009). At the same time, positive selection, financing advantages, or differences in motivation and effort among employees at frontier firms may also contribute (Dahl and Sorenson, 2013). Regardless of the specific channel, these patterns point to the important parent–spinout knowledge inheritance.

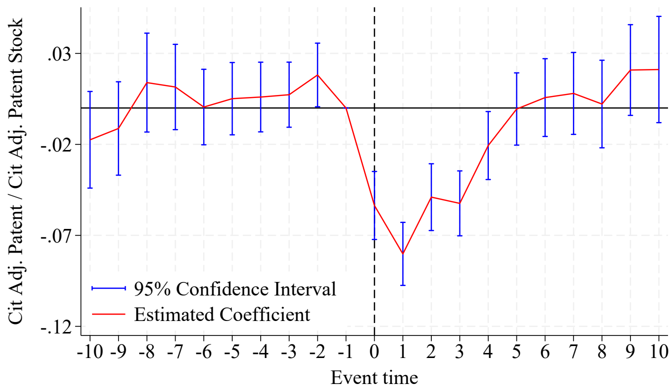
Fact 2: Parents experience innovation loss after spinout separation

Spinout formation, while an important source of innovation and entrepreneurship, also creates natural tensions between incumbent firms and departing employees. Firms regularly express concerns that employee mobility may harm their business, particularly when it involves key inventors who contribute disproportionately to the firm's innovative capacity or technological position (Saxenian, 1994). This subsection provides empirical evidence consistent with these concerns. We ask whether

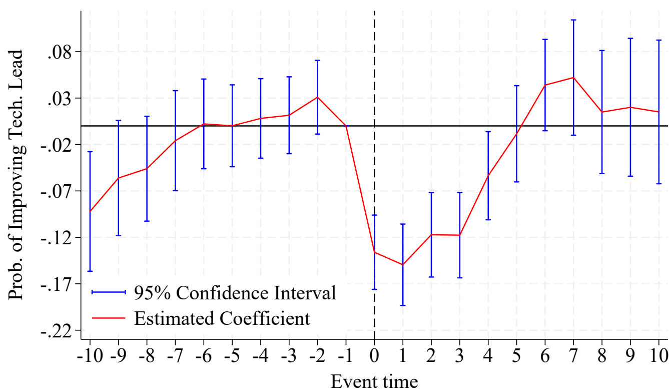
[12] Additional robustness checks—including alternative definitions of technological lead and additional spinout outcome variables—are presented in Appendix Tables A4 and A5.

Figure 4: The Effect of Spinout Separation on Parent Firms' Innovation

(a) Patenting rate



(b) Probability of improving technological lead



Notes: This figure reports β_k coefficient estimates from the event study in (1), capturing the effect of spinout formation on parent firm outcomes. Panel (a) reports results for the patenting rate, and Panel (b) shows the probability of improving the technological lead. The omitted event time is -1. Red lines plot the estimated coefficients; blue lines show 95% confidence intervals.

spinout formation—specifically through inventor mobility—has negative consequences for parent firms. For example, the departure of key inventors may weaken the parent's innovative capacity or technological position, and newly formed spinouts may create additional competitive pressures.

To empirically identify the effect of spinout spawning on parent firms, we implement a dynamic difference-in-differences design. Specifically, we conduct an event-study analysis comparing parent firms whose inventors depart to form spinouts with parents whose inventors move to other incumbent firms. This strategy relies on the assumption that parent firms in the two groups would have followed similar outcome trajectories after inventor departure, absent spinout formation. Hence, differences in post-departure outcomes identify the differential effect of spinout-related departures relative to mobility to other incumbent firms.

Formally, we restrict the sample to firms experiencing a single inventor-mobility event during the sample period—either a departure to another incumbent firm or the formation of a spinout. An *event* is defined as the last year in which the departing inventor files a patent with the parent. Let T_i denote this year. We then define the event-time indicator $event\_time_{it}^k$, which equals one for firm i in year t if $t - T_i = k$. The estimating equation is:

Table 3: Non-Compete Laws and Spinout Separation

	(1) Logit	(2) Logit	(3) Logit	(4) Neg. Binom	(5) Neg. Binom	(6) Neg. Binom
NCL Index	-0.035***	-0.045**	-0.043**	-0.031***	-0.037**	-0.036**
	(0.0045)	(0.0187)	(0.0196)	(0.0040)	(0.0163)	(0.0156)
Year FE	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓		✓	✓	
State FE		✓			✓	
Firm FE			✓			✓
Other Controls	✓	✓	✓	✓	✓	✓
Observations	182286	182286	54117	182452	182452	54545

Notes: The table reports firm-level regressions of the probability of spawning a spinout (logit models, columns 1–3) and the number of spinouts spawned (negative binomial models, columns 4–6) as a function of the NCL index and parent-firm characteristics. The *NCL index* is the non-compete enforceability measure defined in Appendix A.1. Controls include the log number of patents and citation-weighted patents filed in the past five years, the log number of inventors, firm age, and state-level characteristics such as the number of innovating firms in the same technology class and state, GDP per capita, and population. The sample includes all patenting firms from 1981 to 2000. *** p<0.01, ** p<0.05, * p<0.1.

$$Y_{it} = \beta_0 + \sum_{k \neq -1} \alpha_k \, event\_time_{it}^k + \sum_{k \neq -1} \beta_k \left(event\_time_{it}^k \times spinout_i \right) + \mathbf{\Gamma}_{it} + \gamma_i + \eta_t + \epsilon_{it}, \quad (1)$$

where Y_{it} is a parent firm's outcome in year t, and $spinout_i = 1$ if the departure leads to a spinout. The vector $\mathbf{\Gamma}_{it}$ includes time-varying controls for the firm's main patent class, firm age, and state; γ_i and η_t are firm and year fixed effects. We restrict the sample to firms observed for at least five years and focus on a ten-year window around the event.[13] The final sample consists of 43,034 firm-year observations across 4,393 firms: 34% experience a spinout departure, and the remaining 66% serve as the control group.

The coefficients of interest, β_k, capture the differential effect of spinout formation relative to regular mobility. Since the α_k coefficients absorb the baseline dynamics around any inventor departure, the β_k terms isolate the incremental effect of spinout creation on parent-firm outcomes. Figure 4 plots the coefficients for two outcomes capturing parent-firm innovation. Panel (a) reports the parent firm's patenting rate, measured as the ratio of annual citation-weighted patents to the existing patent stock. Panel (b) shows the probability that the parent firm improves its technological lead relative to the previous year. The estimates indicate no pre-trends, supporting the validity of the comparison. Following a spinout departure, however, parent firms experience a clear, temporary decline. The innovation rate falls by roughly 8% in the year after the event and remains about 5% lower for several subsequent years, returning to baseline by year 5. The probability of improving the technological lead displays a similar pattern, dropping by about 15% in the first few years and recovering on a comparable horizon.

Overall, spinout formation imposes sizable costs on parent firms by temporarily reducing innovation rates, and even as innovation flows return to baseline, the interim decline implies lasting shortfalls in the accumulated innovation stock and slower technological advancement.

[13] This restriction is not crucial but yields a more stable set of parent firms.

Fact 3. Spinout formation is lower with stricter non-compete enforcement

The tensions documented in Fact 2 align with the motivations that have led firms and policymakers to adopt legal instruments—most notably non-compete agreements—to limit employee mobility. Indeed, among establishments with more than 50 employees, half use non-competes for at least some workers, and one-third use them for all employees, with high-skill and technical workers even more likely to face such restrictions (Colvin and Shierholz, 2019). The broader policy debate remains active, ranging from state-level efforts to strengthen enforceability to federal proposals aimed at restricting or prohibiting non-compete clauses.[14]

Motivated by the widespread use of non-compete agreements to limit employee mobility, we examine whether non-compete enforcement is associated with lower formation of innovating spinouts. To do so, we exploit substantial variation in the enforceability of non-compete agreements across U.S. states, as captured by the *NCL index* developed by Garmaise (2011).[15]

Table 3 summarizes the relationship between non-compete enforcement and spinout formation. Columns (1)–(3) estimate the probability that a firm spawns a spinout using logit models, and columns (4)–(6) estimate the number of spinouts using negative binomial models. The regressions control for parent-firm characteristics—the log number of patents, citation-weighted patents filed in the prior five years, the log number of inventors, and firm age—as well as state-level covariates, including the number of innovating firms in the same technology class and state, GDP per capita, and population. Fixed effects vary across specifications. Across all models, stricter enforcement—as captured by a higher NCL index—is associated with significantly fewer spinouts.[16]

Overall, the results indicate that stricter non-compete enforcement is associated with lower spinout formation by inventors. These findings for innovating spinouts align with prior evidence that stronger enforcement reduces labor mobility in general (Fallick, Fleischman and Rebitzer, 2006; Marx, Strumsky and Fleming, 2009; Garmaise, 2011) and suppresses firm entry (Samila and Sorenson, 2011; Starr, Balasubramanian and Sakakibara, 2018; Jeffers, 2019).

3 Model

The empirical evidence documented above highlights two central features of entrepreneurship through inventor mobility: the superior performance of innovating spinouts and their systematic relationship with parent-firm technological strength, alongside the innovation costs borne by parent firms following inventor departures. Building on this evidence, in this section, we develop a Schumpeterian growth model that embeds and quantifies the fundamental tradeoff between knowledge diffusion, creative destruction, and appropriability associated with spinout formation. The framework builds on standard models of endogenous growth with entry and incumbent innovation (Aghion and Howitt, 1992; Acemoglu and Akcigit, 2012; Akcigit and Kerr, 2018; Acemoglu, Akcigit, Alp, Bloom and Kerr, 2018; Peters, 2020), but incorporates endogenous occupation choice

[14] For example, Massachusetts Bill S.998 (2017–2018); the Workforce Mobility Act of 2019 (S.2614); and President Biden's Executive Order 14036 (2021).

[15] See Appendix A.1 for details on the construction of the index and its variation over time.

[16] Appendix Table A9 shows robustness to an alternative measure of non-compete enforceability from Starr (2019).

and inventor mobility, allowing skilled workers to transition into entrepreneurship. A key feature is that the composition and quality of entrants are endogenously shaped by incumbents' innovation decisions and inventors' separation choices, generating feedback between firm dynamics, entry, and growth. The remainder of this section discusses the model in more details.

3.1 Preferences and Final Good Technology

Time is continuous. The representative household consists of a measure L of unskilled and $\bar{S}$ measure of skilled people and has logarithmic preference over the final consumption good C. Household maximizes expected lifetime discounted utility,

$$U = \int\limits_0^\infty e^{-\rho t} \ln C_t dt,$$

where ρ is the discount rate. Household holds a balanced portfolio of all the firms in the economy, $\mathcal{A}_t$. Its budget constraint is therefore $C_t + \dot{\mathcal{A}}_t = r_t \mathcal{A}_t + \mathcal{W}_t$, where r_t is interest rate, $\mathcal{W}_t$ is the total wage bill, and the final good is a numeraire.

The final good is produced competitively by combining intermediate goods using the following logarithmic aggregator:

$$\ln Y_t = \int_0^{\bar{\mathcal{F}}} \ln y(j,t) dj, \tag{2}$$

where $y(j,t)$ is the intermediate good from product line j at time t, and $\bar{\mathcal{F}} \leq 1$ is the measure of active product lines, as described below.

Denote the price of the intermediate good produced in product line j at time t by $p(j,t)$. Profit-maximizing final good producers choose intermediate input to solve:

$$\max_{y(j,t)} \left[\exp \int_0^{\bar{\mathcal{F}}} \ln y(j,t) dj - p(j,t) y(j,t), \right] \quad \forall t.$$

This maximization leads to the following unit-elastic demand function:

$$y(j,t) = \frac{Y_t}{p(j,t)}. \tag{3}$$

3.2 Intermediate Goods Market

An intermediate good in an active product line $j \in [0, \bar{\mathcal{F}}]$ can be produced by two firms competing *á la* Bertrand. Firm i has the following production technology utilizing labor input scaled by time-variant firm-specific productivity:

$$y_i(j,t) = q_i(j,t) l_i(j,t), \tag{4}$$

where $l_i(j,t)$ denotes unskilled labor input, and $q_i(j,t)$ is firm-specific productivity in product line j that evolves endogenously as described below.

Index by i a firm with a leading technology, and a follower by $-i$, such that $q_i(j,t) > q_{-i}(j,t)$.

The products supplied by the two firms are perfect substitutes. Under Bertrand competition, only the leading firm i remains active in equilibrium. The leader sets its price equal to the follower's marginal cost, such that

$$p(j,t) = \frac{w_t^u}{q_{-i}(j,t)}, \tag{5}$$

where w_t^u denotes an equilibrium unskilled-labor wage rate.[17] As a result of the demand curve given by (3) and the price in (5), the profit of an intermediate goods producer in product line j is

$$\Pi_i(j,t) = \left(1 - \frac{q_{-i}(j,t)}{q_i(j,t)}\right) Y_t. \tag{6}$$

Notice that the profits of a firm are scaled by total output in the economy (a standard market size effect) and only depend on the ratio of current leading technology over the follower's technology in the product line. Hence, the incentive of the leading firm is to widen this technology gap to increase profits. This, in turn, can be achieved through costly research and development (R&D). The next section describes this process of R&D.

3.3 Firm Heterogeneity and Productivity Dynamics

To advance their productivity, intermediate-good firms must invest in R&D.[18] Firms are heterogeneous in their R&D efficiency, which is largely determined at entry and characterized by a permanent *quality type* $\tau \in \{H, L\}$, where H denotes high-type firms with greater R&D efficiency and L denotes low-type firms with lower efficiency.

Motivated by empirical evidence on parent innovation losses following spinout formation, firms in the model also experience a temporary reduction in R&D capabilities arising from inventor mobility. This is captured by a *parent state* $P \in \{0, 1\}$, where $P = 1$ indicates that the firm's R&D manager has recently departed to form a spinout.

To conduct R&D, firms choose an innovation intensity z, which determines the Poisson arrival rate of innovation. The total cost of achieving innovation intensity z is:

$$\mathcal{C}(z,\tau,P) = \begin{cases} w^s(j,t) + \dfrac{z^\gamma(j,t)}{\gamma B^\tau} Y_t & \text{if } P = 0 \\ \dfrac{z^\gamma(j,t)}{\gamma \alpha B^\tau} Y_t & \text{if } P = 1 \end{cases} \tag{7}$$

The R&D cost function has two components. First, $w^s(j,t)$ denotes the wage bill for the R&D manager, which is incurred only when $P = 0$. Second, the variable cost $\frac{z^\gamma(j,t)}{\gamma B^\tau} Y_t$ is convex in innovation intensity ($\gamma > 1$) and scales with aggregate output Y_t. The productivity parameter B^τ reflects the firm's R&D efficiency, with $B^H > B^L$, indicating that high-type firms achieve greater innovation outcomes for the same resource expenditure. The parameter $0 < \alpha < 1$ captures the temporary

[17] We can also interpret this structure as the pricing decision of a firm facing a competitive fringe that can produce at some base level of technology $q_{-i}(j,t)$ freely accessible to everyone.

[18] In what follows, we refer to intermediate-good firms simply as firms.

reduction in innovation efficiency when $P = 1$.

If the firm's innovation is successful, within a small time interval Δt, it improves the previous productivity by a step size λ, where $\lambda > 1$:

$$q_i(j, t + \Delta t) = \lambda q_i(j, t).$$

In the model, inactive followers act as a competitive fringe, and productivity improvements are indexed relative to their productivity. Suppose the productivity of a competitive fringe in product line j is given by $q_{-i}(j,t) = \lambda^{n_{-ij}} q_0$, and the productivity of an incumbent is $q_i(j,t) = \lambda^{n_{ij}} q_0$, where q_0 is some initial level of productivity. Then we can define the number of step improvements made by the incumbent relative to the competitive fringe in product line j as $n_j(t) \equiv n_{ij}(t) - n_{-ij}(t)$, referred to as the *technology gap* of product line j. This technology gap evolves endogenously as a result of entry, exit, and innovation by incumbents in each product line. For example, if the incumbent successfully innovates, the gap in the product line increases by one: $n_j(t + \Delta t) = n_j(t) + 1$.

Going back to equation (6), we can rewrite the incumbent's static profit as:

$$\Pi_i(j,t) = \left(1 - \lambda^{-n_j(t)}\right) Y_t. \tag{8}$$

Hence, the model produces a convenient structure for profits as a function of the technology gap n. This technology gap and its evolution will be the main objects of interest in what follows.[19]

3.4 The Allocation of Skilled Labor

This section describes the allocation of skilled labor in the economy and the optimization problem for each type of skilled worker. At any point in time, a constant (exogenous) measure $\bar{\mathcal{S}}$ of skilled people in the economy is allocated into three groups:

$$\text{Skilled labor} = \underbrace{\text{Entrepreneurs}}_{\bar{\mathcal{F}}} + \underbrace{\text{R\&D managers}}_{\bar{\mathcal{M}}} + \underbrace{\text{Outsiders}}_{\bar{\mathcal{S}}-\bar{\mathcal{F}}-\bar{\mathcal{M}}}$$

The total measure of active entrepreneurs, $\bar{\mathcal{F}}$, corresponds to the measure of active product lines. The total number of R&D managers currently employed in the market is $\bar{\mathcal{M}} \le \bar{\mathcal{F}}$, implying that some firms may operate without an R&D manager (a parent state with $P = 1$). Both $\bar{\mathcal{F}}$ and $\bar{\mathcal{M}}$ are endogenous outcomes of the model. The remaining $\bar{\mathcal{S}} - \bar{\mathcal{F}} - \bar{\mathcal{M}}$ skilled people are referred to as outsiders.

Denote by $V_t^{\text{firm}}(n, \tau, P)$ the value function of an entrepreneur (incumbent firm) with technology gap n, permanent quality type $\tau \in \{H, L\}$, and a parent state $P \in \{0, 1\}$. Entrepreneurs decide on the innovation rate and unskilled labor hiring for production. Denote by $V_t^{\text{manager}}(n, \tau)$ the value function of an R&D manager working for a firm with characteristics $(n, \tau, P = 0)$. R&D managers collect wages and decide on their separation rate, which determines the likelihood of creating a spinout firm (*spinout entry*). Finally, denote the value function of being an outsider by

[19] In what follows, for brevity, firm subscript i is dropped.

V_t^{out}. Outsiders can either start a job as R&D managers or enter the market as entrepreneurs (*regular entry*).

From this point onward, we restrict attention to a stationary equilibrium in which all aggregate variables grow at the same rate as aggregate output and the allocation of skilled workers across groups is time-invariant. Accordingly, we normalize all value functions by aggregate output Y_t and denote normalized variables with lower-case letters (e.g., $v^{\text{firm}}(n,\tau,P) \equiv V_t^{\text{firm}}(n,\tau,P)/Y_t$). Where no confusion arises, we suppress the time subscript t. The following sections describe in detail the optimization problems faced by each group of skilled workers.

3.4.1 Outsiders

Skilled individuals in the pool of outsiders face two options: attempt to start an entrepreneurial venture (*regular entry*) or seek employment as an R&D manager. Let v^{entry} denote the value of entrepreneurial entry and v^{work} the value of entering the labor market as an R&D manager. The value of being an outsider is:

$$v^{\text{out}} = \max\{v^{\text{entry}}, v^{\text{work}}\}. \tag{9}$$

Regular Entry. To become an entrepreneur, an outsider must successfully implement an idea—a process involving uncertainty. The outsider pays a cost $\frac{e\nu^2}{2}$ to achieve a Poisson arrival rate ν for the idea, where e reflects the innovation efficiency of regular entrants. If successful, the entrant creatively destroys the incumbent in a random product line and improves productivity by one step ($n = 1$). Upon entry, firms draw their permanent quality type: high-type $\tau = H$ with probability $\tilde{\mu}$ or low-type $\tau = L$ with probability $1 - \tilde{\mu}$. An entering firm is immediately matched with an R&D manager, so the successful entrant becomes a firm with state $(1, \tau, P = 0)$. If the idea fails, the individual remains in the pool of outsiders.

