Entrepreneurship through Employee Mobility, Innovation, and Growth*

Salomé Baslandze Ia Vardishvili

Abstract

Firm-level productivity differences are big and are largely ascribed to ex-ante heterogeneity in the entrepreneurs' growth potential at birth. Where do these ex-ante differences come from, and what can the policy do to encourage the entry of high-growth entrepreneurs? We study empirically and by means of a quantitative growth model the *spinout* firms -– the firms founded by former employees of the incumbent firms. By focusing on innovating spinouts identified through inventor mobility in the patent data, we establish three core facts: (i) spinouts outperform regular entrants over their lifecycle; (ii) firms with greater technological lead generate more successful spinouts; and (iii) parent firms experience a persistent decline in innovation following spinout events. Motivated by these findings, we develop a structural model of innovation and firm dynamics in which heterogeneous spinouts endogenously emerge from employee decisions. Spinouts influence growth through four channels: direct entry, incumbent disincentives, knowledge diffusion, and firm composition. Growth decompositions reveal that spinout dynamics are quantitatively important for aggregate innovation and growth. We find that stricter non-compete laws reduce spinout formation, dampening innovation and growth.

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

JEL Classifications: O30, O43.

*Baslandze: Federal Reserve Bank of Atlanta and CERP. Vardishvili: Auburn University. The views expressed here are those of the author and do not necessarily reflect the views of the Federal Reserve System.

1 Introduction

Firm-level productivity differences are large, with only a handful of high-growth firms accounting for the majority of innovation and productivity growth in the U.S. (Bartelsman and Doms, 2000; Haltiwanger, Hurst, Miranda and Schoar, 2017). Although recent empirical evidence suggests that these firm-level differences are largely ascribed to ex-ante heterogeneity in growth profiles at birth (Pugsley, Sedlacek and Sterk, 2018). In this paper, we focus on a specific type of ex-ante heterogeneity often overlooked in the growth and firm dynamics literature – the heterogeneity coming from the prior employment background of firms' founders. we show both empirically and by means of a quantitative growth model that *spinout* entrants – the firms established by former employees of incumbent firms – play an important role in innovation, growth, and firm dynamics.

Spinout entrants often turn into exceptionally productive high-growth firms, often reshaping the whole industries (Klepper, 2002; Klepper and Sleeper, 2005; Franco and Filson, 2006). Examples of transformational spinout firms are ample. Figure 1 shows a small part of a large spinout family tree spawned by Bell Telephone Laboratories established in 1952. After the stages of prolific spawning of new and exceptionally productive spinouts, the semiconductor industry grew, achieving sales of more than $400 billion today. A more recent example is Zoom Video Communications – entrepreneurial venture by a former head of Cisco Webex engineering team, that swept the crowded communications market and saw unprecedented growth during the 2020 pandemic.

Although spinout entrants may be more productive, the process of spinout creation entails tension between incumbents and the employees leaving their firms to pursue their own entrepreneurial ventures.[1] Indeed, employers are increasingly concerned about the harm to their businesses caused by employee mobility, as manifested by existing employer protection regulations such as non-compete policies and the continual demands to strengthen them.[2][3] If this tension results in incumbents' lower appropriability of innovation investments, their innovation incentives will decline.[4]

To understand this interaction between spinout entry and incumbents' innovation incen-

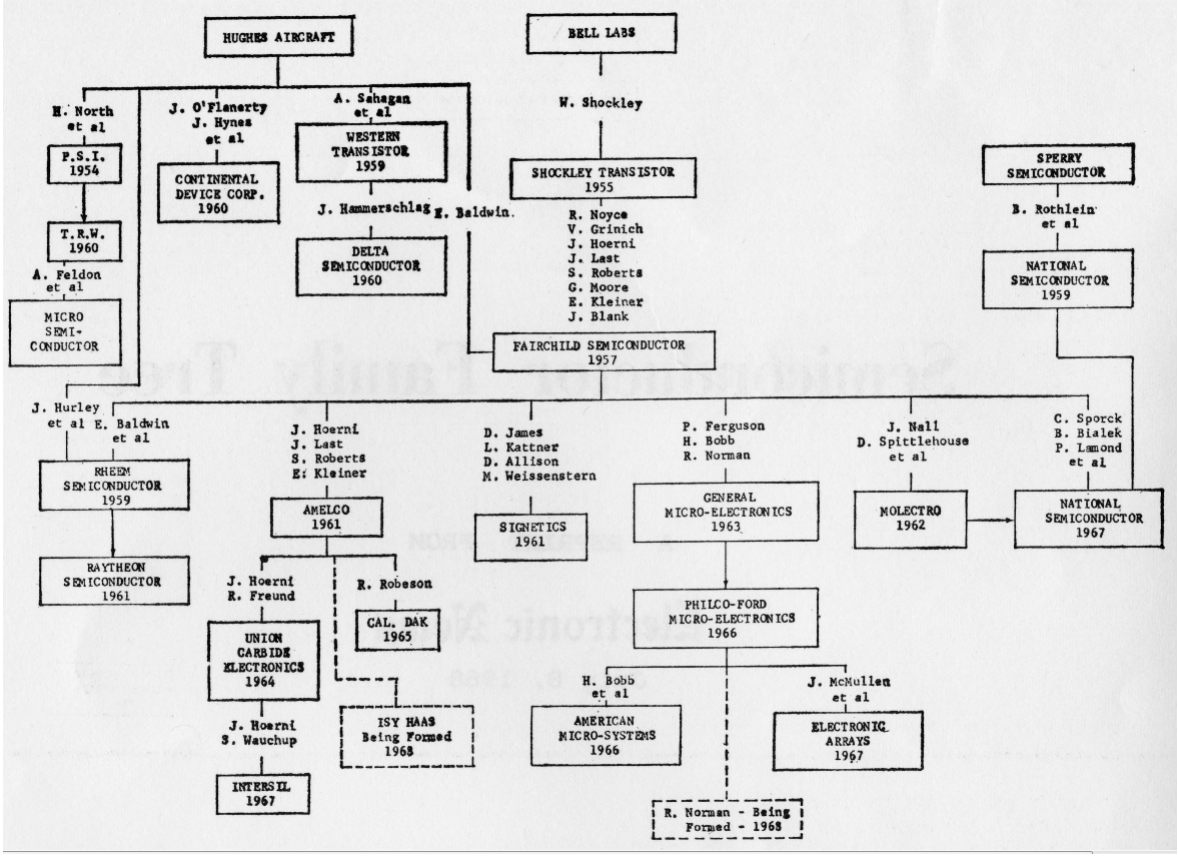
[1] See Pakes and Nitzan (1983) and Anton and Yao (1995) for the first theoretical treatments of this tension between inventors and employers.

[2] Half of the establishments with more than 50 employees use non-compete clauses in employee agreements for *some* employees, and the third of the establishments use them for *all* employees (Colvin and Shierholz, 2019).

[3] The debate persists around non-compete regulations limiting the employee mobility, as reflected by a recent House Bill requesting to strengthen existing regulations (Bill S.998, "An Act relative to the judicial enforcement of noncompetition agreements", 2017-2018 legislative session) and a later bill which prohibits the use of non-compete agreements (S.2614 - Workforce Mobility Act of 2019, introduced in the 116th Congress, 2019-2020.). See also President Biden's Executive Order 14036 of July 9, 2021 targeting non-competes.

[4] These concerns can be concisely summarized in this powerful quip by Intel general counsel Roger Borovoy, 1997: "Don't let your employees do to you what you did to your former boss." It is worth noting that Intel itself is a spinout from Fairchild Semiconductor.

Figure 1: Spinouts in Semiconductor Industry



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

tives and the quantitative implications for aggregate innovation and growth, we build a rich structural model of innovation and firm dynamics, where firm heterogeneity arises from endogenous decisions of innovation workers to become entrepreneurs and create spinouts. With this model at hand, we quantitatively analyze the role of non-compete laws (NCL) hindering the employee mobility, in promoting aggregate innovation and growth.

We begin the study by empirically analyzing spinout firms and by providing motivating stylized facts that guide the modeling. To identify the innovating spinout firms, we use a detailed datasets on patents and the universe of patenting firms from NBER-USPTO and combine it with the disambiguated inventors dataset from Harvard Patent Network Dataverse project (Lai, D'Amour, Yu, Sun and Fleming, 2011) to track individual inventor across firms. A firm is defined as a spinout if at least one inventor on a patent application filed in the firm's entry year has worked in a different firm before that year. A sizable share of innovating firms enter as spinouts: 28% of the patenting entrants, the total of 18,012 firms.

The advantage of using patents and inventors dataset to analyze spinout firms is twofold. First, the model in this paper focuses on the innovating firms that drive technological

progress in the economy; and patents have been widely used in the literature as the main systematic metric to identify the innovating firms (Griliches, 1981; Hall, Thoma and Torrisi, 2007; Kogan, Papanikolaou, Seru and Stoffman, 2017; Argente, Baslandze, Hanley and Moreira, 2020). Second, the data on rich patent characteristics offers the possibility to proxy for individual's innovation quality as well as quality and technological capabilities of a firm–objects that are hard to get with other datasets and that are crucial to discipline the model.

The three main stylized facts emerge from the data. First, spinout entrants significantly outperform regular entrant firms throughout their entire life. Spinouts file more and higher-quality patents, live longer, grow faster, are more R&D-intensive, and generate more patents per R&D dollars spent. Second, firms with a bigger technological lead spawn more successful spinouts. Specifically, spinout firms are more innovative on many dimensions if their parent firms are in the top percentiles of patent quality distribution in their technology classes. Hence, the data supports a sort of learning or inheritance, whereby working in the leading firm is linked with the probability of creating a high-quality spinout firm. However, this process also entails a core tension. We find that parent firms suffer a persistent decline in their own innovation immediately following a spinout event. Finally, we document the role of policy in mediating this process, showing that stricter non-compete laws are associated with a lower rate of spinout formation.

In the second part of the paper, we build a general equilibrium endogenous growth model consistent with main empirical facts from the data. Building on the Schumpeterian growth models (Aghion and Howitt, 1992; Acemoglu and Akcigit, 2012; Peters, 2020) with entry and incumbents' innovation, we introduce new features of individuals occupation choice, spinout entry, and non-compete restrictions.

In the model, skilled people are allocated into three groups: entrepreneurs running the firms, R&D managers conducting innovation in the firms, and outsiders contemplating entry into one of the above occupations. Motivated by the first empirical fact that spinouts significantly outperform regular entrant firms throughout their entire life, we introduce heterogeneous firm-specific quality types determined at entry. Some firms enter as high-type, while others enter as low-type firms. Entrepreneurs decide on innovation efforts that push the technology frontier forward. The heterogeneous quality types of their firms determine their efficiency in the innovation process. By innovating, firms move up the technological ladder and increase their market power. R&D managers bargain with entrepreneurs over their wages and can search for outside opportunities to create their own spinout firms. This creates a tension, as a spinout event negatively impacts the parent firm. Motivated by our third empirical fact, the model incorporates a persistent drop in the parent's R&D efficiency after a manager's departure, which lasts until the firm is matched with a new R&D manager. Importantly, building on the second fact that better firms spawn better spinouts, R&D

managers learn on the job; the more technologically advanced their employer, the higher the chances that their startup will be of a better quality type.[5] Hence, a key characteristic of this model is that the entry distribution of firm quality is endogenous, shaped by the incumbents' type distribution, their innovation decisions, and employees' entrepreneurial choices. Finally, the model builds in non-compete restrictions that influence the expected costs of spinout formation by employees.

The four main channels through which spinout formation affects aggregate innovation and growth operate in the model. First is the *direct entry effect* on growth, where more entry positively contributes to innovation and hence growth. Second is the *disincentive effect* of spinout formation on incumbent firms' innovation incentives: similar to the standard appropriability problem, ex-ante incentives of incumbents are lower if they expect their R&D managers to leave and compete with their firms. The third channel is *knowledge diffusion*, whereby spinout entry increases the share of high-type firms in the market. Finally, spinout entry also influences the *firm composition*: more spinout entry promotes more competition and, as a result, increases aggregate innovation efforts.

In the last part of the paper, we conduct our quantitative evaluation. We first calibrate the model to match key targets for innovation, entry, and labor market composition. We then validate the calibrated model by demonstrating its success in replicating a range of important empirical patterns. Specifically, we show that the model generates a stationary distribution of firms across the technology gap that closely matches the data, both overall and for high- and low-type firms separately. Furthermore, the model endogenously produces innovation and separation rates that align well with their empirical profiles and replicates the persistent 10% drop in a parent firm's innovation rate following a spinout event. Finally, we show that the model's implied elasticity of spinout formation with respect to non-compete laws aligns well with the empirical estimates.

Using growth decompositions, we first show that accounting for spinout dynamics is quantitatively important for our understanding of growth process. The static growth decomposition shows that 12% of productivity growth is accounted for by direct entry by spinouts. However, the dynamic growth decomposition that takes into account both entry and an increase in the share of high-quality entrepreneurs through knowledge diffusion increases the contribution of spinouts to aggregate productivity growth. If the spinout dynamics are important for growth, could we design the policies to foster spinout entrepreneurship without distorting the incumbents' innovation incentives?

To understand which policies can boost high-quality entrepreneurship and productivity growth, we provide a set of counterfactual policy experiments. The first policy explores the current non-compete laws in the U.S. Recent evidence indicates that the use of non-compete

[5]This setup also does not rule out the possibility of positive sorting between the firms and the R&D managers. More discussion is in Section 3.

agreements– the clauses in employee contracts that prohibit the employees from working for a competitor or forming a new firm, has been on the rise, with an estimated 28%-47% of private-sector workers being subject to non-compete restrictions.[6] The high-skill employees are even more likely to be subject to non-competes, indicating that for inventors, these restrictions on establishing own ventures might be even more severe.[7] Currently, the U.S. states vary widely in the degree of enforcement of (Garmaise, 2011; Starr, 2019). For example, in California, the courts would not enforce any non-compete agreements, while in Florida they would enforce them in many cases. The policy analysis shows that abolishing non-compete restrictions is welfare-maximizing, mainly due to resulting higher aggregate innovate and growth. State-by-state, the gains from the optimal policy adoption have a wide range, reaching the maximum gain of 11 basis points in growth rate in Florida, Montana, and Tennessee.

Related Literature This paper is related to the large literature on firm dynamics, entrepreneurship, innovation, and growth. Motivated by a large productivity dispersion across firms (Dunne et al., 1988), the basic models of firm dynamics have long incorporated exogenous productivity differences across firms (Hopenhayn, 1992; Hopenhayn and Rogerson, 1993). Although underlying productivity differences between firms have been empirically shown to be largely driven by initial differences at entry (Abbring and Campbell, 2005; Guzman and Stern, 2015; Belenzon et al., 2017; Pugsley et al., 2018; Azoulay et al., 2020; Guzman and Stern, n.d.), the firm dynamics models are mostly silent about the sources of this ex-ante heterogeneity. In this paper we endogenize ex-ante productivity differences based on the employees' choices of entrepreneurship and the dynamics of knowledge diffusion. As a result, the paper considers a new mechanism of endogenous knowledge diffusion that speaks to the recent works on knowledge diffusion and growth (Perla and Tonetti, 2014; Lucas and Moll, 2014; Benhabib et al., 2021).

we build on the general equilibrium models of innovation, firm dynamics, and growth (Aghion and Howitt, 1992; Grossman and Helpman, 1991; Klette and Kortum, 2004; Lentz and Mortensen, 2008; Akcigit and Kerr, 2018; Acemoglu and Akcigit, 2012; Acemoglu and Cao, 2015; Acemoglu, Akcigit, Alp, Bloom and Kerr, 2018; Peters, 2020). While these models are only concerned about firm's innovation decisions, we incorporate the problem of the firm's R&D manager/inventors and analyze the firm's and inventor's interaction and its effects on aggregate firm dynamics and growth. This framework can also be used to jointly analyze various labor market and innovation policies.

This paper also relates to theoretical studies of employee entrepreneurship. The first

[6]The Economic Policy Institute Report on Noncompete Agreements, December 10, 2019.

[7]Interviews of patent holders from Marx (2011) show that non-compete agreements play important role in career paths of the technical professionals.

works in this direction are classic papers by Pakes and Nitzan (1983) and Anton and Yao (1995) who study the optimal contracting problem in an environment where a researcher can learn an idea and decide between continuing working for the firm or creating own firms. These studies do not consider industry dynamics and aggregate outcomes. The closest to this study is Franco and Filson (2006). They study the evolution of an industry where employees can imitate the know-how of the employers and establish new firms. In Franco and Filson (2006), competitive equilibrium is efficient, while here due to monopoly distortions and intertemporal knowledge spillovers from the improved firm type composition in the economy, the equilibrium is not generally efficient. In another related study, Franco and Mitchell (2008) analyze spinouts and industry dynamics with non-compete laws to explain the initial dominance of Route 128 over Silicon Valley and its subsequent reversal.

These models provide important intuitions, but they are stylized and do not allow for quantitative analysis of the spinout formation and its implications for productivity growth and policy. To the best of my knowledge, the only related quantitative macro study is the concurrent work by Sohail (2021).[8] Different from that work, we develop a framework to study the interaction of incumbents' innovation incentives with spinouts' entry, its effect on the evolution of the distribution of firms' qualities and competition, and resulting effect on aggregate growth. This structural framework then allows us to quantify importance of various channels and evaluate optimal innovation and non-compete policies.

Theoretical analysis in this paper is guided by the set of stylized facts that we document using inventors and patent data. These facts are consistent with the growing empirical literature on employee spinouts identified in different datasets[9] hence lending a wide support to the empirical underpinnings of the structural model considered in this paper. For example, a number of papers empirically study characteristics of spinout firms in the automobile industry, laser, disk drive, medical device, legal services, and biotech industries – Klepper (2002), Agarwal et al. (2004b), Klepper and Sleeper (2005), Franco and Filson (2006), Chatterji (2009), Klepper and Thompson (2010), Campbell et al. (2012). The following set of broad facts emerges from the empirical studies. Spinouts account for a sizable share of entry – across industries, the share of spinout entrants ranges from 17% to 26%, and it increases over time as industry matures. Spinout firms usually performing well, often become industry leaders (oftentimes beating their parents), and usually have low failure rates. Spinouts also tend to separate from the firms that are industry leaders, and better firms spawn even better spinouts. In this paper, we find that similar empirical patterns emerge when we consider innovating spinouts across all industries using micro-level

[8] Using data from Mexico, Sohail (2021) shows that spinout spawning is lower for larger firms. Our study is mute on firm size, and it shows that conditional on size, firms with higher technological leadership are more likely to spawn spinouts, lending support to the knowledge inheritance hypothesis, similar to Agarwal et al. (2004a).

[9] Literature often uses word "spinoff" instead of "spinout" that we use here.

data on inventors and firms from the patent data. The contribution of this paper is to incorporate these common stylized facts in the micro-founded macro model to understand aggregate implications of spinout formation for innovation, firm dynamics, and growth.

