Entrepreneurship through Employee Mobility, Innovation, and Growth*

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Abstract

Firm-level productivity differences are large and are mainly 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? I study empirically and by the 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 the inventor mobility in the patent data, I document that spinout entrants significantly outperform regular entrants throughout their entire life. Firms with a bigger technological lead spawn more successful spinouts. Building on these observations, I build a structural model of innovation and firm dynamics, where firm heterogeneity arises from endogenous decisions of innovation workers to become entrepreneurs and create spinouts. The spinout dynamics affect productivity growth through four main channels: direct entry, incumbents' disincentive effect, knowledge diffusion, and the firm composition channel. Growth decompositions show that accounting for spinout dynamics is quantitatively important for our understanding of growth process. I analyze the role of non-compete laws affecting the employee entrepreneurship for aggregate innovation and growth.

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

JEL Classifications: O30, O43.

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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), the models of growth and firm dynamics are mute on sources of this ex-ante heterogeneity. Where do these ex-ante differences come from? In this paper, I 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. I 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. By better understanding aggregate implications of spinout dynamics, we can better design policies aimed at fostering high-growth entrepreneurship, innovation, and growth.

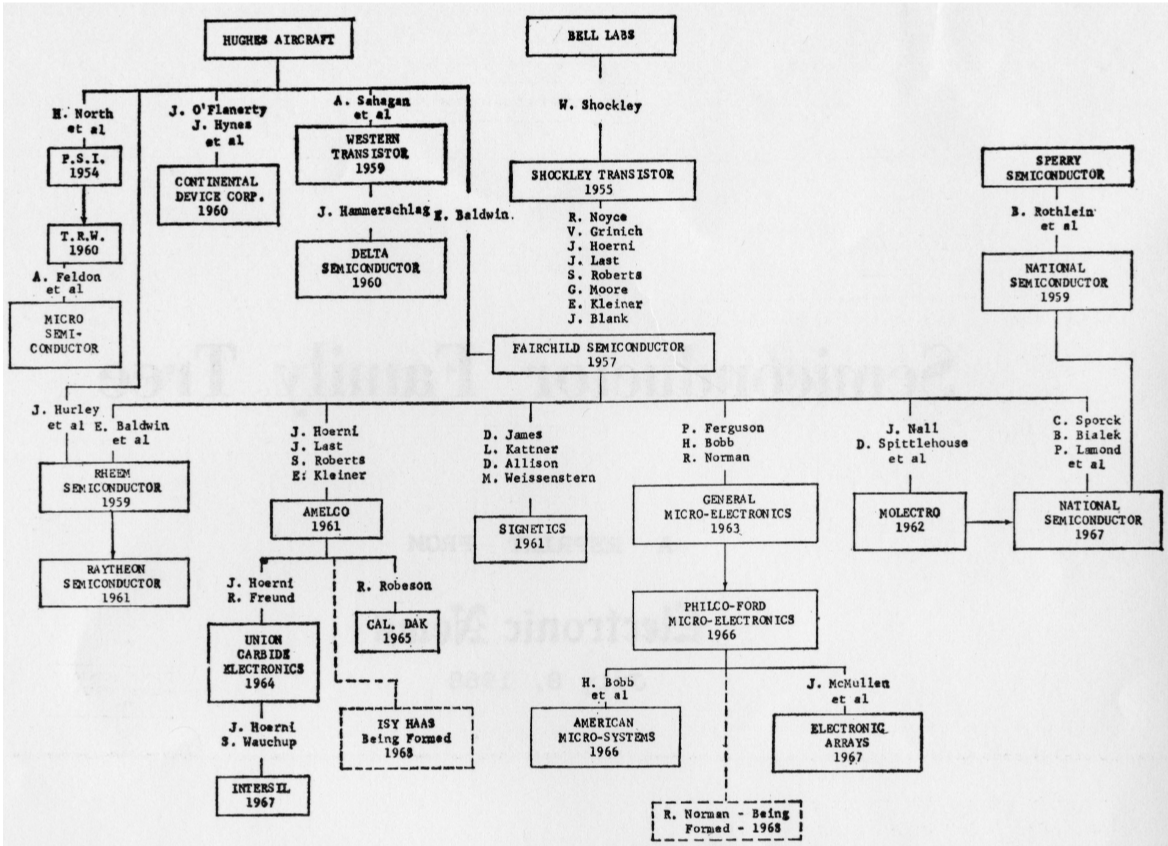
Spinout entrants often turn into exceptionally productive high-growth firms, often reshaping the whole industries. Examples of transformational spinout firms are ample. Figure 1 shows a small part of a large spinout family tree spawned by Bell Telephone Laboratories established in 1952. After the stages 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 a tension between incumbents and the employees leaving their firms to pursue their own entrepreneurial ventures. If this tension results in lower appropriability of returns from innovation investment by incumbents, their ex-ante innovation incentives will decline. 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.[1]

To understand this interaction between spinout entry and incumbents' innovation incentives and the implications for aggregate innovation and growth, I 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, I quantitatively analyze the role of non-compete laws (NCL) hindering the

[1]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



employee mobility, in promoting aggregate innovation and growth.[2]

I begin the study by empirically analyzing spinout firms and by providing motivating stylized facts that guide the modeling. To identify the innovating spinout firms, I 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: 30% of the patenting entrants, the total of 17,295 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

[2]There is an ongoing debate 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.).

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. On the downside, this approach provides just a proxy for spinout firms and can potentially mismeasure the true number of spinouts. In addition, inventors moving to the new firms may not formally be the entrepreneurs or owners of the spinout firms. In this sense, our empirical definition of spinouts is broader than the definition of spinouts just based on owners and in addition includes the founding team of the early inventors in the firm. This approach is similar to Choi, Goldschlag, Haltiwanger and Kim (2019) who show that not just the founders but the early employees play a key role in the firms' subsequent performance.

I provide a set of validation exercises for the identification of spinouts in the data. First, I compare the external sample of 40 spinout firms reported in Franco and Filson (2006) against my data and show that for the overlapping sample of the patenting firms, the spinout status is correctly identified. Second, I show that the main data moments and stylized facts that emerge from this data on innovating firms are very consistent with the existing empirical studies in other settings (described in detail in the literature review). Hence, main motivating empirical facts that emerge from my data are general and support well the broad modeling assumptions.

The two 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.

In the second part of the paper, I 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, I 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, I 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 entrepreneurs' firms determine their efficiency in the innovation process. By innovating, the firms move up the technological ladder and increase their market power. R&D managers bargain with entrepreneurs over their wages and, while being on the job, can search for ideas and outside opportunities to create their own spinout firms. Importantly, building on the second fact that better firms spawn better spinouts, R&D managers learn on the job – more technologically advanced is their employer, higher are the chances that their start-up quality is of a better type.[3] Hence, an important new characteristic of this model is that the entry distribution of the firm quality types is endogenous through the feedback from the incumbents' type distribution, their innovation decisions, and the employees' entrepreneurial choices. Finally, the model builds in the 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, I quantitatively evaluate these various channels to understand the role of spinout formation for aggregate innovation and growth and to conduct counterfactual policy analysis. By calibrating the model to match growth, innovation, entry, and workforce composition targets in the data, I first demonstrate that the model is successful at replicating several important non-targeted data moments. The model quantitatively matches the observed declining spinout entry rate in the states with weaker non-compete restrictions, as well as facts on competition, spinout separation, and the dynamics of wages with firm size.

Using growth decompositions, I first show that accounting for spinout dynamics is quantitatively important for our understanding of growth process. The static growth decomposition shows that 7% of productivity growth is accounted for by spinout entrants. 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

[3]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.

without distorting the incumbents' innovation incentives?

Next, I provide a set of counterfactual policy experiments to understand which policies can boost high-quality entrepreneurship and productivity growth. The first policy explores the current non-compete laws in the U.S. Recent evidence indicates that the use of non-compete 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.[4] 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.[5] 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 the welfare-maximizing optimal uniform non-compete policy. 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 I 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).

I 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, I incorporate the problem of the

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

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

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 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 my 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).[6] Different from that work, I develop a comprehensive 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 me 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 I document using inventors and patent data. These facts are consistent with the growing empirical literature on employee spinouts identified in different datasets [7] 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

[6] Using data from Mexico, Sohail (2021) shows that spinout spawning is lower for larger firms. My 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 (Agarwal et al., 2004a).