The value of entry is:

$$\rho v^{\text{entry}} = \max_{\nu \geq 0} \left\{ -\frac{e\nu^2}{2} + \nu \left(\mathbb{E}_\tau \left[v^{\text{firm}}(1,\tau,P=0) \right] - v^{\text{out}} \right) \right\}. \tag{10}$$

The flow value ρv^{entry} reflects the trade-off between the cost of developing an idea, $\frac{e\nu^2}{2}$, and the expected gain from successful entry at rate ν. Upon success, the entrant receives the expected firm value $\mathbb{E}_\tau \left[v^{\text{firm}}(1,\tau,P=0) \right] = \tilde{\mu}\, v^{\text{firm}}(1,H,0) + (1-\tilde{\mu})\, v^{\text{firm}}(1,L,0)$; upon failure, the entrant retains the outside option v^{out}. The optimal entry rate follows from the first-order condition:

$$\nu = \frac{\mathbb{E}_\tau \left[v^{\text{firm}}(1,\tau,P=0) \right] - v^{\text{out}}}{e}. \tag{11}$$

A higher expected firm value or lower outside option increases entry, while a higher entry cost e reduces it.

R&D Manager Job Search. Rather than pursuing entrepreneurship, a skilled outsider may seek employment as an R&D manager. The job search requires an instantaneous cost c, and the outsider is matched with a firm at an endogenously determined rate θ, where matches are randomly assigned to firms demanding R&D managers. If the outsider does not find a job, they return to the pool of outsiders with value v^{out}. The value of searching for a job as an R&D manager is:

$$\rho v^{\text{work}} = -c + \theta \left(\mathbb{E}_{n,\tau} \left[v^{\text{manager}}(n, \tau) \right] - v^{\text{out}} \right). \tag{12}$$

The term $\mathbb{E}_{n,\tau} \left[v^{\text{manager}}(n, \tau) \right]$ is the expected value of being an R&D manager, taken over the possible firms the outsider may join. This expectation depends on the equilibrium distribution of firms demanding an R&D manager, discussed in subsequent sections.

3.4.2 Entrepreneur's Value and Innovation Decision

We now characterize the value functions and optimal innovation decisions of entrepreneurs operating incumbent firms with state (n, τ, P), where n denotes the firm's position on the technology ladder, τ its permanent quality type, and P its parent state.

Firms with $P = 0$. A firm in state $(n, \tau, P = 0)$ has the following Bellman equation:[20]

$$\rho v^{\text{firm}}(n, \tau, 0) = \max_{z \geq 0} \left\{ \begin{array}{l} \pi(n) - \omega(n, \tau) - \dfrac{z(n, \tau, 0)^{\gamma}}{\gamma B^{\tau}} \\ + z(n, \tau, 0) \left[v^{\text{firm}}(n+1, \tau, 0) - v^{\text{firm}}(n, \tau, 0) \right] \\ + a(n, \tau) \left[v^{\text{firm}}(n, \tau, 1) - v^{\text{firm}}(n, \tau, 0) \right] \\ + (I^s + I^o) \left[v^{\text{out}} - v^{\text{firm}}(n, \tau, 0) \right] \\ + \phi \max \left\{ -c_f, \, v^{\text{out}} - v^{\text{firm}}(n, \tau, 0) \right\} \end{array} \right\} \tag{13}$$

The flow value consists of the following components. The firm receives instantaneous profits $\pi(n)$, pays the R&D manager a wage $\omega(n, \tau) \equiv \frac{w_t(n,\tau)}{Y_t}$, and incurs variable R&D costs $\frac{z^{\gamma}}{\gamma B^{\tau}}$. Innovation occurs at the chosen rate $z(n, \tau, 0)$; each successful innovation advances the firm one step up the technology ladder, raising its value from $v^{\text{firm}}(n, \tau, 0)$ to $v^{\text{firm}}(n+1, \tau, 0)$. At rate $a(n, \tau)$, the R&D manager departs to form a spinout, transitioning the firm to the parent state $P = 1$. The firm also faces two types of exit risk: (i) *creative destruction* at rate $I^s + I^o$, driven by spinouts and regular entrants innovating on the firm's product line, and (ii) *endogenous obsolescence*, where the firm exits if it cannot cover the fixed cost shock c_f that arrives at Poisson rate ϕ. Upon exit, the entrepreneur becomes an outsider with value v^{out}.

[20] A detailed derivation is provided in Appendix B.1.

Firms in Parent State, $P = 1$**.** When the R&D manager departs to form a spinout, the firm transitions to the parent state $P = 1$. The Bellman equation in this state is:

$$\rho v^{\text{firm}}(n,\tau,1) = \max_{z \geq 0} \begin{Bmatrix} \pi(n) - \chi - \dfrac{z(n,\tau,1)^{\gamma}}{\gamma \alpha B^{\tau}} \\ + z(n,\tau,1) \left[v^{\text{firm}}(n+1,\tau,1) - v^{\text{firm}}(n,\tau,1) \right] \\ + q \left[v^{\text{firm}}(n,\tau,0) - v^{\text{firm}}(n,\tau,1) \right] \\ + (I^s + I^o) \left[v^{\text{out}} - v^{\text{firm}}(n,\tau,1) \right] \\ + \phi \max \left\{ -c_f,\, v^{\text{out}} - v^{\text{firm}}(n,\tau,1) \right\} \end{Bmatrix} \tag{14}$$

The structure mirrors the $P = 0$ case with several key differences. First, the firm is not matched with an R&D manager, so it pays no managerial wage and faces no spinout risk. Second, innovation efficiency falls by a factor $\alpha < 1$, capturing the productivity loss we document empirically following spinout separation. This parameter summarizes the potential human capital loss or organizational disruptions from the departure of a key inventor, as well as heightened competition from the newly formed spinout. Third, the firm incurs a flow cost χ representing vacancy and search costs as it seeks to rebuild innovation capacity. The firm exits the parent state at rate q upon hiring a new R&D manager, returning to $P = 0$. The remaining terms—profits, innovation gains, creative destruction, and obsolescence risk—operate as before.

Optimal Innovation Decision. Taking first-order conditions of equations (13) and (14) yields the optimal innovation rates:

$$z^*(n,\tau,P) = \max \left\{ 0,\, \left(\alpha^{\mathbf{1}_{P=1}} B^{\tau} \right)^{\frac{1}{\gamma-1}} \left[v^{\text{firm}}(n+1,\tau,P) - v^{\text{firm}}(n,\tau,P) \right]^{\frac{1}{\gamma-1}} \right\} \tag{15}$$

where $\mathbf{1}_{P=1}$ is an indicator equal to one when the firm is in the parent state. The optimal innovation rate depends on the incremental value of advancing one step on the technology ladder and the firm's R&D efficiency. High-type firms ($\tau = H$) have greater efficiency $B^H > B^L$ and thus choose higher innovation intensities, all else equal. Firms in the parent state operate with reduced efficiency αB^{τ}, leading to lower innovation rates. Since hiring a new R&D manager occurs only at a rate q, firms that experience spinout separation exhibit temporarily lower innovation intensity—and thus lower productivity growth—compared to those that do not spawn spinouts. This mechanism is consistent with Fact 2, which documents declines in parent-firm innovation following spinout formation.

3.4.3 R&D Managers and Spinout Entry

An R&D manager employed at a firm with characteristics $(n,\tau,0)$ earns wage $\omega(n,\tau)$ and can exert separation effort $a(n,\tau) \geq 0$ to attempt to found a spinout. Separation effort captures the resources required to develop an independent idea, assemble a founding team, and launch a new firm. The associated cost is $\frac{k}{n}\frac{a(n,\tau)^2}{2}$, which declines with the firm's technological lead n. This specification reflects that managers in more advanced firms benefit from superior knowledge, networks, reputation, and access to finance and talent, lowering the effective cost of spinout formation.

Upon successful separation, the manager founds a spinout that enters a random product line, improves on existing productivity, and creatively destroys the incumbent there.[21] The manager also pays a fixed cost $F \geq 0$ (in final output) reflecting non-compete restrictions. In practice, spinout founders face heterogeneous legal outcomes (Garmaise, 2011)—some pay fees, others are forced to shut down, and some incur no costs—and F represents the average of these possibilities.

As with regular entrants, spinouts draw a permanent innovation type upon entry. A spinout founded by a manager from a firm with lead n draws high innovation quality ($\tau = H$) with probability $\mu(n)$, which is increasing in n. Consistent with the evidence in Fact 1, this captures knowledge inheritance: managers from technologically leading firms are more likely to generate high-quality entrants. This inheritance may reflect direct technical learning as well as broader advantages—such as superior experience, networks, inventor quality, or the ability to identify and implement promising ideas. While related to diffusion mechanisms in Lucas and Moll (2014) and Perla and Tonetti (2014), diffusion here operates through the creation of new, heterogeneous firms rather than the replication of existing ideas.

Upon entry, each spinout is immediately matched with an R&D manager. The value of being an R&D manager at a firm $(n, \tau, 0)$ therefore satisfies:

$$\rho v^{\text{manager}}(n,\tau) = \max_{a(n,\tau)\geq 0} \left\{ \begin{array}{l} \omega(n,\tau) - \dfrac{k}{n}\dfrac{a(n,\tau)^2}{2} \\ + z(n,\tau,0)\left[v^{\text{manager}}(n+1,\tau) - v^{\text{manager}}(n,\tau)\right] \\ + a(n,\tau)\left(\mathbb{E}_\tau\left[v^{\text{firm}}(1,\tau,0)\right] - F - v^{\text{manager}}(n,\tau)\right) \\ + (I^s + I^o)\left[v^{\text{out}} - v^{\text{manager}}(n,\tau)\right] \\ + \phi \cdot \mathbb{I}\left(v^{\text{firm}}(n,\tau,0) - c_f \leq v^{\text{out}}\right)\left[v^{\text{out}} - v^{\text{manager}}(n,\tau)\right] \end{array} \right\}. \tag{16}$$

The right-hand side has a natural interpretation. The first term is the manager's wage net of separation costs. The second captures employer innovation at rate $z(n, \tau, 0)$, which advances the firm one step up the technology ladder. The third reflects the option to separate at rate $a(n, \tau)$: upon success, the manager obtains the expected value of a new spinout, $\mathbb{E}_\tau[v^{\text{firm}}(1, \tau, 0)] = \mu(n)v^{\text{firm}}(1, H, 0) + (1 - \mu(n))v^{\text{firm}}(1, L, 0)$, net of the non-compete cost F. The final terms account for firm exit—through creative destruction or endogenous obsolescence—which leaves the manager with outside value v^{out}.

Optimal Separation Effort. The optimal separation rate satisfies

$$a^*(n,\tau) = \max\left\{0,\ \frac{\mathbb{E}_\tau\left[v^{\text{firm}}(1,\tau,0)\right] - F - v^{\text{manager}}(n,\tau)}{\frac{k}{n}}\right\}. \tag{17}$$

Separation occurs whenever the expected net gain from founding a spinout exceeds the value of remaining employed. A higher probability of forming a high-quality spinout, $\mu(n)$, increases this expected value, making separation more attractive for managers in technologically leading firms.

[21]With a continuum of product lines, the probability of replacing the former employer is zero. The parent firm is affected through the manager's departure, which shifts it to state $P = 1$ with lower innovation efficiency.

However, separation entails an opportunity cost: staying allows the manager to accumulate knowledge, improving future spinout prospects through higher $\mu(n+1)$ and higher wages $\omega(n+1,\tau)$. The separation decision thus depends critically on the learning schedule $\{\mu(n)\}_{n=1}^{N}$ and the strength of non-compete restrictions F.

3.4.4 Wage Determination

At the beginning of each period, a firm in state $P=0$ and its R&D manager bargain over the wage $\omega(n,\tau)$. Wages are determined via Nash bargaining, with the manager's bargaining weight given by β. If agreement is reached, the match continues: the firm chooses its innovation rate $z(n,\tau,0)$ and the manager chooses her separation effort $a(n,\tau)$, yielding continuation values $v^{\text{firm}}(n,\tau,0)$ and $v^{\text{manager}}(n,\tau)$. If bargaining breaks down, both parties receive their outside option v^{out}.

The wage solves

$$\omega(n,\tau) = \arg\max_{\omega\geq 0}\left[S^{\text{firm}}(\omega)\right]^{1-\beta}\left[S^{\text{manager}}(\omega)\right]^{\beta},$$

where $S^{\text{firm}}(\omega) \equiv v^{\text{firm}}(n,\tau,0) - v^{\text{out}}$ and $S^{\text{manager}}(\omega) \equiv v^{\text{manager}}(n,\tau) - v^{\text{out}}$ denote the firm's and manager's surpluses.

As shown in Appendix B.2, the Nash problem implies the following surplus-sharing condition:

$$\beta S^{\text{firm}} = (1-\beta)\, S^{\text{manager}}\left(1 - \underbrace{\frac{da^*(n,\tau)}{d\omega}\left[v^{\text{firm}}(n,\tau,P=1) - v^{\text{firm}}(n,\tau,P=0)\right]}_{\text{retention gain}}\right). \tag{18}$$

Relative to standard bargaining, wages here affect not only the division of surplus but also its size. Because the R&D manager can endogenously choose separation effort, a higher wage reduces the probability of spinout formation and thereby raises the firm's continuation value. As a result, wages serve a dual role: they compensate the manager and act as a retention device.

The term labeled "retention gain" captures this effect. The elasticity $\frac{da^*(n,\tau)}{d\omega}$ measures how responsive separation is to compensation, while the value difference $v^{\text{firm}}(n,\tau,P=1) - v^{\text{firm}}(n,\tau,P=0)$ reflects the loss incurred when the firm transitions to the lower-efficiency parent state following a departure. Together, these components determine how much the firm is willing to pay to reduce separation risk and preserve innovation capacity.[22]

3.5 The Steady-State Equilibrium

We begin by describing the main equilibrium objects before formally defining the steady state equilibrium.

Stationary Distribution. As firms enter, exit, innovate, and experience spinout separations, they move along the technology ladder and transition between regular and parent states. Let $\xi(n,\tau,P)$ denote the measure of firms with technology gap n, innovation type τ, and parent status P. In the

[22] This mechanism parallels wage-setting with endogenous quit behavior in on-the-job search models, where firms raise wages to retain valuable workers (Burdett and Mortensen, 1998; Postel-Vinay and Robin, 2002).

stationary equilibrium, individual firms transition across states, but the measure of firms in each state (n, τ, P) remains constant. Thus, inflows and outflows must balance in every state.

For firms with an R&D manager ($P = 0$) and $n \geq 2$, the flow balance condition is

$$\xi(n-1,\tau,0)\, z(n-1,\tau,0) + q\,\xi(n,\tau,1) = \xi(n,\tau,0)\left[a(n,\tau) + z(n,\tau,0) + I^s + I^o + \phi\mathbb{I}^{exit}(n,\tau,0)\right]. \tag{19}$$

Inflows arise from successful innovation by firms at $(n-1, \tau, 0)$ and from parent firms that exit their state by matching with a new R&D manager at rate q. Outflows occur due to spinout separation, further innovation, and exit through creative destruction or endogenous obsolescence.

For parent firms ($P = 1$), the corresponding balance condition for all $n \geq 1$ is

$$\xi(n-1,\tau,1)\, z(n-1,\tau,1) + \xi(n,\tau,0)\, a(n,\tau) = \xi(n,\tau,1)\left[z(n,\tau,1) + q + I^s + I^o + \phi\mathbb{I}^{exit}(n,\tau,1)\right]. \tag{20}$$

Here, inflows come from innovation by parent firms and from regular firms whose inventors spawn spinouts. Outflows reflect innovation, re-matching with a manager, or exit.

Entry into the bottom of the ladder ($n = 1$) differs from higher states. For brevity, we illustrate the flow condition for $(1, H, 0)$; Appendix B.4 presents the full set of equations.

$$\begin{aligned}\text{For } (1,H,0): \quad & \sum_{n,\tau,P} \xi(n,\tau,P) a(n,\tau,P) \mu(n) + I^o \tilde{\mu} + q\xi(1,H,1) \\ & \qquad = \xi(1,H,0)\left[a(1,H,0) + z(1,H,0) + I^s + I^o + \phi\mathbb{I}^{exit}(1,H,0)\right].\end{aligned} \tag{21}$$

The first term captures high-type spinout entry from all incumbent firms, accounting for the probability $\mu(n)$ of drawing a high-quality idea. Outside entrants arrive at rate $I^o \tilde{\mu}$, and parent firms re-match with managers at rate q. As with all new firms, entrants begin in state $P = 0$ and are matched with an R&D manager.

The implied measure of firms with an R&D manager is

$$\bar{\mathcal{M}} = \sum_{n,\tau} \xi(n,\tau,P=0). \tag{22}$$

Finally, stationarity of aggregate entry and exit implies that the mass of exiting firms equals the flow of new entrants into inactive product lines:

$$\sum_{n,\tau,P} \phi\mathbb{I}^{exit}(n,\tau,P)\, \xi(n,\tau,P) = (I^o + I^s)\,(1 - \bar{\mathcal{F}}), \tag{23}$$

which also pins down the measure of active product lines $\bar{\mathcal{F}}$.

Allocation of Skilled Labor. In equilibrium, if a positive mass of skilled outsiders chooses between entrepreneurship and R&D management, indifference between the two options must hold. Using (9), this implies

$$v^{\text{out}} = v^{\text{entry}} = v^{\text{work}}. \tag{24}$$

This condition pins down the allocation of skilled outsiders between new firm entry and R&D management.

Equilibrium Matching Rate, θ. The matching rate (tightness) θ is endogenously determined by the demand for R&D managers and the number of outsiders choosing to search for a job. Denote by $\bar{\mathcal{S}}_0$ the number of outsiders choosing to search for an R&D job. In turn, the demand for R&D managers comes from three sources: regular entrants– I^o; spinout entrants– I^s; and the incumbent firms who are in state $P = 1$. Recall that the measure of incumbents without an R&D manager is $\bar{\mathcal{F}} - \bar{\mathcal{M}}$, and the exogenous rate at which they are matched to the managers is q. Hence, at every point in time, $q(\bar{\mathcal{F}} - \bar{\mathcal{M}})$ jobs will be filled. Equating the supply and demand for R&D managers leads to the equilibrium matching rate for outsiders:

$$\theta = \frac{I^o + I^s + q(\bar{\mathcal{F}} - \bar{\mathcal{M}})}{\bar{\mathcal{S}}_0}. \tag{25}$$

Aggregate Regular Entry, I^o. If $\bar{\mathcal{S}}_0$ is the measure of outsiders choosing to search for an R&D job, then the remaining $(\bar{\mathcal{S}} - \bar{\mathcal{F}} - \bar{\mathcal{M}} - \bar{\mathcal{S}}_0)$ pursue entrepreneurship. This implies that the total regular entry is:

$$I_0 = (\bar{\mathcal{S}} - \bar{\mathcal{F}} - \bar{\mathcal{M}} - \bar{\mathcal{S}}_0)\nu. \tag{26}$$

Aggregate Spinout Entry, I^s. As a result of R&D managers' separation decisions, the total mass of new spinout firms, I^s, is:

$$I^s = \sum_{n,\tau} a(n,\tau)\zeta(n,\tau,1). \tag{27}$$

Unskilled Labor Market. The market for unskilled labor has to be cleared by the equilibrium wage. Demand for unskilled labor comes from the production decisions of firms, while the supply is inelastic and is equal to L. Combining equations (3), (4), and (5), and denoting by ω^u the normalized equilibrium wage rate of unskilled labor, we get

$$q_j l_j = \frac{1}{\omega^u} q_{-j},$$

hence the labor demand of the incumbent in product line j is

$$l_j = \frac{1}{\omega^u}\lambda^{-n_j} \tag{28}$$

This implies the following market clearing condition:

$$L = \sum_{\tau,n,M} \frac{\xi(\tau,n,M)}{\lambda^n \omega^u}. \tag{29}$$

Proposition 1 *Steady-state growth rate can be expressed as*

$$g = \left(\sum_{n,\tau,P} \xi(n,\tau,P) z(n,\tau,P) + I^s + I^o\right) \ln\lambda. \tag{30}$$

The proof is in Appendix B.5. This Proposition makes it clear that four factors determine the steady state growth rate of the economy: i) innovation decisions of incumbent firms in various states; ii) the distribution of firms across states; iii) entry by spinouts; and iv) entry by outsiders.