Finally, a large and mainly empirical literature studies various effects of non-compete laws. Empirically, the studies have documented that stricter enforcement of non-competes limits labor mobility (Fallick, Fleischman and Rebitzer, 2006; Marx, Strumsky and Fleming, 2009; Garmaise, 2011) and firm entry (Samila and Sorenson, 2011; Starr, Balasubramanian and Sakakibara, 2018; Jeffers, 2019); stricter non-competes are also related to higher or riskier investment by firms, especially in knowledge-intensive industries, supporting the idea that employee mobility reduces firms' incentives to invest (Conti, 2014; Jeffers, 2019; Barnett and Sichelman, 2020). Consistent with the observed empirical tradeoff between increased firm entry and job-to-job mobility on the one hand and lower firm investment incentives on the other hand, scholars and policymakers have had diverse opinions on aggregate implications and overall desirability of non-competes (Saxenian, 1994; Gilson, 1999; Barnett and Sichelman, 2020). To the best of our knowledge, this is the first paper that attempts to quantify these opposing effects of non-competes on the aggregate innovation and growth and evaluates optimal non-compete policies. A concurrent paper by Shi (2021) also studies non-compete policies in a structural macro model, but her focus is on the job-to-job mobility and wage contracts of executives, while the effect through spinout entry, innovation, and knowledge diffusion is the focus of the current work. Nevertheless, both of our analyses show that optimal policy is not to enforce the non-competes.

2 Data and Motivating Empirical Facts

To identify and characterize innovating spinout firms, we use micro-level datasets on patents, firms, and inventors. The data analysis serves two major purposes: first, it helps the theory to build on empirically motivated assumptions; and second, it helps to calibrate the model, quantify relevant channels, and conduct counterfactual policy experiments. We start by describing the data and then presenting four main empirical facts underpinning the model in Section 2.2.

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 USPTO patent dataset drawn from the NBER Patent Data Project (Hall et al., 2001). The NBER patent data contains all granted patents by the U.S. Patent and Trademark Office during the 1976-2006 period. We use a 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.[10] 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 innovative output quality as well as track individual inventors over time across different firms.

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

2.1.2 Sample and the Identification of Spinout Firms

The innovating firms are classified into entrant firms by identifying the firm's entry year as the year the firm makes its first patent application. A firm's exit year is defined as the grant year of its last patent in the data. Clearly, the firm entry and exit dates defined based on the patent application dates do not necessarily coincide with the firm's exact entry and exit dates in the economy. Nevertheless, these are good proxies to measure a firm's entry and exit into innovation – the focus of this paper. The first patenting year well describes the firm's entry into the innovation stage – similar to the firm entry in the model in the next section; while the firm's last patent describes its exit from the innovation stage – again, in line with firm exit in the model.

To identify spinouts, we track inventors' mobility across firms by following inventors'

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

patenting records. A firm is defined as a *spinout entrant* if at least one inventor on a patent application made in the firm's entry year has worked in a different firm before that year.[11] To reduce the measurement error, we exclude spinouts if the time gap between the inventor's last date in the previous firm and in a new spinout firm is greater than 5 years. We also make sure we do not tag inventors as moving to another firm if this move occurred as a result of mergers and acquisition activities (*Dynass* file from PD database helps to identify these types of reorganizations.) Alternatively, the entrant is classified as a *regular entrant*.

The following example illustrates the spinout identification. Computer Memories Inc. was a California-based manufacturer of hard disks during the 1980's. The firm has seven granted patents in the data. Ara W. Nazarian was an inventor on two of those patents filed in 1983 ($US4578625$ and $US4685007$). In 1986, this inventor filed $US4786995$ under Peripheral Technology Inc.; and $US4786995$ is also the first patent by this firm. Hence, Peripheral Technology Inc. is classified as a spinout entrant.[12]

The main sample focuses on entrants born between 1981 and 1999. This period is chosen to address potential truncation issues in the data. Because the dataset includes only patents granted from 1976 onward, entrants are identified starting in 1981 to minimize the left truncation issue. Similarly, as the data ends in 2006 due to the time lag between patent application and its grant, we naturally observe fewer patents closer to the end of the sample. Hence, to reduce the right truncation problem, the last year in which entrants are identified is 1999. The timeframe from 1981 to 1999 allows for considerable time to observe entrants' future activities, and measure their performance and potential exit. That said, a firm that applied for a patent prior to 1981 is classified as an *incumbent* and will appear as such in our sample starting in 1981.

2.1.3 Descriptive Summary Statistics

Table 1 provides summary statistics of the data, with Panel A focusing on all the innovating firms appearing in the patent data. We observe 63,561 firms born during the period 1981–1999, referred to as "entrants," and 11,408 firms that began operating before 1981, referred to as "incumbents." The average longevity of entrant firms is 3.9 years, with an average of 6 patents and 107 citation-weighted patents.[13] In contrast, the average longevity

[11] An alternative definition that leads to similar empirical results looks at the background of all inventors in the firm's first two years after entry.

[12] Indeed, using alternative data sources, Franco and Filson (2006) analyze the history of hard disc drive industry in the U.S., and list Peripheral Technology Inc. as a firm established by a former employees of other firms. Peripheral Technology enters the economy in 1985 and exits in two years through acquisition. In our data, this firm enters in 1986 and exits in 1988 – the year of its last patent application. It is also worth noting that Computer Memories Inc. announced its departure from the hard disc drive industry in 1986, coinciding exactly with the last year it files a patent in the data.

[13] Due to the nature of forward citations, which take time to accumulate, we use the truncation-adjusted number of citations from Hall et al. (2001).

of incumbent firms is 14.9 years, with an average of 67 patents and 946 citation-adjusted patents.

Among the entrant firms, 18,012 (28.3%) are identified as spinout entrants, while the remaining 45,549 are classified as regular entrants. The average longevity of spinout entrants is 4.3 years; they file an average of 11 patents, with 204 citation-adjusted patents per firm. In contrast, regular entrants have an average longevity of 3.4 years, file 4 patents on average, and produce 69 citation-adjusted patents per firm.

Despite representing only 28.3% of entrants—2.5 times fewer than regular entrants—spinout firms account for a disproportionate share of patent filings. During the sample period 1981–2006, spinout entrants are responsible for 52.8% of patents filed by entrants (16.7% of all patents filed). This disparity is further evident when considering the impact of their patents: spinout entrants account for 54% of all citations-adjusted patents by entrants (20% of citations-adjusted patents of all firms). These results already hint at the superior patenting performance of spinouts relative to regular entrants.

Panel B of Table 1 presents summary statistics for a subset of firms matching to Compustat, resulting in 1,539 entrant and 2,880 incumbent firms. Among entrants, we identify 803 spinout and 736 regular entrants. Only publicly listed firms, which tend to be larger and positively selected, appear in Compustat. Hence, the fact that the sample contains 5.2% of spinout and only 1.9% of regular entrants further attests to the superiority of spinout firms. Yet, despite this selection into going public, we see that spinout entrants still exhibit stronger performance both in terms of innovation outcomes and across various financial and operational metrics. On average, spinout entrants are larger in terms of assets, sales, and employment and demonstrate a higher allocation of resources to R&D compared to regular entrants.

2.1.4 Discussion and the Validation Exercises

Before delving into the empirical analysis, it is important to discuss two issues related to the identification of spinouts. First, our focus is on the innovating spinouts identified via inventor mobility: this misses non-innovating spinout firms in the economy and those innovating spinouts created via non-inventor mobility.[14] However, this sample and spinout definition allows us to focus on firms most important for innovation and technological progress in the economy, which are the main focus of our analysis. Innovating firms are the main drivers of technological progress and growth, and patents have long been considered the main systematic metrics of innovation correlating both with firm and aggregate growth (Griliches, 1981; Hall et al., 2007; Kogan et al., 2017; Argente et al., 2020). Innovating firms also consistently outperform non-innovating ones across every productivity and

[14]The diagram in Appendix Figure 12 visually illustrates how our definition of innovating spinouts and regular entrants compares to the broader definitions of spinouts and regular entrants in the literature.

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.

growth metric in Compustat data (Appendix Table 9). Focusing our attention on innovating spinouts established via inventor mobility further narrows our analysis to the most successful spinouts: inventors' experience and early involvement in the firm's formation should play a critical role in the subsequent performance of the firm. Indeed, Islam and Zein (2020) shows that firms led by inventor CEOs outperform firms whose CEOs lack prior inventor experience. Meanwhile, Choi et al. (2019) highlights the critical role of founders and early employees in shaping a firm's future success. Therefore, the analysis of a comprehensive dataset on the universe of patenting firms, coupled with the identification of spinouts via inventor mobility, allows us to zoom into the main drivers of technological progress in the economy and obtain rich measures of inventors' and firms' innovation and technological capabilities. These measures, not available from other datasets, are crucial to discipline our analysis of the innovation-led growth model.

Second, the identification of innovating spinouts via inventor mobility may still suffer from measurement error. We do not observe firm owners and cannot assert that the first inventor in a spinout firm is an owner. In addition, as discussed earlier, our focus is on firm entry into innovation, which is not necessarily the same as the first year the company was created. Thus, our empirical definition of spinouts is broader than the usual definition of spinouts just based on owners of the firms, and it entails the founding team of inventors

in the early years of the innovating firm. This approach is akin to Choi et al. (2019), who emphasize that early joiners who are non-founder employees in the first year of a startup play a critical role in explaining a firm's future performance.

We validate our approach using the following two exercises. First, we compare our definition of spinouts with the traditional definition found in the literature. The influential work by Franco and Filson (2006) analyzes the rigid disk drive industry using detailed industry reports, reporting 40 spinout entrants from 1977 to 1993, along with their founding years, lifespans, and parent firms. We apply our methodology to independently classify these entrants into spinout and regular entrants and report the original and our own classification in Appendix Table 8. Out of 40 spinout firms identified by Franco and Filson (2006), 25 are innovating – have USPTO patents and are in our data. Out of these 25 innovating spinouts, 21 (84%) can be classified as spinouts via inventor mobility[15]. Hence, spinout identification using inventor mobility captures the innovative spinout entry into the economy well.[16]

It is also worth noting that, consistent with our earlier discussion, our definition of spinouts singles out particularly innovative and successful firms. Relative to non-innovating spinouts reported by Franco and Filson (2006), the innovating spinouts survive in the market for longer. Within innovating spinouts, those identified by us as spinouts via inventor mobility significantly outperform those we classified as regular entrants in terms of survival, number, and quality of innovations. These findings reinforce that firms formed through inventor mobility possess a crucial ex-ante characteristic that drives their superior post-entry innovation and growth trajectories, further highlighting the importance of this subset of firms in advancing technological progress and economic growth.

Lastly, the central data moments and stylized facts that emerge from this data on innovating firms are very consistent with the existing studies in the literature that focus on spinouts in various samples (see the literature review in Section 1 for more details). For example, the share of spinout entrants among all entrants in our sample is 24.8%,[17] which is in the range of other studies in the literature. Likewise, the facts on the superior performance of spinouts and knowledge inheritance from parents are consistent with findings in other studies in different contexts. This assures us that stylized facts on innovating spinouts are more general, extend beyond the sample of patenting firms, and give strong micro-foundations for modeling.

[15] In 2 out of these 21 cases, the gap between the founding inventor's last year in the previous firm and the spinout's entry year is more than 5 years.

[16] Notably, firm entry years in our sample lag true founding years by an average of 1.3 years.

[17] Using the spinout definition not restricted to the 5-year gap between inventor's last year in the parent firm and the entry year of the spinout results in 32% of entrants

2.2 Motivating Empirical Facts

This section motivates the model by presenting four key empirical findings. First, we document that spinout firms exhibit systematically higher performance than regular entrants throughout their life cycle, contributing to the persistent heterogeneity in firm productivity (Fact 1). Furthermore, we show that the quality of spinouts is positively associated with the technological lead of their parent firms (Fact 2), suggesting that more advanced incumbents tend to generate higher-quality spinouts. Second, we highlight a tension between the benefits of spinouts and their costs to parent firms. Specifically, Fact 3 shows that a spinout event is followed by a persistent decline in the parent firm's innovation rate, pointing to the disruptive nature of inventor departures. Finally, Fact 4 provides evidence that stricter enforcement of non-compete agreements is associated with a lower likelihood of spinout formation.

Fact 1. Spinout entrants outperform regular entrants

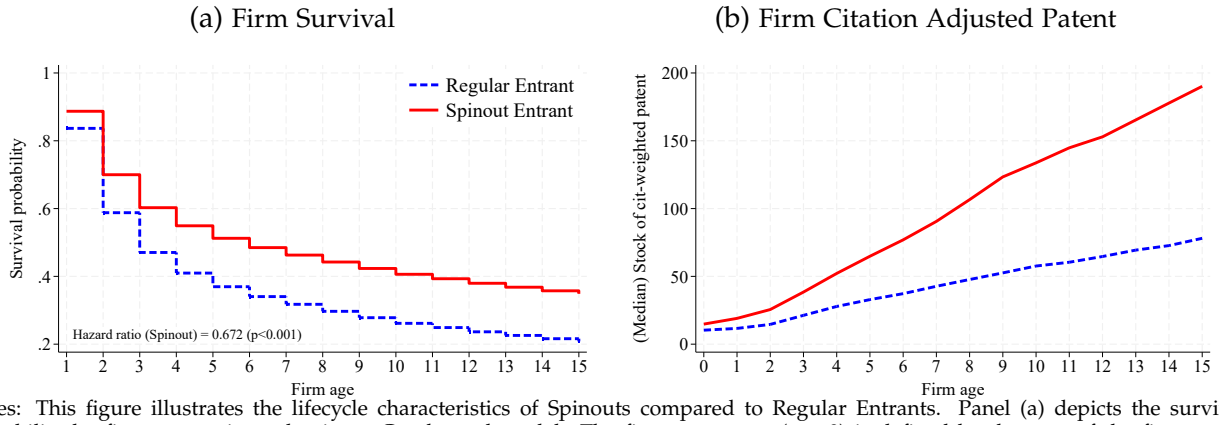
This analysis begins by highlighting the significant differences in the outcomes of entrant firms based on the prior experience of their founders.

Figure 2 illustrates the lifecycle dynamics of spinout and regular entrants from the Patent Data. Panel (a) shows that spinout entrants have a higher survival rate over their lifecycle compared to their regular counterparts. By age 15, approximately 36% of spinout entrants remain active, whereas only 20% of regular entrants survive. The hazard ratio for spinout firms is 0.67 (p-value < 0.001), implying a 33% lower risk of exit compared to regular entrants. Panel (b) of Figure 2 depicts the median stock of citation-adjusted patents by firm age, emphasizing that spinout entrants consistently outperform regular entrants in innovation output throughout their lifecycle. By age 15, the median spinout firm has accumulated 200 citation-adjusted patents, compared to just 70 for the median regular entrant.

Next, Table 2 compares various outcome variables for spinouts and regular entrants. Panel A is based solely on the patent data sample and compares lifetime outcome varaibles. As seen, conditional on being in the same cohort, operating in the same technology class and the state, spinout firms file 54% ($= exp(0.432)$) more patents during their lifetime. These firms issue not just larger number of patents, but also more impactful patents: spinouts have both more citations-weighted patent counts and more of high-quality patents in the top percentiles of the quality distribution of patents. Likewise, the number of years they are present in the patent data is also higher.

Panel B of Table 2 extends the analysis to Compustat data, providing additional evidence of the superior performance of spinout firms. Despite the strict selection process for going public, Column (1) shows that spinout entrants, conditional on being in the same

Figure 2: Lifecycle Dynamics of Spinouts and Regular Entrants



Notes: This figure illustrates the lifecycle characteristics of Spinouts compared to Regular Entrants. Panel (a) depicts the survival probability by firm age, estimated using a Cox hazard model. The firm entry year (age 0) is defined by the year of the first patent application, while the exit year is determined by the last patent's grant year. We focus on entrant firms established between 1981 and 2000, considering a firm to have exited the market if its last patent grant year is before 2000. This approach ensures that firms are not censored from above, allowing for a clearer view of survival dynamics. The hazard ratio for spinout firms is 0.67 (p-value < 0.001), indicating a 33% lower risk of exit relative to regular entrants. Panel (b) presents the median cumulative number of citation-adjusted patents by firm age within each entrant type, highlighting the greater cumulative innovation output of spinouts over time.

cohort, of the same age, and operating in the same sector and state, continue to outperform regular entrants in patenting activity. Additional financial data from Compustat, presented in Columns (2)–(4), indicate that spinout entrants, on average, are larger in terms of sales and employment and allocate more resources to R&D compared to regular entrants. Columns (5)–(7) further reveal that spinout firms are more R&D-intensive, and their R&D spending is more efficient, as measured by citation-weighted patents and the number of top patents per R&D dollar spent. Finally, Column (8) shows that spinout firms achieve an average sales growth rate 2.3 percentage points higher than that of regular entrants.

Overall, these findings indicate that firms established as spinouts from other innovating firms are more innovative relative to firms established with no such prior background. This finding indicates that differences in entry type highlighted in this paper explain at least part of the large persistent ex-ante productivity differences across firms (Dunne et al., 1988; Pugsley et al., 2018; Guzman and Stern, n.d.).

Fact 2. Spinouts Quality is Positively Associated with Parent's Technology Lead

Next, we document that within spinout firms, the characteristics of parent firms matter for the quality of spinouts. Figure 3 compares spinouts spawned from parents with different technological leads. First, we construct firms' patent quality distribution based on the citations-weighted patent counts in the last 5 years in their technology class, and then define parents' technological lead based on 20 quantiles of this distribution. Panel (a) of Figure 3 then shows the estimated coefficients of lifetime citations-weighted patent counts of a spinout as a function of parent's technological lead at the time of spinout separation.