[7] Literature often uses word "spinoff" instead of "spinout" that I use here.

failure rates. Spinouts also tend to separate from the firms that are industry leaders, and better firms spawn even better spinouts. In this paper, I find that similar empirical patterns emerge when I consider innovating spinouts across all industries using micro-level 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 my 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, I use micro-level datasets on patents, firms, and inventors. The data 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. Hence, after describing the data, Section 3.2 documents two main empirical facts underpinning the model assumptions; while Section 5 then matches the model to the data and presents counterfactual exercises.

2.1 Patent and Inventors Data and Identification of Spinouts

Data Sources This section details data sources, identification of spinout firms, and other variables construction.

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. I use a detailed information on 1,841,499 patents assigned to 1,457,121 U.S. entities (assignees). For each patent, I use the following patent characteristics: patent's technology classification, patent claims, the number of forward patent citations received – a widely-used measure 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, I focus on patents of the U.S. corporate assignees.[8] For each patenting firm, I 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 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 of innovating firms in the U.S. and more that 650 thousands unique inventors working in those firms. The advantage of this data match is that it allows us to measure firm's innovative output quality as well as track individual inventors over time across different firms.

Firms are classified into incumbent and entrant firms by identifying firm's entry year as the year the firm makes its first patent application. Since the data does not contain information on patents granted before 1976, to decrease the left truncation problem, I identify entrants starting from 1981. Likewise, since 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. As a result, the benchmark sample focuses on entrants who are born in the years 1981-1999. This allows for considerable time to observe entrants' future activities and measure their performance and potential exit. A firm applying for a patent prior to 1981 is classified as an incumbent. A firm's exit year is defined as the grant year of its last patent in the data.

The firm entry and exit dates defined based on the patent application/grant dates do

[8]Using extensive firm name cleaning and tracking firm reorganizations, PD provides unique company identifiers for each corporate assignee.

not necessarily coincide with the exact entry and exit dates of the firm in the economy. Nevertheless, these are good proxies to measure firm's entry and exit into innovation – the focus of this paper. The first patenting year well describes the entry of the firm into the innovation stage – similar to the firm entry in the model; while the firm's last patent describes its exit from the innovation stage – again, in line with firm exit in the model.

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, I link the matched dataset to the financial data for publicly listed firms from the Compustat North American Fundamentals (Annual).[9] As a result, the empirical section will consistently refer to two data samples: "Patent Data" is the sample on all the patenting firms in our data, and "Compustat + Patent Data" refers to the subsample of the firms matched to Compustat.

The identification of spinout firms To identify spinouts, I track inventors' mobility across firms by following inventors' 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.[10] [11] To reduce the measurement error, I 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. However, I illustrate robustness of the empirical results keeping these firms in the sample. 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 (*US*4578625 and *US*4685007). In 1986, this inventor filed *US*4786995 under Peripheral Technology Inc.; and *US*4786995 is also the first patent by this firm. Hence, Peripheral Technology Inc. is classified as a spinout entrant.[12]

Discussion and the validation exercises The identification of spinout firms using patents and inventors data offers several advantages as well as has certain limitations. In terms of advantages, first, theory in this paper focuses on innovating firms that drive technological progress in the economy; and patents have been widely used in the literature as the main

[9] NPDP project provides the linking procedure between patent data and the Compustat database.

[10] 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.

[11] I discard the inventor mobility cases if they occur because of mergers or acquisitions and between subsidiaries of the same firm. *Dynass* file from NPDP database helps to identify these types of reorganizations.

[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.

systematic data on innovation across firms and over time (Griliches, 1981; Hall et al., 2007; Kogan et al., 2017; Argente et al., 2020). Hence, the analysis of the large dataset on the universe of patenting firms and identification of spinout firms within these innovating firms maps the data well to the model. 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.

On the other hand, there are several reasons for why identification of spinouts using inventors' mobility could mismeasure true number of spinouts, even within innovating firms. First, an inventor who moves to the new firm may not formally be an owner of the spinout firm. However, to the extent that the first inventors in a new firm define the technological abilities and innovation direction of a firm, this approximates well our model where mobility happens via R&D workers. In this sense, our empirical definition of spinouts is broader than the definition of spinouts just based on owners of the firms and in addition entails the founding team of early inventors in the firm. This approach is similar to Choi et al. (2019) which shows that not just founders but initial employees at the firm play a crucial role in determining firm's future success. Second, this definition would miss the spinouts established through the mobility of non-inventor employees, which might be an important channel of knowledge transfer as well. However, through the lens of the model, mobility and knowledge diffusion occur through the moves of R&D workers, and the data on inventors should capture well these moves.

Nevertheless, it is useful to provide certain benchmark and assess our identification of spinouts relative to that benchmark. For that, I provide two layers of validation. The first validation exercise is to compare my definition of spinouts with the external sources defining spinout firms. Franco and Filson (2006) analyze rigid disk drive industry and using detailed industry reports, obtain the history of all entrants in 1977-1993. The authors identify and list the names of 40 spinout entrants, their founding year, life span, and the names of their parents. Among these, for 76% (19 firms) of innovating spinouts that match to the USPTO data (the total of 25 firms), my data confirms the firms' spinout type. In addition, the non-matches mainly come from the spinouts established in the early years of the sample, which because of the left truncation in my sample, do not allow me to accurately define firm type.[13]

Second, the main data moments and stylized facts that emerge from this data on innovating firms are very consistent with the existing studies in the literature (described in details in the literature review). For example, the share of spinout entrants among all en-

[13]As expected, firms' entry years in my sample are lagging compared to true founding years on average by 1.3 years.

Table 1: Summary Statistics

Patent data	Spinout Entrants	Regular Entrants	Incumbents
Number of firms	17295	46888	11452
Years in sample	4.28	3.69	23.07
Number of spinouts spawned	0.29	0.14	0.82
Number of parents	1.22	.	.
Lifetime number of patents	11.09	4.55	67.77
Lifetime number of cit-weighted	199.85	77.11	950.64
Patent + Compustat data			
Number of firms	777	2229	2249
Years in sample	9.70	9.19	29.82
Number of spinouts spawned	0.91	0.41	2.25
Number of parents	1.36	.	.
Lifetime number of patents	79.39	28.58	244.32
Lifetime number of cit-weighted patents	1618.07	585.40	3605.18
Sales(yearly)	919.65	938.10	3283.89
Sales growth (yearly)	23.62%	17.95%	10.13%
Employees (yearly)	3.77	3.61	12.34
Assets(yearly)	1219.56	1569.49	4361.11
R&D Expenditure (yearly)	61.12	47.76	108.46

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.

trants in my sample is 24.8%[14], which is in the range of other studies in the literature. Likewise, the facts on the superior performance of spinouts, knowledge inheritance, and spinout separation probabilities are also supported by the existing patterns from other data sources. These studies are discussed in Section 1, while Sections 2.2 and 5 describe these empirical facts in details. Taking all together, these validations assure that the data on patenting firms and inventors' mobility presents a good laboratory to analyze the innovating spinout dynamics and to discipline the theoretical model.

Summary statistics Table 1 provides summary statistics of the data. During years 1981-1999, we observe 64,183 entrant firms with the average longevity of 3.8 years and on average 6.3 patents and 110 citations-weighted patents.[15] Among these entrants, 17,295 firms are spinouts. Spinout and regular entrants account for nearly equal share of patents in 1981-2006 – for 16% and 17% of the total patent filings by all firms, respectively. The comparison of the share of spinouts and regular entrants with their respective patenting shares already

[14]Using the spinout definition not restricting to the 5-year gap between inventor's last year in the parent firm and the entry year of the spinout results in 32.0% of entrants

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

hints to the superior patenting activity of the spinout firms compared to regular entrants. Patents-Compustat data match reduces the sample size, but the share of spinout firms remains similar. Spinout firms are also larger and spend more on R&D, on average.

2.2 Motivating Empirical Facts

Two main building blocks of the model are empirically motivated here. First, I document that firm quality is significantly higher if it enters as a spinout; and second, spinout's quality is even higher if it is spawned from a firm with a bigger technological lead.