The definition below summarizes the steady state equilibrium:

Definition (Steady-State Equilibrium) *Given the non-compete policy F, a steady-state equilibrium is a tuple* $\{v^{\text{firm}}(n,\tau,P), v^{\text{manager}}(n,\tau), v^{\text{out}}, v^{\text{work}}, v^{\text{entry}}, z(n,\tau,P), a(n,\tau), \nu, I^o, I^s, \omega(n,\tau), \omega^u, \xi(n,\tau,P), \bar{\mathcal{F}}, \bar{\mathcal{M}}, \bar{\mathcal{S}}_0, g, r, \theta\}$*, such that:*

(i) $v^{firm}(n,\tau,P)$, $v^{manager}(n,\tau)$ *satisfy equations (13), (14), and (16);*

(ii) v^{out}, v^{work}*, and* v^{entry} *are given by equations (10), (12), and (24);*

(iii) $z(n,\tau,P)$ *and* $a(n,\tau)$ *satisfy first-order conditions (15) and (17);*

(iv) *Entry rate by outsiders,* I^o*, satisfies equation (26), where* ν *maximizes (10);*

(v) *Spinout entry rate* I^s *is given by equation (27);*

(vi) *Wages of R&D managers satisfy (18)*, and *unskilled wage clears labor market in (29);*

(vii) *Stationary distribution* $\xi(n,\tau,P)$*, measure of firms with R&D managers* $\bar{\mathcal{M}}$*, and measure of active firms* $\bar{\mathcal{F}}$ *satisfy (19) - (23);*

(viii) *Tightness* θ *satisfies (25), and* $\bar{\mathcal{S}}_0$*– outsiders' indifference condition in* (24).

(ix) *Aggregate growth rate,* g*, is given by equation (30);*

(x) *Interest rate satisfies Euler equation:* $\rho = g - r$*.*

Finally, the steady-state welfare of a representative household at time $t = 0$ can be written as:[23]

$$\text{Welfare}(0) = \frac{\ln Q(0) - \ln\lambda \sum_{n,\tau,P} n\,\xi(n,\tau,P) \; - \; \bar{\mathcal{F}}\,\ln\omega^u}{\rho} + \frac{g}{\rho^2} + \frac{\ln(1-I)}{\rho}, \tag{31}$$

where $Q(0)$ denotes the initial aggregate quality index, and I denotes total (normalized) investment, equal to the sum of entry and search costs, spinout costs, non-compete costs, innovation expenditures, and fixed operating costs:

$$\begin{aligned} I \;=\; & \underbrace{\frac{e\nu^2}{2}\left(\bar{\mathcal{S}} - \bar{\mathcal{F}} - \bar{\mathcal{M}} - \bar{\mathcal{S}}_0\right)}_{\text{regular entry}} + \underbrace{c\,\bar{\mathcal{S}}_0}_{\text{search cost}} + \underbrace{\sum_{n,\tau}\frac{k}{n}\frac{a(n,\tau)^2}{2}\,\xi(n,\tau,1)}_{\text{spinout effort}} \\ & + \underbrace{\sum_{n,\tau}\xi(n,\tau,1)\,a(n,\tau)\,F}_{\text{non-compete cost}} + \underbrace{\sum_{n,\tau}\frac{z(n,\tau,1)^\gamma}{\gamma B^\tau}\,\xi(n,\tau,1) + \sum_{n,\tau}\frac{z(n,\tau,0)^\gamma}{\alpha\,\gamma B^\tau}\,\xi(n,\tau,0)}_{\text{innovation cost}} \\ & + \underbrace{\chi\sum_{n,\tau}\xi(n,\tau,0)}_{\text{vacancy cost}} + \underbrace{\sum_{n,\tau,M}\phi\,c_f\left(1 - \mathbb{I}^{exit}(n,\tau,P)\right)\xi(n,\tau,P)}_{\text{fixed operating cost}}. \end{aligned} \tag{32}$$

[23] See Appendix B.6 for detailed derivations.

4 Calibration and Model Fit

This section details the calibration of the model and assesses its performance in reproducing key empirical regularities. To bring the model to the data, we begin by defining the empirical counterparts of the model's key objects—firm quality type τ and technological gap n—which serve as calibration inputs. We then discipline the model's parameters using a combination of externally set values, direct estimation, and internally calibrated moments. Finally, we assess the model's fit by examining how well it reproduces both the targeted moments and the broader set of empirical facts documented in Section 2.2.

4.1 Calibration

We begin by mapping the model's theoretical constructs of firm type and technological gap to observable measures in the data, which will be used to calibrate model parameters. In the model, a firm's quality type, $\tau \in \{H, L\}$, is fixed over time, with high-type firms being more innovative. To capture this innovation advantage empirically, we classify a firm as high-type if it belongs to the top quartile of lifetime innovation output—measured by its lifetime citation-adjusted patent count, residualized for entry cohort and technology-class fixed effects.

The model's technological gap, n, captures a firm's relative position on the technology ladder, which consists of N equidistant (log) innovation steps. We set the maximum achievable gap to $N = 20$.[24] To construct an empirical proxy, we build a 20-bin measure of technological leadership within each technology category and year. For each firm, we proxy the strength of its current technological portfolio by its citation-adjusted five-year patent stock used in prior analyses, and assign the firm to the technology category in which it most frequently patents.[25] Within each category-year, we divide the log range of five-year citation-adjusted patent stocks into 20 equal intervals, normalizing the lowest bin to include firms with patent stocks at or below the entrant level.[26] A firm's position on this 20-point ladder defines its technological gap n at each point in time.

Having established empirical counterparts for quality type τ and technological gap n, we construct an unbalanced annual panel of firms, which allows us to map key model objects—such as innovation, separation, exit dynamics, and the distribution of firms—directly to the data. We are now ready to describe the calibration of the model's structural parameters, which proceeds in three steps as summarized in Table 4. First, standard parameters are set externally based on values from the literature. Second, parameters governing the probability of entry for high-type firms are estimated directly from the data. Finally, the remaining parameters are calibrated internally by minimizing the distance between key empirical moments and their model-generated counterparts.

Externally Calibrated Parameters.— Panel A of Table 4 lists externally calibrated parameters. The annual discount rate is set to 4%, so $\rho = 0.04$. Curvature of the R&D cost function γ determines

[24] Setting N higher does not affect results since almost no firms approach the maximum gap in equilibrium.

[25] Firms are not observed in years without patents. We therefore build a balanced lifecycle panel from the first to the last patent grant year and compute patent stocks over this balanced sample.

[26] Results are similar when using the minimum stock instead of the entrant level, but normalizing by entrants ensures that firms start at $n = 1$, consistent with the model.

Table 4: Calibration

Parameter	Description	Value	Source/Targeted moment
	***Panel A.** Externally Calibrated Parameters*		
ρ	Discount rate	0.04	Standard
γ	R&D cost curvature	2.0	Acemoglu et al. (2018)
β	R&D manager's bargaining weight	0.05	Hagedorn and Manovskii (2008)
	***Panel B.** Estimated Parameters*		
η_0	$\mu(n)$: Prob. H-type spinout by parent n	-0.81^{***}	Data, Equation (34)
η_1	$\mu(n)$: Prob. H-type spinout by parent n	0.05^{***}	Data, Equation (34)
$\tilde{\mu}$	Prob. H-type regular entrant	0.198^{***}	Data
	***Panel C.** Internally Calibrated Parameters*		
L	Supply of unskilled labor	145.5	Labor market
S	Supply of skilled labor	4.5	Labor market
c	Manager job-search cost	0.052	Labor market
λ	Step size of innovation	1.15	Growth rate
B^H	R&D efficiency (H-type)	1.1	Innovation rates
B^L	R&D efficiency (L-type)	0.15	Innovation rates
α	Scaling parameter (parent state)	0.35	Event-study
q	Parent recovery rate	0.5	Event-study
χ	Vacancy/search cost	0.1	Labor market
e	Entry cost parameter	29	Entry dynamics
κ	Separation cost parameter	25.9	Entry dynamics
F	Non-compete policy cost	0.22	Entry dynamics
c_f	Fixed operation cost	0.7	Exit dynamics
ϕ	Fixed operation cost arrival rate	0.18	Exit dynamics

Note: This table reports the calibration of model parameters. Panel A lists externally calibrated parameters taken from the literature. Panel B presents parameters estimated from logit regressions, which govern the probability that entrants are high-type (see Figure 12). Statistical significance is denoted by $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.10$. Panel C reports parameters calibrated internally by matching model outcomes to empirical moments.

the elasticity of innovation with respect to R&D. Several papers have empirically evaluated this elasticity. Following Acemoglu et al. (2018) who discuss this evidence in detail, we set $\gamma = 2$.

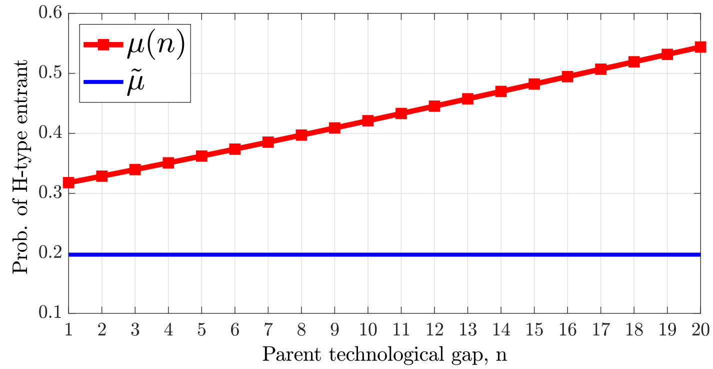
Next, we calibrate the bargaining parameter β. In the model, endogenous separation raises the manager's effective bargaining weight above the Nash parameter β. Rewriting the Nash solution yields:

$$\frac{S^{\text{manager}}}{S^{\text{manager}} + S^{\text{firm}}} = \underbrace{\beta + (1-\beta)\,\frac{da^*(n,\tau)}{d\omega}\left[\,v^{\text{firm}}(n,\tau,P=1) - v^{\text{firm}}(n,\tau,P=0)\,\right]}_{\beta^{\text{effective}}(n,\tau)}. \tag{33}$$

The option to form a spinout increases the manager's effective bargaining weight whenever the firm values retention–i.e., when losing the manager is costly $(v^{\text{firm}}(n,\tau,1) - v^{\text{firm}}(n,\tau,0) < 0)$ and when higher wages reduce separation risk $(\frac{da^*}{d\omega} < 0)$. Following Hagedorn and Manovskii (2008), we set $\beta = 0.05$ as the baseline weight absent retention concerns. In equilibrium, effective weights rise to 6–21% across n (Appendix Figure 12), capturing the retention premium generated by the spinout outside option.[27] This mechanism directly shapes mobility incentives, and we later show that it

[27] Consistent with evidence that surplus division is largely determined by outside options rather than the Nash parameter (Cahuc et al., 2006; Kline et al., 2019).

Figure 5: Estimated Probability of Entering as a High-type Firm, by Entrant Type



Note: The figure plots the estimated probability of high-type entry for spinouts, $\mu(n)$, as defined in equation (34), and the corresponding constant probability for regular entrants, $\tilde{\mu}$.

produces a separation–effort policy function consistent with the data.

Estimated Parameters.— Panel B of Table 4 reports parameters that govern the likelihood that new entrants are high-type, which we estimate directly from the data. Motivated by the empirical relationship between spinout quality and the parent's technological lead (Figure 3), we model the probability that a spinout is high-type as a logistic function of the parent's technology gap n:

$$\mu(n) = \frac{1}{1 + e^{-(\eta_0 + \eta_1 n)}}. \tag{34}$$

We estimate η_0 and η_1 using a logit regression of a high-type indicator on the parent's technology gap n, controlling for cohort and technology-class fixed effects and the log number of parent firms when multiple parents are present, thereby isolating how the probability of high-type spinout formation varies with n. The estimated coefficients are positive and statistically significant, implying that the probability of high-type spinout formation rises with the parent firm's technology gap, in line with our empirical evidence on knowledge inheritance. For regular entrants, the probability of being high-type, $\tilde{\mu}$, is constant and estimated directly from the data.

Figure 12 illustrates the implied probabilities of $\mu(n)$ and $\tilde{\mu}$. The probability that a spinout is high-type increases from 31.7% when the parent is at the lowest technology gap ($n = 1$) to 54.4% when the parent is at the technological frontier ($n = 20$). In contrast, the probability that a regular entrant is high-type is only 19.8%. Thus, even spinouts from the least advanced parents are 1.6 times as likely to be high-type as regular entrants, highlighting a strong knowledge-inheritance and knowledge diffusion that underpins the model's dynamics.

Internally Calibrated Parameters.— Panel C of Table 4 reports the internally calibrated parameters, obtained by minimizing the distance between selected empirical moments and their model-implied counterparts. Although parameters are calibrated jointly, it is useful to highlight the moments most informative for identifying each group.

We begin with labor market parameters. The supply of unskilled labor (L) and skilled labor (S), together with the R&D manager job-search cost (c), are disciplined by the skilled wage premium, the share of skilled workers in the labor force, and the skilled unemployment rate. Data from the *Survey of Industrial Research and Development (SIRD)* indicate that 960.4 thousand scientists and engineers were engaged in R&D in 1991, corresponding to roughly 0.8% of the U.S. labor force.[28] The skilled wage premium of 2.27 is taken from the *Occupational Employment Statistics (OES)* Survey, and the skilled unemployment rate—averaging 2.5%—from the *Bureau of Labor Statistics*.

Next, the innovation step size (λ) and R&D efficiency parameters (B^H, B^L) govern aggregate growth, innovation intensity, and its allocation across firm types. We discipline these parameters using three moments: average U.S. GDP growth of 3.1%, the economy-wide innovation rate, and the relative innovation rates of high- versus low-type firms. The latter two moments are derived from our firm-level panel. We map the model's innovation rate directly to the data by measuring empirical innovation as the annual probability that a firm advances to a higher technology level. The average innovation probability in the data is 15.6%. To estimate relative innovation rates, we run a logit regression of the innovation probability on a high-type indicator, controlling for cohort, year, and technology-class fixed effects, as well as the log number of inventors to account for firm size. The estimated coefficient on the high-type indicator implies that high-type firms are approximately 3.4 times more likely to move up the technology ladder than low-type firms.

Parameters α and q govern parent-firm dynamics following a spinout. The parameter α captures the fraction of R&D efficiency retained after a manager's departure, while q determines the expected duration in the parent state. We identify these parameters using the event study in Figure 4, which shows that a parent firm's probability of improving its technology level declines by about 0.13 following a spinout and recovers within roughly five years. Specifically, we target the magnitude of this decline and the recovery horizon to discipline α and q, respectively. The vacancy cost parameter χ is calibrated to match aggregate vacancy costs of approximately 2% of value added, consistent with empirical estimates in the macro–labor literature.

The parameters governing entry dynamics—the outsider entry cost (e), the separation cost for spinouts (κ), and the non-compete policy cost (F)—determine the regular entry rate and the spinout entry rate under regimes with and without non-compete enforcement. These parameters are disciplined using entry rates from firm-level data. The average regular entry rate is 10.9%, the spinout entry rate is 4.2%, and the spinout entry rate rises to 5.5% in states without non-compete enforcement.[29]

Finally, firm exit arises from creative destruction and endogenous obsolescence, governed by the operating cost shock magnitude (c_f) and its arrival rate (ϕ). We discipline these parameters using cohort-based survival probabilities. Approximately 84% of entrants survive to age 1, while about 21% remain active at age 10. Early survival rates primarily identify c_f, while longer-horizon survival is more informative about ϕ.

[28]Source: National Patterns of R&D Resources in 1994.

[29]Non-compete enforcement classifications follow Garmaise (2011); see Appendix A.1.

Table 5: Targeted and Untargeted Moments: Data versus Model

Moment	**Data**	**Model**
Panel A. Targeted moments		
Skilled wage premium	2.3	2.2
Share of skilled workers in labor force (%)	0.8	0.9
Skilled workers' unemployment rate (%)	2.5	2.6
GDP growth rate (%)	3.1	3.1
Average annual probability of innovation	0.16	0.18
Relative innovation rate of H- vs L-type	3.4	3.8
Drop in innovation rate after spinout event (p.p.)	13.0	13.0
Recovery horizon after spinout event (years)	5	5
Regular entry rate (%)	10.9	10.7
Spinout entry rate (%)	4.2	4.2
Spinout entry rate w/o NCL (F=0) (%)	5.5	5.5
Survival rate up to age 1 (%)	0.84	0.81
Survival rate up to age 10 (%)	0.21	0.21
Vacancy cost in value added (%)	2.0	2.0
Panel B. Untargeted moments		
H-type firm share	38.4	39.2
H-type firm share at entry	24.1	24.5
H-type firm share among spinouts at entry	35.5	36.5

Note: Panel A reports the moments in the data and the model that are explicitly targeted in the calibration, while Panel B reports untargeted validation moments. Data sources are described in the calibration section.

4.2 Model Fit

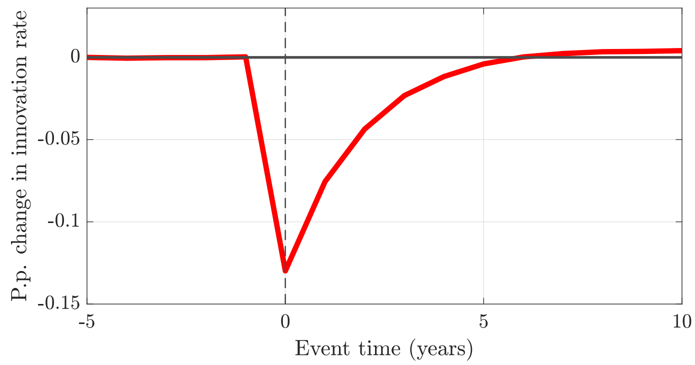
In this section, we validate the calibrated model by showing that it replicates both the targeted moments and key untargeted features of the data. We first show that the model closely matches the empirical moments used in calibration. We then examine untargeted margins and show that the model endogenously generates realistic differences between high- and low-type firms in innovation, separation, and survival. These dynamics produce firm distributions and a selection process that align well with the data. Together, these exercises confirm the model's ability to reproduce firm heterogeneity and spinout formation, providing a foundation for the counterfactual and policy analyses that follow.

4.2.1 Targeted Moments

We first evaluate the model's fit on the targeted moments summarized in Table 5. The calibrated economy features a skilled wage premium of about 2.2, very close to the empirical premium of 2.3. Skilled workers account for roughly 0.9% of the labor force (0.8% in the data), and their unemployment rate is 2.6%, nearly identical to the observed 2.5%.

On the innovation side, the economy grows at an annual rate of 3.1%, consistent with the average U.S. GDP growth over 1980–2000. Firms innovate with an average annual probability of 17.6%. For comparability, both model-implied and empirical innovation rates are expressed at an annual frequency. High-type firms are substantially more innovative: their innovation rate is 3.8 times that of low-type firms, compared with 3.4 in the data.

Figure 6: The Effect of Spinout Separation on Parent Company



Note: This figure shows the effect of a spinout separation on parent firm innovation in the model. The event study plots the change in innovation rate for parents that lose a manager to a spinout at event time 0, relative to otherwise identical parents that do not. The design replicates the empirical event study in Figure 4. In the model, only a single separation per parent is considered, ensuring consistency between model and data.

The model also replicates the event-study evidence on the effect of spinout separation on parent innovation. We reproduce this exercise in the model by comparing parents that lose a manager to a spinout with observationally identical parents that do not, restricting attention to a single separation per parent to mirror the empirical design. Figure 6 shows that the model reproduces both the sharp initial decline in parent innovation following a spinout and the gradual recovery over time as parent firms rehire managers. The magnitude and persistence of the innovation loss closely match the empirical estimates summarized in Table 5.