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	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
State FE	YES	YES	YES	YES
Observations	63554	60617	63554	63554
Mean	0.751	3.112	0.198	0.781

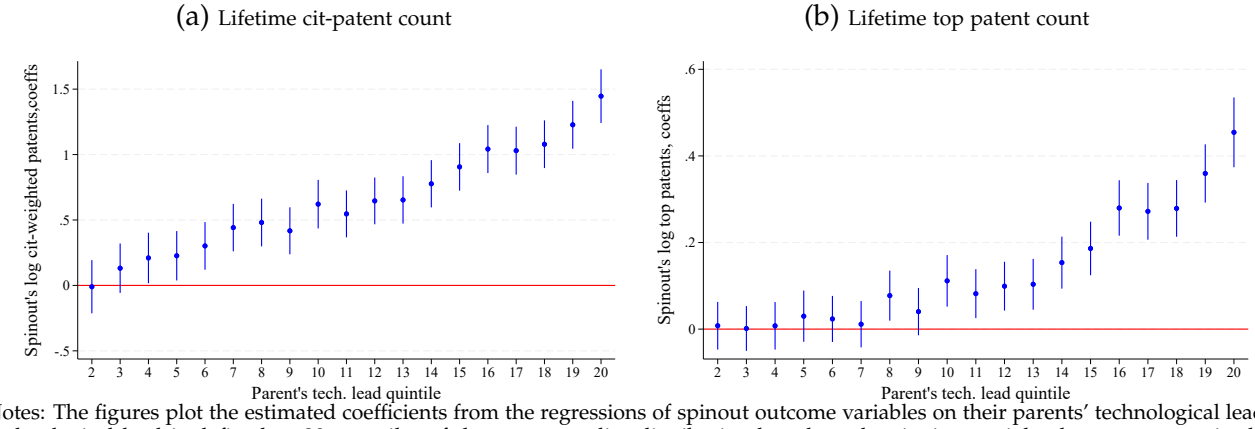
-Panel B. Compustat + Patent Data-

	(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	YES	YES	YES	YES
Age FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
State FE	YES	YES	YES	YES
Observations	7108	13594	12930	12729
Mean	4.096	4.359	-0.582	1.498

	(5) Log R&D/Empl	(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	YES	YES	YES	YES
Age FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
State FE	YES	YES	YES	YES
Observations	11499	12729	12729	11996
Mean	2.112	5.241	0.027	0.108

Note: The table compares spinout and regular entrants along various outcome variables in different columns. Each observation corresponds to a firm that entered the data in the 1981-2000 period. *Spinout entrant* is a dummy equal to one if a firm is a spinout. Panel A considers all firms in the patent data, while Panel B limits the sample to those firms that match to Compustat. Patents, cit-patents, and top patents are the total number of all patents, citations-adjusted patents, and top patents granted to the firm during the whole sample period, respectively. 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. Lifespan is the difference between the last and the first year the firm appears in the data. The variables in Panel B are averages over all years the firm is present in the Compustat data. Mean growth refers to the average sales growth of the firm. Regressions control for entrants' cohort, their technology class (*nclass*), and state fixed effects. Robust standard errors are in parentheses. p<0.01, ** p<0.05, * p<0.1.

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



Notes: The figures plot the estimated coefficients from the regressions of spinout outcome variables on their parents' technological lead. Technological lead is defined as 20 quantiles of the patent quality distribution based on the citations-weighted patent counts in the last five years in the technology class of the firm. The outcome variable in Panel (a) is spinout's lifetime log citations-weighted patent counts; the outcome variable in Panel (b) is spinout's lifetime log number of top patents. The plots show the point estimates with the corresponding 95% confidence intervals. The regressions also control for the number of parents, parent's number of patents in the last 5 years, technology class, state, and spinouts cohort fixed effects.

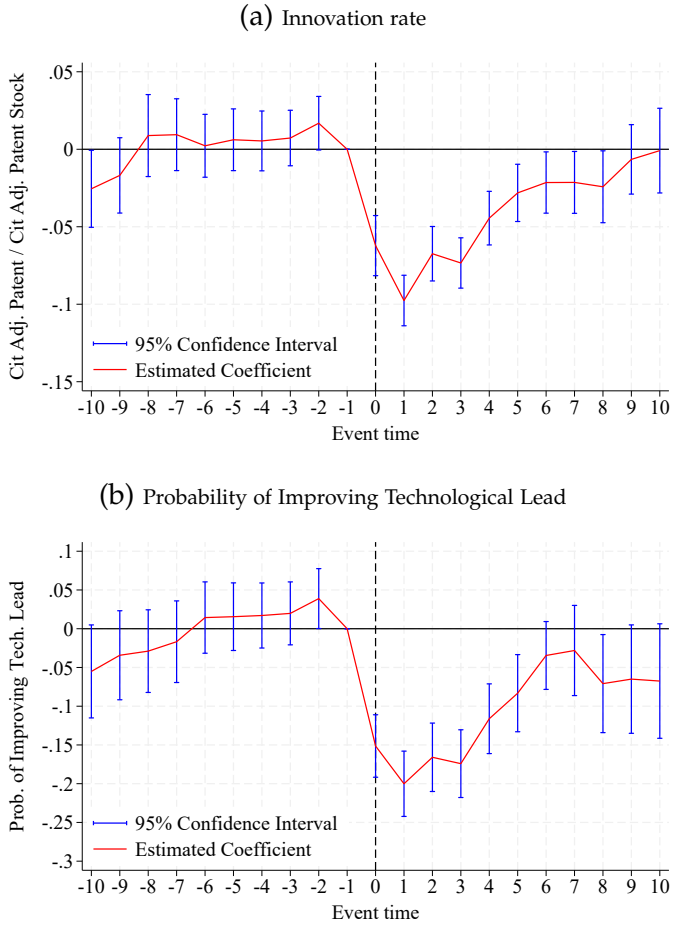
The regressions also control for the number of parents, parent's number of patents in the last 5 years, technology class, state, and spinouts' cohort fixed effects. Panel (b) illustrates similar results where outcome variable is the lifetime number of top patent counts of the spinout.

We see that spinouts are significantly more innovative when they are spawned from parents who hold bigger technological lead. Since the regressions control for the stock of patents, the estimated coefficients show additional effect associated with the *quality* of parents' patent stock and its relative technological lead. In fact, as Appendix Table A.2 illustrates, parents' quality of patents, measured in different ways, is an important correlate with spinouts' performance, but not the quantity. These results should not be necessarily interpreted as spinouts learning from a specific patent filed by the parent, but rather as a broader parents-to-spinouts knowledge inheritance, similar to the relationship built in the model. It is easier to identify high-quality ideas, to learn about entrepreneurial opportunities, or how to successfully implement these ideas in the market by working in the firms at the technology frontier (Chatterji, 2009).[18] Further robustness checks to spinouts' other outcome variables and the definition of parents' technological lead are given in Appendix Tables A.4 and A.3.

Although spinout entrants are more productive, the process of spinout creation entails tension between incumbents and the employees leaving their firms to pursue their own

[18]These results are also consistent with additional stories, such as the positive sorting, better access to financing, or different motivation and effort of employees of leading firms (Dahl and Sorenson, 2013).

Figure 4: The Effect of Spinout Separation on Parent Company



Notes: This figure depicts the association between spinout events and parent companies' innovation outcomes. Panel (a) examines citation-weighted patents, while panel (b) explores the probability of improving the technological lead. The analysis includes fixed effects for state, patent class, firm age, and year. Event_time= -1 is chosen as baseline.

entrepreneurial ventures.[19] Employers are increasingly concerned about the harm to their businesses caused by employee mobility, as manifested by existing employer protection regulations such as non-compete policies and the continual demands to strengthen them.[20][21] Motivated by these observations, the next two sections examine key relationships relevant to this tension. First, we explore whether spinout formation is associated with changes in

[19]See Pakes and Nitzan (1983) and Anton and Yao (1995) for the first theoretical treatments of this tension between inventors and employers.

[20]Half of the establishments with more than 50 employees use non-compete clauses in employee agreements for *some* employees, and the third of the establishments use them for *all* employees (Colvin and Shierholz, 2019).

[21]The debate persists around non-compete regulations limiting the employee mobility, as reflected by a recent House Bill requesting to strengthen existing regulations (Bill S.998, "An Act relative to the judicial enforcement of noncompetition agreements", 2017-2018 legislative session) and a later bill which prohibits the use of non-compete agreements (S.2614 - Workforce Mobility Act of 2019, introduced in the 116th Congress, 2019-2020.). See also President Biden's Executive Order 14036 of July 9, 2021 targeting non-competes.

the competitive edge of parent companies (Fact 3). Second, we investigate how the strength of non-compete laws relates to spinout formation (Fact 4).

Fact 3: Spinout is Associated with Reduced Competitiveness of Parent Firms

First, we investigate whether spinout formation through inventor mobility affects the competitive edge of the parent firm. We conduct an event study. The event year is defined as the year an inventor leaves the parent firm to join another company, referred to as a "mobility event." Mobility events are divided into two categories: (1) the inventor moves to an incumbent company or (2) the inventor establishes a new spinout company. The first category serves as the baseline, enabling us to isolate and analyze the additional impact of spinout events—specifically, the effect of inventors creating new companies—on the parent firm's innovation activity and competitive standing in the years surrounding and following the spinout.

Methodology.— We estimate the effect of spinout formation on the parent's competitive edge using a fixed-effects regression model that controls for firm-specific, year, and state-level fixed effects. The regression equation is specified as follows:

$$Y_{it} = \beta_0 + \sum_{S \neq 10} \beta_S \left(\text{event_time}_{iS} \times \text{spinout}\right) + \sum_{S \neq 10} \alpha_S \text{event_time}_{iS} + \boldsymbol{\Gamma_i} + \eta_t + \epsilon_{it},$$

where Y_{it} indicates the parent firm's competitive outcome in year t, and $\texttt{event_time}_{it}$ represents the number of years relative to the mobility event, with $S = 10$ omitted as the baseline category. The variable `spinout` equals 1 if the mobility event is a spinout and 0 if it involves an inventor moving to an incumbent firm. $\boldsymbol{\Gamma_i}$ combines firm-level fixed effects for state, patent class, and firm age. η_t represents year fixed effects, and ϵ_{it} represents the error term. The primary coefficient of interest is β_S, which estimates the differential effect of spinout formation relative to inventor mobility to an incumbent firm, isolating the unique impact of spinouts on the parent firm's competitive edge.

Sample.— We focus our analysis on firms that experience a *single* mobility event, defined as either an inventor moving to an incumbent company or leaving to establish a spinout. We limit the analysis to firms that are at least five years old, The findings remain robust when firms of all ages are included in the analysis.

Results.— Figure 4 presents the coefficients β_k from the event study regression for two outcome variables. Panel (a) examines the dynamics of the parent company's innovation

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	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	NO	YES	YES	NO
State FE	NO	YES	NO	NO	YES	NO
Firm FE	NO	NO	YES	NO	NO	YES
Other Controls	YES	YES	YES	YES	YES	YES
Observations	182286	182286	54117	182452	182452	54545

Note: The table presents firm-level regressions of the probability of spawning a spinout (logit models in columns 1-3) and the count of spawned spinouts (negative binomial models in columns 4-6) as a function of the NCL index and other firm characteristics. *NCL index* is the non-competition index defined in Appendix D. Other controls are the log number of patents and citation-adjusted patents filed in the last five years, the log number of inventors, firm age as well as the measures of state-level competition over time (number of innovating firms in the same technology class and state), GDP per capita, and population. The sample includes all patenting firms in the period 1981-2000. $p<0.01$, ** $p<0.05$, * $p<0.1$.

rate, measured as the ratio of annual citation-adjusted patents to the stock of citation-adjusted patents (up to and including the year). Panel (b) investigates the probability of a positive change in the parent company's technological lead, defined in line with prior measures. The red line shows the estimated coefficients, while the blue lines indicate the 95% confidence intervals.

Panel (a) shows that in the years preceding the spinout event, there is no significant difference in the innovation rate between parent companies that produce a spinout and those that lose an inventor to another company. However, starting from the year of the spinout event, the innovation rate of parent companies producing a spinout drops significantly—by approximately 10%—and remains persistently lower for over seven years. Notably, this negative effect gradually diminishes over time. A similar pattern is observed in Panel (b), where the probability of improving the technological lead declines by approximately 20% within the first two years following a spinout event, but this effect also gradually recovers in the subsequent years.

Overall, these findings suggest that spinout events are associated with a negative impact on the parent company's innovation rate and technological lead. However, this negative effect diminishes gradually over time, suggesting some recovery in the years following the spinout.

Fact 4. Spinout Formation Decreases with Stricter Non-compete Laws

Next, we show that spinout formation decreases with stricter non-compete laws. Toward the goal, we explore spinout entry as a function of the strength of the non-compete laws in the data. The non-compete laws governing the enforcement of non-compete clauses in

employee contracts that prohibit the employees from working for a competitor or forming a new firms vary across U.S. states. we rely on empirical measures of the strength of state-level non-compete laws, *NCL index*, from Garmaise (2011) and Starr (2019).[22]

Table 3 shows that stricter enforcement (a higher *NCL index*) is associated with lower spinout formation. These regressions look at the probability of spinout separation from the firm (logit models in columns 1 and 2) and the count of established spinouts (negative binomial models in columns 3 and 4) as a function of parent firm characteristics – the log number of patents and citation-adjusted patents filed in the last 5 years, the log number of inventors, firm age, and fixed effects (columns 2 and 4), as well as state-level characteristics – competition over time (the number of innovating firms in the same technology class and state), GDP per capita, and population.

Motivated by these observations, we next employ a dynamic general equilibrium endogenous growth framework to examine the tension between incumbents' innovation incentives and spinout entry, to quantify the contribution of spinout firms to the aggregate economy, and design policies that maximize aggregate welfare.

3 Model

Overview— To understand the role of spinouts for innovation and firm dynamics, we build a general equilibrium endogenous growth model consistent with main empirical facts from the data. Building on Schumpeterian growth models (Aghion and Howitt, 1992; Acemoglu and Akcigit, 2012; Acemoglu and Cao, 2015; Akcigit and Kerr, 2018; Peters, 2020) with entry and incumbents' innovation, we introduce new features of individuals occupation choice, spinout entry, and non-compete restrictions. An important new characteristic of the model is that entry distribution of firm types is endogenous through feedback from the incumbents' type distribution, their innovation decisions, and workers' entrepreneurship choices.

The stylized facts documented in Section 2.2 guide the main building blocks of this model. First, spinout entrants significantly outperform regular entrant firms throughout their entire life. This permanent heterogeneity motivates the introduction of fixed firm-specific quality types that are determined at entry. Second, firms with bigger technological lead spawn more innovative spinouts. This motivates modeling a type of learning or inheritance, whereby working in the leading firm increases the probability of creating a high-type entrant. Third, in the data, a spinout event is associated with a drop in the parent company's innovation. This motivates us to model a persistent drop in R&D efficiency after spinout formation, lasting until the parent firm is matched with a new R&D manager.

[22] See Appendix D for more details about data.

Fourth, stronger non-compete laws are associated with a lower likelihood of spinout formation. The model introduces a parameter for non-compete laws (NCL) that increases the cost of establishing a spinout firm, capturing this policy-driven friction.

In the model, skilled people are allocated into three groups: entrepreneurs running the firms, R&D managers (inventors) conducting innovation in the firms, and outsiders contemplating entry into one of the above occupations. Entrepreneurs, heterogeneous in their quality types, decide on innovation efforts that push the technology frontier forward. By innovating, they further their technological leadership and gain more market power. R&D managers collect wages and, while on the job, can search for ideas and outside opportunities to create their own spinout firms. Importantly, R&D managers learn on the job – the more technologically advanced their employer, the higher the chances that their start-up quality is of a better type. After presenting the model and validating it against other empirical regularities in the data, the model will be used to understand both qualitatively and quantitatively the effects of spinout entry and non-compete laws on aggregate innovation and growth.

3.1 Preferences and Final Good Technology

Time is continuous. The representative household consists of a measure L of unskilled and $1+\mathcal{S}$ measure of skilled people and has logarithmic preference over the final consumption good C. Household maximizes expected lifetime discounted utility of

$$U = \int_0^\infty e^{-\rho t} \ln C_t dt,$$

where ρ is household's discount rate. Household holds a balanced portfolio of all the firms in the economy, $\mathcal{A}_t$. Hence, its budget constraint can be written as $C_t + \dot{\mathcal{A}}_t = r_t \mathcal{A}_t + \mathcal{W}_t$, 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:

$$\ln Y_t = \int_0^1 \ln y(j,t) dj, \tag{1}$$

where $y(j,t)$ is the intermediate good from product line j at time t.

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:

$$\max_{y(j,t)} \left[\exp \int_0^1 \ln y(j,t) dj - p(j,t) y(j,t), \right] \quad \forall t$$

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

$$y(j,t) = \frac{Y_t}{p(j,t)}. \tag{2}$$

3.2 Intermediate Goods Market

An intermediate good in product line $j \in [0,1]$ 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:

$$y_i(j,t) = q_i(j,t) l_i(j,t), \tag{3}$$

where $l_i(j,t)$ is 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 $q_i(j,t) > q_{-i}(j,t)$. Products of these competing firms are perfect substitutes. Hence, Bertrand competition between the two firms ensures that only firm i remains active. Furthermore, this leading firm sets a price equal to the marginal cost of a follower, such that

$$p(j,t) = \frac{w_t^u}{q_{-i}(j,t)}, \tag{4}$$

where w_t^u denotes an equilibrium wage rate of unskilled labor.[23] As a result of the demand curve given by (2) and the price in (4), the profit of an intermediate goods producer in product line j is

$$\Pi_i(j,t) = \left(1 - \frac{q_{-i}(j,t)}{q_i(j,t)}\right) Y_t \tag{5}$$

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 current level of productivity, intermediate-good firms need to invest in R&D.[24] Firms are heterogeneous in their R&D efficiency. Each firm has a permanent *quality*

[23] 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.

[24] In what follows, intermediate-good firms are just referred to as firms.

type $\tau \in \{H, L\}$, where H denotes more R&D-efficient high-type firms and L corresponds to less R&D-efficient low-type firms.

Beyond their quality type heterogeneity, firms also vary in their R&D management status. A firm may either be matched with an R&D manager ($M = 1$) or temporarily unmatched ($M = 0$). Unlike the quality type τ, which is permanent, a firm's R&D management status evolves endogenously due to its R& manager's mobility and the rate at which a new manager is being hired, as discussed in a later section. This management status introduces an additional source of time-varying firm heterogeneity that influences the costs and productivity of R&D investment.

To conduct R&D, firms choose an innovation intensity z, which determines the Poisson arrival rate of innovation. The total cost of achieving an innovation intensity z, denoted as $\mathcal{C}(z, \tau, M)$, depends on the firm's quality type τ and its R&D manager status M. The cost function is defined as follows:

$$\mathcal{C}(z, \tau, M) = \begin{cases} w^s(j,t) + \dfrac{z^\gamma(j,t)}{\gamma B^\tau} Y_t & \text{if } M = 1 \\ \dfrac{z^\gamma(j,t)}{\gamma \alpha B^\tau} Y_t & \text{if } M = 0 \end{cases} \tag{6}$$

If a firm conducts R&D with a manager ($M = 1$), it incurs a fixed cost $w^s(j,t)$, representing the wage bill for the R&D manager, and a variable cost component $\frac{z^\gamma(j,t)}{\gamma B^\tau} Y_t$. The variable cost is convex in innovation intensity ($\gamma > 1$) and is in terms of 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 are more productive in research and can achieve greater innovation outcomes with the same level of resources.

If a firm loses its R&D manager due to their mobility, it continues to conduct R&D activities without a manager– a state with $M = 0$. In this state, the firm no longer bears the manager's wage cost but experiences a decline in R&D efficiency. Specifically, its productivity parameter drops to αB^τ, where $0 < \alpha < 1$, reflecting the inefficiency of conducting R&D without a manager.