Spinouts vs Regular Entrants

I start the analysis by documenting substantial differences in outcomes of entrant firms depending on prior experience of their founders. Table 2 compares lifetime outcome variables for spinouts and regular firms. Panel A is based solely on the patent data sample, while Panel B considers the sample of firms that also appear in Compustat. As seen, conditional on being in the same cohort, operating in the same technology class and the state, spinout firms file 46% ($= exp(0.376)$) 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. A better performance of spinout firms is also reflected in the Compustat data. Spinout firms that become publicly traded are more R&D-intensive and have on average 3.4 percentage points higher sales growth than regular firms that are publicly traded. In addition, their R&D spending is more efficient as measured by the citations-weighted patents and the number of top patents per R&D dollar spent.

Overall, these findings indicate that firms established as spinouts from other innovating firms are more productive and 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.).

Spinouts Quality and Parent's Technology Lead

Next, I document that within spinout firms, the characteristics of parent firms matter for the quality of spinouts. Figure 2 compares spinouts spawned from parents with different technological leads. First, I 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 2 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-

	Log Patents	Log Cit-Patents	Log Top Patents	Log Lifespan
Spinout entrant	0.384***	0.511***	0.187***	0.131***
	(0.009)	(0.013)	(0.009)	(0.005)
Cohort FE	YES	YES	YES	YES
Tech class FE	YES	YES	YES	YES
State FE	YES	YES	YES	YES
Observations	64176	61303	64176	64176
Mean	0.752	3.111	0.198	0.812

-Panel B. Compustat + Patent Data-

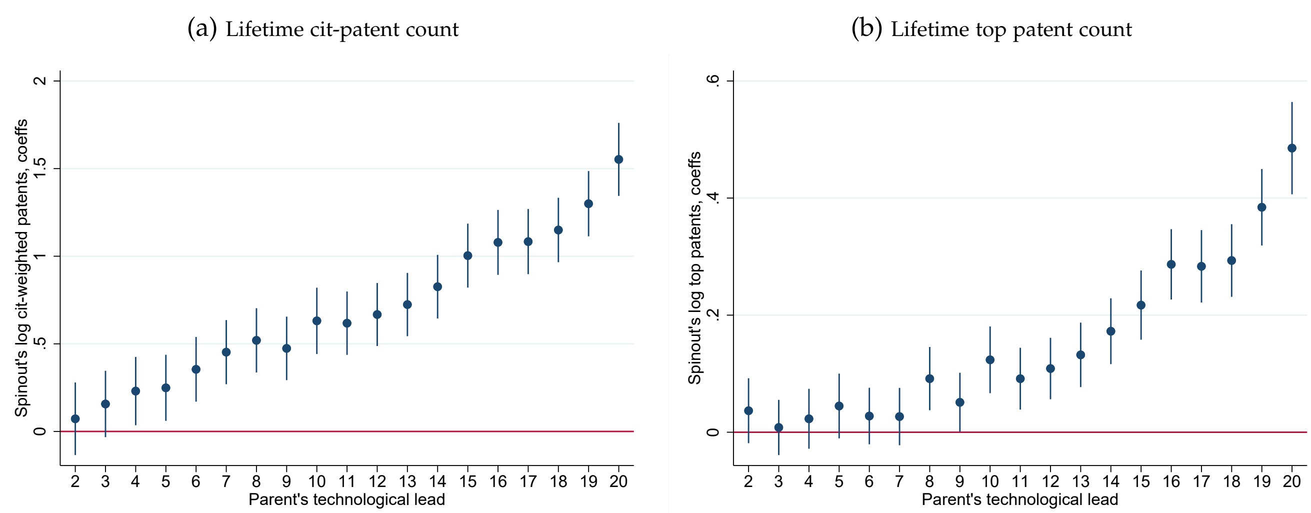
	log R&D/Empl	Mean growth	Cit-Patent/R&D	Top patent/R&D
Spinout entrant	0.155***	0.0461***	176.9***	1.141***
	(0.051)	(0.014)	(39.08)	(0.272)
Cohort FE	YES	YES	YES	YES
Tech class FE	YES	YES	YES	YES
State FE	YES	YES	YES	YES
Observations	2269	2609	2316	2316
Mean	3.135	0.247	162.64	1.035

Note: The table compares spinout and regular entrants along various outcome variables in different columns. Each observation corresponds to a firm that enters in the data in 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 period, respectively. Top patents are defined as the patents whose truncation-adjusted citations are above the 90th percentile of the citations 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.

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).[16] 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.

Figure 2: 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 5 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.

[16]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).

3 Model

Overview— To understand the role of spinouts for innovation and firm dynamics, I 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, I 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' entrepreneurial choices.

Two main 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 heterogeneity motivates me to introduce heterogeneous firm-specific quality types 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.

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. Entrepreneurs, heterogeneous in their quality types, decide on innovation efforts that push the technology frontier forward. By innovating, they acquire technological leadership and market power. R&D managers collect wages and while being on the job, can search for ideas and outside opportunities to create their own spinout firms. Importantly, R&D managers learn on the job – more technologically advanced is their employer, higher are the chances that their start-up quality is of a better type. The model also introduces a parameter for NCL that affects the cost of establishing a spinout firm. 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 in the U.S.

3.1 Preferences and Final Good Technology

Time is continuous. The representative household consists of a measure L of unskilled and $2 + S$ measure of skilled people and has logarithmic preference over consumption good C_t. 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 and $\mathcal{W}_t$ is the total wage bill.

Final good is produced 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.

Market for final good production is perfectly competitive, and the final good price is the numeraire. 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 the only active producer is firm i. Furthermore, this leading firm sets a price equal to the marginal cost of a follower, such that[17]

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

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

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

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 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 in order to increase profits. This, in turn, can be achieved through costly research and development (R&D). Next section describes this process of R&D.

3.3 Firm Heterogeneity and the Productivity Dynamics

To advance their current level of productivity, intermediate good firms[18] need to invest in R&D. Firms are heterogeneous in their R&D efficiency. Each firm has a permanent *quality 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.

R&D process requires hiring an R&D manager and spending resources proportional to the intensity of innovation chosen. In particular, to generate z Poisson arrival rate of innovation, firm needs to pay the following

$$\text{R\&D cost} = w^s(j,t) + \frac{z^\gamma(j,t)}{\gamma B^\tau} Y_t \tag{6}$$

where first part, $w^s(j,t)$, is a fixed cost – wage bill for the R&D manager. The second part of the cost is a variable cost that increases and is convex in the chosen intensity of innovation arrival rate z ($\gamma > 1$). $B^H > B^L$ and shows that high-type firms are more productive at research than low-type firms. In other words, high-type firms are more likely to upgrade their productivity, for the same amount of resources spent.

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 competitive fringe, and it is convenient to index productivity improvements relative to their productivity. Say, the productivity of a competitive fringe in product line j is $q_{-i}(j,t) = \lambda^{n_{-ij}} q_0$, and the productivity of an incumbent is $q_i(j,t) = \lambda^{n_{ij}} q_0$, where q_0 is some initial level of productivity. Then denote the number of step improvements made by the incumbent relative to the competitive fringe in its product line by $n_j(t) \equiv n_{ij}(t) - n_{-ij}(t)$, which we refer to as product line j's *technology gap*. This

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

technology gap will be endogenously evolving as a result of entry, and 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 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.[19]

3.4 The Allocation of Skilled Labor

This section describes the allocation of skilled labor in the economy and an optimization problem of each type of labor separately. At any point in time, a constant measure of skilled people in the economy is allocated into three groups:

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

The measures of entrepreneurs and of R&D managers are equal to one each: there is measure one of product lines in the economy, and each producing (leader) firm is associated with one entrepreneur and hires one R&D manager. In addition, measure S of outsiders can enter as R&D managers or try to become entrepreneurs.