Entry dynamics likewise align closely with the data. To maintain consistency with the empirical definition, we measure entry as a share of active firms, $\bar{\mathcal{F}}$.[30] The annual entry rate of regular firms is 10.7% in the model versus 10.9% in the data. Spinouts account for 4.2% of entrants both in the model and the data. Without non-compete enforcement ($F = 0$), the spinout entry rate rises to 5.5%, exactly matching the empirical counterpart.

Finally, the model generates realistic survival dynamics. About 81% of entrants survive their first year, compared with 84% in the data; by age ten, 21% of the original cohort remains active, closely matching the empirical benchmark.

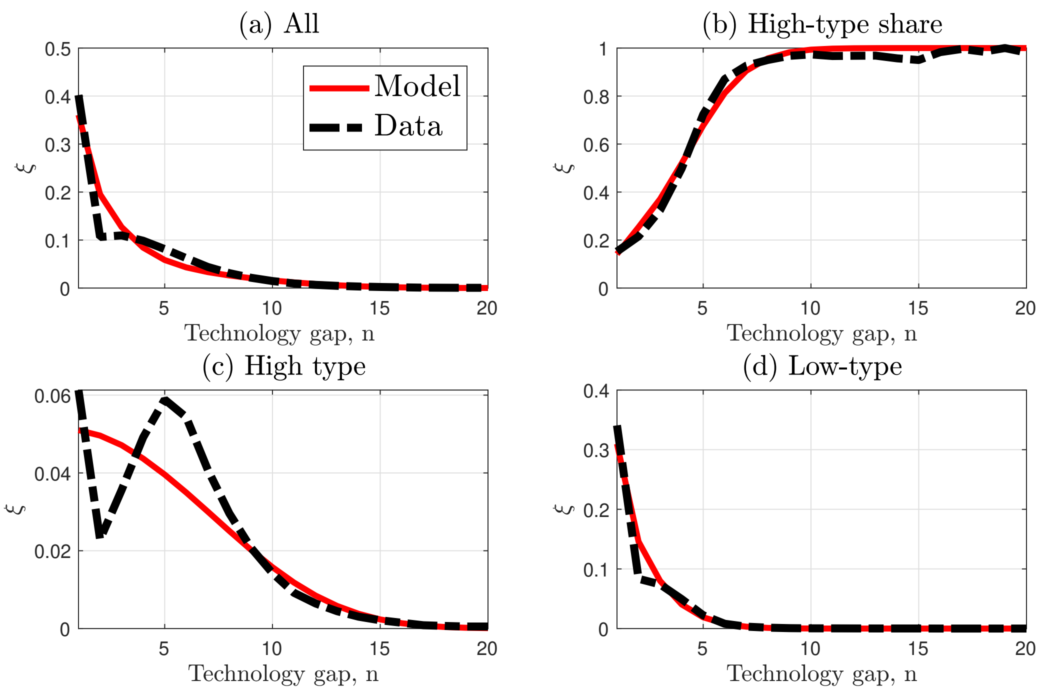
4.2.2 Untargeted Moments

In this section, we show that the model also replicates key aggregate and type-specific dynamics that were not explicitly targeted in the calibration, confirming that the heterogeneity and the core mechanisms on entry, innovation, separation, and exit embedded into the framework are consistent with the data.

First, the model matches several untargeted aggregate moments related to the prevalence of high-type firms. As reported in Panel B of Table 5, the model predicts that 39.2% of active firms are high-type, closely aligning with the 38.4% observed in the data. The implied high-type share among all new entrants is 24.5% (24.1% in the data), and among spinout entrants is 36.5% (35.5% in the data).

[30] Spinout and regular entry rates are computed as $i_s = I^s/\bar{\mathcal{F}}$ and $i_o = I^o/\bar{\mathcal{F}}$.

Figure 7: Firm Distribution Across Technology Gap by Type: Data vs. model



Note: This figure compares the stationary distribution of firms in the model and the data. Panel (a) shows the overall distribution across technology gaps. Panel (b) reports the share of high-type firms within each gap, which rises sharply toward the frontier. Panels (c) and (d) present the distributions of high-type and low-type firms separately. The model counterparts are generated from the stationary equilibrium, while the data distributions are computed from our unbalanced panel of innovating firms.

Beyond these shares, Figure 7 shows that the model generates a stationary distribution of firms across the technology gap that closely matches its empirical counterpart. Panel (a) illustrates that both the model and the data feature a high concentration of firms at low technology gaps, with density falling sharply as firms approach the frontier. Panel (b) highlights the selection mechanism: the share of high-type firms rises steeply with the technology gap, and very few low-type firms progress beyond $n = 5$ – a pattern the model captures well. Differential dynamics of high- and low-type firms are further depicted in Panels (c) and (d), which show that high-type firms are disproportionately represented at higher technology gaps, whereas low-type firms bunch at lower gaps. While the empirical distribution for high-type firms exhibits more variability at lower gaps, the model reproduces the overall patterns and the relative differences between types well.

Three main equilibrium forces shape these distributions, and we validate each against the data. The *innovation decision* allows more productive (high-type) firms to climb the technology ladder more rapidly. The *separation decision*, combined with the knowledge-inheritance channel ($\mu(n)$), determines the quality of new spinout entrants and hence influences the economy's type composition. Finally, *exit dynamics*, driven by creative destruction and endogenous obsolescence, disproportionately eliminate less productive low-type firms. In what follows, we compare the model's innovation and separation policy functions, as well as survival profiles, to their empirical counterparts to validate these mechanisms directly.

Innovation Policy Function.— The first mechanism we validate is the firm's innovation decision, represented in the model by the policy function $z(n, \tau, M)$, which gives the Poisson arrival rate of successful innovations that move a firm to the next technology level. We translate these intensities into annual innovation probabilities and compute average model-implied innovation rates by firm type and technology gap. On the data side, as before, we construct a comparable measure by defining innovation as the annual probability that a firm advances to a higher technology level. To recover how innovation varies with the technology gap and firm type in the data, we estimate a logit model using our unbalanced panel of innovating firms, allowing this probability to depend on the technology gap, firm type, and their interaction, while controlling for cohort, year, technology class, and the log number of inventors. From this specification, we compute predicted innovation probabilities for each type at each technology gap, holding all other variables at their sample means. Figure 8 Panel A presents the comparison. Figure (a) shows that the model replicates both the level and the broadly declining shape of the average innovation profile. In the model, this pattern reflects diminishing incremental gains from advancing to the next technology level (see equations (8) and (15)). Figures (b) and (c) display the profiles separately for high- and low-type firms. In the data, high-type firms innovate more often, and both types exhibit declining innovation rates as the technology gap increases. The model reproduces these patterns closely, indicating that it captures the key heterogeneity in innovation behavior across firm types.

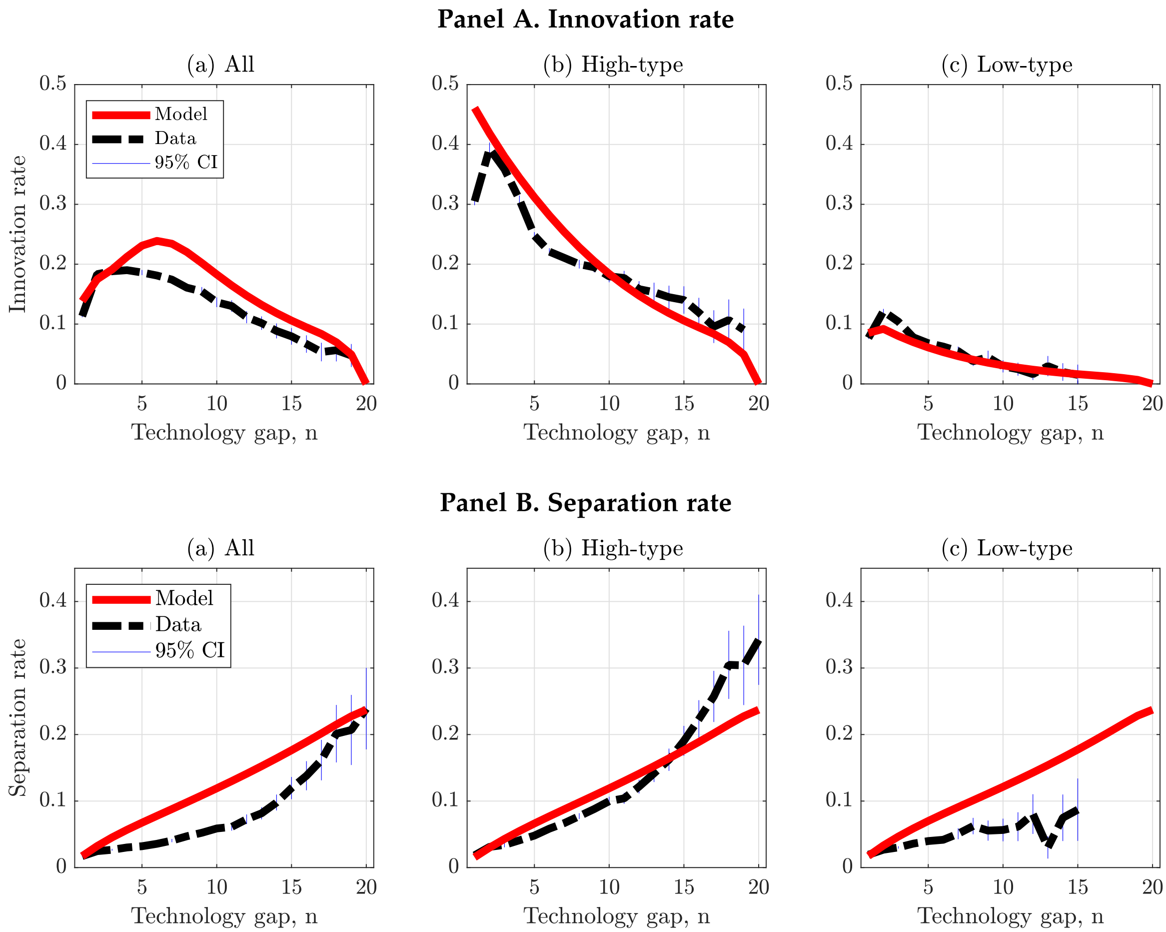
Separation Policy Function.— We next examine the separation margin, which in the model is governed by the policy function $a(n, \tau)$ giving the Poisson hazard that an R&D manager leaves the parent firm to form a spinout. For comparability with the data, we express this hazard in annual probability terms.

In the data, we construct an analogous measure by defining separation as an indicator for whether a firm spawns at least one spinout in a given year. To recover how separation varies with the technology gap, we estimate a logit model identical to the one used for innovation, but with this separation indicator as the dependent variable. From the estimated model, we compute predicted separation probabilities for each firm type at each gap, holding other covariates at their sample means. Figure 8 Panel B plots the resulting empirical separation profiles (dashed black lines). In the data, separation rates rise sharply with the technology gap, especially for high-type firms, whereas low-type firms remain unlikely to spawn even at large gaps. This pattern uncovers an important empirical regularity: high-type parents disproportionately generate spinouts, and their propensity to do so increases as they achieve higher levels of technological leadership. Appendix D.1 shows that this finding is robust across alternative specifications and that firms with greater technological leadership—proxied by citation-adjusted patents—are significantly more likely to spawn spinouts. This pattern is consistent with evidence from Klepper and Sleeper (2005) and Franco and Filson (2006) in the rigid disk drive and laser industries, who show that technologically superior firms are more likely to generate spinouts.[31]

The model produces an upward-sloping separation profile with the technology gap that closely

[31] Using administrative data from Sweden, Engbom (2020) documents a generally negative relationship between employer productivity and the probability of starting a firm, which reverses for employers in the top decile of the productivity distribution. Because our sample consists of innovative firms operating at the technological frontier, our findings align with this upper-tail pattern.

Figure 8: Firm Policy Functions Across Technology Gaps by Type: Data vs. model

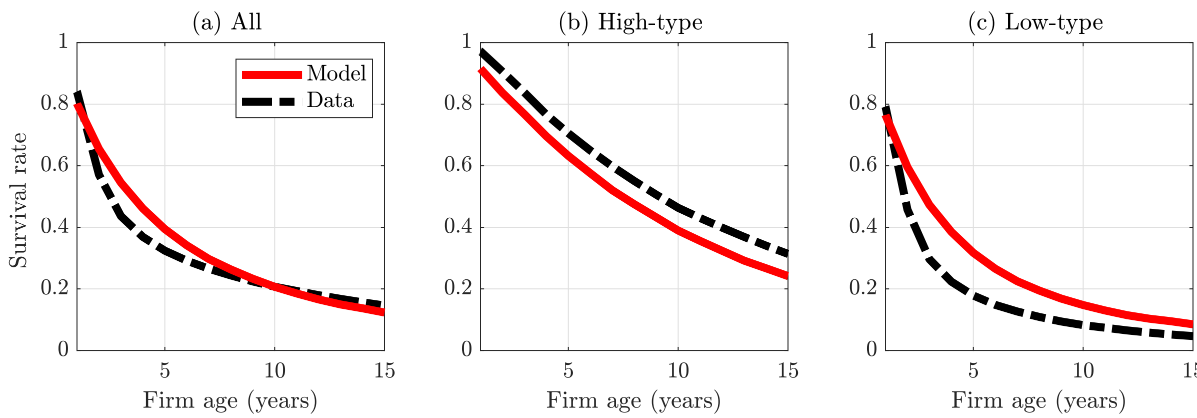


Note: This figure compares innovation and separation policy functions in the model and in the data. Model Poisson intensities $z(n, \tau, M)$ and $a(n, \tau)$ are translated into annual probabilities. For comparability, innovation in the data is defined as the annual probability that a firm advances to a higher technology level, while separation is defined as the annual probability that a firm spawns at least one spinout. Both empirical policy functions are estimated from our unbalanced panel using logit regressions with controls for cohort, year, technology class, and firm scale. Empirical estimates are reported with 95% confidence intervals.

matches the empirical pattern. This arises from three forces: the probability $\mu(n)$ that a spinout inherits the high type increases with the parent's gap; the cost of exerting separation effort, k/n, declines with the gap; and higher wages offered by more advanced parents counteract these incentives. Together, these channels generate the upward-sloping separation profile that aligns well with the empirical evidence in Panel B of Figure 8. Observed deviations at very large gaps, especially for low-type firms, carry little information, as very few firms occupy those states (recall Figure 7)—leaving empirical rates imprecisely estimated and these deviations negligible for further quantitative analysis. Since we do not target separation moments by gap or type, the fit demonstrates that the model successfully captures the key mechanisms and heterogeneity in spinout formation across firm types and technology gaps.

Firm Survival.—Finally, we compare exit dynamics in the data and the model. In the data, we compute survival rates as the share of firms in each entry cohort that remain active at a given age and plot these profiles in Figure 9. On average, only about 38 percent of firms survive to age five,

Figure 9: Firm Lifecycle Survival Profiles across types: Data vs. model



Note: This figure compares survival rates in the data and the model. In the data, survival is measured from our unbalanced firm panel as the fraction of an entry cohort still active at each age. In the model, survival is computed analogously by tracking entry cohorts in the simulated continuous-time economy, with Poisson exit hazards translated into annual probabilities.

and by age fifteen the share falls to roughly 15 percent. These patterns are consistent with the classic "up-or-out" dynamics emphasized in the firm dynamics literature: most entrants exit within their first few years, while only a small minority grow and survive to older ages (e.g., Haltiwanger, Jarmin and Miranda (2013)).

Empirical survival outcomes also differ systematically by firm type. High-type firms are much more resilient: around 71 percent of them survive to age five, compared to only about 31 percent of low-type firms—roughly half the rate of their high-type counterparts. This stark contrast underscores the central role of heterogeneity in shaping firm lifecycles. Combined with their higher innovation rates, the greater survival of high-type firms helps explain why they are disproportionately represented at higher technology gaps, as documented in the firm distribution above.

Turning to the model, survival rates are computed analogously by tracking entry cohorts over time in the simulated continuous-time economy, translating outcomes into annual survival probabilities to ensure comparability with the data. Figure 9 shows that the average survival rates of cohorts closely tracks the data counterpart. Importantly, the model also replicates the heterogeneity across firm types: high-type firms exhibit markedly higher survival rates than low-type firms, consistent with the patterns documented in the data. This difference arises because endogenous obsolescence shocks in the model disproportionately affect low-type entrants, leading them to exit earlier and more frequently than their high-type counterparts.

Taken together, these exercises show that the model closely reproduces the core lifecycle forces—innovation, spinout formation, and exit—that shape the stationary firm distribution. This demonstrates that the model successfully embeds the heterogeneity underlying firm dynamics, providing a reliable foundation for the quantitative analysis that follows.

5 Quantitative Analysis

Having validated the model, we now quantify how spinout formation shapes innovation, firm dynamics, and aggregate growth, and evaluate policies that influence inventor mobility and entry. We begin with a growth decomposition showing that spinouts account for a disproportionate share of high-type firms and growth. We then examine the key mechanisms through which spinouts affect the aggregate economy, quantifying both their positive contributions to growth and welfare and their adverse effects on incumbent innovation. Finally, we evaluate policies that affect spinout-driven entrepreneurship, including non-compete laws and subsidies targeted toward different entrant types.

5.1 Growth Decompositions

We begin by quantifying the sources of aggregate productivity growth in the simulated stationary economy, focusing on the roles of firm-type heterogeneity and spinout origin. A central result is that spinouts substantially shape the distribution of firm types and, through this channel, contribute disproportionately to growth. Table 6 summarizes the decomposition.

The Role of Creative Destruction.— Entrants account for 14.8 percent of active firms yet generate 41.6 percent of aggregate growth, with continuing firms contributing the remaining 58.4 percent. This disproportionate role of entrants aligns with evidence on the contribution of new firms to creative destruction and reallocation (Foster et al., 2008; Lentz and Mortensen, 2008; Acemoglu et al., 2018). Normalizing by group size (column (c)), entrants are roughly four times more growth-efficient than continuing firms (2.8 vs. 0.7), reflecting the immediate creative-destruction effect triggered at entry.

The Role of Ex-ante Heterogeneity for Growth.— To understand the role of firm heterogeneity in shaping growth, Panel B decomposes growth (active firms, excluding creative destruction) by firm type. Although only 40 percent of active firms are high-type, they account for nearly three-quarters of innovation-driven growth. Put differently, on average, a high-type firm contributes about 4.5 times more to growth than a low-type firm. This pattern is consistent with evidence that persistent type differences give rise to substantial heterogeneity in growth contributions (Bartelsman and Doms, 2000; Haltiwanger et al., 2017).

The Role of Spinouts in Growth.— To assess how much of this growth heterogeneity is driven by a central mechanism of our paper—spinout entry—Panel C decomposes growth by firm origin in the stationary distribution of the economy. Spinouts constitute 31.1 percent of continuing firms, closely matching the empirical share of 28 percent documented in Table 1. They generate 37.3 percent of continuing-firm growth, implying that spinouts are about 1.3 times more growth-efficient than regular-origin firms. This efficiency gap arises from composition: over half of spinouts are high-type, compared to one-third of regular entrants. Moreover, 84 percent of spinout growth is produced by high-type members (versus 69 percent for regular-origin firms). Spinout entry, therefore, significantly shifts the firm composition toward high-quality firms.