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 an 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 (5), we can rewrite the incumbent's static profit as

$$\Pi_i(j,t) = \left(1 - \lambda^{-n_j(t)}\right) Y_t \tag{7}$$

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.[25]

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 measure $1 + \mathcal{S}$ of skilled people in the economy is allocated into three groups:

$$\text{Skilled people} = \underbrace{\text{Entrepreneurs}}_{1} + \underbrace{\text{R\&D managers}}_{\bar{\mathcal{M}}} + \underbrace{\text{Outsiders}}_{\mathcal{S}-\bar{\mathcal{M}}}$$

Since a measure of product lines in the economy is one, and each product line is associated with a single producing firm, the measure of entrepreneurs is also one. The total number of R&D managers currently employed in the market is $\bar{\mathcal{M}}$, implying that $1 - \bar{\mathcal{M}}$ is the measure of entrepreneurs without an R&D manager ($\bar{\mathcal{M}}$ is determined endogenously). The remaining $\mathcal{S} - \bar{\mathcal{M}}$ skilled people are classified as outsiders.

Denote by $V_t^{\text{firm}}(n, \tau, M)$ the value function of an entrepreneur (incumbent firm) with technology gap n, permanent quality type $\tau \in \{H, L\}$, and R&D management status $M \in \{0, 1\}$. Entrepreneurs decide on innovation rate and hiring unskilled labor for production. Denote by $V_t^{\text{manager}}(n, \tau)$ the value function of an R&D manager working for a firm with characteristics $(n, \tau, M = 1)$. R&D managers collect wages and decide on their separation rate, which determines the likelihood of creating a spinout firm (*spinout entry*). As will be clear below, $V_t^{\text{manager}}(n, \tau)$ depends on the characteristics of the employing firm for two reasons: differences in wages and differences in the probabilities of forming a high-type spinout. Finally, denote the value function of being an outsider by 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 only focus on the economy in a stationary equilibrium where all values grow at the same rate as the aggregate output and an allocation of skilled

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

people across different groups is stable. Hence, we will normalize all values by Y_t and denote the normalized values by their respective lower-case letters (e.g., $v^{firm}(n,\tau,M) = \frac{V_t^{firm}(n,\tau,M)}{Y_t}$). Hence, the time subscript t is dropped where it does not cause confusion. The following sections separately describe in detail the problems of each group of skilled people.

3.4.1 Entrepreneur's Value and Innovation Decision

We now characterize the value functions and optimal innovation decisions of entrepreneurs operating incumbent firms with characteristics (n,τ,M), where n denotes the firm's position on the technological ladder, τ its quality type, and M its R&D management status. We describe the value functions of firms with and without an R&D manager separately below.

Firm with an R&D Manager ($M = 1$). If a firm operates with an R&D manager ($M = 1$), the entrepreneur collects instantaneous profits from production $\pi(n)$, pays the manager a wage $\omega(n,\tau)$ ($\equiv \frac{w_t(n,\tau)}{Y_t}$), and incurs a variable R&D cost to innovate. Successful innovation at rate $z(n,\tau,M=1)$ advances the firm one step on the technological ladder, increasing its value from $v^{\text{firm}}(n,\tau,M=1)$ to $v^{\text{firm}}(n+1,\tau,M=1)$. The firm also faces a risk of creative destruction by entrants, which forces the entrepreneur to exit and join the pool of outsiders, leading to value v^{out}. The entry comes from spinouts at a rate I^s or from outsiders at a rate I^o. Additionally, if the R&D manager leaves the firm to create a spinout—at a rate $a(n,\tau)$—the parent firm temporarily transitions to a state without an R&D manager ($M = 0$). These dynamics are captured in the following value function:

$$\rho v^{\text{firm}}(n,\tau,M=1) = \max_{z(n,\tau,M=1)\geq 0} \left\{ \begin{array}{l} \pi(n) - \omega(n,\tau) - \dfrac{z(n,\tau,M=1)^\gamma}{\gamma B_\tau} \\ + z(n,\tau,M=1)\left[v^{\text{firm}}(n+1,\tau,M=1) - v^{\text{firm}}(n,\tau,M=1)\right] \\ + (I^s + I^o)\left[v^{\text{out}} - v^{\text{firm}}(n,\tau,M=1)\right] \\ + a(n,\tau)\left[v^{\text{firm}}(n,\tau,M=0) - v^{\text{firm}}(n,\tau,M=1)\right] \end{array} \right\} \tag{8}$$

Notice that as a result of spinout separation and stochastic arrival of new hires, in equilibrium, there will always be a positive measure $1 - \bar{\mathcal{M}}$ of firms without R&D managers.

Firm without an R&D Manager ($M = 0$). The entrepreneur may operate without an R&D manager ($M = 0$) after losing the manager due to inventor mobility and not yet employing a new one. In this case, the entrepreneur continues to collect profits from production $\pi(n)$ but no longer pays an R&D manager wage ($\omega(n,\tau) = 0$). The firm can still engage in R&D activities, albeit with reduced efficiency, by choosing an innovation intensity $z(n,\tau,M=0)$; a successful innovation advances the firm from $v^{\text{firm}}(n,\tau,M=0)$ to $v^{\text{firm}}(n+1,\tau,M=0)$. As before, the firm also faces risk of creative destruction by entrants (spinouts or

outsiders) at a rate $I^s + I^o$, forcing the entrepreneur to exit and join the pool of outsiders with value v^{out}. We assume that, at an exogenous rate q, the firm hires a new R&D manager, transitioning back to the state with higher innovation efficiency $M = 1$. Note that without an R&D manager, the firm is not exposed to the risk of spinout formation. These dynamics are captured in the following value function:

$$\rho v^{\text{firm}}(n, \tau, M = 0) = \max_{z(n,\tau,M=0)\geq 0} \left\{ \begin{array}{l} \pi(n) - \dfrac{z(n, \tau, M = 0)^\gamma}{\gamma \alpha B_\tau} \\ + z(n, \tau, M = 0) \left[v^{\text{firm}}(n + 1, \tau, M = 0) - v^{\text{firm}}(n, \tau, M = 0) \right] \\ + (I^s + I^o) \left[v^{\text{out}} - v^{\text{firm}}(n, \tau, M = 0) \right] \\ + q \left[v^{\text{firm}}(n, \tau, M = 1) - v^{\text{firm}}(n, \tau, M = 0) \right] \end{array} \right\} \tag{9}$$

Optimal Innovation Decision. Having characterized the entrepreneur's value functions, we now turn to the entrepreneur's optimal innovation decision, $z(n, \tau, M)$. For a firm with an R&D manager, taking the first-order condition (FOC) of equation (8) with respect to $z(n, \tau, M = 1)$ yields:

$$z(n, \tau, M = 1) = max \left\{ 0, \quad B_\tau^{\frac{1}{\gamma-1}} \left[v^{\text{firm}}(n + 1, \tau, M = 1) - v^{\text{firm}}(n, \tau, M = 1) \right]^{\frac{1}{\gamma-1}} \right\} \tag{10}$$

Similarly, for a firm without a manager, the FOC of (9) yields:

$$z(n, \tau, M = 0) = max \left\{ 0, \quad (\alpha B_\tau)^{\frac{1}{\gamma-1}} \left[v^{\text{firm}}(n + 1, \tau, M = 0) - v^{\text{firm}}(n, \tau, M = 0) \right]^{\frac{1}{\gamma-1}} \right\} \tag{11}$$

These conditions characterize the entrepreneur's innovation decisions. The optimal innovation rate depends on the incremental value of advancing one step on the technological ladder—captured by the difference in firm value across adjacent technology levels—as well as the firm's inherent R&D efficiency, B_τ, which differs by quality type $\tau \in \{H, L\}$. Firms with higher R&D efficiency (high-type firms) choose higher innovation intensities, all else equal. Additionally, a firm without an R&D manager operates with reduced R&D efficiency, αB_τ, leading to lower innovation rates compared to firms with a manager. Since the arrival of a new R&D manager occurs only with probability θ, this implies that firms that experience spinouts and operate without a manager will, on average, exhibit persistently lower innovation intensity—and thus lower productivity growth—compared to those that do not experience such separations. This mechanism is consistent with the empirical evidence presented in Fact 3, which shows that parent firms experience a persistent decline in innovation performance following spinout separation driven by the departure of an R&D manager.

3.4.2 R&D Managers and Spinout Entry

An R&D manager working in a firm with characteristics $(n, \tau, M = 1)$ earns a wage $\omega(n, \tau)$. While on the job, the manager can search for outside opportunities to create her own start-up—a spinout firm.[26] To do so, she chooses a separation rate $a(n, \tau) \geq 0$, where $a(n, \tau) = 0$ indicates no effort, incurring a cost $\frac{ka(n,\tau)^2}{2}$ in terms of final output, which reflects the time or monetary expense of developing and implementing an idea into a new start-up and hiring an R&D manager. If the separation effort succeeds, a new spinout firm is created, entering a random product line, improving the existing productivity, and replacing the incumbent in that product line.[27]

If an R&D manager succeeds in creating a spinout firm, she incurs a fixed cost $F \geq 0$ (in terms of final output) due to non-compete restrictions, which vary with the strength of non-compete laws.[28] In practice, spinout founders face varied legal outcomes (Garmaise, 2011): some pay fees, others may be forced to shut down operations, and some incur no legal costs. In the model, F captures the average of these possibilities.

Upon entry, firms draw different realizations of their permanent innovation quality and initial technology gap, generating firm heterogeneity in both their growth trajectories and initial conditions. First, in terms of innovation quality, we assume that the spinout entrant draws a high hype ($\tau = H$) with probability $\mu(n)$ that depends on the parent firm's technological lead n. Consistent with the empirical Fact 2, $\mu(n') > \mu(n)$ if $n' > n$, reflecting that better ideas are generated in technologically leading firms. This form of knowledge inheritance—where R&D managers are more likely to generate high-quality spinouts as their parent firms attain greater technological leadership—may arise from direct technical learning or from non-technical factors such as experience, networks, and improved ability to recognize and implement high-quality ideas. While conceptually related to knowledge diffusion channels in the literature (Lucas and Moll, 2014; Perla and Tonetti, 2014), in this model, spinouts diffuse knowledge by creating new high-quality startups rather than by replicating their parent firms' ideas.

Second, in terms of the initial technology gap, we assume spinouts draw an initial gap $\tilde{n}$ from a distribution $G(\tilde{n} \mid \tau)$, where $G(\tilde{n} \mid H)$ first-order stochastically dominates $G(\tilde{n} \mid L)$. The idea is that an initial idea may correspond to a smaller or larger jump relative to the current market technology —quantified as an improvement by a factor of $1 + \lambda^{\tilde{n}}$— and the size of this jump is, on average, larger for high-type firms.

Finally, each entering spinout is immediately matched with an R&D manager upon entry. The resulting value function of an R&D manager working at a firm with characteristics

[26] The model abstracts away from job-to-job transitions.

[27] With a continuum of product lines, the probability of the spinout replacing its former employer is zero, so it does not directly threaten the parent firm; however, as described earlier, the manager's departure causes the parent firm to transition to a state without an R&D manager ($M = 0$), reducing its innovation efficiency.

[28] In quantitative exercises, we will also allow F to vary with the employer firm's technology gap.

$(n, \tau, M = 1)$ is:

$$\rho v^{\text{manager}}(n,\tau) = \max_{a(n,\tau)\geq 0} \left\{ \begin{array}{l} \omega(n,\tau) - \dfrac{ka(n,\tau)^2}{2} \\ + z(n,\tau,M=1)\left[v^{\text{manager}}(n+1,\tau) - v^{\text{manager}}(n,\tau)\right] \\ + \left(I^s + I^o\right)\left[v^{\text{out}} - v^{\text{manager}}(n,\tau)\right] \\ + a(n,\tau)\left(\mathbb{E}_{\tau,\tilde{n}}\left[v^{\text{firm}}(\tilde{n},\tau,M=1) \mid n\right] - F - v^{\text{manager}}(n,\tau)\right) \end{array} \right\}. \quad (12)$$

This continuous-time value function can be interpreted as follows. The left-hand side, $\rho v^{\text{manager}}(n,\tau)$, is the flow value of an R&D manager at a firm with characteristics (n,τ). The right-hand side includes the components of this value. The first line represents the instantaneous wage $\omega(n,\tau)$ minus the separation cost $\frac{ka(n,\tau)^2}{2}$. The second line accounts for the employer's innovation at rate $z(n,\tau,M=1)$, advancing the firm to $(n+1,\tau,M=1)$ and updating the manager's value to $v^{\text{manager}}(n+1,\tau)$. The third line reflects the risk of creative destruction at rate $I^s + I^o$, forcing the manager to join the pool of outsiders with value v^{out}. The last line captures the change in value if separation succeeds at rate $a(n,\tau)$: the expected value of the new spinout, $\mathbb{E}_{\tau,\tilde{n}}\left[v^{\text{firm}}(\tilde{n},\tau,M=1) \mid n\right] = \mu(n)\sum_{\tilde{n}} G(\tilde{n}|H)v^{\text{firm}}(\tilde{n},H,M=1) + (1-\mu(n))\sum_{\tilde{n}} G(\tilde{n} \mid L)v^{\text{firm}}(\tilde{n},L,M=1)$, where the expectation is taken over the spinout's type τ and initial step size $\tilde{n}$, minus the non-compete cost F and the current value $v^{\text{manager}}(n,\tau)$.

Optimal Separation Effort. The first-order condition for the separation rate $a(n,\tau)$ is:

$$a(n,\tau) = \max\left\{0, \ \frac{\mathbb{E}_{\tau,\tilde{n}}\left[v^{\text{firm}}(\tilde{n},\tau,M=1) \mid n\right] - F - v^{\text{manager}}(n,\tau)}{k}\right\}. \quad (13)$$

This condition implies that the R&D manager separates ($a(n,\tau) > 0$) if the expected net benefit of creating a spinout, $\mathbb{E}_{\tau,\tilde{n}}\left[v^{\text{firm}}(\tilde{n},\tau,M=1) \mid n\right] - F - v^{\text{manager}}(n,\tau)$, exceeds zero. A higher probability of forming a high-type spinout, $\mu(n)$, increases the expected value, especially for managers in technologically leading firms with larger n, making separation more attractive. However, staying offers an opportunity cost: it enables the manager to learn more, potentially improving future spinout prospects, as captured by the value gain $v^{\text{manager}}(n+1,\tau) - v^{\text{manager}}(n,\tau)$.[29] Hence, the separation decision depends on the learning schedule $\{\mu(n)\}_{n=1}^{N}$, and stricter non-compete restrictions (higher F) discourage separation.

3.4.3 Wage Determination

At the beginning of each period, firms with $M = 1$ and their R&D managers bargain over wages– $\omega(n,\tau)$. The wage rate is set through Nash bargaining, with β being the

[29] Additionally, staying increases her wages if the firm innovates, since $\omega(n+1,\tau) > \omega(n,\tau)$.

R&D manager's bargaining weight. If the agreement is achieved, the wage is set, and the firm and the R&D manager continue the match, obtaining values $v^{\text{firm}}(n, \tau, M = 1)$ and $v^{\text{manager}}(n, \tau)$, respectively: the firm chooses innovation rate $z(n, \tau, M = 1)$, and the R&D manager chooses the separation rate $a(n, \tau)$.[30] If they disagree, the manager walks away with an outside value v^{out}, while the firm moves to a state without a manager ($M = 0$), yielding the entrepreneur a value of $v^{\text{firm}}(n, \tau, M = 0)$. The Nash bargaining implies the following linear sharing rule:

$$\beta \left[v^{\text{firm}}(n, \tau, M = 1) - v^{\text{firm}}(n, \tau, M = 0) \right] = (1 - \beta) \left[v^{\text{manager}}(n, \tau) - v^{\text{out}} \right]. \tag{14}$$

3.4.4 Outsiders

Finally, the skilled individuals may also belong to a group of outsiders – a measure $S - \mathcal{M}$ of people who face two options: they can either attempt to start an entrepreneurial venture (*regular entry*) or seek employment as R&D managers. Let v^{entry} denote the value of entrepreneurial entry, and v^{work} the value of entering the labor market as an R&D manager. Then, the value of being an outsider is:

$$v^{out} = \max\{v^{entry}, v^{work}\}. \tag{15}$$

Regular entry. To become an entrepreneur, an outsider must successfully implement an idea– a process involving uncertainty. The outsider pays a cost $\frac{ev^2}{2}$ to achieve a Poisson arrival rate ν for the idea, where the parameter e reflects the innovation efficiency of regular entrants. If successful, the firm enters a random product line, creatively destroys the incumbent, and improves the productivity level in that product line. While entrants are ex-ante homogeneous, they become heterogeneous ex-post across two margins: permanent innovation quality and initial technology gap- similar to the spinout entrants. First, entrants draw their permanent quality type, becoming high-type $\tau = H$ with probability $\tilde{\mu}$ and low-type $\tau = L$ with probability $1 - \tilde{\mu}$. Second, the initial productivity improvement occurs by a step size $\tilde{n}$, drawn again from distribution $G(\tilde{n} \mid \tau)$. As before, an entering firm is immediately matched with an R&D manager upon entry. Thus, if successful, the entrant becomes a firm with state variables $(\tilde{n}, \tau, M = 1)$; if the idea fails, the person remains among the skilled outsiders. The resulting value of entry can be written as:

$$\rho v^{\text{entry}} = \max_{\nu \geq 0} \left\{ -\frac{e\nu^2}{2} + \nu \left(\mathbb{E}_{\tau, \tilde{n}} \left[v^{\text{firm}}(\tilde{n}, \tau, M = 1) \right] - v^{\text{out}} \right) \right\}, \tag{16}$$

[30] Bargaining takes into account the firm's expected separation intensity (unobservable to the firm), but if by the end of the period, the manager is successful in creating the spinout, renegotiations are not allowed.

The flow value of entry ρv^{entry} consists of the following terms on the right-hand side. First, an entrant incurs an instantaneous cost of developing an idea, given by $-\frac{e\nu^2}{2}$. Next, upon successful entry at rate ν, the entrant receives the expected value of operating a product line, represented by the term $\mathbb{E}_{\tau,\tilde{n}}\left[v^{\text{firm}}(\tilde{n},\tau,M=1)\right] = \tilde{\mu}\sum_{\tilde{n}} G(\tilde{n} \mid H)v^{\text{firm}}(\tilde{n},H,M=1) + (1-\tilde{\mu})\sum_{\tilde{n}} G(\tilde{n} \mid L)v^{\text{firm}}(\tilde{n},L,M=1)$, where the expectation is taken over the firm's type τ and initial technology lead $\tilde{n}$. If the entry is not successful, the entrant remains among the skilled outsiders and receives v^{out}.[31] The rate ν is chosen to maximize the flow value of entry, resulting in the first-order condition:

$$\nu = \frac{\mathbb{E}_{\tau,\tilde{n}}\left[v^{\text{firm}}(\tilde{n},\tau,M=1)\right] - v^{\text{out}}}{e}. \tag{17}$$

This condition indicates that a higher expected firm value or a lower outside option v^{out} increases the incentive to enter, while a higher entry cost parameter e reduces the entry rate.