Denote by $V_t^{firm}(n,\tau)$ a discounted present value of entrepreneur (incumbent firm) who possesses a technology gap n and has a permanent quality type τ. Entrepreneurs (firms) decide on investment in R&D and hiring unskilled labor. Denote by $V_t^{manager}(n,\tau)$ the value of an R&D manager who works for a firm with (n,τ) characteristics. R&D managers collect wages and decide on separation rate – *spinout entry*. As will be clear below, $V_t^{manager}(n,\tau)$ depends on the characteristics of the employee firm for two reasons: because of the differences in wages and because of the differences in the probabilities of high-type spinout formation. Finally, denote the value of being an outsider by V_t^{out}. Outsiders can start a job as R&D managers or they can 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. Hence, we will normalize all values by Y_t and denote the normalized values by their respective lower-case letters (e.g., $v^{firm}(n,\tau) = \frac{V_t^{firm}(n,\tau)}{Y_t}$). Hence, the time subscript t is dropped where it does not cause a confusion. Next sections separately describe in details the problems of each group

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

of skilled people.

3.4.1 Outsiders

An outsider faces two options – either to attempt to start an entrepreneurial venture or to become an R&D manager. Denote the value of entrepreneurial entry by v^{entry} and the value of entry to the labor market as v^{work}. Then,

$$v^{out} = \max\{v^{entry}, v^{work}\} \tag{8}$$

To become an entrepreneur, the outsider has to successfully implement an idea. Success is uncertain. Paying cost $\frac{e\nu^2}{2}$ ensures Poisson arrival rate of idea ν. If the idea is implemented successfully, the entrepreneur enters into a random product line and improves existing technology level in that product line by λ. As a result, the entering firm creatively destroys the existing incumbent and starts production with the minimal technology gap of $n = 1$.[20] Upon entry, the entrepreneur draws a permanent type of its firm τ: probability of drawing a high type H equals to $\tilde{\mu}$. If the idea is not successfully implemented, outsider remains in the group of outside skilled people. Using the standard Euler equation derived from household optimization, $g = r - \rho$, we can write the Bellman equation for the value of entry in the following way:[21]

$$\rho v^{entry} = \max_{\nu \geq 0} \left(-\frac{e\nu^2}{2} + \nu(\tilde{\mu} v^{firm}(1, H) + (1 - \tilde{\mu}) v^{firm}(1, L) - v^{entry}) \right) \tag{9}$$

The flow value of entry consists of the following terms on the right-hand side. First, an entrant incurs instantaneous cost of developing an idea (first term on the right-hand side). Next, upon a successful entry with probability ν, the entrant gets an expected value of holding a product line, where expectation is taken over the firm's type τ. If firm is not successful at entry, it retains its value of v^{entry}. Hence, the incremental value is the term in the brackets. ν is chosen to maximize the total value. Denote aggregate entry from outsiders by I^o:

$$I^o = S\nu \tag{10}$$

Next, consider the value of becoming an R&D manager. First, as will become clear below, the only new demand for R&D managers in this economy comes from firms with a technology gap $n = 1$: these are either the newly-created firms – regular entrants established by outsiders or spinout entrants, or existing firms losing their R&D managers who spawned spinouts. Second, I assume that outsiders find jobs instantaneously and are ran-

[20] Since the previous incumbent turns into a competitive fringe, the new gap relative to the previous technology is 1.

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

domly matched to the firms demanding R&D managers. As a result, if we denote by α the (endogenously determined) share of firms demanding R&D managers who are of type H, we can express v^{work} as following:[22]

$$v^{work} = \alpha v^{manager}(1, H) + (1 - \alpha) v^{manager}(1, L) \tag{11}$$

In equilibrium, outsiders have to be indifferent between the two options open to them. As a result, from equation (8) we get:

$$v^{out} = v^{entry} = v^{work} \tag{12}$$

3.4.2 R&D Managers and Spinout Entry

An R&D manager who works in a firm with (n, τ) characteristics earns wage $w(n, \tau)$. While on the job, the manager can search for outside opportunities to create her own start-up – a spinout firm.[23] For that, she chooses a separation rate $a(n, \tau)$, where $a(n, \tau)$ can also be zero, indicating that the worker chooses not to separate. The separation effort is costly and it costs $\frac{ka(n,\tau)^2}{2}$ in terms of final output. One can think of this cost as the time or monetary cost necessary to develop an idea and implement it into a new start-up.

If separation effort is successful, a new spinout firm is created. It enters into a random product line, improves upon the existing level of the productivity by λ, and hence replaces the incumbent in that product line. Because there is a continuum of product lines, the probability of spinout landing on the product line of her former employee is zero. In this sense, the new spinout firm will not directly threat the former employer by replacing it. However, once the R&D manager leaves, the employer loses part of its current value, and its technological lead diminishes from n to 1. One way to think about this structure is to think of new technologies as being largely embedded in the human capital of a firm; once the main part of the firm's human capital – the R&D manager, leaves a firm, firm has to rebuild its technological advantage from scratch. Alternatively, one could model competitive threat from spinouts by assuming spinouts replace parents in their product lines. However, this creative destruction of a parent would be an extreme assumption not well-supported by the data. First, evidence shows that many spinout firms do not directly compete in the same narrow technologies as their parents (Chatterji, 2009). Second, although existing work shows that spinouts often outperform their parents and harm their performance (Wezel et al., 2006; Campbell et al., 2012), this process does not usually result in instantaneous exit of the parent firms. Hence, a more appropriate intermediate approach is to model this

[22] Note that once matched with a firm, the manager does not have an incentive to destroy the match by joining the pool of outsiders and searching again. Section 3.5 shows that this is not optimal since the value of being an outsider is not higher than the lowest value that an R&D manager can get.

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

negative effect on parents as a gradual process where parent firm loses its technology gaps upon spinout entry.

When a new spinout is created, it incurs costs associated with non-compete restrictions. In particular, a spinout pays the fixed cost $F \geq 0$ (in terms of final output) which depends on the strength of the existing non-compete laws.[24] In reality, there is a wide range of legal outcomes that founders of spinout firms may face (Garmaise, 2011): in some cases, spinouts would have to pay the fees, in others they may need to shut down the operations completely, and in others they may not incur any legal costs. In the model, one can think of the parameter F representing an average of all these possibilities.

New spinouts may have successful ideas and enter the market with a high quality type $\tau = H$. Alternatively, they draw quality type $\tau = L$. As in the data, the probability of drawing high type depends on the firm an R&D manager works for: better spinout ideas are generated in technologically leading firms. Formally, a spinout draws a type $\tau = H$ with probability $\mu(n)$, where $\mu(n') > \mu(n)$ if $n' > n$. Hence, the model features a type of spinout-parent knowledge inheritance: over time, as employers acquire higher technological leadership, workers' entrepreneurial ventures are more successful. This inheritance can come through the direct learning of technical knowledge or through a non-technical experience that helps to identify high-quality ideas and knowing how to successfully bring them to the market. This channel resembles the knowledge diffusion channels emphasized in recent literature (Lucas and Moll, 2014; Perla and Tonetti, 2014), but in the current model, spinout firms do not replicate the ideas of their parents but rather diffuse knowledge by creating new high-quality start-ups.

As a result of workers' separation decisions, each firm in the economy faces the probability of creative destruction from spinouts separating from other product lines. Denote this aggregate spinout entry rate by I^s. We are now ready to write down the value of an R&D manager who works at (n, τ) firm as follows:

$$\rho v^{manager}(n,\tau) = \max_{a(n,\tau)\geq 0} \left\{ \begin{aligned} &\omega(n,\tau) - \frac{ka^2(n,\tau)}{2} \\ &+ a(n,\tau)[\mu(n)v^{firm}(1,H) + (1-\mu(n))v^{firm}(1,L) - F - v^{manager}(n,\tau)] \\ &+ (I^s + I^o)[v^{out} - v^{manager}(n,\tau)] \\ &+ z(n,\tau)[v^{manager}(n+1,\tau) - v^{manager}(n,\tau)] \end{aligned} \right\} \tag{13}$$

This continuous-time value function can be interpreted as following. The left-hand side is the flow value of an R&D manager at (n, τ) firm. The right-hand side includes the components that make up this value. The first line is instantaneous wage bill (where $\omega(n, \tau) = w(n, \tau)/Y$) less the separation cost. The second line shows the change in the

[24] In Section **??**, F will also vary with the employer firm's technology gap.