The Role of Spinouts in Ex-ante Firm Heterogeneity.— Given that spinouts are disproportionately

Table 6: Growth Decomposition

Total growth rate $g = 3.1\%$

	Share of firms, % (a)	Share of growth, % (b)	Rel. contrib. $(b)/(a)$ (c)
Panel A. The Role of Creative Destruction			
Entrants	14.8	41.6	2.8
Panel B. The Role of Ex-ante Heterogeneity for Growth			
High-type	40.1	74.5	1.9
Low-type	59.9	25.0	0.4
Panel C. The Role of Spinouts in Growth			
Spinout-origin	31.1	37.3	1.1
High-type	54.2	84.0	1.6
Low-type	45.8	16.0	0.4
Regular-origin	68.9	62.2	0.9
High-type	33.8	69.4	2.1
Low-type	66.2	30.6	0.5
Panel D. The Role of Spinouts in Ex-ante Heterogeneity			
High type, spinout-origin	42.0	–	–
High type, regular-origin	58.0	–	–

Note: The table presents growth decomposition in the model. We simulate a stationary economy and track firms by type and origin to decompose aggregate growth into its contributions.

high-type, we finally quantify their contribution to the aggregate pool of high-type firms. Panel D shows that 42 percent of all high-type incumbents are of spinout origin, even though regular entrants are nearly three times as numerous at birth. This finding implies that entrepreneurship via inventor mobility provides a micro-founded explanation for the persistent differences across firms at entry and is an important source of the ex-ante heterogeneity and growth emphasized by Sterk et al. (2021).

5.2 The Macroeconomics of Spinout Formation

The growth decompositions above showed that spinouts play a central role in shaping firm-type heterogeneity and make a sizable contribution to aggregate productivity growth. In this section, we use model counterfactuals to understand and quantify the key channels through which the process of spinout formation affects the aggregate economy. Examining these mechanisms is particularly important in light of the intensifying national debate over employee mobility—federal policymakers have moved toward limiting non-compete agreements to allow workers to move more freely across firms and to foster idea diffusion and new-firm creation (Executive Order 14036, 2021; FTC, 2024), while many business groups contend that increased mobility would weaken innovation incentives and firm competitiveness (U.S. Chamber of Commerce, 2024).[32] Our structural model, tightly disciplined by micro evidence on innovation and separation dynamics, enables us to isolate both the positive effects of spinout formation on growth—through the creation of new and higher-quality

[32]For example, see Executive Order 14036 on Promoting Competition in the American Economy (2021); FTC Final Rule on Non-Compete Agreements (2024); and U.S. Chamber of Commerce Comments on the FTC Proposed Rule to Ban Noncompetes (2024).

Table 7: The Macroeconomics of Spinout Formation

	Baseline	**Counterfactual Analysis** *(p.p. dev. relative to baseline)*	
		No spinouts (F=∞)	**No harm to parents** (q=100, α=1)
	(1)	(2)	(3)
Direct-entry effect:			
Entry rate	**14.9**	-1.8	0.4
Spinout entry rate	**4.2**	-4.2	0.8
Regular entry rate	**10.8**	2.3	-0.4
Entrant growth	**1.29**	-0.20	0.06
Incumbent growth	**1.76**	-0.13	0.17
Type-composition effect:			
High-type firm share	**40.4**	-6.1	1.1
Spinout-origin firm share	**30.7**	-30.7	5.1
Growth from high-type	**1.33**	-0.22	0.15
Growth from low-type	**0.43**	0.09	0.02
Aggregate effect:			
Aggregate growth (p.p.)	**3.05**	-0.33	0.22
CE welfare (%)	**0.00**	-2.0	+2.43

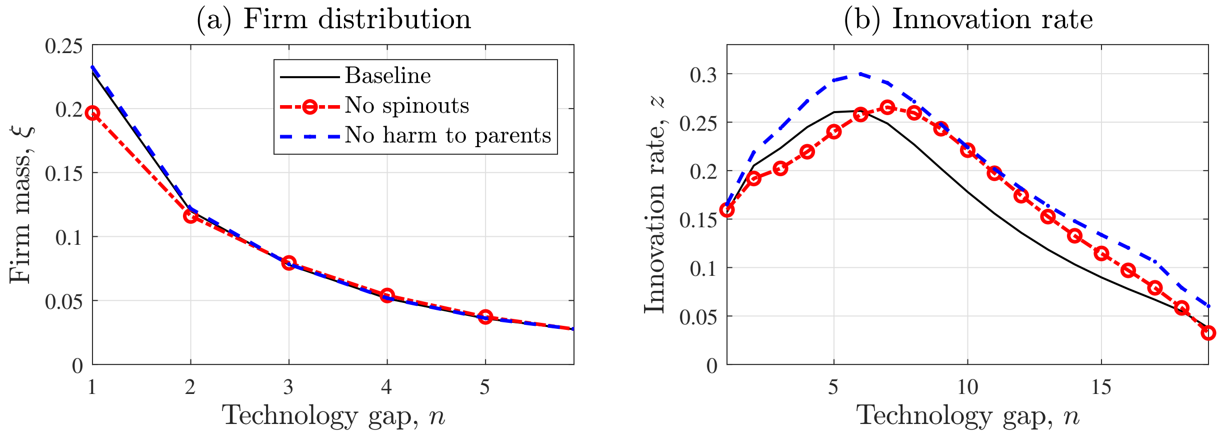
Note: This table illustrates the macroeconomic implications of spinout formation for firm composition, growth, and welfare using two counterfactuals. Column (2) ("No Spinouts") shuts down spinout formation entirely by setting $F = \infty$. Column (3) ("No harm to parents") allows spinouts to form as in the baseline but removes the temporary productivity loss experienced by parent firms by setting $\alpha = 1$ and $q = 100$.

firms—and the negative channels often emphasized in this debate, such as the potential harm to incumbent firms' innovation incentives. Quantifying the contribution of each channel to growth and welfare provides the foundation for further policy analysis.

There are four main channels through which the creation of innovating spinouts affects macroeconomic outcomes in our model. The first is the *direct-entry effect*: entry of spinouts intensifies creative destruction and adds to entrant-driven growth. The second is the *type-composition effect*: since spinouts are disproportionately high-type at entry and survive longer on the market, their entry shifts the stationary firm distribution toward higher-growth entrepreneurs, magnifying aggregate innovation. The third mechanism is the *pro-competitive effect*: higher entry pushes industries toward younger, closer competitors, lowering markups and strengthening incumbents' incentives to innovate. Finally, the model captures the central *incumbent-innovation effect*: reflecting both the direct negative effect of spinout on the parent firm and the reduction in incumbents' ex-ante innovation incentives due to the possibility of future inventor departures–effects that feature prominently in policy debates over mobility and appropriability.

We begin by examining how spinout-driven entrepreneurship affects aggregate growth and welfare through these channels. Column (2) of Table 7 presents the "No spinouts" counterfactual ($F = \infty$), with all outcomes reported as percentage-point deviations relative to the baseline economy. The *direct-entry effect* is apparent in the sharp decline in entry, which falls by 1.8 percentage points and lowers entrant-driven growth by 0.20 percentage points. At the same time, the *type-composition effect* is quantitatively important: the high-type share declines by 6.1 percentage points because the economy loses the primary source of high-type entrants—spinouts themselves. This lowers

Figure 10: The Macroeconomics of Spinout Formation. Firm Distribution and Innovation Rates



Note: This figure compares the equilibrium firm distribution (panel a) and average innovation rates (panel b) across firm technology gaps in the baseline economy and two counterfactual regimes. "Baseline" corresponds to the calibrated economy. "No harm to parents" counterfactual removes the innovation-efficiency loss experienced by parent firms following inventor departures (setting $\alpha = 1$ and $q = 100$). "No spinouts" counterfactual shuts down spinout formation entirely (setting $F = \infty$). These counterfactuals isolate the *pro-competitive* and *incumbent-innovation* effects of spinout formation.

the contribution of high-type incumbents to growth by 0.22 points. The *pro-competitive effect* is quantitatively modest, with Figure 10 (a) showing only a small reduction in mass at the smallest technology gap ($n = 1$). Finally, consistent with the *incumbent-innovation effect*, the absence of spinouts strengthens incumbents' innovation incentives, as shown in Figure 10 (b); however, note that aggregate incumbent innovation nonetheless declines because of the significant contraction in the mass of high-type firms.

Overall, in the "No spinouts" counterfactual, the *direct-entry* and *type-composition* channels dominate and account for the 0.33 percentage-point decline in aggregate growth and the 2.0 percent welfare loss relative to the baseline. The takeaway is that spinout creation meaningfully sustains both the level and quality of entry in the economy, and these forces translate into sizable long-run gains.

Despite their overall positive contribution to growth, we next show that spinout formation imposes an economically significant negative effect on incumbent innovation. To isolate this effect, we examine the "No harm to parents" counterfactual, in which spinouts occur as in the baseline but impose no loss on parent firms ($\alpha = 1$, $q = 100$). In this scenario, because spinout formation no longer reduces the parent firm's innovation efficiency, the risk of future departures also no longer depresses incumbents' incentives to innovate. Column (3) of Table 7 reports the results of this exercise. Incumbent-driven growth rises by 0.17 percentage points, accounting for most of the 0.22 percentage-point increase in aggregate growth and the associated 2.43 percent welfare improvement. Figure 10, Panel B isolates the disincentive component of this channel by showing the incumbent innovation policy function. When the threat of spinout departure is removed, incumbents increase innovation across the entire technology-gap distribution, with an average rise of about 0.22. This confirms that the appropriability loss created by spinout formation meaningfully dampens incumbent-firm R&D in the baseline.

Taken together, these exercises show that the macroeconomic impact of spinout creation is shaped by large offsetting forces. On the positive side, spinouts raise both the quantity and quality of entry, which in turn boosts innovation and growth. On the negative side, inventor separations depress incumbents' innovation, and this effect is quantitatively sizable. The combination of strong benefits and strong costs makes the optimal regulation of inventor mobility inherently non-trivial—a tension that underlies the policy debate surrounding non-compete agreements and sets the stage for the policy analysis that follows.

5.3 Policy Experiments

In this section, we analyze two sets of policy experiments: non-compete policies that restrict inventor mobility and spinout formation, and directed entry subsidies.

5.3.1 Non-Compete Laws

We first evaluate whether non-compete policies that restrict inventor mobility ultimately raise or lower aggregate growth and welfare. Panel A of Figure 11 plots changes in aggregate growth and CE welfare as we vary non-compete enforcement strength through the mobility-cost parameter F, where the dotted vertical line marks our calibrated baseline for the US economy. Both growth and welfare rise monotonically as mobility barriers fall: eliminating non-competes ($F = 0$) raises aggregate growth by 0.10 percentage points and increases welfare by 1.44 percent in consumption-equivalent terms.

Panel B reveals the mechanism. As expected, entry rises with lower mobility frictions. More surprisingly, average incumbent innovation also increases despite individual incumbents facing higher spinout risk. This reflects a powerful compositional effect: lower mobility barriers generate more high-type entrants who innovate more and survive longer, pushing up the economy-wide innovation rate and dominating any negative incentive effects on individual incumbents. Additional characteristics of the $F = 0$ economy appear in column (2) of Table 8.

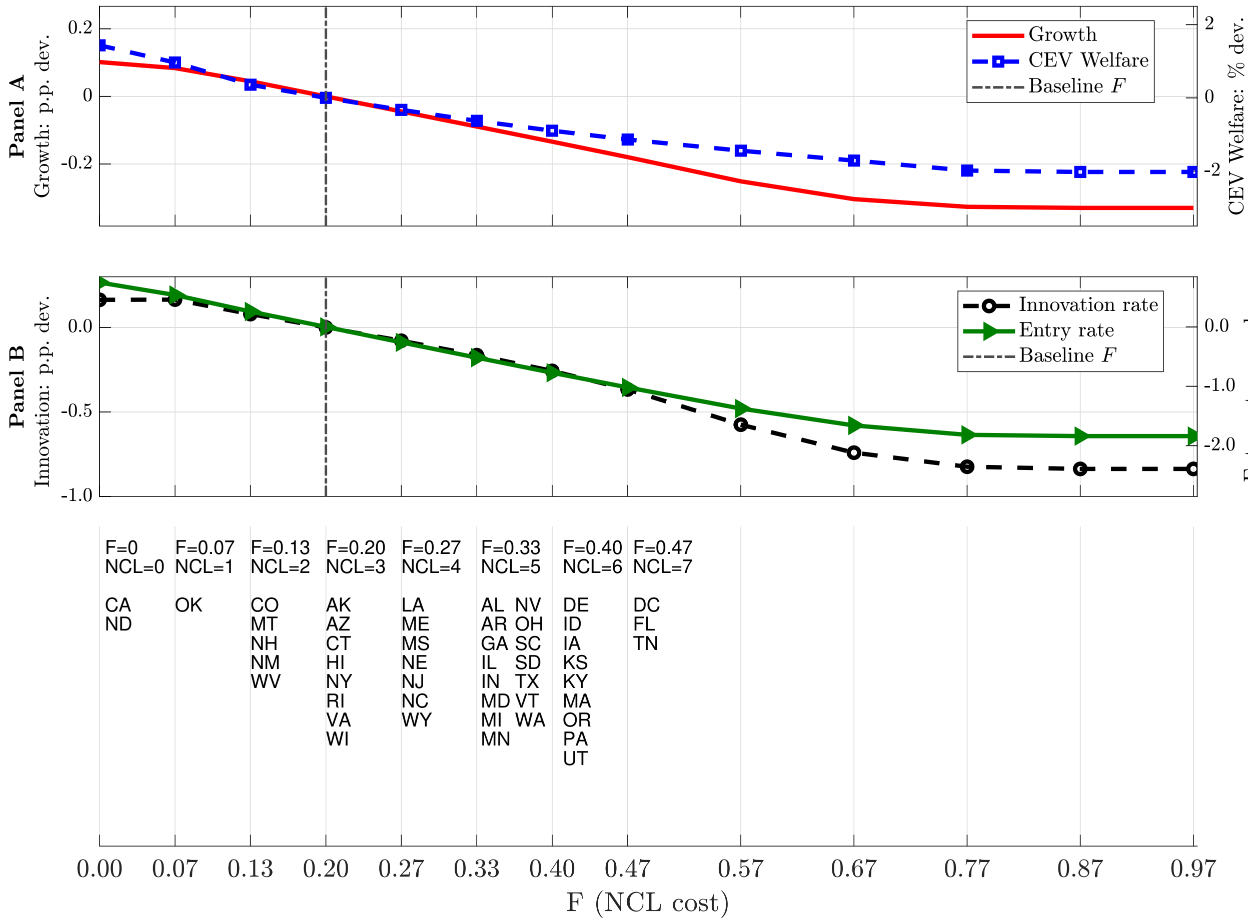
Figure 11 also maps values of F to U.S. states to illustrate the empirically plausible range of non-compete enforcement.[33] Economies with policy regimes as in the strictest-enforcement states—such as Florida, Tennessee, and Washington, DC—would experience the largest gains from abolishing non-competes, with growth increasing by up to 0.28 percentage points and welfare by 2.57 percent in CE terms. All other enforcement levels also yield positive gains.[34]

These results complement Shi (2021), who studies optimal non-compete regulation through job-to-job transitions and wage contracting in the managerial labor market. While we focus instead on firm entry, innovation, and growth, both analyses point to sizable welfare losses associated with prevailing non-compete restrictions.

[33]Using the NCL index of Garmaise (2011), we normalize no-enforcement states to $F = 0$, assign the calibrated benchmark value $F = 0.22$ to the median NCL index, and obtain intermediate values by linear interpolation.

[34]These comparisons consider a hypothetical economy with uniform enforcement at a given level, holding all other factors fixed.

Figure 11: Non-Compete Laws and the Cost of Restricting Spinout–Driven Entrepreneurship



Note: This figure plots deviations in growth, welfare, innovation, and entry from the calibrated baseline as functions of the non-compete cost F. Panel A reports growth (left axis) and welfare (right axis), while Panel B reports the innovation rate (left axis) and the entry rate (right axis). The dashed vertical line marks the calibrated baseline value $F = 0.20$. The bottom panel maps values of F to U.S. states to illustrate the empirically plausible range of non-compete enforcement, using the Non-Compete Law (NCL) index of Garmaise (2011). Values of F are mapped to discrete NCL categories by normalizing no-enforcement states to $F = 0$, assigning the calibrated benchmark value $F = 0.22$ to the median NCL index, and interpolating linearly between these points. The state groupings shown along the horizontal axis reflect this mapping.

5.3.2 Targeted Entry Subsidies

Entry and R&D subsidies are common industrial-policy tools used to promote entrepreneurship and innovation (Lerner, 1999; Criscuolo et al., 2019). Their effectiveness, however, depends critically on how targeted they are and whether recipients generate meaningful returns on public spending. Motivated by our finding that firms of spinout origin contribute disproportionately to growth, we ask whether targeting entry subsidies by entrant type can deliver larger growth gains and welfare improvements. From an implementation standpoint, entry type—spinout versus regular—is directly observable from founder backgrounds, making such targeting feasible.

To compare the effectiveness of different subsidy designs, we consider three cost-equivalent policies (each costing one percent of GDP): a uniform subsidy applied to all entrants (the standard approach), a subsidy targeted exclusively at spinouts, and a subsidy directed only at regular entrants. Columns (3)–(5) of Table 8 report the results of subsidies applied in the baseline economy. The

Table 8: Policy Experiments

	Baseline	**No NCL**	**Entry Subsidy**			**Entry Subsidy & No NCL**		
		(F=0)	Uniform	Spinout	Regular	Uniform	Spinout	Regular
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Entry rate	**14.9**	0.7	2.3	1.5	2.1	3.2	1.8	3.1
Spinout entry	**4.2**	1.3	-0.3	2.8	-1.2	1.5	3.5	0.2
Regular entry	**10.8**	-0.5	2.5	-1.3	3.2	1.8	-1.7	2.9
Entrant growth	**1.29**	0.07	0.18	0.14	0.15	0.26	0.17	0.25
Incumbent growth	**1.76**	0.03	-0.11	0.00	-0.13	-0.09	0.03	-0.12
Firm composition:								
High-type share	**40.4**	1.5	-0.6	3.4	-2.1	1.0	4.3	-0.4
Spinout-origin share	**30.7**	7.2	-5.2	15.0	-10.8	3.6	18.6	-3.3
Growth from high-type	**1.33**	0.05	-0.06	0.07	-0.10	-0.01	0.11	-0.06
Growth from low-type	**0.43**	-0.03	-0.05	-0.07	-0.04	-0.08	-0.09	-0.06
Aggregate effects:								
Aggregate growth (p.p.)	**3.05**	0.10	0.07	0.14	0.02	0.17	0.20	0.13
CE welfare (%)	**0.00**	1.44	0.897	-0.946	0.964	3.79	-0.106	3.43

Note: This table evaluates policies that affect spinout-driven entrepreneurship, including non-compete laws and subsidies targeted toward different entrant types. Column (2) reports the counterfactual without non-compete laws ($\bar{F} = 0$). Columns (3)–(5) allocate 1% of GDP to entry-subsidy schemes in the baseline economy. Columns (6)–(8) implement the same subsidies in an economy without non-compete laws. All entries are percentage-point deviations relative to Column (1).

typical uniform subsidy raises overall entry, driven mainly by regular entrants for whom the subsidy is more effective, while slightly crowding out spinout entry. This shift lowers average firm quality and reduces incumbent innovation—both because firms are of lower quality and due to stronger creative destruction—ultimately yielding a modest increase in aggregate growth (0.07 p.p.) and a welfare gain of 0.89%.

Targeting the subsidy to spinouts (Column 4) produces markedly different aggregate dynamics. Entry rises, now driven by high-growth spinouts. Their greater contribution to productivity raises aggregate growth to nearly twice the effect of a uniform subsidy. Despite these growth gains, the policy reduces welfare. High spinout entry brings economy-wide costs—separation-effort costs, non-compete costs, and vacancy costs for parents—which crowd out consumption (see equation (32)) and outweigh the growth benefits. By contrast, targeting only regular entrants (Column 5) alleviates these crowding-out forces and delivers a positive welfare gain, though its growth effects are the weakest among the three policies.

The last three columns combine the optimal no–non-compete policy (No-NCL) with the same entry subsidies. The qualitative ranking across subsidy types remains intact, but the quantitative responses strengthen substantially, underscoring that the effectiveness of subsidies depends on the degree of inventor mobility.