R&D Manager Job Search. Rather than pursuing entrepreneurship, a skilled outsider may choose to 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 skilled outsiders, obtaining the value v^{out}. The value of searching for a job as an R&D manager, v^{work}, is given by:

$$\rho v^{\text{work}} = -c + \theta\left(\mathbb{E}_{n,\tau}\left[v^{\text{manager}}(n,\tau)\right] - v^{\text{out}}\right). \tag{18}$$

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

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 $\mathcal{S}_0$ 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_0; spinout entrants– I_s; and the incumbent firms who are in state $M=0$. Recall that the measure of incumbents without an R&D manager is $1-\mathcal{M}$, and the exogenous rate at which they are matched to the managers is q. Hence, at every point in time, $q(1-\mathcal{M})$ jobs will be filled. Equating the supply and demand for R&D managers leads to the equilibrium matching rate for outsiders:

$$\theta = \frac{I_0 + I_s + q(1-\mathcal{M})}{\mathcal{S}_0}. \tag{19}$$

[31] A detailed derivation of this continuous-time value function representation is in Appendix A.

3.5 The Stationary Distribution

As firms enter, exit, and innovate, they move up and down the technology ladder, while spinout separation due to inventor mobility causes transitions between states with and without an R&D manager ($M \in \{0,1\}$). Let $\xi(n,\tau,M)$ denote the measure of firms with technology gap n, quality type τ, and R&D manager status M. In the stationary equilibrium, while individual firms change their positions in the technology space and management status, the overall measure of firms in each state (n,τ,M) remains constant, implying that the inflow into and outflow from each state must balance.

Let I_H^s and I_L^s denote the total entry rates of high-type and low-type spinouts, and I_H^o and I_L^o denote the total entry rates of high-type and low-type regular entrants, defined as:

$$I_H^s = \sum_{n'=1}^{N} a(n',H)\xi(n',H,1)\mu(n'), \quad I_L^s = \sum_{n'=1}^{N} a(n',L)\xi(n',L,1)(1-\mu(n')),$$

$$I_H^o = I^o\tilde{\mu}, \quad I_L^o = I^o(1-\tilde{\mu}),$$

where n' indexes the parent firm's technology gap, $\mu(n')$ is the probability of a high-type spinout conditional on separating from the parent with a gap n', and $\tilde{\mu}$ is the probability of a high-type regular entrant- as described earlier.

Then, for all $n \geq 1$, the following equation describes the inflow and outflow of firms with managers ($M = 1$) with technological gap n and quality type $\tau \in \{H,L\}$ (using 1 for brevity instead of $M = 1$):

$$\begin{aligned} 1\{n>1\}\xi(n-1,\tau,1)z(n-1,\tau,1)+q\xi(n,\tau,0)+\xi(n,\tau,1)\left(I_\tau^s+I_\tau^o\right)G(n|\tau) \\ = \xi(n,\tau,1)\left[a(n,\tau)+z(n,\tau,1)+I^s+I^o\right]. \end{aligned} \tag{20}$$

The left-hand side represents the inflow into $(n,\tau,1)$. First, firms at $(n-1,\tau,1)$ innovate at rate $z(n-1,\tau,1)$ to reach technology gap n; since there is no inflow by innovation when $n = 1$, the first term is multiplied by an indicator function $1\{n > 1\}$. Second, firms at $(n,\tau,0)$ are matched with a manager at rate q and transition to $M = 1$. Lastly, new entrants of type τ with technology gap n enter at rate $\left(I_\tau^s + I_\tau^o\right)G(n|\tau)$. The right-hand side represents the outflow from $(n,\tau,1)$. The measure $\xi(n,\tau,1)$ of firms may exit their state for the following reasons: they move to a no-manager state due to spinout separation at rate $a(n,\tau)$; they innovate at rate $z(n,\tau,1)$ to advance to $(n+1,\tau,1)$; or they exit due to creative destruction by entrants at rate $I^s + I^o$.

Next, for all $n \geq 1$, the following equation describes the inflow and outflow of firms without managers ($M = 0$) in state $(n,\tau,0)$, with technological gap n and quality type

$\tau \in \{H, L\}$:

$$1\{n > 1\}\xi(n-1,\tau,0)z(n-1,\tau,0) + \xi(n,\tau,1)a(n,\tau) = \xi(n,\tau,0)\left[z(n,\tau,0) + I^s + I^o + q\right]. \tag{21}$$

The left-hand side represents the inflow into $(n, \tau, 0)$. Similar to before, the first term represents the firms at $(n-1, \tau, 0)$ that innovate at rate $z(n-1, \tau, 0)$ to reach technology gap n. In addition, the firms at $(n, \tau, 1)$ transition to $M = 0$ due to spinout separation at rate $a(n, \tau)$. The right-hand side represents the outflow from $(n, \tau, 0)$. Here, the measure $\xi(n, \tau, 0)$ of firms diminishes as they innovate at rate $z(n, \tau, 0)$ to advance to $(n+1, \tau, 0)$, face creative destruction by entrants at rate $I^s + I^o$, or hire a manager at rate q, transitioning to $M = 1$.

3.6 The Steady State Equilibrium

Before summarizing the steady state equilibrium, let us lay out final components of the equilibrium.

Aggregate Spinout Entry, I^s. As a result of R&D managers' separation decisions, each firm faces creative destruction from spinouts separating from other product lines. The total separation efforts across all firms determine the aggregate spinout entry rate I^s:

$$I^s = \sum_{n=1}^{N} \sum_{\tau \in \{H,L\}} a(n,\tau)\xi(n,\tau,1), \tag{22}$$

where $\xi(n, \tau, 1)$ represents the measure of firms with technology gap n, quality type τ, and an R&D manager ($M = 1$).

Equilibrium in the Market for Outsiders. In equilibrium, if there is a non-degenerate number of skilled people attempting to become R&D managers or entrepreneurs, it must be the case that, from equation (15), we have:

$$v^{\text{out}} = v^{\text{entry}} = v^{\text{work}}. \tag{23}$$

Note that allocation of outsiders between R&D managers and new entrants is pinned down by this condition.

Aggregate Regular Entry, I_0. If S_0 is the number of outsiders choosing to search for an R&D job, then the remaining $S - S_0$ pursue entrepreneurship. Thease implies that the entry

rate of regular entrants is:

$$I_0 = (\mathcal{S} - \bar{\mathcal{M}} - \mathcal{S}_0)\nu. \tag{24}$$

Labor Market. The labor allocation for skilled people has been already described; However, 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 (2), (3), and (4), 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

$$l_j = \frac{1}{\omega^u} \lambda^{-n_j} \tag{25}$$

This implies the following market clearing condition:

$$L = \sum_{\tau,n,M} \frac{\xi(\tau,n,M)}{\lambda^n \omega^u}. \tag{26}$$

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*

$$\{v^{\text{firm}}(n,\tau,M), v^{\text{manager}}(n,\tau), v^{\text{out}}, v^{\text{work}}, v^{\text{entry}}, z(n,\tau,M), a(n,\tau), \nu, I^o, I^s, \omega(n,\tau), \omega^u, \xi(n,\tau,M), g, r, \theta\}$$

such that
(i) $v^{firm}(n,\tau,M)$, $v^{manager}(n,\tau)$ *satisfy equations (12), (8) and (9);*
(ii) v^{out}, v^{work}, *and* v^{entry} *are given by equations (16), (18), and (23);*
(iii) $a(n,\tau)$ *and* $z(n,\tau)$ *satisfy first-order conditions (13),(10) and (11);*
(iv) *Entry rate by outsiders,* I^o, *satisfies equation (24), where* ν *maximizes (16);*
(v) *Spinout entry rate* I^s *is given by equation (22);*
(vi) *Wages of R&D managers satisfy (14);*
(vii) *Wage of unskilled labor clears labor market in (26);*
(viii) *Stationary distribution* $\xi(n,\tau)$ *satisfies (20) and (21);*
(ix) *Aggregate growth rate is given by equation (27);*
(x) *Interest rate satisfies Euler equation,* $\rho = g - r$,

(xi) θ *satisfies equation (19).*

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

$$g = \left(\sum_{n} \sum_{\tau} \sum_{M} \xi(n, \tau, M) z(n, \tau, M) + \sum_{\tau} \sum_{n} \left(I_{\tau}^{s} + I_{\tau}^{o} \right) G(n|\tau) n \right) \ln \lambda. \tag{27}$$

The proof is in Appendix C. This Proposition makes it clear that the steady state growth rate of the economy is determined by four factors: i) innovation decisions of incumbent firms at different levels of the technology gap; ii) the distribution of firms across the technology gaps; iii) entry by spinouts; and iv) entry by outsiders, and v) the distribution of entrants across technology gaps, where entrants of type τ improve productivity by λ^n with probability $G(n|\tau)$.

At this point, we can summarize the main channels through which non-compete policies affecting spinout separation influence growth. Because the possibility of spinout negatively affects incentives of parent firms to innovate, evaluating the benefits of spinout formation depends on the quantitative importance of various channels in the model. Four main channels operate in the model. First is the *direct entry effect* on growth, where more spinout entry positively contributes to innovation and growth. Second is the negative *disincentive effect* of spinout formation on incumbent firms' innovation incentives that is similar to the standard appropriability problem. The third channel is *knowledge diffusion*, whereby the spinout entry increases the share of high-type firms in the market. Finally, spinout entry also influences the *firm composition*: higher spinout entry shifts the composition of firms towards lower technology gaps, hence promoting more competition and, as a result, aggregate innovation efforts.

3.7 Welfare

Consider the steady-state welfare of a representative household at time $t = 0$:

$$\text{Welfare}(0) = \int_{0}^{\infty} e^{-\rho t} ln C_t dt, \tag{28}$$

The final output is divided into consumption and investment. Denote the total investment (normalized by output) by I. There are four types of investment activities in this economy: 1) Outsiders invest in developing new ideas to enter as entrepreneurs; 2) R&D managers invest in developing new ideas to spin-out; 3) founded spinouts pay non-compete costs; and 4) entrepreneurs invest in innovation. These lead to the following equation for the total investment undertaken in this economy:

$$I = \frac{ev^2}{2}S + \sum_{n,\tau}\frac{ka^2(n,\tau)}{2}\xi(n,\tau) + \sum_{n,\tau}\xi(n,\tau)a(n,\tau)F + \sum_{n,\tau}\frac{z(n,\tau)^\gamma}{\gamma B^\tau}\xi(n,\tau) \tag{29}$$

As a result, we can write the aggregate consumption as $C = (1-I)Y$ and rewrite equation (28) in the following way:

$$\text{Welfare}(0) = \frac{\ln Y(0)}{\rho} + \frac{g}{\rho^2} + \frac{1-I}{\rho}$$

Next, we can derive steady-state value of $\ln Y(0)$ from equations (1) and (4) and use in the previous equation to get (see the detailed derivations in Appendix B):

$$\text{Welfare}(0) = \frac{\ln Q(0) - \ln\lambda\sum_{n,\tau} n\xi(n,\tau) - \ln\omega^u}{\rho} + \frac{g}{\rho^2} + \frac{\ln(1-I)}{\rho} \tag{30}$$

In the steady state, all the equilibrium variables entering this expression are constant. For the steady state comparisons of different economies with different non-compete policies, it is sufficient to compare two economies with the same levels of initial productivity level $Q(0)$ and different policies F. Our non-compete policies will affect aggregate growth by providing different innovation incentives to incumbents and spinouts. This growth rate has the first-order effect on welfare, as seen from the above. In addition, non-compete policies will alter the steady-state distribution of firms across technology gaps as well as equilibrium labor share. If the economy has a low entry and creative destruction, more firms will enjoy higher technology gaps and, hence, higher markups leading to lower welfare (as seen by negative terms in the expression (30)). It is worth noting that $Q(0)$ is an arbitrary number and hence the proportional changes in welfare resulting from the changes in the policy are not informative. However, ordinal rankings are well defined and hence welfare-maximizing policies can be found by comparing the welfare numbers from (30).

4 Calibration and Model Performance

This section outlines the calibration procedure and evaluates how well the model captures key features of the data. We proceed in three steps. First, we describe our methodology for mapping the model's theoretical constructs—such as firm quality and technological gap—to observable proxies in the data. Second, we detail the calibration strategy used to discipline the model parameters using key empirical moments. Finally, we assess the model's performance by showing that it replicates both the targeted moments and a broader set of empirical facts documented in Section 2.2.

4.1 Empirical Measures of Firm Type and Technology Gap

A key step in our analysis is to map the model's concepts of firm quality and technological leadership to their empirical counterparts.

In the model, a firm's quality type is constant over time, and high-type firms are more innovative than their low-type competitors. As a result, we define a firm as an high-type in the data if it ranks in the top quartile based on its lifetime innovation output, proxied by the lifetime citation-adjusted patent count of the firm, residualized for cohort and technology class fixed effects.

Second, we construct an empirical proxy for a firm's technological gap, n. In the model, the technology ladder has N equidistant innovation steps, and we set the maximum achievable gap to $N = 20$.[32] To mirror this, we construct a 20-bin measure from the data. For each patent category, we first identify the minimum and maximum cumulative patent stocks achieved by any firm over the sample period. We divide the logarithmic range between the minimum and maximum into 20 equal intervals. A firm's position on this 20-point scale, which defines its technological gap n, is determined by its cumulative patent stock. An important implication of this methodology is that by using a cumulative measure, a firm's calculated technology gap, n, is non-decreasing over time, ensuring our empirical proxy aligns with the model's structure where firms only move up.

4.2 Calibration

This section describes the calibration of the model's structural parameters. We determine the parameter values in three steps, as summarized in Table 4. First, a set of standard parameters is set externally based on established values in the literature. This group includes the discount rate (ρ), the curvature of the R&D cost function (γ), and the R&D manager's bargaining power (β). Second, parameters governing the probability of entry for high-type firms are estimated directly from the data. These include $\mu(n)$, the probability of a spinout being high-type, which depends on the parent's technology gap, and $\tilde{\mu}$, the probability of a regular entrant being high-type. Finally, the remaining parameters are calibrated internally by jointly minimizing the distance between key empirical moments and their model-generated counterparts. This group includes parameters for R&D efficiency (B^H, B^L), the innovation step size (λ), costs of entry and separation (e, κ, F), and other parameters governing firm and labor market dynamics (α, q, c, L, S).

Externally Calibrated Parameters.— Panel A of 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 the elasticity of innovation with respect to R&D. Several papers have empiri-

[32] Setting N higher does not alter the results since, as will be seen from the equilibrium solution, the share of firms achieving a gap close to $N = 20$ is very low.

Table 4: Calibrated Parameters

	Value	Description	Target/Source	Data	Model
		Panel A. *Externally Calibrated Parameters*			
ρ	0.04	Discount rate	Standard	–	–
γ	2,86	R&D cost curvature	Acemoglu et al. (2018)	–	–
β	0.20	R&D manager's barg. power	Hagedorn and Manovskii (2008)	–	–
		Panel B. *Estimated Parameters*			
$\hat{\eta_0}; \hat{\eta_1}$	-1.4; 0.08	$\mu(n)$; Equation 31	Prob. high-type spinout by n	–	Figure 5
$\hat{\tilde{\eta}_0}$	-1.4	$\tilde{\mu}$; Equation 32	Prob. high-type regular	–	0.195
		Panel C. *Internally Calibrated Parameters*			
L	126	Unskilled labor supply	Skilled-to-unskilled wage ratio	2.27	2.27
S	0.95	Skilled outsiders	Share of skilled people in LF	1%	1.5%
c	9.5	Cost of manager job search	R&D workers u-rate	2.5%	2.9%
λ	1.09	Step size of innovation	Growth rate	3.1%	3.0%
B^H	1.5	R&D cost efficiency	Avg. R&D intensity (NSF)	3.8%	3.8%
B^L	0.5	R&D cost efficiency	Ratio H/L innovation quality	1.92	1.46
e	4.0	Entry cost parameter	Outside entry rate	10.4%	10.2%
κ	9.4	Separation cost parameter	Spinout entry rate $NCL = 0$	5.2%	5.2%
F	0.12	NCL parameter	Spinout entry rate	4.2%	4.2%
α	0.2	R&D prod. w/o manager	Drop in innov. rate after spinout	10%	10%
q	0.5	Prob. finding rate	Persistence of innov. rate drop	5	5

cally evaluated this elasticity. Following Acemoglu et al. (2018) who discuss this evidence in detail, we set $\gamma = 2$. In the benchmark calibration, we set β to 0.05 following Hagedorn and Manovskii (2008).

Estimated Parameters.— Panel B of Table 4 lists parameters estimated directly from the data. These parameters characterize the probability of entry for high-type firms, which we model using logistic functions.

For spinouts, the probability of entering as a high-type, $\mu(n)$, is a function of the parent firm's technology gap, n:

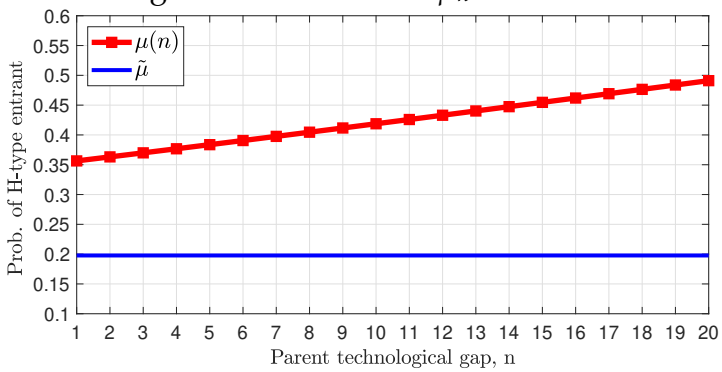
$$\mu(n) = \frac{1}{1 + e^{-(\eta_0 + \eta_1 n)}}. \tag{31}$$

This specification is motivated by our empirical finding that parents with a greater technological lead produce higher-quality spinouts (Figure 3). For regular entrants, the probability of being high-type, $\tilde{\mu}$, is constant:

$$\tilde{\mu} = \frac{1}{1 + e^{-\tilde{\eta}_0}}. \tag{32}$$

We estimate the parameters η_0, η_1, and $\tilde{\eta}_0$ using logit regressions. To estimate the parameters for $\mu(n)$, we regress a high-type dummy for spinouts on their parent's technology gap, n, while including controls for parent characteristics as well as cohort and technology-class fixed effects. The estimation confirms a positive and significant relationship, yielding parameter values that correspond to an entry probability, $\mu(n)$, that increases from 36% for $n = 1$ to 49% for $n = 20$, as plotted in Figure 5. Following a similar procedure for regu-

Figure 5: Calibration: μ_n estimates



Notes: The figure reports the estimates for the μ_n parameters used in the model calibration

lar entrants (controlling only for cohort and technology class fixed effects), we estimate a constant probability of being high-type, $\tilde{\mu}$, of 19.8%.

Notice that a spinout created via inventor mobility, even from a parent at the lowest technology level ($n = 1$), has a 36% probability of being high-type. This is nearly double the 19.8% probability for a regular entrant, underscoring the significant ex-ante quality advantage conferred by the knowledge inheritance channel.