worker's value when the separation is successful at the rate $a(n, \tau)$. In particular, this change is equal to the expected value of a new start-up less the legal costs associated with non-compete restrictions minus the current value. The third line shows a change in the worker's value if the employer firm is replaced by an entrant (spinout or outside entrant). This happens at rate $I^s + I^o$. In such a case, employer firm exits the market, and the R&D manager joins the pool of outsiders in the economy. Finally, the last term indicates the possibility of the employer's innovation. If this innovation is successful at the rate $z(n, \tau)$, employer advances one step ahead and the worker's value changes to $v^{manager}(n+1, \tau)$. The first-order condition of the problem implies:

$$a(n, \tau) = \max\left\{0, \frac{\mu(n)v^{firm}(1, H) + (1-\mu(n))v^{firm}(1, L) - F - v^{manager}(n, \tau)}{k}\right\} \tag{14}$$

This condition indicates that on the one hand, R&D manager has an incentive to separate if the probability of drawing the high type $\mu(n)$ is high. On the other hand, the R&D manager faces the opportunity cost of separation: if she waits, she has an opportunity to learn more on the job and increase the future probability of a better spinout ($v^{manager}(n+1, \tau) - v^{manager}(n, \tau)$ term in equation (13)).[25] Hence, the choice to separate crucially depends on the shape of the learning schedule $\{\mu(n)\}_n$. Finally, all else equal, more stringent non-compete restrictions (higher F) reduce workers' incentives to separate.

3.4.3 Entrepreneurs

An entrepreneur who runs an incumbent firm with (n, τ) characteristics gets the following value. She collects instantaneous profits from production, pays the R&D manager, and incurs variable R&D cost. Successful innovation at rate $z(n, \tau)$ increases firm's value one step ahead on a technological ladder to $v^{firm}(n+1, \tau)$. At the rate $I^s + I^o$, entrants hit the incumbent's product line replacing it and forcing the entrepreneur to join the pool of outsiders. Finally, the R&D manager may successfully leave the firm by creating a spinout. As described above, this destroys the firm-R&D manager match and brings down the incumbent's technological lead to $n = 1$. All these cases are reflected in the following specification for entrepreneur's value:

$$\rho v^{firm}(n, \tau) = \max_{z(n,\tau)\geq 0} \left\{ \begin{array}{l} \pi(n) - \omega(n, \tau) - \dfrac{z(n, \tau)^\gamma}{\gamma B^\tau} + z(n, \tau)(v^{firm}(n+1, \tau) - v^{firm}(n, \tau)) \\ + (I^s + I^o)(v^{out} - v^{firm}(n, \tau)) + a(n, \tau)(v^{firm}(1, \tau) - v^{firm}(n, \tau)) \end{array} \right\} \tag{15}$$

[25] In addition, by staying with he firm, her wages will also increase if firm innovates: as we will see, $\omega(n+1, \tau) - \omega(n, \tau) > 0$.

where $\pi(n) = 1 - \lambda^{-n}$ is the normalized flow profit (equation (7)). The first-order condition of the entrepreneur's maximization problem gives:

$$z(n,\tau) = \max\{0, B^{\tau\frac{1}{\gamma-1}}(v^{firm}(n+1,\tau) - v^{firm}(n,\tau))^{\frac{1}{\gamma-1}}\} \tag{16}$$

This condition states that innovation incentives depend on the incremental value that an entrepreneur can get from advancing one step ahead. H-type entrepreneurs invest in innovation and grow more, as reflected by positive dependence on B^{τ}. In addition, the future spinout possibility reduces the firm's value and decreases innovation incentives, similar to the standard R&D investment appropriability problem.

3.5 Wage Determination and the Summary of the Dynamics

In this section, I describe how the wages $\omega(n,\tau)$ are set and summarize the dynamics between the firm and the R&D manager. The wage rate is determined by Nash bargaining. At the beginning of each period, an R&D manager and an entrepreneur bargain over the wages. If both agree on the wage, firm and R&D manager collaborate and get the values $v^{firm}(n,\tau)$ and $v^{manager}(n,\tau)$, respectively. If they disagree, the manager can walk away and get an outside value of v^{out}, while the firm loses its match-specific productivity and its technology gap diminishes to 1 (similar to the case of spinout separation), so entrepreneur gets the value of $v^{firm}(1,\tau)$. Linear sharing rule prescribed by Nash bargaining implies:

$$\beta(v^{firm}(n,\tau) - v^{firm}(1,\tau)) = (1-\beta)(v^{manager}(n,\tau) - v^{out}) \tag{17}$$

where β denotes R&D manager's bargaining weight. Or, in other words, an R&D manager gets a β share of the joint net surplus.

Notice that equation (17) for $n = 1$ implies that

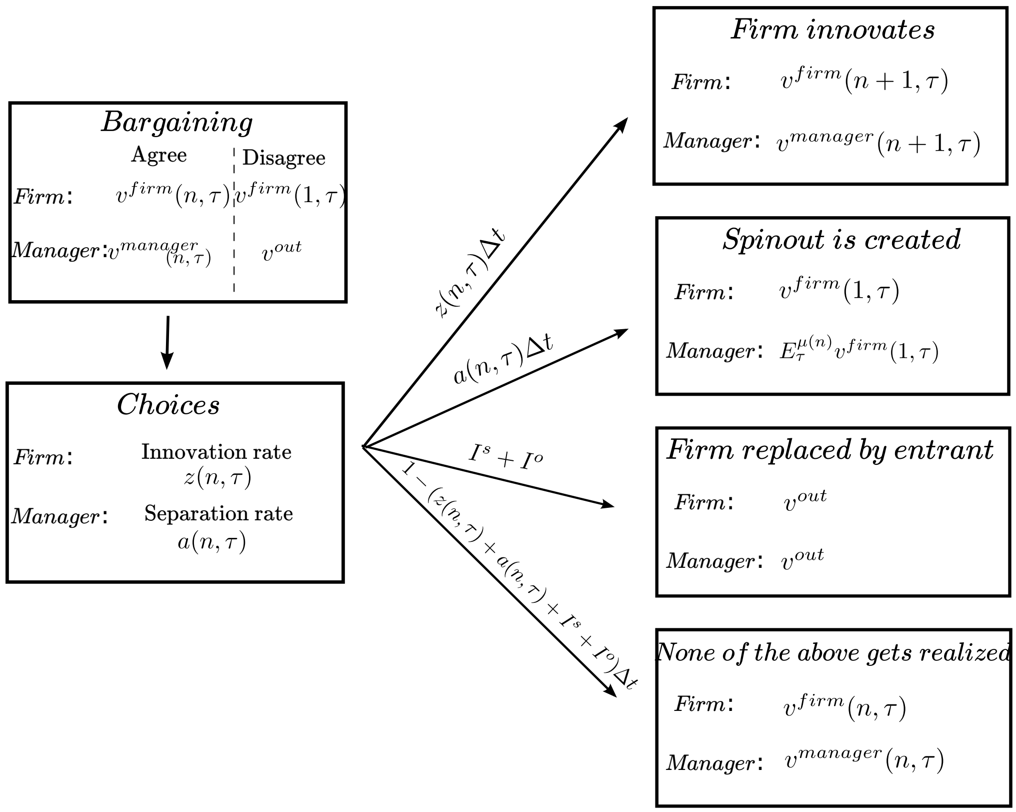
$$v^{manager}(1,H) = v^{manager}(1,L) = v^{out} \tag{18}$$

This ensures that the R&D manager who ends up working in a L-type firm will not have an incentive to search again to land a job in a H-type firm. Notice also that in expectation H-type firms offer higher learning opportunities to their managers – since high-type firms are more likely to increase their technological lead, R&D managers working in the high-type firms are more likely to get high-quality draws for their potential entrepreneurial ventures. This implies that in order for (18) to hold, low-type firms have to pay higher wages. Hence, in this model R&D managers pay for the possibility to move up the technological ladder with an employer.[26] We will come back to this point in Section 5.

[26]This implication is similar to the results from the models where workers pay for on-the-job training in the firms Acemoglu (1997).

The summary of the dynamics between a firm and its R&D manager is illustrated in the diagram in Figure 4. In the beginning of a period, manager and the firm bargain. The manager and the firm negotiate over the wage but not over the worker's separation intensity that is unobservable to the firm. After the agreement, worker may still find it profitable to choose a positive separation intensity $a(n,\tau)$. Hence, the next step within the time interval t is for the firm to choose the innovation rate $z(n,\tau)$ and for the R&D manager to choose the separation rate $a(n,\tau)$.