Overall, these experiments highlight the importance of pre-entry heterogeneity for policy design. Spinout subsidies generate the largest growth gains; regular-entrant subsidies generate the largest welfare gains; and in all cases, non-compete laws significantly weaken policy effectiveness by limiting the formation of high-type innovators. Removing such restrictions enhances the impact of any entry-subsidy scheme, regardless of the policy objective.

6 Conclusion

This paper shows that innovating spinouts—firms founded by inventors leaving incumbent innovators—are a central endogenous source of ex-ante firm heterogeneity, high-growth entrepreneurship, and aggregate productivity growth. Using comprehensive U.S. inventor–patent data, we document two central features of entrepreneurship through inventor mobility: the superior performance of innovating spinouts, which is systematically related to parent-firm technological strength, and the temporary reduction in innovation experienced by parent firms following inventor departures. Building on this evidence, we develop a Schumpeterian growth model with endogenous occupational choice and firm entry that embeds and quantifies the fundamental tradeoff between knowledge diffusion, creative destruction, and appropriability associated with spinout formation. The quantitative analysis highlights the disproportionate role of spinouts in shaping firm heterogeneity and long-run growth, even as they impose economically significant innovation costs on incumbent firms. Policies that restrict inventor mobility—particularly non-compete enforcement—significantly reduce growth-enhancing entrepreneurial activity and lower long-run growth.

More broadly, this paper highlights inventor mobility as a central—yet relatively underexplored—mechanism linking labor markets, firm dynamics, and long-run growth, and motivates a rich agenda for future research. By embedding spinout formation in a quantitative framework, our analysis provides a tractable foundation for studying how other features, such as access to finance, learning opportunities, or market structure, shape inventor mobility and innovation outcomes. At the same time, the documented superior performance of spinouts and the innovation losses borne by incumbents motivate future empirical work to further explore the underlying micro-level channels. Finally, our analysis draws attention to a core tension in innovation policy: the same reallocation of inventive talent that fuels high-growth entrepreneurship can also erode incumbent appropriability, a tension that extends beyond non-compete enforcement to other institutions and firm behaviors governing the allocation of inventors—including intellectual property regimes and strategic hiring and retention practices by large incumbents—with broad implications for innovation, knowledge diffusion, and long-run growth.

References

Abbring, Jaap H. and Jeffrey Campbell, "A Firm's First Year," Tinbergen Institute Discussion Papers 05-046/3, Tinbergen Institute 2005.

Acemoglu, Daron and Ufuk Akcigit, "Intellectual Property Rights Policy, Competition and Innovation," *Journal of the European Economic Association*, 2012, *10* (1), 1–42.

_ , _ , Harun Alp, Nicholas Bloom, and William Kerr, "Innovation, Reallocation, and Growth," *American Economic Review*, November 2018, *108* (11), 3450–91.

Agarwal, Rajshree, Raj Echambadi, April M. Franco, and Mb Sarkar, "Knowledge Transfer through Inheritance: Spin-out Generation, Development, and Survival," *The Academy of Management Journal*, 2004, *47* (4), 501–522.

Aghion, Philippe and Peter Howitt, "A Model of Growth through Creative Destruction," *Econometrica*, 1992, *60* (2), 323–51.

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

Anton, James and Dennis A Yao, "Start-ups, Spin-offs, and Internal Projects," *Journal of Law, Economics, and Organization*, 1995, *11* (2), 362–78.

Argente, David, Salomé Baslandze, Douglas Hanley, and Sara Moreira, "Patents to Products: Product Innovation and Firm Dynamics," FRB Atlanta Working Paper 2020-4, Federal Reserve Bank of Atlanta April 2020.

Barnett, Jonathan M. and Ted Sichelman, "The Case for Noncompetes," *University of Chicago Law Review*, 2020, *87* (4).

Bartelsman, Eric J. and Mark Doms, "Understanding Productivity: Lessons from Longitudinal Microdata," *Journal of Economic Literature*, September 2000, *38* (3), 569–594.

Benhabib, Jess, Jesse Perla, and Christopher Tonetti, "Reconciling Models of Diffusion and Innovation: A Theory of the Productivity Distribution and Technology Frontier," *Econometrica*, 2021, *89* (5), 2261–2301.

Bishara, Norman D., "Fifty Ways To Leave Your Employer: Relative Enforcement of Covenants Not To Compete, Trends, and Implications for Employee Mobility Policy," *University of Pennsylvania Journal of Business Law*, 2011, *13*, 751.

Burdett, Kenneth and Dale T Mortensen, "Wage Differentials, Employer Size, and Unemployment," *International Economic Review*, 1998, *39* (2), 257–273.

Cahuc, Pierre, Fabien Postel-Vinay, and Jean-Marc Robin, "Wage Bargaining with On-the-Job Search: Theory and Evidence," *Econometrica*, 2006, *74* (2), 323–364.

Campbell, Benjamin A., Martin Ganco, April M. Franco, and Rajshree Agarwal, "Who leaves, where to, and why worry? employee mobility, entrepreneurship and effects on source firm performance," *Strategic Management Journal*, 2012, *33* (1), 65–87.

Chatterjee, Satyajit and Esteban Rossi-Hansberg, "Spinoffs and the Market for Ideas," *International Economic Review*, 2012, *53* (1), 53–93.

Chatterji, Aaron K., "Spawned with a silver spoon? Entrepreneurial performance and innovation in the medical device industry," *Strategic Management Journal*, 2009, *30* (2), 185–206.

Choi, Joonkyu, Nathan Goldschlag, John Haltiwanger, and J. Daniel Kim, "Founding Teams and Startup Performance," Working Papers 19-32, Center for Economic Studies, U.S. Census Bureau November 2019.

Colvin, Alexander J.S. and Heidi Shierholz, "Noncompete agreements," Economic Policy Institute Report December 2019.

Conti, Raffaele, "Do non-competition agreements lead firms to pursue risky R&D projects?," *Strategic Management Journal*, 2014, *35* (8), 1230–1248.

Criscuolo, Chiara, Ralf Martin, Henry G. Overman, and John Van Reenen, "Some Causal Effects of an Industrial Policy," *American Economic Review*, January 2019, *109* (1), 48–85.

Dahl, Michael S. and Olav Sorenson, "The who, why, and how of spinoffs," *Industrial and Corporate Change*, 09 2013, *23* (3), 661–688.

Dunne, Timothy, Mark Roberts, and Larry Samuelson, "Patterns of Firm Entry and Exit in U.S. Manufacturing Industries," *RAND Journal of Economics*, 1988, *19* (4), 495–515.

Engbom, Niklas, "Misallocative Growth?," Working Paper April 2020.

Fallick, Bruce, Charles Fleischman, and James Rebitzer, "Job-Hopping in Silicon Valley: Some Evidence Concerning the Microfoundations of a High-Technology Cluster," *The Review of Economics and Statistics*, 2006, *88* (3), 472–481.

Foster, Lucia, John Haltiwanger, and Chad Syverson, "Reallocation, Firm Turnover, and Efficiency: Selection on Productivity or Profitability?," *American Economic Review*, March 2008, *98* (1), 394–425.

Franco, April and Matthew Mitchell, "Covenants not to Compete, Labor Mobility, and Industry Dynamics," *Journal of Economics Management Strategy*, 09 2008, *17*, 581–606.

Franco, April Mitchell and Darren Filson, "Spin-outs: knowledge diffusion through employee mobility," *The RAND Journal of Economics*, 2006, *37* (4), 841–860.

Garmaise, Mark J., "Ties that Truly Bind: Noncompetition Agreements, Executive Compensation, and Firm Investment," *Journal of Law, Economics, Organization*, 2011, *27* (2), 376–425.

Gilson, Ronald J., "The Legal Infrastructure of High Technology Industrial Districts: Silicon Valley, Route 128, and Covenants Not to Compete," *New York University Law Review*, 1999, *575.*

Griliches, Zvi, "Market value, RD, and patents," *Economics Letters*, 1981, *7* (2), 183 – 187.

Guzman, Jorge and Scott Stern, "The state of American entrepreneurship: New estimates of the quantity and quality of entrepreneurship for 32 US States, 1988–2014," *American Economic Journal: Economic Policy*, 2020, *12* (4), 212–243.

Hagedorn, Marcus and Iourii Manovskii, "The Cyclical Behavior of Equilibrium Unemployment and Vacancies Revisited," *The American Economic Review*, 2008, *98* (4), 1692–1706.

Hall, Bronwyn, Adam Jaffe, and Manuel Trajtenberg, "The NBER Patent Citations Data File: Lessons, Insights and Methodological Tools," NBER Working Paper 8498 2001.

_ , Grid Thoma, and Salvatore Torrisi, "The Market Value of Patents and RD: Evidence from European Firms," *Academy of Management Proceedings 2007*, 10 2007, *2007.*

Haltiwanger, John, Erik Hurst, Javier Miranda, and Antoinette Schoar, *Measuring Entrepreneurial Businesses: Current Knowledge and Challenges*, University of Chicago Press, 2017.

_ , Ron S. Jarmin, and Javier Miranda, "Who Creates Jobs? Small versus Large versus Young," *The Review of Economics and Statistics*, 2013, *95* (2), 347–361.

Harhoff, Dietmar, Francis Narin, F. M. Scherer, and Katrin Vopel, "Citation Frequency And The Value Of Patented Inventions," *The Review of Economics and Statistics*, 1999, *81* (3), 511–515.

Hopenhayn, Hugo A., "Entry, Exit, and firm Dynamics in Long Run Equilibrium," *Econometrica*, 1992, *60* (5), 1127–1150.

Hopenhayn, Hugo and Richard Rogerson, "Job Turnover and Policy Evaluation: A General Equilibrium Analysis," *Journal of Political Economy*, 1993, *101* (5), 915–938.

Islam, Emdad and Jason Zein, "Inventor CEOs," *Journal of Financial Economics*, February 2020, *135* (2), 505–527.

Jeffers, Jessica, "The Impact of Restricting Labor Mobility on Corporate Investment and Entrepreneurship," Working Paper December 2019.

Klepper, Steven, "The capabilities of new firms and the evolution of the US automobile industry," *Industrial and Corporate Change*, 08 2002, *11* (4), 645–666.

_ and Peter Thompson, "Disagreements and intra-industry spinoffs," *International Journal of Industrial Organization*, 09 2010, *28*, 526–538.

_ and Sally Sleeper, "Entry by Spinoffs," *Management Science*, 2005, *51* (8), 1291–1306.

Klette, Tor Jakob and Samuel Kortum, "Innovating Firms and Aggregate Innovation," *Journal of Political Economy*, 2004, *112* (5), 986–1018.

Kline, Patrick, Neviana Petkova, Heidi Williams, and Owen Zidar, "Who profits from patents? rent-sharing at innovative firms," *The quarterly journal of economics*, 2019, *134* (3), 1343–1404.

Kogan, Leonid, Dimitris Papanikolaou, Amit Seru, and Noah Stoffman, "Technological Innovation, Resource Allocation, and Growth*," *The Quarterly Journal of Economics*, 03 2017, *132* (2), 665–712.

Lai, Ronald, Alexander D'Amour, Amy Yu, Ye Sun, and Lee Fleming, "Disambiguation and Co-authorship Networks of the U.S. Patent Inventor Database (1975 - 2010)," 2011.

Lentz, Rasmus and Dale T. Mortensen, "An Empirical Model of Growth through Product Innovation," *Econometrica*, 2008, *76* (6), 1317–1373.

Lerner, Josh, "The government as venture capitalist: the long-run impact of the SBIR program," *The Journal of Business*, 1999, *72* (3), 285–318.

Lucas, Robert E. and Benjamin Moll, "Knowledge Growth and the Allocation of Time," *Journal of Political Economy*, 2014, *122* (1), 1–51.

Malsberger, Brian M, *Covenants not to compete : a state-by-state survey*, 4th ed.. ed., Washington, DC: Bureau of National Affairs, 2004.

Marx, Matt, "The Firm Strikes Back: Non-compete Agreements and the Mobility of Technical Professionals," *American Sociological Review*, 2011, *76* (5), 695–712.

_ , Deborah Strumsky, and Lee Fleming, "Mobility, Skills, and the Michigan Non-Compete Experiment," *Management Science*, 2009, *55* (6), 875–889.

Pakes, Ariel and Shmuel Nitzan, "Optimum Contracts for Research Personnel, Research Employment, and the Establishment of "Rival" Enterprises," *Journal of Labor Economics*, October 1983, *1* (4), 345–365.

Perla, Jesse and Christopher Tonetti, "Equilibrium Imitation and Growth," *Journal of Political Economy*, 2014, *122* (1), 52–76.

Peters, Michael, "Heterogeneous Markups, Growth, and Endogenous Misallocation," *Econometrica*, 2020, *88* (5), 2037–2073.

Postel-Vinay, Fabien and Jean-Marc Robin, "Equilibrium wage dispersion with worker and employer heterogeneity," *Econometrica*, 2002, *70* (6), 2295–2350.

Samila, Sampsa and Olav Sorenson, "Noncompete Covenants: Incentives to Innovate or Impediments to Growth," *Management Science*, 2011, *57* (3), 425–438.

Saxenian, AnnaLee., *Regional advantage : culture and competition in Silicon Valley and Route 128*, Harvard University Press Cambridge, Mass, 1994.

Shi, Liyan, "The Macro Impact of Noncompete Contracts," Technical Report 2021.

Sohail, Faisal, "From employee to entrepreneur: Learning, employer size, and spinout dynamics," *Journal of Economic Dynamics and Control*, 2021, *133*, 104270.

Starr, Evan, "Consider This: Training, Wages, and the Enforceability of Covenants Not to Compete," *ILR Review*, 2019, *72* (4), 783–817.

— **, Natarajan Balasubramanian, and Mariko Sakakibara**, "Screening Spinouts? How Noncompete Enforceability Affects the Creation, Growth, and Survival of New Firms," *Management Science*, 2018, *64* (2), 552–572.

Sterk, Vincent, Petr Sedláček, and Benjamin Pugsley, "The nature of firm growth," *American Economic Review*, 2021, *111* (2), 547–579.

Trajtenberg, Manuel, "A Penny for Your Quotes: Patent Citations and the Value of Innovations," *The RAND Journal of Economics*, 1990, *21* (1), 172–187.

Appendices

A Empirical Appendix

Appendix Table A1: Spinout Firm: A Methodological Comparison with Franco and Filson (2006)

Franco and Filson (2006) methodology TABLE 1				Our methodology						
Founding year	Life span	Spinout	Parent(s)	Spinout status	Parent(s)	Patent year First	Patent year Last	Patenting (active) years	No. of patents	No. cit adj. patents
1977	19, Acquired	Micropolis	**Pertec**	YES	**Pertec**	1979	1996	18	39	1199
1978	12, Exited	Priam	**Memorex**	YES	**Memorex**	1979	1988	10	19	396
1979	3, Acquired	Irwin Int. Industries	**Sycor**	YES	**Sycor**	1981	1981	1	2	31
1979	18, Still Active	Seagate	**Shugart Associates**	YES	**Shugart Associates**	1981	2003	23	1069	23792
1980	6, Exited	Computer Memories	**Pertec**	YES	**Pertec**	1983	1986	4	7	73
1980	10, Acquired	Miniscribe	Storage Tech.	YES	Xerox, Tandon Magnetics	1981	1989	9	19	496
1980	17, Still Active	Quantum	**Shugart Associates**	YES	**Shugart Associates**	1980	2004	25	480	13220
1981	5, Acquired	Amcodyne	**Storage Tech.**	YES	**Storage Tech.**	1982	1984	3	5	179
1982	14, Acquired	Maxtor	Quantum	YES	Discreton	1985	2006	22	517	7586
1982	10, Exited	Microscience Int	Datapoint	YES	Lapine	1987	1990	4	5	57
1982	15, Still Active	Syquest	Seagate	YES	IBM	1982	2000	19	42	1619
1983	4, Exited	Lapine	Irwin Int.	YES	Ontrax Corp	1984	1985	2	2	65
1985	2, Acquired	Peripheral Technology	**Computer Memomies**	YES	**Computer Memories**	1986	1988	3	2	96
1986	10, Acquired	Conner Peripherals	**Miniscribe**, Seagate	YES	**Miniscribe**, Amcodyne	1987	1995	9	95	3391
1986	5, Exited	PrairieTek	**Miniscribe**	YES	**Miniscribe**, Amcodyne	1988	1991	4	3	375
1987	7, Acquired	Kalok	Lapine	YES	Seagate	1988	1990	3	3	53
1990	7, Still Active	Integral Peripherals	**PrairieTek**	YES	**PrairieTek**, Technicare	1990	1997	8	48	1576
1990	2, Exited	Orca Technology	Mastor,Priam	YES	Raymond Eng Inc	1992	1992	1	1	40
1991	4, Exited	MiniStor	Maxtor	YES	Seagate	1992	1995	4	4	170
1981	6, Acquired	Tecstor	Microdata	NO	Zerox, Digital Data	1983	1983	1	1	22
1986	6, Exited	Brand Technologies	Computer Memories	NO	Pertec	1987	1988	2	2	56
								Avg: 8.3 (10.5)	**112.6**	**2594.8**
								Med: 4.0 (7.0)	**5.0**	**179.3**
1977	8, Exited	Int. Memories	Memorex	NO*		1978	1980	3	5	110
1981	6, Acquired	Ataswe	International Memories	NO*		1981	1985	5	9	229
1983	5, Exited	Tulin	Ampex,Qume	NO*		1983	1983	1	1	19
1988	3, Acquired	Areal Technology	Maxtor	NO*		1990	1991	2	3	81
								Avg: 2.3 (5.8)	**4.5**	**109.6**
								Med: 2.0 (6.5)	**4.0**	**95.3**
The remaining 14 non-patenting spinouts**								**Avg: 0.0 (3.9)**	**0.0**	**0.0**
								Med: 0.0 (3.0)	**0.0**	**0.0**

Note: The first four columns summarize the founding year, lifespan, name, and parent company for 25 spinout companies from Table 1 in Franco and Filson (2006), where we traced patenting activity. The remaining columns indicate whether our methodology identified the companies as spinouts ("YES") or regular entrants ("NO"), along with information on their parent companies (if spinout), the start and end years of their patenting activity, and their total number of patents and citation-adjusted patents. The “Last" patent is defined by the final year in our sample, 2006.
* Our methodology identifies the following companies as regular entrants because their first patents were filed by inventors appearing in USPTO patent activity for the first time. These inventors (patents) are: International Memories (Alfred Hasler, US4194225A), Ataswe (Frank C. GibeauPaul, US4415941; Paul L. Farmer, US4415941), Tulin (John S. Squire, US4510429), and Areal Technology (Tab C. Nielsen, US5268800).
** We identified no patenting activity in the USPTO for the following 15 spinout companies (founding years, lifespan) as reported by Franco and Filson (2006): Dastek (1978, 3, Acquired), Ibis (1980, 10, Exited), Rodime (1980, 11, Exited), Rotating Memory Systems (1980, 2, Acquired), Evotek (1981, 2, Exited), Applied Information Memories (1982, 3, Exited), Cogito (1982, 6, Exited), Microcomputer Memories (1982, 5 yrs, Exited), Vertex Peripherals (1982, 3, Acquired), Epelo (1984, 1, Exited), Josephine County Technology (1984, 4, Exited), Micro Storage Corp (1984, 2, Exited), Comport (1987, 3, Exited), Ecol.2 (1990, 1, Exited), and Gigastorage International (1993, 4, Active). Note that all of these companies either exited the market or were acquired, except for Gigastorage International. For Gigastorage, we found no patenting activity, except for Gigastorage Corporation, which patented in Taiwan (TW346917U) from 1998 to 2006. Due to this ambiguity, we excluded Gigastorage from our analysis, and the statistics reported in the last row pertain only to the remaining companies. From the remaining 14 companies, our methodology identified three spinouts (parent)—Dastek (IBM), Ibis (Eaton Corporation), and Rodime (IBM)—and classified Josephine County Technology as a regular entrant. However, in all four cases, their patenting activity occurred outside the lifespans reported by Franco and Filson (2006), leading us to conclude that these were likely different companies. As a result, we excluded them from the list of regular or spinout entrants.