Internally Calibrated Parameters.— Panel C of Table 4 lists the internally calibrated parameters. First, we discipline the model's labor market by calibrating the supply of unskilled labor, L, and skilled outsiders, S, to match the composition of the U.S. labor force in the 1990s. Second, the job search cost, c, is chosen to match a 2.5% unemployment rate for skilled workers. This procedure yields values of $L = 126$, $S = 0.96$, and $c = 4.9$.[33]

The innovation step size, λ, which governs how firm-level innovation translates into aggregate growth, is calibrated to match the average U.S. GDP growth rate of 3.1% during the sample period. The R&D efficiency parameters, B^H and B^L, jointly determine the economy's overall R&D intensity and the innovation gap between high- and low-type firms. They are calibrated to match two moments simultaneously: first, an average R&D-to-sales ratio of 3.8%, consistent with data for all R&D-performing companies in 2000 from the National Science Foundation's "Sales and Employment of R&D-Performing Industries"; and second, a relative innovation output of 9.5, which represents the ratio of average lifetime citation-adjusted patent counts between high- and low-type firms in our data. This joint calibration yields parameter values of $\lambda = 1.09$, $B^H = 1.5$, and $B^L = 0.5$.

Next, the parameters governing entry dynamics—the entry cost for outsiders (e), the cost of separation for spinouts (κ), and the non-compete policy cost (F)—are jointly calibrated to match three targeted moments from the data. First, the outsider entry cost, e, is set to match the regular entry rate of 10.4%. Second, the separation cost, κ, and the

[33]Data from the Survey of Industrial Research and Development (SIRD) for the early 1990s indicates a total U.S. labor force of approximately 126 million and 0.96 million scientists and engineers engaged in R&D. The skilled wage premium of 2.27 is taken from the OES Survey.

baseline non-compete cost, F, are chosen to jointly match two spinout-related targets: an overall spinout entry rate of 4.2% , and a higher rate of 5.4% specifically in states with no non-compete enforcement. The data on non-compete law (NCL) restrictions across states is from Garmaise (2011), as detailed in Appendix D.

Finally, two parameters, α and q, govern the dynamics of parent firm after a spinout event. In the model, α represents the fraction of R&D efficiency a parent firm retains after its manager departs, while q is the Poisson arrival rate at which the firm finds a new manager, determining the expected duration of this low-efficiency period. We calibrate these parameters to match the dynamics from our empirical event study (Fact 3). The efficiency drop, α, is set to match the magnitude of the initial 10% decline in the parent's innovation rate. The hiring rate, q, is set to match the persistence of this shock, which has a recovery period of approximately five years in the data. This procedure yields values of $\alpha = 0.2$ and $q = 0.5$.

In this version of the paper, we calibrate $g_H = g_L = 0$, which means that all new firms, regardless of type, enter with a technology gap of $n = 1$.

4.3 Model Performance

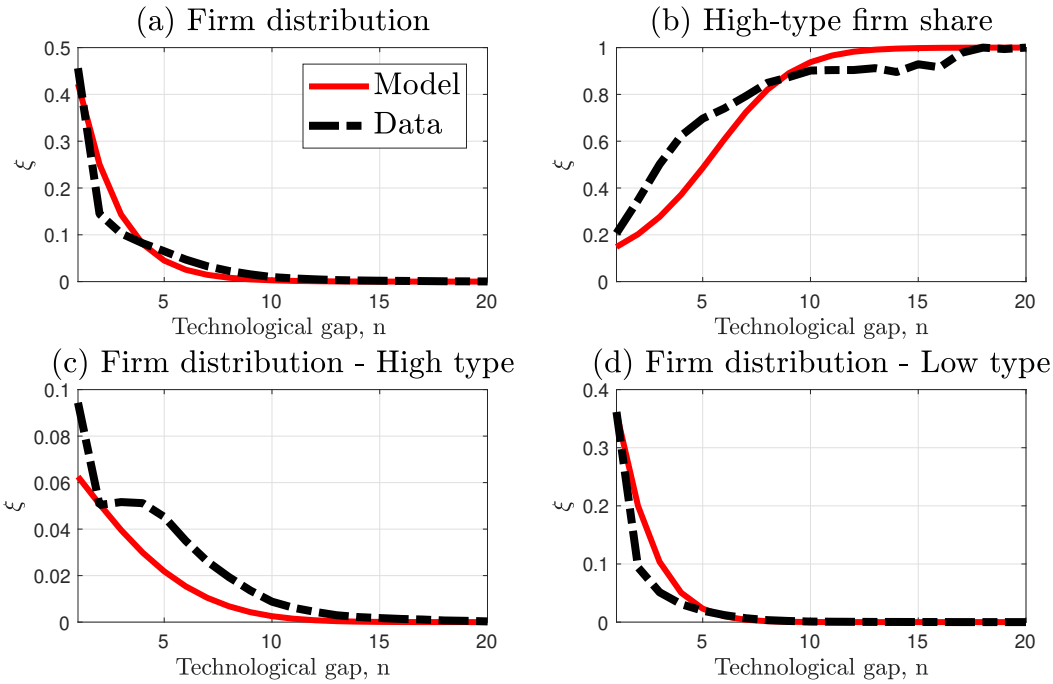
In this section, we evaluate the quantitative performance of the calibrated model by comparing its predictions to several key empirical moments. We begin by showing that the model replicates the stationary distribution of firms across the technology gap, closely matching the empirical distributions for the full sample as well as for high- and low-type firms—despite these patterns not being directly targeted in the calibration. The model also generates innovation and spinout separation rates that align well with the data, again without being explicitly targeted. Importantly, the model captures a core empirical tension: while spinouts are, on average, more productive, a spinout event leads to a persistent decline in the parent firm's innovation capacity—a moment that is explicitly targeted in the calibration. Finally, the model closely replicates the observed elasticity of spinout formation with respect to non-compete laws, further validating its use as a tool for policy analysis.

4.3.1 Distribution of Firms: Data vs. Model

We begin the evaluation of the model's performance by comparing the equilibrium distribution of firms generated by the model to its empirical counterpart, as shown in Figure 6. Overall, the model's entry, exit, and innovation dynamics produce a stationary distribution of firms that matches the data very well.

Panel (a) displays the overall distribution of firms across the technology gap, n. Both the model and the data show a high concentration of firms at small gaps, with the firm density decreasing sharply as the technology gap widens. The model provides a good fit to this

Figure 6: Firm Distribution



empirical distribution. This overall pattern is further broken down by firm type in Panels (c) and (d), which show that the model accurately replicates the individual distributions for high- and low-type firms, respectively.

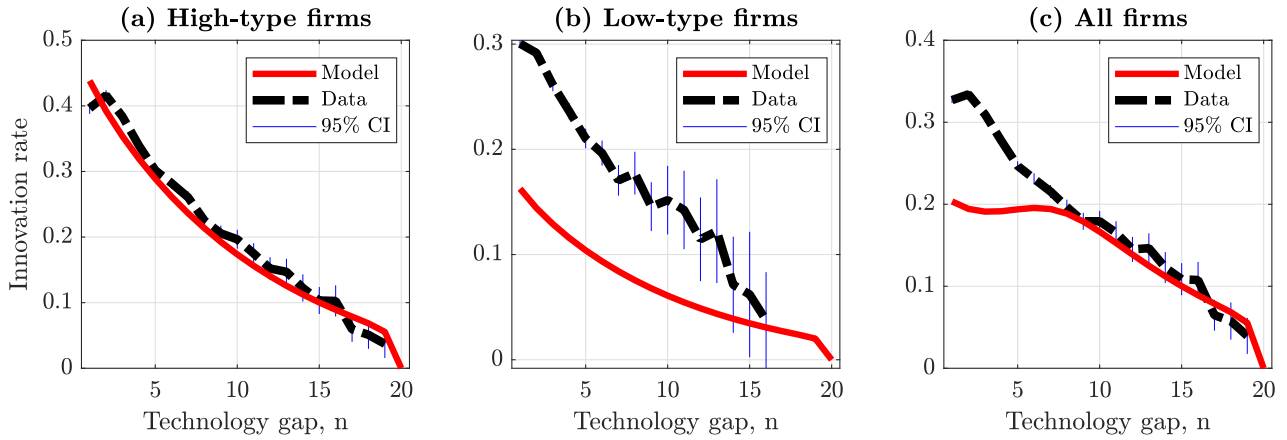
Furthermore, the model successfully captures the important compositional dynamics shown in Panel (b). This panel illustrates that the share of high-type firms within a given technology gap increases with the level of that gap, approaching 100% at the technology frontier. This demonstrates that the model endogenously generates a srong selection mechanism, where firms with a greater technological lead are predominantly high-type.

4.3.2 Innovation Rate: Data vs. Model

Figure 7 shows innovation rates from the model and the data for high-type, low-type, and all firms combined. In the model, the innovation rate is plotted as $z(n, \tau)$ averaged over τ. In the data, the innovation rate is calculated as the probability of a firm moving up from technology gap n to $n+1$ for high- and low-type separately. The measurement of the technological gap in the data is described in Section 4.1.

The model reproduces the innovation rate of high-type firms very well. For these firms, the innovation probability in both the model and the data starts around 0.45 at a low technology gap and declines to approximately 0.05. While the model qualitatively captures that low-type firms have a lower probability of innovation than high-type firms and matches the declining profile, it consistently underestimates the innovation rate by about 0.10 across all

Figure 7: Innovation rate: Data vs. Model



technology gaps. Finally, the last panel shows that the average probability of innovation across all firms matches the data very well, especially for technology gaps greater than six.

4.3.3 Spinout Separation: Data vs. Model

Next, we examine how the model's predictions for the spinout separation rate compare to the data, as shown in Figure 8. The model successfully replicates the key empirical patterns. A central finding across all panels is that the separation rate is increasing with the firm's technology gap, n. In the model, the separation rate rises from approximately 5% at the lowest technology gap to around 15% at the highest levels.

The model provides a good quantitative fit for both high-type and low-type firms, matching the upward-sloping profile seen in the data. For the empirical estimates, it is important to note that the separation rates for firms at the highest technological levels ($n > 16$) are estimated less precisely, as indicated by the wider confidence intervals. This is due to the smaller number of firms observed at these large technology gaps, especially for low-type firms.

The model generates this increasing relationship between the employer's technology gap and the R&D manager's separation rate, a, through two main opposing forces. The first force, which encourages separation, is the growing probability $\mu(n)$ of creating a high-type venture when spinning out from a more technologically advanced firm. The second force, which discourages separation, is the rising wage offered for staying at the parent firm.[34]

To additionally test the positive relationship between technological leadership and spinout creation, we present a detailed regression analysis. Table 5 shows the relationship between

[34] Another consideration is the option value of waiting to increase the chances of forming a high-type spinout in the future. This effectively increases the opportunity cost of separating immediately. Hence, when the learning curve is steep, incentives to separate are lower.

Figure 8: Separation rate: Data vs. Model

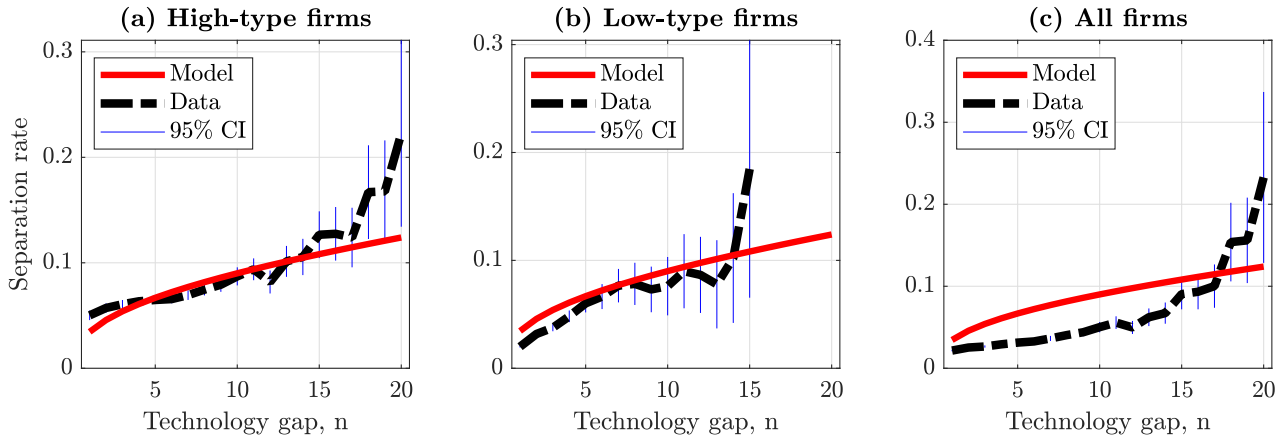


Table 5: Technological Leadership and Spinout Separation

	(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	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Industry FE	YES	NO	YES	NO
State FE	YES	NO	YES	NO
Firm FE	NO	YES	NO	YES
Observations	184442	53424	184598	53794

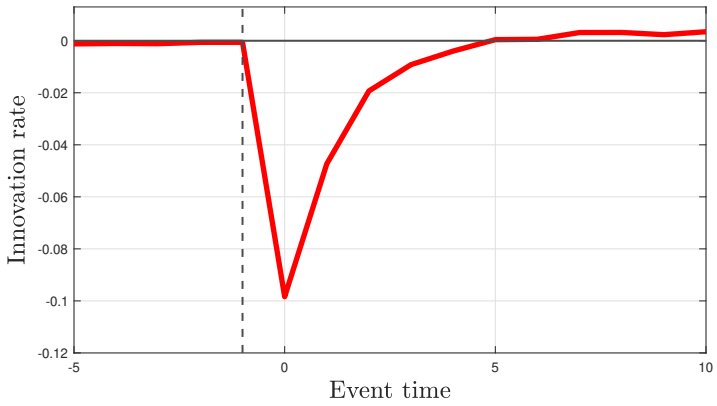
Note: The table presents firm-level regressions of the probability of spawning a spinout (logit models in columns 1 and 2) and the count of spawned spinouts (negative binomial models in columns 3 and 4) as a function of the technological leadership of the firm (parent) and other firm characteristics. 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.

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.[35]

This finding on higher spinout separation in more technologically advanced firms is

[35] Appendix Tables A.5 and A.6 confirm robustness of these results to different definitions of the employer's technological leadership.

Figure 9: The effect of spinout separation on parent company



also consistent with earlier findings by Klepper and Sleeper (2005) and Franco and Filson (2006) from the rigid disk drive and laser industries.[36]

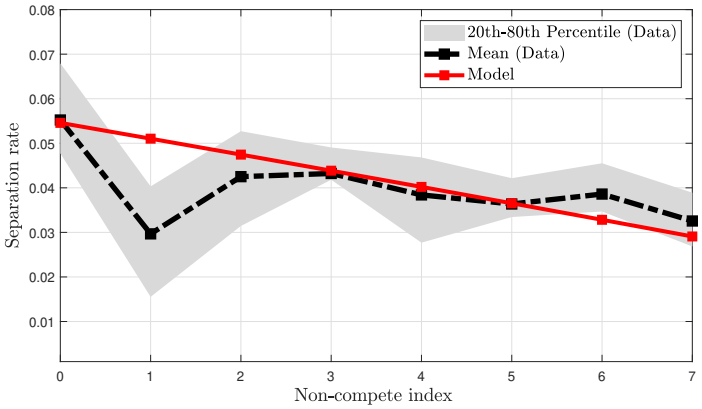
4.3.4 The Effect of Spinout Separation on Parent Company

A key empirical finding, documented in Fact 3, is the negative impact a spinout event has on the parent company's innovation. Figure 4 shows that, in the data, a parent firm's innovation rate drops by approximately 10%-20% immediately following a spinout and remains persistently lower for several years. This moment is explicitly targeted in the calibration to ensure the model captures the disruptive effect of employee-driven spinouts on incumbent firms. This moment is explicitly targeted in the calibration to ensure the model captures the disruptive effect of inventor-driven spinouts on incumbent firms.

Figure 9 plots the result of a simulated event study within the model. Consistent with the empirical evidence, the model generates a sharp and persistent decline in the parent firm's innovation rate. The magnitude of the initial drop in the model is approximately 10%, falling squarely within the range of the empirical estimates. Furthermore, the model captures the transient nature of this shock, showing a gradual recovery that completes around year five. In the model, this effect is driven by the loss of the R&D manager. When a manager leaves to form a spinout, the parent firm's R&D efficiency drops and remains lower until a new manager can be hired. This strong quantitative alignment provides

[36]Using administrative data from Sweden, a recent study by Engbom (2020) finds generally a negative relationship between employer's productivity and a probability of starting a firm. This relationship flips the sign, however, when the employer is in the top decile of the productivity distribution in the economy. Since our data focus on innovating firms who are in the very top of the productivity distribution in the economy, our evidence is also consistent with Engbom (2020). A related evidence on spinout separation comes from Sohail (2021). Using individual-level data from Mexico and the U.S., the study shows a negative relationship between firm size and spinout entry. Notice that unlike Sohail (2021), here we focus on the technological leadership (patenting) of the firm, *conditional* on firm size. In addition, the data in this study contain firms that innovate which is a special sample of the firms where learning and technological knowledge diffusion is presumably more important.

Figure 10: Spinout separation rate over non-compete laws: Data vs. Model



further support for the model's mechanisms linking employee mobility and incumbent innovation.

4.3.5 Non-Compete Laws

Before using the model for policy analysis, this section demonstrates that it can replicate the empirical elasticities of spinout separation rates with respect to non-compete enforcement (F). As shown in the empirical section (Table 3), stricter non-compete enforcement, indicated by a higher *NCL index*, is associated with lower spinout separation rates. Figure 10 corroborates this at the macro level, where the black dashed line shows that states with stricter non-compete laws have a lower share of spinout entrants.

We test if our model can reproduce this dynamic. The model is already calibrated to match the average spinout rate from the data, which serves as the baseline when non-compete laws are absent ($F = 0$). To compare the model to the data, we map the empirical non-compete index (which ranges from 0 to 7) to the model's enforcement parameter, F. This mapping ensures that the model's spinout rates align with the data at the index's endpoints. The red line in Figure 10 plots the model's predictions, demonstrating that the model effectively captures the elasticity of spinout separation across varying levels of non-compete enforcement.

5 Quantitative Evaluation

Given the model's ability to replicate key empirical facts, we now use it to investigate the aggregate implications of the spinout process. This section quantifies the importance of the central trade-off in the model: the positive effects of high-quality entry and knowledge diffusion from spinouts versus the negative disincentive effect on parent firms. We analyze this by first decomposing aggregate growth to isolate the contribution of spinouts, and

then by conducting policy experiments on non-compete laws to evaluate how policy can mediate this trade-off to improve growth and welfare.

5.1 Growth Decompositions

We now use the structure of the model to analyze the sources of aggregate productivity growth. From equation (1), we can decompose growth into contributions from entrants and incumbents. Table 6 presents this decomposition, showing that entrants account for 43% of total growth, despite making up only 15.1% of all firms. This share is consistent with prior estimates emphasizing the outsized role of new firms in driving growth (Foster et al., 2008; Lentz and Mortensen, 2008; Acemoglu et al., 2018). Within entrants, spinouts contribute 12.4% to total growth, roughly one-third of the entry-driven growth.