Figure 3: Summary of the Dynamics between a Firm and its R&D manager



Within a small time interval Δt, the following scenarios may get realized. First, with probability $z(n,\tau)\Delta t$, the firm advances one step ahead and gets the value of $v^{firm}(n+1,\tau)$, while the manager gets $v^{manager}(n+1,\tau)$. Second, with probability $a(n,\tau)\Delta t$, in period $t+\Delta t$ worker separates, pays the cost of separation and gets expected value of the spinout entry – $\mu(n)v^{firm}(1,H) + (1-\mu(n))v^{firm}(1,L)$ that is denoted on the diagram as $E_\tau^{\mu_n} v^{firm}(1,\tau)$. In this case, the firm gets $v^{firm}(1,\tau)$. Third, the incumbent firm may get replaced by an entrant that improves upon its technology. In this case, both the entrepreneur and its R&D manager get the exit values of v^{out}. Because time is continuous, probability of two or more of these events being realized at the same time is zero. As a result, the remaining possibility is for none of the scenarios to get realized. In such a case, both the manager and the firm continue getting same values in state (n,τ).

3.6 The Stationary Distribution

As a result of entry, exit, and the innovation process, firms move up and down the technology ladder. Denote by $\xi(n,\tau)$ the measure of firms that currently possess a technology gap of n and are of τ-type. In the stationary equilibrium, although individual firms enter, exit and constantly change their position in the technology space, the overall measure of firms in different states stays the same. This implies that the inflow and outflow into and from each state should balance each other.

In particular, for all $n \geq 2$, the following should hold:

$$\xi(n-1,\tau)z(n-1,\tau) = \xi(n,\tau)(a(n,\tau) + I^s + I^o + z(n,\tau)) \tag{19}$$

The left-hand side of the equation (19) represents inflow into (n,τ) state. This only comes from the successful innovation efforts of firms that are one step behind at $n-1$ and are of type τ. The right-hand side of the equation is the outflow from (n,τ) state. It can happen for three reasons: if spinouts separate from (n,τ)-firms, if (n,τ)-firms are replaced through creative destruction by entrants – at rate $I^s + I^o$, or if firms in (n,τ) state successfully innovate and advance ahead.

The entry into state with $n = 1$ is different. The left-hand side of Equation 20 shows the inflow into $(1,H)$ state. The first term comes from the spinout separation from all firms taking into account that only μ fraction of spinouts draw high-quality ideas and create H-type firms. The second term stands for the entry of firms that were high-type, had a technology gap n but because of spinout separation lost their technological advantage to $n = 1$. Finally, the third term comes from the outside entry with I^o intensity; fraction $\tilde{\mu}$ of them draw type H. The right-hand side of the (20) is similar to the description of outflow in equation (19): outflow happens because of spinout separation, creative destruction, or successful innovation by incumbents.

$$\sum_{n,\tau}\xi(n,\tau)a(n,\tau)\mu(n) + \sum_{n}\xi(n,H)a(n,H) + I^o\tilde{\mu} = \xi(1,H)(a(1,H) + I^s + I^o + z(1,H)) \tag{20}$$

Similar logic applies to the case with $\tau = L$:

$$\sum_{n,\tau}\xi(n,\tau)a(n,\tau)(1-\mu(n)) + \sum_{n}\xi(n,L)a(n,L) + I^o(1-\tilde{\mu}) = \xi(1,L)(a(1,L) + I^s + I^o + z(1,L)) \tag{21}$$

3.7 The Steady State Equilibrium

Before summarizing the steady state equilibrium, let us lay out final components of the equilibrium. Aggregate spinout entry rate comes from the separation efforts by R&D managers in all firms in the economy and is equal to

$$I^s = \sum_{n,\tau} \xi(n,\tau) a(n,\tau). \tag{22}$$

Labor Market. The labor allocation for skilled people has been already described; it is clear that by construction it is always balanced.[27] 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

$$l_j = \frac{1}{\omega^u} \lambda^{-n_j} \tag{23}$$

This implies the following market clearing condition:

$$L = \sum_{\tau,n} \frac{\xi(\tau,n)}{\lambda^n \omega^u}. \tag{24}$$

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*

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

such that

(i) $v^{firm}(n,\tau)$, $v^{manager}(n,\tau)$ *satisfy equations (13) and (15);*

(ii) v^{out}, v^{work}, *and* v^{entry} *are given by equations (8), (9), and (12);*

(iii) $a(n,\tau)$ *and* $z(n,\tau)$ *satisfy first-order conditions (14) and (16);*

(iv) *Entry rate by outsiders,* I^o, *satisfies equation (10), where* ν *maximizes (9);*

(v) *Spinout entry rate* I^s *is given by equation (22);*

(vi) *Wages of R&D managers satisfy equations (11), (12), (17), and (18);*

[27] At each point in time, if a firm is replaced by a regular entrant, two skilled people (an entrepreneur and an R&D manager of an exiting firm) join outsiders' pool, and two skilled people exit the pool of outsiders (an entrepreneur and an R&D manager of an entering firm). Similar accounting holds for spinout entry. Hence, in the total pool of skilled people which is measure $2 + S$, measure one is always running a firm, another measure one is always employed as R&D manager, and measure S is in the outsider's pool.

(vii) *Wage of unskilled labor clears labor market in (24);*

(viii) *Stationary distribution $\xi(n,\tau)$ satisfies (19), (20), and (21);*

(ix) *Aggregate growth rate is given by equation (25);*

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

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

$$g = \ln \lambda (I^s + I^o + \sum_{n,\tau} \xi(n,\tau) z(n,\tau)). \tag{25}$$

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. All these innovations increase aggregate productivity by λ.

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 standard appropriability problem. 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*: higher spinout entry shifts the composition of firms towards lower technology gaps hence promoting more competition and as a result aggregate innovation efforts.

3.8 Welfare

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

$$\text{Welfare}(0) = \int_0^\infty e^{-\rho t} lnC_t dt, \tag{26}$$

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 into developing new ideas to enter as entrepreneurs; 2) R&D managers invest into 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:

$$I = \frac{ev^2}{2}S + \sum_{n,\tau} \frac{ka^2(n,\tau)}{2}\xi(n,\tau) + \sum_{n,\tau} \xi(n,\tau)a(n,\tau)F + \sum_{n,\tau} \frac{z(n,\tau)^\gamma}{\gamma B^\tau}\xi(n,\tau) \tag{27}$$

As a result, we can write the aggregate consumption as $C = (1 - I)Y$ and rewrite equation (26) 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):

$$\text{Welfare}(0) = \frac{\ln Q(0) - \ln \lambda \sum_{n,\tau} n\xi(n,\tau) - \ln \omega^u}{\rho} + \frac{g}{\rho^2} + \frac{\ln(1 - I)}{\rho} \tag{28}$$

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 (28)). 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 (28).

4 Quantitative Analysis

This section takes the model to the data. First, I lay out the model solution algorithm and describe the calibration. Next, I characterize the model fit and explore quantitative properties of the model. Finally, I quantitatively analyze the role of various policies in promoting aggregate innovation and growth.

4.1 Calibration

This section describes the calibration of structural parameters of the model. The model has the following parameters: $\rho, \lambda, \gamma, \beta, \tilde{\mu}, \{\mu_n\}_{n=1}^N, B^H, B^L, L, S, e, F, \kappa$. The calibration proceeds in two steps. First, a set of parameters is fixed externally based on estimates from the literature or estimated directly from the data. Second, the remaining set of parameters is calibrated internally by minimizing the distance between important empirical moments and the corresponding moments generated by the model.

The first panel of Table 3 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 empirically evaluated this elasticity. Following Acemoglu et al. (2018) who discuss this evidence in detail, I set $\gamma = 2$. In the benchmark calibration, I set β to 0.05 following Hagedorn and Manovskii (2008).