Appendix Table A2: Innovative vs. Non-innovative Entrants

	- Compustat + Patent Data-			
	(1) Log Assets	(2) Log Sales	(3) Log Empl	(4) Log R& D
Non-innovative entrant	-1.147***	-0.953***	-0.862***	-1.296***
	(0.0217)	(0.0256)	(0.0211)	(0.0231)
Cohort FE	✓	✓	✓	✓
Age FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
State FE	✓	✓	✓	✓
Observations	108853	85175	87147	33066
Mean	4.852	4.365	-0.583	1.498

	(5) Log R&*D* /Empl	(6) Log sales empl	(7) Sales growth	(8) Empl growth
Non-innovative entrant	-0.449***	-0.077***	-0.049***	-0.025***
	(0.018)	(0.012)	(0.0061)	(0.0046)
Cohort FE	✓	✓	✓	✓
Age FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
State FE	✓	✓	✓	✓
Observations	28957	68386	73109	73679
Mean	2.112	5.037	0.108	0.0500

Note: The table compares innovative entrants with patents to non-innovative entrants—firms that enter in the Compustat dataset between 1981 and 1999 and never patent—along various outcome variables in different columns. *Non-innovative entrant* is a dummy equal to one if a firm is a non-innovative entrant. Robust standard errors are in parentheses. p<0.01, ** p<0.05, * p<0.1.

Appendix Table A3: Parent's Characteristics and Performance of Spinouts

-Panel A-

	Log number of cit-weighted patents of spinout			
Log parents' patents	0.063***	-0.337***	-0.063***	-0.029**
	(0.005)	(0.016)	(0.008)	(0.012)
Log parents' cit-patents		0.392***		
		(0.015)		
Parents' tech lead pctile			0.067***	
			(0.003)	
Log parents' top patents				0.138***
				(0.017)
Log num of parents	0.558***	0.556***	0.551***	0.559***
	(0.041)	(0.041)	(0.042)	(0.041)
Cohort FE	✓	✓	✓	✓
Tech class FE	✓	✓	✓	✓
State FE	✓	✓	✓	✓
Observations	16672	16582	16672	16672

-Panel B-

	Log number of top patents of spinout			
Log parents' patents	0.022***	-0.110***	-0.013***	-0.032***
	(0.002)	(0.007)	(0.004)	(0.005)
Log parents' cit-patents		0.129***		
		(0.007)		
Parents' tech lead pctile			0.019***	
			(0.001)	
Log parents' top patents				0.081***
				(0.007)
Log num of parents	0.190***	0.189***	0.188***	0.191***
	(0.021)	(0.021)	(0.021)	(0.021)
Cohort FE	✓	✓	✓	✓
Tech class FE	✓	✓	✓	✓
State FE	✓	✓	✓	✓
Observations	17268	17166	17268	17268

Notes: The table reports regressions of spinouts' outcome variables on parental characteristics measured at the time of spinout separation. Each observation is a spinout firm entering between 1981 and 2000. The outcome variable in Panel A is the spinout's lifetime log citations-weighted patent count; in Panel B, it is the lifetime log number of top patents. Top patents are defined as those with truncation-adjusted citation counts above the 90th percentile of the citation distribution within the same filing year and technology class. Control variables include the log number of parents, parents' log number of patents, citations-weighted patents, top patents, and the technological-lead percentile. For spinouts with multiple parents, parental patent counts are summed. The technological-lead percentile is based on 20 quantiles of the citation-weighted patent-quality distribution over the previous five years within the parent's technology class (*cat–ocl*). All regressions include spinout cohort, technology-class, and state fixed effects. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Appendix Table A4: Parent Characteristics and Performance of Spinouts: Other Outcome Variables

-Panel A-

	Log longevity of spinout			
Log parents' patents	0.029***	-0.064***	-0.013***	0.030***
	(0.003)	(0.011)	(0.005)	(0.008)
Log parents' cit-patents		0.091***		
		(0.010)		
Parents' tech lead pctile			0.023***	
			(0.002)	
Log parents' top patents				-0.001
				(0.010)
Log num of parents	0.197***	0.197***	0.196***	0.197***
	(0.024)	(0.024)	(0.024)	(0.024)
Cohort FE	✓	✓	✓	✓
Tech class FE	✓	✓	✓	✓
State FE	✓	✓	✓	✓
Observations	17268	17166	17268	17268

-Panel B-

	Log number of patents of spinout			
Log parents' patents	0.057***	-0.078***	-0.005	0.058***
	(0.004)	(0.013)	(0.006)	(0.010)
Log parents' cit-patents		0.132***		
		(0.011)		
Parents' tech lead pctile			0.032***	
			(0.002)	
Log parents' top patents				-0.002
				(0.013)
Log num of parents	0.475***	0.474***	0.471***	0.475***
	(0.034)	(0.034)	(0.034)	(0.034)
Cohort FE	✓	✓	✓	✓
Tech class FE	✓	✓	✓	✓
State FE	✓	✓	✓	✓
Observations	17268	17166	17268	17268

Notes: This table replicates the specifications in Table A3 using alternative outcome variables. Panel A reports results for the spinout's log longevity; Panel B for the spinout's lifetime log number of patents. All regressions include controls for parental characteristics at the time of separation, along with spinout cohort, technology-class, and state fixed effects. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Appendix Table A5: Parent Characteristics and Performance of Spinouts: Robustness

-Panel A-

	Log number of citations-weighted patents of spinout		
	Narrower tech class	*Global percentile*	*Entry-year vars*
Log num of parents	0.539***	0.556***	0.622***
	(0.042)	(0.042)	(0.046)
Log parents' patents	-0.046***	-0.065***	-0.056***
	(0.008)	(0.008)	(0.010)
Parents' tech lead pctile	0.060***	0.070***	0.073***
	(0.003)	(0.003)	(0.006)
Cohort FE	✓	✓	✓
Tech class FE	✓	✓	✓
State FE	✓	✓	✓
Observations	16672	16672	9701

-Panel B-

	Log number of top patents of spinout		
	Narrower tech class	*Global percentile*	*Entry-year vars*
Log num of parents	0.185***	0.190***	0.215***
	(0.021)	(0.021)	(0.025)
Log parents' patents	-0.009***	-0.013***	-0.016***
	(0.003)	(0.004)	(0.005)
Parents' tech lead pctile	0.017***	0.019***	0.025***
	(0.001)	(0.001)	(0.002)
Cohort FE	✓	✓	✓
Tech class FE	✓	✓	✓
State FE	✓	✓	✓
Observations	17268	17268	10005

Notes: This table reports robustness checks for the specifications in column (3) of Table A3. The first column redefines parents' technological-lead percentile using a finer technology classification (*nclass*). The second column defines technological lead based on citation distributions across all firms, irrespective of technology class. The last column measures parental characteristics in the spinout's entry year rather than at the separation date. All regressions include cohort, technology-class, and state fixed effects. *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table A6: Probability of pinout eparation. Different Proxy for Parent's Technological Leadership.

-Panel A: Top Patents

	(1) Logit	(2) FE Logit	(3) Neg. Binom	(4) FE Neg. Binom
Log top patents	0.269***	0.137***	0.228***	0.081***
	(0.0147)	(0.0334)	(0.0120)	(0.0264)
Patents, Inventors, Age	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Industry FE	✓		✓	
State FE	✓		✓	
Firm FE		✓		✓
Observations	184442	53424	184598	53794

-Panel B: Contemporaneous measure

	(1) Logit	(2) FE Logit	(3) Neg. Binom	(4) FE Neg. Binom
Log cit-patents yr	0.127***	0.060***	0.112***	0.040***
	(0.0099)	(0.0167)	(0.0092)	(0.0145)
Patents, Inventors, Age	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Industry FE	✓		✓	
State FE	✓		✓	
Firm FE		✓		✓
Observations	184442	53424	184598	53794

Note: Table repeats the analysis in Table A.1, but using different measures of the parent's technological leadership. Panel A uses the log number of top patents filed by the firm within the last 5 years. Top patents are defined as those whose truncation-adjusted citations are above the 90th percentile of the citation distribution of patents filed in the same year and technology class. Panel B uses the log count of citations-adjusted patents in a year. Additional controls are the log number of patents, number of inventors, and firm age together with fixed effects, as reported in the table. The sample covers the period 1981-2000.

Appendix Table A7: Probability of spinout separation. Patents + Compustat sample.

-Panel A: Patent data

	(1) Logit	(2) FE Logit	(3) Neg. Binom	(4) FE Neg. Binom
Log cit-patents 5yrs	0.130***	0.085	0.179***	0.100
	(0.0497)	(0.1008)	(0.0390)	(0.0752)
Patents, Inventors, Age, R&D, Sales, Assets, Num. employees	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Industry FE	✓		✓	
State FE	✓		✓	
Firm FE		✓		✓
Observations	15834	9986	16462	10186

-Panel B: Patent + Compustat data

	(1) Logit	(2) FE Logit	(3) Neg. Binom	(4) FE Neg. Binom
Log top patents 5yrs	0.268***	0.209***	0.193***	0.100**
	(0.0355)	(0.0685)	(0.0260)	(0.0471)
Patents, Inventors, Age, R&D, Sales, Assets, Num. employees	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Industry FE	✓		✓	
State FE	✓		✓	
Firm FE		✓		✓
Observations	15834	9986	16462	10186

Note: Table repeats the analysis in Table A.1 using the merged Patents + Compustat dataset. Panel A uses the same measure of a parent's technological leadership as in the benchmark table– log count of citations-adjusted patents filed by the firm within the last 5 years. Panel B uses the log number of top patents filed by the firm within the last 5 years. Top patents are defined as those whose truncation-adjusted citations are above the 90th percentile of the citation distribution of patents filed in the same year and technology class. Additional controls include the log number of patents and inventors, firm age, log number of employees, log assets, sales growth, log R&D per labor, and fixed effects, as reported in the table. The sample covers the period 1981-2000.

A.1 Non-Compete Laws: Additional Data Details

Non-compete covenants are clauses in employment contracts that restrict employees from joining a competitor or forming a new competing firm. The laws governing the enforceability of these agreements—referred to as non-compete laws (NCL)—vary substantially across U.S. states.

Malsberger (2004) conducted a comprehensive state-by-state survey assessing twelve dimensions of non-compete enforceability. Two states, California and North Dakota, void non-compete agreements entirely, while the remaining states differ in the types of contracts they enforce and the permissible scope, geographic reach, duration, and other terms. Based on these survey responses, Garmaise (2011) constructed a state-level non-compete enforceability index ranging from 0 to 9, where higher values indicate stricter enforcement.

More recently, Starr (2019), building on Bishara (2011), developed an alternative index for the years 1991 and 2009 that captures variation in state non-compete laws over time. Table A8 reports all three indexes for each state. The indexes are highly correlated, but because the Starr index exhibits meaningful time variation, we use it as our benchmark in the regression analysis and show robustness with an alternative index. Specifically, we combine the 1991 and 2009 values and construct a linear interpolation for intervening years:

$$NCL^{Starr}(t) = NCL^{Starr}_{1991} + \frac{NCL^{Starr}_{2009} - NCL^{Starr}_{1991}}{18}(t - 1991). \tag{35}$$

Although the U.S. Constitution's Full Faith and Credit Clause requires states to respect the public acts and judicial decisions of other states, the extent to which this applies to non-compete enforcement across state lines remains unclear. For example, in the 1998 case *Application Group, Inc. v. Hunter Group, Inc.*, a California court held that California law applied to non-California employees seeking employment in California, effectively limiting the reach of out-of-state non-compete provisions. More broadly, ambiguity over which state's laws govern a potential spinout may increase ex-ante uncertainty for employees and deter mobility, thereby working in employers' favor.

Appendix Table A8: Non-Compete Enforceability Index Across U.S. States

State	NCL Garmaise'11	NCL1991 Starr'19	NCL2009 Starr'19	State	NCL Garmaise'11	NCL1991 Starr'19	NCL2009 Starr'19
Alabama	5	0.36	0.36	Montana	2	-0.63	-0.65
Alaska	3	-1.33	-0.98	Nebraska	4	-0.13	-0.13
Arizona	3	-0.16	0.15	Nevada	5	-0.62	0.03
Arkansas	5	-0.62	-0.58	New Hampshire	2	0.26	0.26
California	0	-3.76	-3.79	New Jersey	4	0.47	0.9
Colorado	2	0.38	0.38	New Mexico	2	0.74	0.74
Connecticut	3	0.62	1.26	New York	3	-0.73	-1.15
Delaware	6	0.18	0.52	North Carolina	4	0.18	0.18
DC	7	0.12	0.12	North Dakota	0	-4.23	-4.23
Florida	7	1.15	1.6	Ohio	5	-0.18	0.08
Georgia	5	0.45	0.02	Oklahoma	1	-0.8	-0.94
Hawaiwe	3	-0.83	-0.17	Oregon	6	0.14	0.14
Idaho	6	-0.01	0.77	Pennsylvania	6	-0.14	0.14
Illinois	5	0.55	0.95	Rhode Island	3	-0.67	-0.33
Indiana	5	0.7	0.7	South Carolina	5	-0.2	-0.27
Iowa	6	0.19	1.01	South Dakota	5	0.37	1.02
Kansas	6	0.69	1.21	Tennessee	7	0.22	0.45
Kentucky	6	0.61	0.85	Texas	5	-0.04	-0.28
Louisiana	4	-0.7	0.5	Utah	6	1	1
Maine	4	0.06	0.41	Vermont	5	0.3	0.6
Maryland	5	0.15	0.6	Virginia	3	0.09	-0.29
Massachusetts	6	0.87	0.48	Washington	5	0.64	0.34
Michigan	5	0.07	0.46	West Virginia	2	-0.8	-0.8
Minnesota	5	-0.07	-0.07	Wisconsin	3	0.16	-0.09
Mississippi	4	-0.2	0.04	Wyoming	4	-0.65	0.23

Note: The table presents the non-competition indexes from Garmaise (2011) and Starr (2019).

Appendix Table A9: Non-Compete Laws and Spinout Formation. Alternative NCL index.

	(1) Logit	(2) Logit	(3) Logit	(4) Neg. Binom	(5) Neg. Binom	(6) Neg. Binom
NCL index	-0.035***	-0.555***	-0.040	-0.045***	-0.394**	-0.060*
	(0.0072)	(0.1911)	(0.0412)	(0.0063)	(0.1697)	(0.0358)
Log patents	-0.099***	-0.101***	-0.079	-0.100***	-0.089***	-0.094*
	(0.0220)	(0.0221)	(0.0566)	(0.0202)	(0.0203)	(0.0487)
Log cit-patents	0.160***	0.154***	0.123***	0.154***	0.147***	0.113***
	(0.0116)	(0.0117)	(0.0326)	(0.0108)	(0.0108)	(0.0284)
Log inventors	0.538***	0.553***	0.910***	0.553***	0.553***	0.859***
	(0.0193)	(0.0194)	(0.0531)	(0.0179)	(0.0179)	(0.0469)
Log age	-0.240***	-0.239***	0.017	-0.251***	-0.247***	-0.014
	(0.0107)	(0.0108)	(0.0337)	(0.0098)	(0.0098)	(0.0275)
State competition	0.202***	-0.012	0.226**	0.019	0.100	0.084
	(0.0264)	(0.1349)	(0.1067)	(0.0250)	(0.1200)	(0.0852)
Log GDP pc	-1.071***	-1.239***	-1.580***	0.159*	0.164	-1.346***
	(0.0665)	(0.0991)	(0.1342)	(0.0881)	(0.2786)	(0.0995)
Log population	-0.164***	-1.299***	-0.265**	-0.019	-1.032***	-0.143
	(0.0277)	(0.3357)	(0.1187)	(0.0253)	(0.3001)	(0.0956)
Year FE	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓		✓	✓	
State FE		✓			✓	
Firm FE			✓			✓
Observations	184375	184375	53232	184529	184529	53600

Notes: The table reports firm-level regressions of the probability of spawning a spinout (logit models, columns 1–3) and the number of spinouts spawned (negative binomial models, columns 4–6) as a function of the NCL index and other firm characteristics. The specifications use the alternative non-compete enforcement index defined in (35). *Log patents*, *log cit-patents*, and *log inventors* refer to the number of patents, citation-adjusted patents, and inventors in the previous five years, respectively. The sample includes all patenting firms from 1981 to 2000.

B Theoretical Appendix

B.1 Derivation of the R&D Manager's Bellman Equation.

We derive the Bellman equation for $V_t^{\text{manager}}(n,\tau)$, the value of an R&D manager employed by a firm in state $(n,\tau,P=0)$. New spinout and regular entrant firms are immediately matched with a manager, and the manager chooses separation effort $a_t \geq 0$ to potentially form a spinout.

Over a short time interval $[t,t+\Delta t)$, the manager receives an instantaneous flow payoff equal to her wage net of the cost of separation effort, $\left[w_t(n,\tau) - \frac{k}{n}\frac{a_t^2}{2}Y_t\right]\Delta t$. At the end of the interval, several mutually exclusive transitions may occur. With probability $a_t\Delta t$, the manager successfully separates and founds a spinout, obtaining the expected firm value $\mu(n)V_{t+\Delta t}^{\text{firm}}(1,H,0) + (1-\mu(n))V_{t+\Delta t}^{\text{firm}}(1,L,0)$ minus the non-compete cost $FY_{t+\Delta t}$. With probability $z(n,\tau,0)\Delta t$, her current employer successfully innovates, advancing one step on the technology ladder and increasing the manager's continuation value to $V_{t+\Delta t}^{\text{manager}}(n+1,\tau)$. With probability $(I^s + I^o)\Delta t$, the employer is replaced through creative destruction by a spinout or regular entrant, in which case the manager becomes an outsider with value $V_{t+\Delta t}^{out}$. Finally, with probability $\phi\,\mathbb{I}^{exit}(n,\tau,0)\Delta t$, the employer faces an obsolescence shock that forces exit, again sending the manager to the outsider state. If none of these events occur—which happens with the remaining probability $1-[a_t + z(n,\tau,0) + I^s + I^o + \phi\,\mathbb{I}^{exit}(n,\tau,0)]\Delta t$—the manager continues in the same firm and retains the value $V_{t+\Delta t}^{\text{manager}}(n,\tau)$.

Putting these components together, the value function satisfies

$$\begin{aligned}
V_t^{\text{manager}}(n,\tau) = \max_{a_t \geq 0} \Big\{ & \left[w_t(n,\tau) - \tfrac{k}{n}\tfrac{a_t^2}{2}\,Y_t\right]\Delta t \\
& + e^{-\int_t^{t+\Delta t} r_s ds}\Big[a_t\Delta t\big(\mu(n)V_{t+\Delta t}^{\text{firm}}(1,H,0) + (1-\mu(n))V_{t+\Delta t}^{\text{firm}}(1,L,0) - F\,Y_{t+\Delta t}\big) \\
& \quad + z(n,\tau,0)\Delta t\,V_{t+\Delta t}^{\text{manager}}(n+1,\tau) + (I^s+I^o)\Delta t\,V_{t+\Delta t}^{out} \\
& \quad + \phi\,\mathbb{I}^{exit}(n,\tau,0)\Delta t\,V_{t+\Delta t}^{out} + \big(1-\Lambda_t\Delta t\big)\,V_{t+\Delta t}^{\text{manager}}(n,\tau)\Big]\Big\},
\end{aligned}$$

where $\Lambda_t \equiv a_t + z(n,\tau,0) + I^s + I^o + \phi\,\mathbb{I}^{exit}(n,\tau,0)$ is the total hazard rate of leaving the current state.