Because the number of firms varies significantly across groups, it is useful to consider not only aggregate contributions but also the average contribution per firm, normalized by group size. To this end, the final column of Table 6 reports a per-firm growth contribution index, defined as the ratio of a group's growth contribution to its share in the total firm population. This measure captures how much each group contributes to growth relative to its size. Entrants exhibit a per-firm growth index of 2.85, more than four times higher than that of incumbents (0.67), underscoring their disproportionate role in driving productivity growth. Among entrants, spinouts stand out with the highest per-firm contribution (2.95), nearly 4.4 times that of incumbents. Regular entrants also contribute strongly, with an index of 2.81, about 5% lower than spinouts.

Among incumbents, high-type firms account for 25.1% of aggregate growth, while low-type firms contribute 31.9%. However, the per-firm measure reveals that high-type firms are over twice as productive on average (1.02) compared to low-type firms (0.45), who, despite their numerical dominance, contribute substantially less on a per-firm basis. These direct contributions do not capture the important dynamic effects that amplify growth through knowledge diffusion and firm upgrading. High-type firms are more likely to generate spinouts, and spinouts themselves are more likely to be of high type, contributing to a virtuous cycle of innovation.

Finally, the bottom panel of Table 6 decomposes growth by firm size, conditional on being an incumbent. Small incumbent firms (defined as those with $n \leq 5$) account for the vast majority of firms—78.9%—and contribute 51.4% of total growth. In contrast, large incumbent firms ($n > 5$) make up only 6% of the population but contribute 5.6% to aggregate growth. Although the overall growth contribution of small firms is substantial due to their numerical dominance, their average impact per firm is lower: the per-firm growth index for small firms is 0.65, compared to 0.93 for large firms.

This difference in per-firm growth reflects underlying firm heterogeneity. While the

Table 6: Growth Decomposition

Total growth rate: 3.00%

Firm Group	Share of Firms (%)	Growth Contribution (%)	Per-Firm Growth Contribution
All Firms	**100.0**	**100.0**	**1.00**
Entrants	15.1	43.0	2.85
Regular Entrants	10.9	30.6	2.81
Spinouts	4.2	12.4	2.95
Incumbents	84.9	57.0	0.67
By Type:			
High-Type	24.7	25.1	1.02
Low-Type	70.2	31.9	0.45
By Size:			
Small Firms ($n \leq 5$)	78.9	51.4	0.65
Large Firms ($n > 5$)	6.0	5.6	0.93

Note: This table presents the decomposition of total growth (3.00%) across different groups of firms. The column labeled "Share of Firms (%)" shows each group's proportion in the overall firm population. "Growth Contribution (%)" reports each group's share in total aggregate growth. The final column, "Per-Firm Growth Contribution," is the ratio of growth contribution to firm share and captures each group's relative contribution to growth on a per-firm basis.

innovation rate declines with firm size n, high-type firms—those with significantly higher innovation capabilities—are more likely to grow and reach larger sizes. As shown in Figure 6(b), these high-type firms are disproportionately represented among large incumbents. Hence, the higher average growth efficiency of large firms is not a result of size per se, but rather the strong selection effect: only the more innovative (high-type) firms tend to scale, making size an outcome of, and a proxy for, underlying innovation strength. This pattern provides further evidence that high-type firms are, on average, more productive and essential drivers of long-run growth.

5.2 Policy Counterfactuals

This section first considers the effect of non-compete laws on industry dynamics and exploits optimal non-compete policies. The first column of Table 7 reports some illustrative equilibrium statistics from the benchmark economy matched to the average statistics from the U.S. To find the growth-maximizing value of F, we recalculate the steady state equilibrium of the economies characterized by different parameter values of F and search for F that maximizes aggregate growth given in equation (27). It turns out that relationship between g and F is close to monotonic, and $F = 0$ is the value that maximizes growth. In particular, moving from the benchmark estimate of non-compete laws to the case with no non-compete restrictions increases growth by 7 basis points. Notice that this gain is for the average value of non-compete restrictions, and there are larger gains for the states with

stricter existing protection. Figure 11 lists the gains across different states from moving from their existing levels of regulations to the optimal level with zero protection. Across states, the gains range from zero to 11 percentage points. The welfare calculation using equation (30) shows that $F = 0$ also maximizes the consumer welfare.

Next, we explore the main channels that drive these results. The channels through which non-compete laws affect growth can be divided into *direct entry effect, composition effect, knowledge diffusion, and disincentive effect*. *Direct entry effect* refers to the direct effect of non-compete restrictions on separation incentives of R&D managers. From Table 7, we see that spinout entry rate I^s is larger in the case of no-restrictions. Because entry directly contributes to growth, this largely determines higher overall growth rate in the economy with no non-compete protection. *Composition effect* refers to the effect of non-compete laws on distribution of firms across technology gaps, n. In Table 7 it can be seen by comparing the total share of firms with $n = 1$ ($\xi(1, \cdot)$) to the total share of firms with $n = 10$ ($\xi(10, \cdot)$). Because of higher entry, in the economy with no non-compete restrictions, distribution of firms is shifted to the left. This, in turn, has a positive effect on growth as more competitive firms with lower markups innovate more. The third *knowledge diffusion* effect refers to the fact that because bigger share of entry comes from spinouts, there are more high-type firms in the economy with weaker non-competes. The table illustrates that although this effect is present (see $\xi(\cdot, H)$), it is not quantitatively large.

Finally, non-compete laws impact the incumbents' innovation incentives. The *disincentive effect* refers to the fact that for each n, incentives of firms to innovate are lower because of lower appropriability of returns from R&D investments. This effect can be clearly seen by comparing innovation rates $z(1, \cdot)$ and $z(10, \cdot)$ in the columns with benchmark and no non-compete protection. This negative disincentive effect is quite large and significantly dampens positive impact from the other effects. In particular, notice that the average innovation rate in the economy (see *Mean z* row) is somewhat lower in the economy with no restrictions. On net, however, the positive effect dominates, and it is both growth- and welfare-enhancing to abolish non-compete enforcement.

Given that the disincentive effect is quantitatively large, we next ask if it is possible to design the state-dependent policies that could diminish the disincentive effect, while not largely affecting the spinout entry rate. We focus on particular type of state-dependent policies that offer non-compete protection based on incumbent's current technological leadership. In other words, instead of considering the uniform F, we consider F as a function on n. The last column of Table 7 considers the effect of the policy that gives the highest protection to the firms with $n \leq 5$ and no protection afterwards. We see that this policy clearly reduces both growth and welfare. It turns out that setting the protection the opposite way is more beneficial. In particular, as the third column illustrates, giving the full protection to the firms with the highest five technology gaps is actually growth-enhancing.

Table 7: Non-compete Policy Experiments

	Benchmark NCL	No NCL	Protection of Higher n	Protection of Lower n
$z(1,\cdot)$	1.0790	1.0115	1.0395	1.1224
$z(10,\cdot)$	0.8174	0.7797	0.9034	0.7503
$\xi(1,\cdot)$	0.3180	0.3964	0.3798	0.2464
$\xi(10,\cdot)$	0.0128	0.0088	0.0101	0.0168
$\xi(\cdot,H)$	0.2816	0.2822	0.2765	0.2824
Mean z	0.3534	0.3417	0.3487	0.3513
$a(1,\cdot)$	0.0515	0.1059	0.1081	0
$a(10,\cdot)$	0.0926	0.1329	0.0761	0.0974
I^s	0.0317	0.0560	0.0504	0.0127
I^o	0.0706	0.0674	0.0687	0.0742
w^u	0.0197	0.0205	0.0201	0.0192
w^s	0.0848	0.0692	0.0745	0.0961
g^*	3.08%	3.15%	3.17%	2.96%
$Welfare$	120.0126	126.7576	123.4354	115.6200

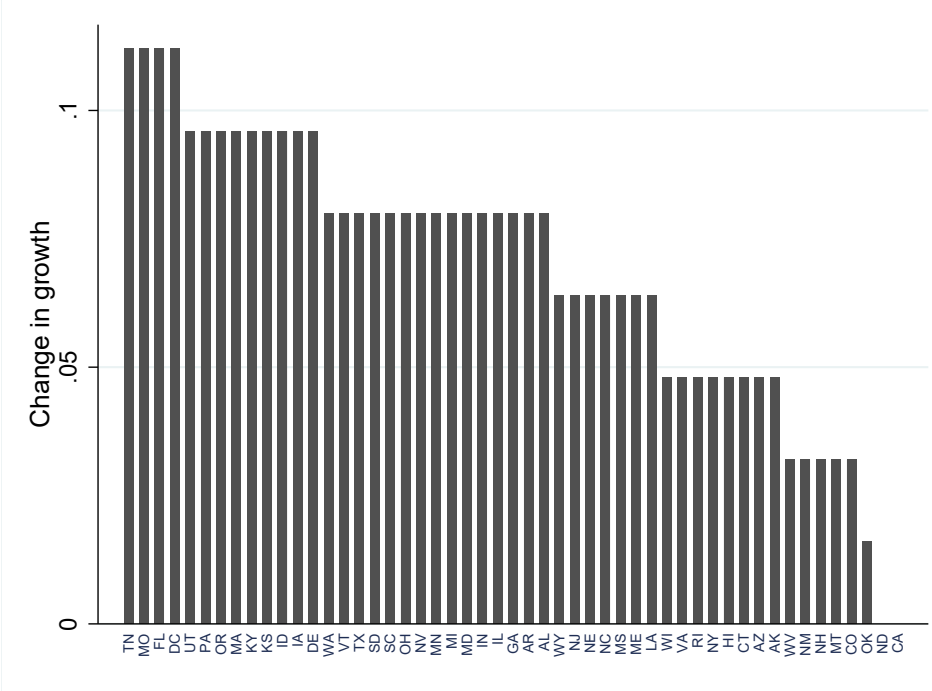
Why does this happen? This can be explained by a *trickle-down effect*: when policies provide higher protection to more advanced firms, this gives incentives to the firms below the threshold to catch up and reach the state with higher protection. This can be clearly seen by looking at the innovation rates of firms $z(1,\cdot)$ and $z(10,\cdot)$ from the Table. At the same time, spinout entry is not affected negatively too much. This results in the higher aggregate growth. However, notice that while maximizing growth, this policy reduces welfare relative to no-protection case. This largely happens because giving protection to technological leaders shifts firm's distribution to the right, and higher markups are associated with welfare losses for consumers.

6 Conclusion

This paper theoretically and empirically studies the role of employee entrepreneurship in innovation and productivity growth. Using the newly constructed data on innovating spinouts from the USPTO patent filings, we find evidence of the superior quality of spinout firms and the strong correlation between spinout quality and the technological leadership of a parent firm.

Motivated by these observations, we study the interaction between incumbents' innovation incentives and spinout entry in a dynamic general equilibrium endogenous growth framework. The developed model provides rich grounds to analyze multiple channels through which the process of employee entrepreneurship affects industry dynamics and aggregate growth. we find that it is welfare improving to abolish existing non-compete restrictions; however, the policy protecting firms with high technological leadership is

Figure 11: Gains from the Optimal Uniform Policy Adoption across States



growth-maximizing.

The dynamics of employee entrepreneurship is an important and understudied question in growth theory. The theoretical framework developed in this work can be applied to jointly study various innovation and labor market policies. The extensions of this work exploring the targeted entry subsidies and analyzing the sensitivity analysis are in progress.

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Empirical Appendix

Figure 12: Spinout vs Regular Entrant

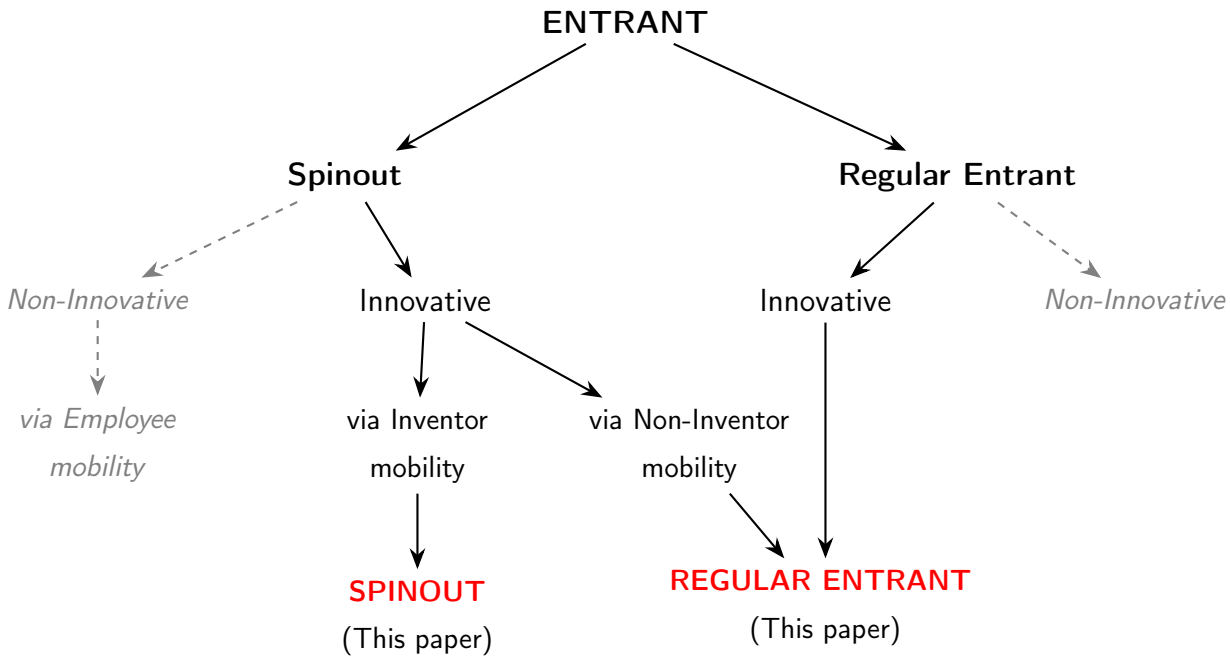


Table 8: Spinout Firm: A Methodological Comparison with Franco and Filson (2006)

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
								Avg:	**9.1 (10.9)**	**124.3**	**2863.9**
								Med:	**4.0 (8.0)**	**7.0**	**374.6**
1977	8, Exited	Int. Memories	Memorex	NO*		1978	1980	3	5	110
1981	6, Acquired	Tecstor	Microdata	NO**	Zerox, Digital Data	1983	1983	1	1	22
1981	6, Acquired	Ataswe	International Memories	NO*		1981	1985	5	9	229
1983	5, Exited	Tulin	Ampex,Qume	NO*		1983	1983	1	1	19
1986	6, Exited	Brand Technologies	Computer Memories	NO**	Pertec	1987	1988	2	2	56
1988	3, Acquired	Areal Technology	Maxtor	NO*		1990	1991	2	3	81
								Avg:	**2.3 (5.8)**	**3.5**	**86.1**
								Med:	**2.0 (6.0)**	**2.5**	**68.4**
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).
** Our methodology classifies Tecstor and Brand Technologies as regular entrants, as their first inventors left their parent companies more than five years before joining these firms.
*** 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.

Table 9: 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	YES	YES	YES	YES
Age FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
State FE	YES	YES	YES	YES
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	YES	YES	YES	YES
Age FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
State FE	YES	YES	YES	YES
Observations	28957	68386	73109	73679
Mean	2.112	5.037	0.108	0.0500

Note: The table compares innovative entrants, spinouts and regular entrants, to non-innovative entrants - firms that enter in compustat dataset between 1981 and 1999 and never patent, along various outcome variables in different columns. *Non-innovative entrants* 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.

Theoretical Appendix

A Derivation of Bellman Equation (12)

As an example, we derive Bellman equation for R&D managers. Other equations are derived in a similar way. We start by writing down the value of being an R&D manager $V_t^{manager}(n,\tau)$ as

$$V_t^{manager}(n,\tau) = \max_{a_t(n,\tau)\geq 0} \left\{ \begin{array}{c} \left[w_t(n,\tau) - \frac{ka_t^2(n,\tau)}{2} Y_t\right]\Delta t + o(\Delta t) \\ +e^{-r_{t+\Delta t}\Delta t} \left[\begin{array}{c} a_t(n,\tau)\Delta t \left(\mu(n) V_{t+\Delta t}^{firm}(1,H) + (1-\mu(n)) V_{t+\Delta t}^{firm}(1,L) - FY_{t+\Delta t}\right) \\ +(I^s + I^o)\Delta t V_{t+\Delta t}^{out} + z_t(n,\tau)\Delta t V_{t+\Delta t}^{manager}(n+1,\tau) \\ +(1 - a_t(n,\tau)\Delta t - (I^s+I^o)\Delta t - z_t(n,\tau)\Delta t) V_{t+\Delta t}^{manager}(n,\tau) \end{array} \right] \end{array} \right.$$

The value at time t consists of wages minus incurred cost of separation during a time interval Δt. Next is the discounted continuation value after Δt. This continuation value is made up of the following parts: the first line in square brackets is a net continuation value from forming a spinout which happens with probability $a_t(n,\tau)\Delta t$ during a time interval Δt. The second line comes from the possibility of creative destruction of an employer firm with probability $(I^s + I^o)\Delta t$, in which case the manager gets $V_{t+\Delta t}^{out}$, and from the possibility of employer's innovation with probability $z_t(n,\tau)\Delta t$, in which case a manager gets $V_{t+\Delta t}^{manager}(n+1,\tau)$. Finally, on the third line, with the remaining probability, manager continues working in the same firm and gets $V_{t+\Delta t}^{manager}(n,\tau)$.