Table 3: Calibrated Parameters

Parameter	Meaning	Value
	Externally Calibrated Parameters (24)	
ρ	Discount rate	0.04
γ	R&D cost curvature	2
β	R&D manager's bargaining weight	0.05
$\{\mu_n\}_{n=1}^{N}$	Prob. of H-type spinout entry from firm n	Figure 4
$\tilde{\mu}$	Prob. of H-type outside entry	0.20
	Internally Calibrated Parameters (8)	
B^H, B^L	R&D cost efficiency	$2.74, 0.049$
L, S	Skill composition	$19, 0.60$
e	Entry cost parameter	6.07
F	NCL parameter	0.60
κ	Separation cost parameter	12.52
λ	Step size of innovation	1.08

Notes: The table reports the calibrated parameter values consistent with moments reported in Table 4.

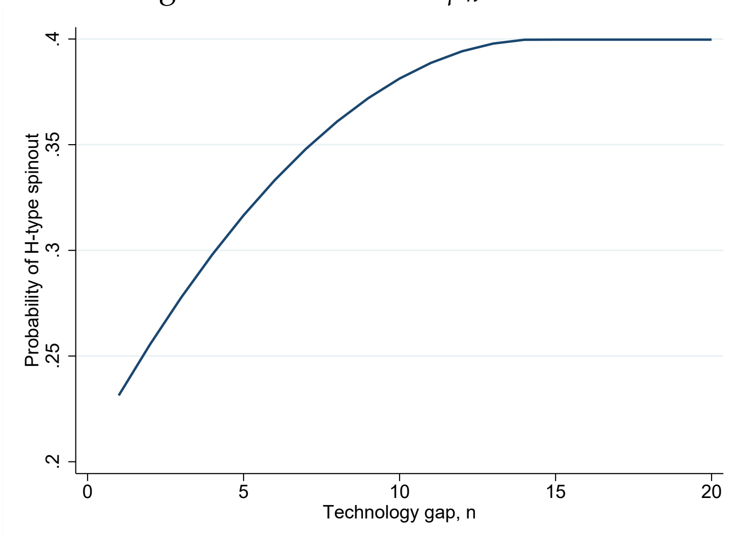
I estimate the probability of spinouts entering as high-type firms, $\{\mu_n\}_{n=1}^{N}$, directly from the data. Figure 2 already provides the first evidence on the positive relationship between the parent's technological lead and spinouts' performance. Here, I map the data closer to the primitives of the model. First, I define H-type and L-type firms in the data. In the model, firm's type is constant over time, and high-type firms are more innovative than their low-type competitors. As a result, I define a firm as H-type if it ranks in the top quartile based on its lifetime innovation output, proxied by the lifetime citations-adjusted patent count of the firm, residualized for firms' cohort and technology class fixed effects. Second, I proxy for n – technological gap of the firm. In the model, technology ladder has N equidistant innovation steps. The value of N, the maximum achievable technology gap, is set to 20.[28] In the data, I consider the patent quality distribution based on the citations-weighted patent counts in the last 5 years in the technology class of the firm, and split it into 20 equal intervals.

Finally, I estimate μ_n – the probability of spawning a H-type spinout from a firm with technology gap n, using the following regression specification:

$$Y_i = \beta_0 + \gamma_1 n + \gamma_2 n^2 + \boldsymbol{X_i \beta} + \varepsilon_i, \tag{29}$$

where Y_i is a dummy equal to one if a spinout i is H-type, and n is a technology gap of spinout's parent.[29] Other controls in $\boldsymbol{X_i}$ include log number of parents, parent's log number of patents in the last 5 years, as well as the cohort and technology class fixed effects. μ_n is then calculated as $\gamma_1 n + \gamma_2 n^2$ plus a constant equal to the average probability of H-type entry from a parent with $n = 1$. The resulting profile for μ_n is plotted in Figure 4. Similarly, I compute the share of regular entrants from the data that are H-type, resulting in $\tilde{\mu} = 0.20$.

Figure 4: Calibration: μ_n estimates



Notes: The figure reports the estimates for the μ_n parameters used in the model calibration. The estimates are based on equation (29). μ_n is then calculated as γ_n plus a constant equal to the average probability of H-type entry of a spinout from a parent with $n = 1$.

The second panel of Table 3 lists internally calibrated parameters. The parameter L can be directly pinned down from the data on labor force composition in the U.S. economy. The share of scientists and engineers in the total employment is about 5%.[30] This implies

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

[29]If the spinout has multiple parents, I take the maximum technology gap among them.

[30]"Individuals in Science and Engineering Occupations as a Percentage of All Occupations." National Science Foundation.

that $\frac{1}{1+L} = 0.05$, resulting in $L = 19$. The remaining seven parameters are calibrated jointly by matching a set of moments. Below, I provide heuristic discussion of the identification and of the role each moment plays in pinning down the model parameters.

Together with L, a parameter S is related to the skill composition in the economy. Hence, in addition to the labor force composition, I match the moment on relative compensation of production and R&D workers in the U.S. economy. Based on the data on average earnings in S&E occupations relative to all the U.S. workers, I match the ratio of the average high-skill wage to the average wage $\frac{\overline{w(n,\tau)}}{w^u \frac{L}{1+L} + \overline{w(n,\tau)} \frac{1}{1+L}}$ to 2.27.[31]

R&D cost parameters B^H and B^L affect both the overall level of R&D intensity by firms as well as innovation differences between high- and low-type firms. The firm-level R&D intensity, measured as R&D-to-sales ratio, in the model is $\omega(n,\tau) + \frac{z(n,\tau)^\gamma}{\gamma B^\tau}$. This value, averaged across all the firms in the economy is then matched to the average R&D spending per sales computed in the sample, which is 0.127.[32]Relative innovation by high- and low-type firms $\frac{\overline{z^H(n,\tau)}}{\overline{z^L(z,\tau)}}$ is mapped to the ratio of average innovation outputs by H-type and L-type firms in the data, proxied, as before, by the lifetime citations-adjusted patent count of the firm, residualized for firms' cohort and technology class fixed effects. This ratio in the data is 9.5. The step size of innovation λ affects how innovation translates into aggregate growth (equation (25)). I match the aggregate growth rate of 3.1%, which is the average growth of the U.S. GDP during the sample period.[33]

The remaining three parameters in the model will directly affect entry rates. Entry cost parameter e affects the outside entry rate. Similarly, k affects cost of separation and as a result the spinout entry, while F is a policy parameter that will impact the spinout entry rate across locations with different NCL policies. To pin down these parameters, I will target the outside and spinout entry rates in the data. Average entry rate in the economy during the sample period is 11%.[34] In my data, spinout entrants account for 28.9% of entry, leading to the average outside entry of $I^o = 7.8\%$ and spinout entry of $I^s = 3.2\%$. Finally, I target the spinout entry rate in the states with no NCL restrictions ($F = 0$) of 4.31%. Data on NCL restrictions across states come from Garmaise (2011) and are described in detail in the Appendix Section F.

The calibration procedure then is to search for the unknown parameters $\Theta \equiv [\lambda, B^H, B^L, L, S, e, F, \kappa]$ to minimize the distance between model-implied moment values m_i^{model} and data moments m^{data} described above. Specifically,

[31]OES Survey, Bureau of Labor Statistics. Science and Engineering Indicators, 2018.

[32]R&D data reported in Compustat often contains zeros. It is not necessarily clear that these missing values always represent zeros. I compute statistics under two alternative scenarios imputing all missing values with zeros and, alternatively, imputing zeros only if firm issues zero patents in recent 5 years and average the resulting values.

[33]Because of large outliers, both lifetime citations-adjusted patent count and R&D-to-sales ratio are winsorized at 1%-95% levels.

[34]Business Dynamics Statistics Dataset, U.S. Census Bureau.

Table 4: Moments: Model vs Data

Description	Data	Model
Growth rate	3.1%	3.08%
Average R&D intensity	0.127	0.096
Ratio of H- to L-type firm innovations	9.5	6.72
Wage ratio $\frac{\overline{w(n,\tau)}}{w^u}$	2.27	1.42
Percent of S&E in workforce	5%	5%
Average outside entry rate	7.8%	8.77%
Average spinout entry rate	3.2%	3.76%
Spinout entry rate with no NCL	4.31%	5.36%

Notes: The table reports data moments and corresponding model counterparts from the calibration exercise.

$$\Theta^* = argmin\Big[\sum_{i=1}^{8} \omega_i \Big(\frac{m_i^{model}(\theta) - m_i^{data}}{m_i^{data}}\Big)^2\Big]^{0.5},$$

where ω_i denotes moment-specific weight. I weight all the moments equally except for the moment on spinout entry that I overweight twice. Resulting estimates of the parameters are given in the second panel of Table 3, and the implied match to the data is illustrated in Table 4. Model does quite well in matching all the moments from the data.