Subtracting $V_t^{\text{manager}}(n,\tau)$ from both sides, dividing by Δt, and taking the limit as $\Delta t \to 0$ yields

$$\begin{aligned}
r_t V_t^{\text{manager}}(n,\tau) - \dot{V}_t^{\text{manager}}(n,\tau) = \max_{a\geq 0} \Big\{ & w_t(n,\tau) - \tfrac{k}{n}\tfrac{a^2}{2}Y_t \\
& + a\Big[\mu(n)V_t^{\text{firm}}(1,H,0) + (1-\mu(n))V_t^{\text{firm}}(1,L,0) - FY_t - V_t^{\text{manager}}(n,\tau)\Big] \\
& + z(n,\tau,0)\left[V_t^{\text{manager}}(n+1,\tau) - V_t^{\text{manager}}(n,\tau)\right] \\
& + (I^s + I^o + \phi\,\mathbb{I}^{exit}(n,\tau,0))\left[V_t^{out} - V_t^{\text{manager}}(n,\tau)\right]\Big\}.
\end{aligned}$$

Dividing by Y_t and using the balanced-growth relationships $\dot{V}_t / Y_t = g\, v^{\text{manager}}$ and $\rho = r - g$ gives

$$\begin{aligned} \rho\, v^{\text{manager}}(n,\tau) = \max_{a \geq 0} \Big\{ & \omega(n,\tau) - \tfrac{k}{n}\tfrac{a^2}{2} \\ & + a\Big[\mathbb{E}_\tau[v^{\text{firm}}(1,\tau,0)] - F - v^{\text{manager}}(n,\tau)\Big] \\ & + z(n,\tau,0)[v^{\text{manager}}(n+1,\tau) - v^{\text{manager}}(n,\tau)] \\ & + (I^s + I^o + \phi\, \mathbb{I}^{exit}(n,\tau,0))\, \big[v^{out} - v^{\text{manager}}(n,\tau)\big] \Big\}, \end{aligned}$$

which coincides with equation (16) in the main text.

B.2 Derivation of the Nash Bargaining Rule.

This section derives equation (18)– the nonlinear Nash–bargaining rule presented in the main text. The wage $\omega(n,\tau)$ solves

$$\omega(n,\tau) = \arg\max_{\omega \geq 0} \big[S^{\text{firm}}(\omega)\big]^{1-\beta} \big[S^{\text{manager}}(\omega)\big]^{\beta}, \tag{36}$$

with $S^{\text{manager}}(\omega) = v^{\text{manager}}(n,\tau) - v^{\text{out}}$ and $S^{\text{firm}}(\omega) = v^{\text{firm}}(n,\tau,P=0) - v^{\text{out}}$.

The first–order condition implies:

$$(1-\beta)\, \frac{1}{S^{\text{firm}}(\omega)} \frac{dS^{\text{firm}}(\omega)}{d\omega} \;+\; \beta\, \frac{1}{S^{\text{manager}}(\omega)} \frac{dS^{\text{manager}}(\omega)}{d\omega} = 0. \tag{37}$$

Next, we derive $\frac{dS^{\text{manager}}(\omega)}{d\omega}$ and $\frac{dS^{\text{firm}}(\omega)}{d\omega}$.

Derivation of $\frac{dS^{\text{manager}}(\omega)}{d\omega}$. To obtain the manager's surplus derivative for the Nash bargaining condition, we differentiate the manager's value function in equation (16) with respect to wage. This yields the following expression:

$$\begin{aligned} \rho\, \frac{dv^{\text{manager}}(n,\tau)}{d\omega} = 1 & - z^*(n,\tau,P=0)\, \frac{dv^{\text{manager}}(n,\tau)}{d\omega} \\ & - a^*(n,\tau)\, \frac{dv^{\text{manager}}(n,\tau)}{d\omega} \\ & - (I^s + I^o)\, \frac{dv^{\text{manager}}(n,\tau)}{d\omega} \\ & - \phi\, \mathbb{I}\big(v^{\text{firm}}(n,\tau,P=0) - c_f \leq v^{\text{out}}\big)\, \frac{dv^{\text{manager}}(n,\tau)}{d\omega}. \end{aligned} \tag{38}$$

Note that the terms involving $\frac{da^*(n,\tau)}{d\omega}$ drop out by the envelope condition: since $a^*(n,\tau)$ solves the manager's first-order condition, changes in the wage do not affect the value function through a^*. The remaining transition rates—$z^*(n,\tau,P=0)$, I^s, I^o, and the exit term with probability ϕ—are exogenous to the manager and do not depend on the wage, so they generate no additional derivative terms.

Solving (38) yields:

$$\frac{dv^{\text{manager}}(n,\tau)}{d\omega} = \frac{1}{\rho + H(n,\tau)}, \tag{39}$$

where $H(n,\tau) \equiv z^*(n,\tau,P=0) + a^*(n,\tau) + I^s + I^o + \phi\,\mathbb{I}\big(v^{\text{firm}}(n,\tau,P=0) - c_f \leq v^{\text{out}}\big)$. This expression has a straightforward interpretation. It is the present value of an additional unit of flow wage received while the match remains in state (n,τ). The effective discount rate combines the manager's subjective discount rate ρ with the total hazard of leaving the state, $H(n,\tau)$, so that the marginal gain from a higher wage is simply that extra dollar discounted at rate $\rho + H(n,\tau)$.

Since $S^{\text{manager}}(\omega) = v^{\text{manager}}(n,\tau) - v^{\text{out}}$ and v^{out} does not depend on ω, we obtain

$$\frac{dS^{\text{manager}}(\omega)}{d\omega} = \frac{1}{\rho + H(n,\tau)}. \tag{40}$$

Derivation of $\frac{dS^{\text{firm}}(\omega)}{d\omega}$. To obtain the derivative of the firm's value with respect to the wage, we differentiate equation (13):

$$\begin{aligned}
\rho\,\frac{dv^{\text{firm}}(n,\tau,P=0)}{d\omega} &= -1 - z^*(n,\tau,P=0)\,\frac{dv^{\text{firm}}(n,\tau,P=0)}{d\omega} \\
&\quad + \frac{da^*(n,\tau)}{d\omega}\big[v^{\text{firm}}(n,\tau,P=1) - v^{\text{firm}}(n,\tau,P=0)\big] \\
&\quad - a^*(n,\tau)\,\frac{dv^{\text{firm}}(n,\tau,P=0)}{d\omega} \\
&\quad - (I^s + I^o)\,\frac{dv^{\text{firm}}(n,\tau,P=0)}{d\omega} \\
&\quad - \phi\,\mathbb{I}\big(v^{\text{firm}}(n,\tau,P=0) - c_f \leq v^{\text{out}}\big)\,\frac{dv^{\text{firm}}(n,\tau,P=0)}{d\omega}.
\end{aligned} \tag{41}$$

The structure of this expression closely parallels the manager case, and the continuation value in state $(n{+}1,\tau)$ does not appear because wages are renegotiated in that state and therefore do not depend on today's wage.[35]

The key difference from the manager case is that $\frac{da^*(n,\tau)}{d\omega} \neq 0$. The manager chooses the spinout hazard $a^*(n,\tau)$, and the firm internalizes that a higher wage lowers the manager's incentive to spin out. Therefore, the firm's derivative includes the additional term

$$\frac{da^*(n,\tau)}{d\omega}\big[v^{\text{firm}}(n,\tau,P=1) - v^{\text{firm}}(n,\tau,P=0)\big],$$

which captures the *retention gain* of the wage on firm value: a higher wage reduces the probability of losing the manager and mitigates the firm's value loss upon transition to $P=1$.

Rearranging (41) delivers:

[35]The expression also omits the derivative of the indicator function. A higher wage increases retention and thus may affect the endogenous exit probability, but this is a second–order effect relevant only for firms exactly at the cutoff. For tractability, we abstract from this term; including it has no quantitative relevance for our results.

$$\frac{dv^{\text{firm}}(n,\tau,P=0)}{d\omega} = -\frac{1}{\rho + H^{\text{firm}}(n,\tau)} + \frac{\frac{da^*(n,\tau)}{d\omega}\left[v^{\text{firm}}(n,\tau,P=1) - v^{\text{firm}}(n,\tau,P=0)\right]}{\rho + H(n,\tau)}. \tag{42}$$

This equation is the firm-side analogue of the manager derivative. The first term captures the direct effect of a higher wage: it is the present value of an additional unit of flow cost to the firm, discounted, as before, at the effective rate $\rho + H(n,\tau)$. The second term reflects the key difference from the manager case. Because the manager's separation decision responds to the wage, a higher wage reduces the spinout hazard $a^*(n,\tau)$ and therefore lowers the probability that the firm transitions to $P = 1$. The derivative $\frac{da^*(n,\tau)}{d\omega}$ multiplies the value loss $v^{\text{firm}}(n,\tau,P=1) - v^{\text{firm}}(n,\tau,P=0)$, so this term captures the *retention gain* from raising the wage: the improvement in continuation value that arises because the manager is less likely to leave.

Since $S^{\text{firm}}(\omega) = v^{\text{firm}}(n,\tau) - v^{\text{out}}$ and v^{out} does not depend on ω, the above expression is also the derivative of firm surplus with respect to wage.

Finally, substituting equations (40) and (42) into the first–order condition (37) yields the nonlinear surplus–sharing rule reported equation (18) of the main text.

B.3 Derivative of the optimal separation policy $a^*(n,\tau)$.

We derive the analytical expression for the derivative of the optimal separation rate with respect to the wage. To do so, we differentiate the manager's optimal separation rule in equation (17) with respect to $\omega(n,\tau)$, which yields the following expression:[36]

$$\frac{da^*(n,\tau)}{d\omega} = \frac{n}{k}\left(\frac{d}{d\omega}\mathbb{E}_\tau\left[v^{\text{firm}}(1,\tau,P=0)\right] - \frac{dv^{\text{manager}}(n,\tau)}{d\omega}\right). \tag{43}$$

The term $\mathbb{E}_\tau\left[\,v^{\text{firm}}(1,\tau,P=0)\,\right]$ is the manager's expected continuation value conditional on spinout, and it does not depend on the wage; hence, using (39), we obtain:

$$\frac{da^*(n,\tau)}{d\omega} = -\,\frac{n}{k}\,\frac{dv^{\text{manager}}(n,\tau)}{d\omega} = -\,\frac{n}{k}\,\frac{1}{\rho + H(n,\tau)}. \tag{44}$$

Thus, in the interior region, the optimal spinout hazard is strictly decreasing in the wage. The responsiveness is proportional to $\frac{n}{k}$—larger when the employer technology gap n is higher and smaller when the adjustment cost k is larger—and is scaled by the effective discount rate $\rho + H(n,\tau)$.

B.4 Flow Balance Conditions for $n = 1$.

The equations below describe inflow-outflow balancing equations for states $(1, H, P = 1)$, $(1, L, P = 0)$, and $(1, L, P = 1)$.

[36] This expression applies in the interior region of the manager's problem, where the optimal separation hazard satisfies $a^*(n,\tau) > 0$. When the corner solution $a^*(n,\tau) = 0$ binds, the derivative with respect to the wage is zero.

$$\text{For } (1,L,0): \quad \sum_{n,\tau,P} \xi(n,\tau,P)a(n,\tau,P)(1-\mu(n)) + I^o(1-\tilde{\mu}) + q\xi(1,L,1) \\ = \xi(1,L,0\left[a(1,L,0) + z(1,L,0) + I^s + I^o + \phi\mathbb{I}^{exit}(1,L,0)\right], \tag{45}$$

$$\text{For } (1,H,1): \quad \xi(1,H,0)a(1,H,0) = \xi(1,H,1)\left[z(1,H,1) + q + I^s + I^o + \phi\mathbb{I}^{exit}(1,H,1)\right], \tag{46}$$

$$\text{For } (1,L,1): \quad \xi(1,L,0)a(1,L,0) = \xi(1,L,1)\left[z(1,L,1) + q + I^s + I^o + \phi\mathbb{I}^{exit}(1,L,1)\right]. \tag{47}$$

B.5 Proof of Proposition 1.

With the log aggregator and stationary factor shares, $\ln Y_t = \int_0^{\bar{\mathcal{F}}} \ln q_i(j,t)\, dj + (\text{constant})$, so along the BGP $g = \dot{\ln Y_t} = \dot{\ln Q(t)}$ where $Q(t) \equiv \int_0^{\bar{\mathcal{F}}} \ln q_i(j,t)\, dj$. Hence, the growth rate of output is:

$$g = \lim_{\Delta t \to 0} \frac{\ln Q(t+\Delta t) - \ln Q(t)}{\Delta t}.$$

In a small interval $[t, t+\Delta t)$ each *successful* innovation in any active line raises $\ln q$ by $\ln \lambda$; multiple arrivals are $o(\Delta t)$. The aggregate expected change is[37]

$$\mathbb{E}[Q(t+\Delta t) - Q(t)] = \left(\sum_{n,\tau,P} \xi(n,\tau,P)\, z(n,\tau,P) + I^s + I^o\right) \ln\lambda\ \Delta t + o(\Delta t).$$

Divide by Δt and let $\Delta t \to 0$ to obtain:

$$g = \left(\sum_{n,\tau,P} \xi(n,\tau,P)\, z(n,\tau,P) + I^s + I^o\right) \ln\lambda.$$

B.6 Derivation of Equation (31).

Starting from

$$\text{Welfare}(0) = \int_0^\infty e^{-\rho t} \ln C_t\, dt = \int_0^\infty e^{-\rho t} \ln\left[(1-I)Y_t\right] dt,$$

and using that on the BGP $Y_t = Y_0 e^{gt}$ and I is constant, we obtain

$$\begin{aligned} \text{Welfare}(0) &= \int_0^\infty e^{-\rho t} \ln(1-I)\, dt + \int_0^\infty e^{-\rho t} \big(\ln Y_0 + gt\big)\, dt \\ &= \frac{\ln(1-I)}{\rho} + \frac{\ln Y_0}{\rho} + \frac{g}{\rho^2}. \end{aligned}$$

Next, expand $\ln Y_0$ using (2), (4), and the labor-demand condition (28). With $\ln Y_0 = \int_0^{\bar{\mathcal{F}}} \ln y(j,0)\, dj$

[37] Note that activation/deactivation of product lines does not add terms: stationarity of the active mass $\bar{\mathcal{F}}$ from (23) implies that lines entering and leaving the integral for $Q(t)$ offset in expectation. Hence only the $\ln \lambda$ jumps from successful innovations—incumbent $z(\cdot)$, spinouts I^s, and outsiders I^o—contribute to $\dot{Q}(t)$ to first order.

and $y(j,0) = q(j,0)l(j,0)$,

$$\begin{aligned}
\ln Y_0 &= \int_0^{\bar{\mathcal{F}}} \ln q(j,0)\, dj + \int_0^{\bar{\mathcal{F}}} \ln l(j,0)\, dj \\
&= \ln Q(0) + \int_0^{\bar{\mathcal{F}}} \ln\left(\frac{1}{\omega^u\, \lambda^{n_j}}\right)\, dj \\
&= \ln Q(0) - \ln\lambda \int_0^{\bar{\mathcal{F}}} n_j\, dj - \bar{\mathcal{F}}\, \ln\omega^u \\
&= \ln Q(0) - \ln\lambda \sum_{n,\tau,P} n\, \xi(n,\tau,P) - \bar{\mathcal{F}}\, \ln\omega^u.
\end{aligned}$$

Substituting this into the welfare expression yields (31).

B.7 Consumption Equivalent Variation in Welfare

We evaluate welfare differences across steady states in terms of the *consumption-equivalent variation*, which expresses the welfare difference as the permanent percentage change in consumption that would make the representative household indifferent between the baseline (B) and a counterfactual (C) steady state.

Specifically,

$$U_0(\xi C_0^C, g^C) = U_0(C_0^B, g^B), \tag{48}$$

where $100(\xi - 1)$ represents the steady-state welfare gain (in percent of consumption) from moving from the baseline to the counterfactual equilibrium.

With log utility, the CEV takes the closed-form expression:[38]

$$\ln\xi = \ln C_0^B - \ln C_0^C + \frac{g^B - g^C}{\rho}. \tag{49}$$

Using $C_0 = (1-I)Y_0$ and assuming that initial aggregate quality Q_0 is identical across steady states, we obtain:

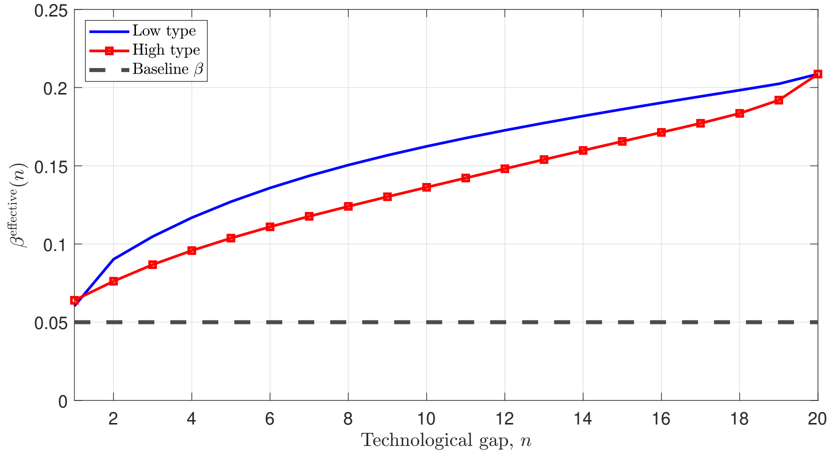
$$\begin{aligned}
\ln\xi = {} & \left[\ln(1-I^B) - \ln(1-I^C)\right] \\
& - \ln\lambda\left(\sum_{n,\tau,P} n\, \xi^B(n,\tau,P) - \sum_{n,\tau,P} n\, \xi^C(n,\tau,P)\right) \\
& - \left[\ln\omega^{u,B} - \ln\omega^{u,C}\right] \\
& + \frac{g^B - g^C}{\rho}.
\end{aligned} \tag{50}$$

In the counterfactual experiments, we report $100(\xi - 1)$ as the consumption-equivalent welfare change associated with the policy or parameter shift.

[38] $U_0(C_0, g) = \int_0^\infty e^{-\rho t} \ln(C_0 e^{gt})\, dt = \frac{\ln C_0}{\rho} + \frac{g}{\rho^2}$.

C Model Calibration Appendix

Figure 12: Effective bargaining power



Notes: The figure plots the effective bargaining weight $\beta^{\text{effective}}(n, \tau)$ defined in equation (33) for high- and low-type managers across the technological gap n.

D Model Performance Appendix

D.1 Separation Rates

To additionally test the positive relationship between technological leadership and spinout creation, we present a detailed regression analysis. Table A.1 shows the relationship between spinout spawning and a firm's technological leadership, proxied by the quality of its patent filings. As earlier, Panel A presents results based on the patent data only, and Panel B includes results for the sample of patenting firms in Compustat. The first two columns present logit regressions for the yearly probability of spinout separation, while the last two columns show negative binomial regressions for the number of spinouts separating from the firm in a year. Across these different samples and specifications, the coefficient on log citations-adjusted patents in the last 5 years is positive and significant. The regressions in addition control for the number of inventors to avoid mechanical dependence between firm size and spinout separation, firm age, year, industry, state, and firm fixed effects (columns 2 and 4). Additional controls are included in the regressions based on Compustat sample.[39]

Appendix Table A.1: Technological Leadership and Spinout Separation

	(1) Logit	(2) FE Logit	(3) Neg. Binom	(4) FE Neg. Binom
Log cit-patents (parent)	0.155***	0.126***	0.147***	0.116***
	(0.0116)	(0.0322)	(0.0108)	(0.0285)
Patents, Inventors, Age	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Industry FE	✓		✓	
State FE	✓		✓	
Firm FE		✓		✓
Observations	184442	53424	184598	53794

Note: The table presents firm-level regressions of the probability of spawning a spinout (logit models in columns 1 and 2) and the count of spawned spinouts (negative binomial models in columns 3 and 4) as a function of the technological leadership of the firm (parent) and other firm characteristics. Technological leadership is proxied by the firm's citations-adjusted patent count filed within the last 5 years. Additional controls are the log number of patents, number of inventors, and firm age together with fixed effects, as reported in the table. The sample covers the period 1981-2000.

[39] Appendix Tables A6 and A7 confirm robustness of these results to different definitions of the employer's technological leadership.