Now, subtract $V_t^{manager}(n,\tau)$ from both sides and divide everything by Δt:

$$\frac{o(\Delta t)}{\Delta t} = \max_{a_t(n,\tau)\geq 0} \left\{ \begin{array}{c} w_t(n,\tau) - \frac{ka_t^2(n,\tau)}{2} Y_t \\ +e^{-r_{t+\delta t}\Delta t} \left[\begin{array}{c} a_t(n,\tau)\left(\mu(n) V_{t+\Delta t}^{firm}(1,H) + (1-\mu(n)) V_{t+\Delta t}^{firm}(1,L) - FY_{t+\Delta t}\right) \\ +(I^s+I^o) V_{t+\Delta t}^{out} + z_t(n,\tau) V_{t+\Delta t}^{manager}(n+1,\tau) \\ -(a_t(n,\tau) + (I^s+I^o) + z_t(n,\tau)) V_{t+\Delta t}^{manager}(n,\tau) \end{array} \right] \\ +\frac{e^{-r_{t+\Delta t}\Delta t} V_{t+\Delta t}^{manager}(n,\tau) - V_t^{manager}(n,\tau)}{\Delta t} \end{array} \right\}$$

Take limits when $\Delta t \to 0$:

$$0 = \max_{a_t(n,\tau)\geq 0} \left\{ \begin{array}{c} w_t(n,\tau) - \frac{ka_t^2(n,\tau)}{2} Y_t \\ +a_t(n,\tau)\left(\mu(n)V_t^{firm}(1,H) + (1-\mu(n))V_t^{firm}(1,L) - FY_t\right) \\ +(I^s + I^o)V_t^{out} + z_t(n,\tau)V_t^{manager}(n+1,\tau) \\ -(a_t(n,\tau) + (I^s + I^o) + z_t(n,\tau))V_t^{manager}(n,\tau) \\ +\lim_{\Delta t\to 0} \frac{e^{-r_{t+\Delta t}\Delta t}V_{t+\Delta t}^{manager}(n,\tau) - V_t^{manager}(n,\tau)}{\Delta t} \end{array} \right\}$$

Notice that $\lim_{\Delta t\to 0} \frac{e^{-r_{t+\Delta t}\Delta t}V_{t+\Delta t}^{manager}(n,\tau) - V_t^{manager}(n,\tau)}{\Delta t}$ is indetermined, so using the l'Hopital's rule, we get $-r_t V_t^{manager}(n,\tau) + \dot{V}_t^{manager}(n,\tau)$. Hence,

$$r_t V_t^{manager}(n,\tau) - \dot{V}_t^{manager}(n,\tau) = \max_{a_t(n,\tau)\geq 0} \left\{ \begin{array}{r} w_t(n,\tau) - \frac{ka_t^2(n,\tau)}{2} Y_t \\ +a_t(n,\tau)\left(\mu(n)V_t^{firm}(1,H) + (1-\mu(n))V_t^{firm}(1,L) - FY_t \right. \\ +(I^s + I^o)(V_t^{out} - V_t^{manager}(n,\tau)) \\ +z_t(n,\tau)(V_t^{manager}(n+1,\tau) - V_t^{manager}(n, \\ -(a_t(n,\tau) + (I^s + I^o) + z_t(n,\tau))V_t^{manager}(n \end{array} \right.$$

Since we are focusing on the steady state equilibrium in which decision rules are constant over time and value functions grow at the same rate as the whole economy, g, we can divide the above equation by Y_t and rewrite in the following way:

$$\rho v^{manager}(n,\tau) = \max_{a(n,\tau)\geq 0} \left\{ \begin{array}{c} \omega(n,\tau) - \frac{ka_t^2(n,\tau)}{2} \\ +a(n,\tau)\left(\mu(n)v^{firm}(1,H) + (1-\mu(n))v^{firm}(1,L) - F - v^{manager}(n,\tau)\right) \\ +(I^s + I^o)(v^{out} - v^{manager}(n,\tau)) \\ +z(n,\tau)(v^{manager}(n+1,\tau) - v^{manager}(n,\tau)) \\ -(a(n,\tau) + (I^s + I^o) + z(n,\tau))v^{manager}(n,\tau) \end{array} \right\}$$

where we used the fact that $\frac{\dot{V}_t^{manager}(n,\tau)}{Y(t)} = gv^{manager}$ and by Euler equation, $\rho = r - g$. This gives us equation (12).

B Proof of Equation (30)

Expanding the expression for the welfare (28) and taking into account that in the steady state equilibrium Y_t grows at rate g, we get

$$\begin{aligned}
Welfare(0) &= \int_0^\infty e^{-\rho t} ln C_t dt \\
&= \int_0^\infty e^{-\rho t} ln(1-I) Y_t dt \\
&= \int_0^\infty e^{-\rho t} ln(1-I) dt + \int_0^\infty e^{-\rho t} \ln e^{gt} Y_0 dt \\
&= -\frac{\ln(1-I) e^{-\rho t}}{\rho}\Big|_0^\infty + \ln Y_0 \int_0^\infty e^{-\rho t} dt + \int_0^\infty g t e^{-\rho t} dt \\
&= \frac{\ln(1-I)}{\rho} + \frac{\ln Y_0}{\rho} + g\left[-\frac{t e^{-\rho t}}{\rho}\Big|_0^\infty + \frac{\int_0^\infty e^{-\rho t} dt}{\rho} \right] \\
&= \frac{\ln(1-I)}{\rho} + \frac{\ln Y_0}{\rho} - g\frac{e^{-\rho t}|_0^\infty}{\rho^2} \\
&= \frac{\ln(1-I)}{\rho} + \frac{\ln Y_0}{\rho} + \frac{g}{\rho^2}
\end{aligned}$$

Now, let us expand $\ln Y_0$:

$$\begin{aligned}
\ln Y_0 &= \int_0^1 \ln y(j,0) dj \\
&= \int_0^1 \ln q(j,0) dj + \int_0^1 \ln l(j,0) dj \\
&= \ln Q(0) + \int_0^1 \ln \frac{1}{\omega^u \lambda^{n_j}} dj \qquad (33) \\
&= \ln Q(0) - \ln \lambda \int_0^1 n_j dj - \ln \omega^u \\
&= \ln Q(0) - \ln \lambda \sum_{n,\tau} n \xi(n,\tau) - \ln \omega^u
\end{aligned}$$

The second line used (3) and the third line used labor demand (25). Hence, we arrived at equation (30).

n,$\tau \xi(n,\tau) z(n,\tau)) \ln \lambda$

C Proof of Proposition 1

In steady state, $\ln Y_t = \ln Q(t) + \text{constant terms}$, so the growth in output equals the growth in productivity $Q(t)$:

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

Growth in $Q(t)$ arises from successful innovations by incumbents, spinout entrants, and regular entrants. The probability of successful innovation by incumbents in a time interval Δt, where each innovation improves productivity by λ, is:

$$\Delta t \sum_{n=1}^{N} \sum_{\tau \in \{H,L\}} \sum_{M \in \{0,1\}} \xi(n, \tau, M) z(n, \tau, M),$$

where the summation is over technology gaps $n \in \{1, \ldots, N\}$, quality types $\tau \in \{H, L\}$, and manager states $M \in \{0, 1\}$.

The growth in productivity $Q(t)$ from spinout and regular entrants arises from their successful entry into product lines, where entrants improve technology at different levels depending on their quality type. Let I_H^s and I_L^s denote the total entry rates of high-type and low-type spinouts, and I_H^o and I_L^o denote the total entry rates of high-type and low-type regular entrants, defined as:

$$I_H^s = \sum_{n'=1}^{N} a(n', H) \xi(n', H, 1) \mu(n'), \quad I_L^s = \sum_{n'=1}^{N} a(n', L) \xi(n', L, 1)(1 - \mu(n')),$$

$$I_H^o = I^o \tilde{\mu}, \quad I_L^o = I^o (1 - \tilde{\mu}),$$

where n' indexes the parent firm's technology gap, $\mu(n')$ is the probability of a high-type spinout conditional on n', and $\tilde{\mu}$ is the probability of a high-type regular entrant.

The probability that entrants of type τ innovate and improve the product line by a technology gap λ^n in a time interval Δt is

$$\Delta t \, (I_\tau^s + I_\tau^o) \, G(n|\tau),$$

where $G(n|\tau)$ is the probability that high-type or low-type entrants improve the product line by a technological gap n.

The expected logarithmic productivity at time $t + \Delta t$ is:

$$\ln Q(t+\Delta t) = \Delta t \sum_n \sum_\tau \sum_M \xi(n,\tau,M) z(n,\tau,M) \ln \lambda Q(t)$$
$$+ \Delta t \sum_\tau \sum_n \left(I^s_\tau + I^o_\tau\right) G(n|\tau) \ln \lambda^n Q(t) \tag{33}$$
$$+ \left(1 - \Delta t \sum_n \sum_\tau \sum_M \xi(n,\tau,M) z(n,\tau,M) - \Delta t \sum_\tau \sum_n \left(I^s_\tau + I^o_\tau\right) G(n|\tau)\right) lnQ(t) \tag{34}$$

$$\ln Q(t+\Delta t) = lnQ(t) + \Delta t \sum_n \sum_\tau \sum_M \xi(n,\tau,M) z(n,\tau,M) \ln \lambda$$
$$+ \Delta t \sum_\tau \sum_n \left(I^s_\tau + I^o_\tau\right) G(n|\tau) n \ln \lambda \tag{35}$$

$$\ln Q(t+\Delta t) = lnQ(t) + \Delta t \left(\sum_n \sum_\tau \sum_M \xi(n,\tau,M) z(n,\tau,M) + \Delta t \sum_\tau \sum_n \left(I^s_\tau + I^o_\tau\right) G(n|\tau) n\right) \ln \lambda \tag{36}$$

Taking the limit:

$$g = \lim_{\Delta t \to 0} \frac{\ln Q(t+\Delta t) - \ln Q(t)}{\Delta t} = \left(\sum_n \sum_\tau \sum_M \xi(n,\tau,M) z(n,\tau,M) + \sum_\tau \sum_n \left(I^s_\tau + I^o_\tau\right) G(n|\tau) n\right) \ln \lambda$$

$$g = \left(\sum_n \sum_\tau \sum_M \xi(n,\tau,M) z(n,\tau,M) + \sum_\tau \sum_n \left(I^s_\tau + I^o_\tau\right) G(n|\tau) n\right) \ln \lambda.$$

This growth rate reflects the contributions of incumbents (with fixed improvement λ) and entrants (with heterogeneous improvements λ^n).

$$v^{entry} = M + e\rho - \sqrt{2Me\rho + e^2\rho^2},$$

where $M = \tilde{\mu} v^{firm}(1,H) + (1-\tilde{\mu}) v^{firm}(1,L)$.

Given v^{entry}, compute the resulting aggregate entry by outsiders, I^o, from equation (**??**).

Given the policy functions and entry rate by outsiders, find the stationary distribution $\xi(n,\tau)$ by solving the quadratic system of equations given in equations (**??**), (**??**), (**??**), and (**??**). Compute spinout entry rate I^s from equation (**??**).

Solve for $v^{firm}(n,\tau)$, $v^{manager}(n,\tau)$, and wages $\omega(n,\tau)$ using equations (**??**), (12), (**??**), (14), and (**??**). Use the fact that v^{work} is equal to v^{entry}, which has already been calculated.

Compare $v^{firm}(n,\tau)$ and $v^{manager}(n,\tau)$ to the previous guesses. Iterate this algorithm until both value functions converge.

D Additional Data Details. Non-compete Laws

Non-compete covenants are the clauses in employee contracts that prohibit the employees from working for a competitor or forming a new competing firm. The laws governing the enforcement of non-compete agreements, the non-compete laws (NCL), vary greatly across the U.S. states. Malsberger (2004) conducted a state-by-state survey analyzing twelve questions on different aspects of enforcement of non-compete agreements. There are two states which completely void the non-compete agreements: California and North Dakota. Other states largely vary by the types of contracts enforceable in terms of the scope, geographic area, length, time restriction, and others. Based on the questions analyzed in the survey, Garmaise (2011) derived state-specific non-competition index. Over the U.S. states, the index varies from 0 to 9, with a higher index indicating a stricter enforcement. More recently, Starr (2019) builds on Bishara (2011) and provides a different index for non-compete laws across states for the years 1991 and 2009. Table A.1 lists these three indexes for each state. These indexes are highly correlated, but since the NCL index from Starr (2019) has more time variation, we use this index as the benchmark in the regression analysis. More specifically, we combine the 1991 and 2009 versions of the index and define the final index over time as

$$NCL(t) = NCL_{1991} + \frac{NCL_{2009} - NCL_{1991}}{18}(t - 1991) \tag{37}$$

Notice that, as required by the Full Faith and Credit Clause in the United States Constitution, states within the United States have to respect "public acts, records, and judicial proceedings of every other state". This should mean that even if the spinout founded a new start-up in a state different from the state of the previous employer, the laws of the previous state should be still important. In 1998 though, California set the precedent (Application Group, Inc. vs Hunter Group, Inc.) where the court stated that California law is applicable to non-California employees seeking employment in California. In general, despite the Full Faith and Credit statement, there is still some ambiguity as to which laws should be applicable in each case. This uncertainty though ex-ante may work in favor of employers so that the employees take less risk in trying to compete with the employer.

E Additional Empirical Results

Appendix Table A.1: Non-competition Indexes across the 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
Mississippwe	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 A.2: Parent's Characteristics and Performance of Spinouts

-Panel A-

Log number of cit-weighted patents of spinout

Log num of parents	0.558***	0.556***	0.551***	0.559***
	(0.041)	(0.041)	(0.042)	(0.041)
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)
Cohort FE	YES	YES	YES	YES
Tech class FE	YES	YES	YES	YES
State FE	YES	YES	YES	YES
Observations	16672	16582	16672	16672

-Panel B-

Log number of top patents of spinout

Log num of parents	0.190***	0.189***	0.188***	0.191***
	(0.021)	(0.021)	(0.021)	(0.021)
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)
Cohort FE	YES	YES	YES	YES
Tech class FE	YES	YES	YES	YES
State FE	YES	YES	YES	YES
Observations	17268	17166	17268	17268

Note: The table shows the regressions of spinouts' outcome variables as a function of various parental characteristics at the time of spinout separation. Each observation is a spinout firm entering in the period 1981-2000. The outcome variable in Panel A is spinout's lifetime log citations-weighted patent counts; the outcome variable in Panel B is spinout's lifetime log number of top patents. Top patents are the patents whose truncation-adjusted citations are above the 90th percentile of the citation distribution of patents filed in the same year and technology class. Control variables include the log number of parents, parents' log number of patents and citations-weighted patents, technological lead percentiles, and log number of top patents. If the spinout has multiple parents, the parents' number of patents is added up. The technological lead percentile is a categorical variable with 20 quantiles of the patent quality distribution based on the citations-weighted patent counts in the last five years in the firm's technology class (*cat-ocl*). The regressions also control for spinout's cohort, technology class, and state-fixed effects.

Appendix Table A.3: Parent Characteristics and Performance of Spinouts. Other Outcome Variables

		-Panel A-		
		Log longevity of spinout		
Log num of parents	0.197***	0.197***	0.196***	0.197***
	(0.024)	(0.024)	(0.024)	(0.024)
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)
Cohort FE	YES	YES	YES	YES
Tech class FE	YES	YES	YES	YES
State FE	YES	YES	YES	YES
Observations	17268	17166	17268	17268
		-Panel B-		
		Log number of patents of spinout		
Log num of parents	0.475***	0.474***	0.471***	0.475***
	(0.034)	(0.034)	(0.034)	(0.034)
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)
Cohort FE	YES	YES	YES	YES
Tech class FE	YES	YES	YES	YES
State FE	YES	YES	YES	YES
Observations	17268	17166	17268	17268

Note: Table repeats the analysis of Table A.2, but for other outcome variables. The outcome variable in Panel A is the log longevity of the spinout; the outcome variable in Panel B is spinout's lifetime log number of patents.

Appendix Table A.4: Parent Characteristics and Performance of Spinouts. Robustness

-Panel A

Log number of citations-weighted patents of spinout

	(1)	(2)	(3)
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	YES	YES	YES
Tech class FE	YES	YES	YES
State FE	YES	YES	YES
Observations	16672	16672	9701

-Panel B

Log number of top patents of spinout

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	YES	YES	YES
Tech class FE	YES	YES	YES
State FE	YES	YES	YES
Observations	17268	17268	10005

Note: Table presents the specifications similar to column (3) of Table A.2, but with various robustness checks. The first column redefines parent's technological lead percentile based on the citations distribution with more narrow technology classification (*nclass*); the second column redefines technological lead percentile based on the citations distribution of all firms, irrespective of their technology classification. The third column considers robustness to the definition of the spinout separation time by defining the parental variables in the entry year of the spinout firm.

Appendix Table A.5: Probability of spinout separation. 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	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Industry FE	YES	NO	YES	NO
State FE	YES	NO	YES	NO
Firm FE	NO	YES	NO	YES
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	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Industry FE	YES	NO	YES	NO
State FE	YES	NO	YES	NO
Firm FE	NO	YES	NO	YES
Observations	184442	53424	184598	53794

Note: Table repeats the analysis in Table 5, 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 A.6: 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	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Industry FE	YES	NO	YES	NO
State FE	YES	NO	YES	NO
Firm FE	NO	YES	NO	YES
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	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Industry FE	YES	NO	YES	NO
State FE	YES	NO	YES	NO
Firm FE	NO	YES	NO	YES
Observations	15834	9986	16462	10186

Note: Table repeats the analysis in Table 5 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.

Appendix Table A.7: 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	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	NO	YES	YES	NO
State FE	NO	YES	NO	NO	YES	NO
Firm FE	NO	NO	YES	NO	NO	YES
Observations	184375	184375	53232	184529	184529	53600

Note: The table presents firm-level regressions of the probability of spawning a spinout (logit models in columns 1-3) and the count of spawned spinouts (negative binomial models in columns 4-6) as a function of the NCL index and other firm characteristics. *NCL index* is the non-competition index defined in (37). As before, Log patents, Log cit-patents, and Log inventors refer to the number of patents, citations-adjusted patents, and inventors in the last 5 years, respectively. The sample includes all patenting firms in the period 1981-2000.

Appendix Table A.8: Non-Compete Laws and Spinout Separation. Within-industry and within-state spinouts.

	Within-industry spinouts			Within-industry&state spinouts		
	(1)	(2)	(3)	(4)	(5)	(6)
NCL index	-0.038***	-0.068***	-0.066***	-0.051***	-0.048*	-0.065**
	(0.0052)	(0.0213)	(0.0234)	(0.0063)	(0.0251)	(0.0310)
Log patents	-0.101***	-0.101***	-0.190***	-0.094***	-0.079***	-0.184**
	(0.0246)	(0.0247)	(0.0675)	(0.0298)	(0.0300)	(0.0821)
Log cit-patents	0.221***	0.217***	0.162***	0.225***	0.214***	0.152***
	(0.0125)	(0.0126)	(0.0397)	(0.0158)	(0.0159)	(0.0487)
Log inventors	0.469***	0.477***	1.006***	0.418***	0.422***	1.049***
	(0.0218)	(0.0219)	(0.0640)	(0.0260)	(0.0262)	(0.0780)
Log age	-0.237***	-0.236***	0.080**	-0.269***	-0.268***	0.104**
	(0.0122)	(0.0123)	(0.0401)	(0.0148)	(0.0150)	(0.0480)
State competition	0.165***	0.018	-0.059	0.257***	-0.079	-0.263
	(0.0302)	(0.1554)	(0.1297)	(0.0367)	(0.1887)	(0.1866)
Log GDP pc	-0.962***	-1.082***	-1.260***	-1.136***	-0.968***	-1.201***
	(0.0776)	(0.1138)	(0.1578)	(0.0919)	(0.1385)	(0.2016)
Log population	-0.127***	-1.339***	0.007	-0.168***	-0.937**	0.290
	(0.0312)	(0.3968)	(0.1438)	(0.0374)	(0.4671)	(0.2176)
Year FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	NO	YES	YES	NO
State FE	NO	YES	NO	NO	YES	NO
Firm FE	NO	NO	YES	NO	NO	YES
Observations	183987	183987	42298	183485	183485	30913

Note: The table presents firm-level logit regressions of the probability of spawning a within-industry spinout (columns 1-3) and within-industry and within-state spinout (columns 4-6) as a function of the NCL index and other firm characteristics. The industry is defined based on 6 technology categories (*cat*) in the NBER USPTO data. *NCL index* is the non-competition index defined in Appendix D. The sample includes all patenting firms in the period 1981-2000.