5 Solution Properties and Model Validation

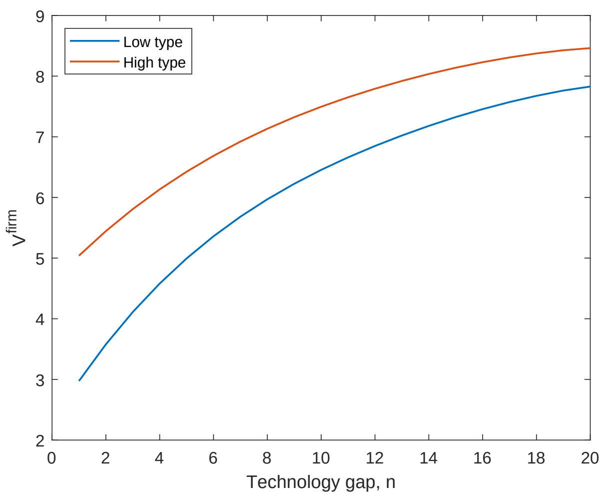
In this section, I discuss basic properties of the equilibrium solution and validate the model against non-targeted moments in the data.

Solution properties Figure 5 shows the value functions of the firm, R&D manager, and the wage rate of the R&D manager over the firm's technology gap.

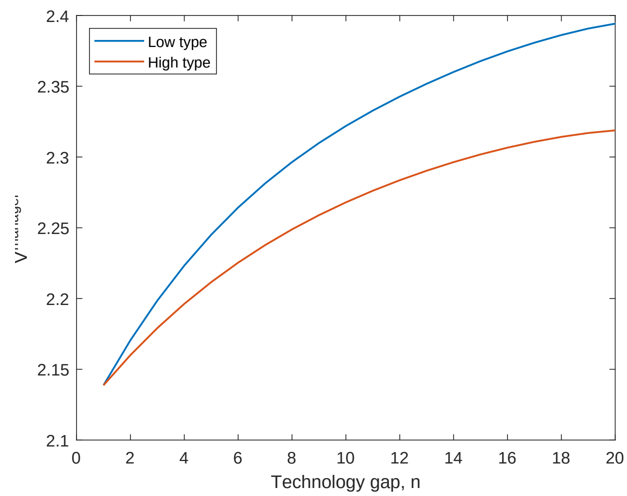
The value of a firm increases with technology gap, reflecting higher profits with higher n. At the same time, the value of an high-type firm is higher than the value of the low-type firm, since the high-type firms have higher probability to innovate and grow in the future. The value function of the R&D manager increases with technology gap, too. There are two reasons for this. First, when total surplus increases, because of bargaining, the share of surplus going to the R&D manager increases, too. However, importantly, there is another reason for higher wage growth. Recall that $\mu(n)$ – the probability of establishing a high-type firm if the R&D manager spawns a spinout, grows with the employer's technology gap. This increases the employee's surplus further. Unfortunately, my data do not contain information on R&D workers' wages, hence I cannot quantitatively validate the results. However, this increasing wage premium property is consistent with a large

Figure 5: Value Functions and R&D manager's Wages

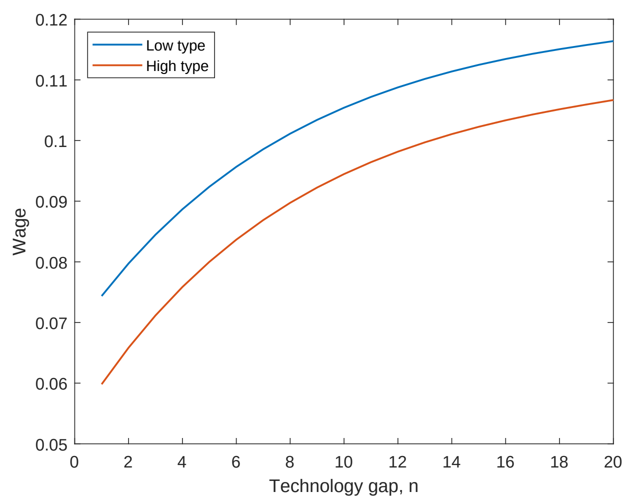
(a) Value function of the firm



(b) Value function of R&D manager



(c) Wages of R&D manager



Notes: Equilibrium solution of the model given the calibrated parameter values.

literature studying a large-firm wage premium (Brown and Medoff, 1989; Card et al., 2013; Song et al., 2019). In addition, Aghion et al. (2018) show that inventors earn more after the firm applies for a patent, especially a highly cited patent, getting closer to the relationship between higher technological leadership and R&D manager's wage documented here.

An interesting feature of the equilibrium wage function is that conditional on the technology gap wage in the low-type firm is higher than the wage in the high-type firm. Why is this the case? Conditional on n, R&D managers in the high-type firm are more likely to move up the technology ladder when firm innovates next period, hence increasing the probability of establishing a high-type spinout in the future. As a result, similar to the intuition from Acemoglu (1997), R&D managers pay for the possibility to move up the technological ladder with an employer. This result is also consistent with wage backloading documented by Moen (2005): the technical staff in RD-intensive firms take lower wages early in the career to pay for the knowledge they accumulate on the job. Lastly, it is worth noting that as seen from Appendix Figure 11, high-type firms reach the high levels of n more frequently than the low-type firms. As a result, since wages are growing with n, employees of high-type firms, on average (unconditional on n), would be more likely to obtain higher wages than the employees of low-type firms.

Next, I quantitatively compare the model-implied average innovation rate, R&D manager's separation rate, and firm size distribution with data. Appendix Figure 11 contains a more detailed description of these functions over technology gaps split by firm type.

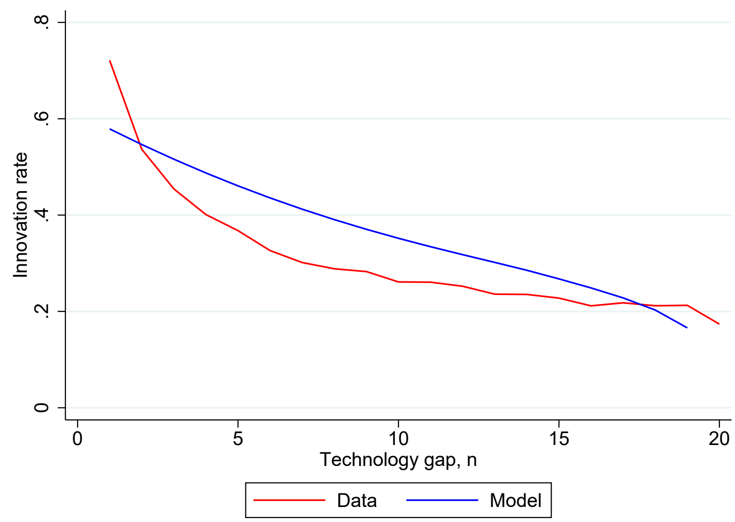
Innovation. Model and data. Figure 6 shows innovation rates of firms from the model and data. For the model, I plot $z(n, \tau)$ averaged over τ. In the data, I calculate the innovation rate of the firm as new citations-adjusted patents over the stock of firm's citations-adjusted patents and plot it over n as calculated in Section 4.1. We see that both in the model and the data, innovation rate declines with firm's technological leadership.[35] In the model, the decline in innovation rate is more gradual than in the data, but overall, the two profiles match well, especially given that the calibration procedure does not not match any moment related to the technology gaps.

Spinout separation. Model and data. Next, I examine the spinout separation rate in the model and the data. Since this function is an important and a new feature of this model, I start by presenting a detailed empirical analysis of spinout separation rate in the data.

Table 5 shows the relationship between spinout spawning and 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

[35] This is also consistent with empirical evidence from Akcigit and Kerr (2018) and Argente et al. (2020).

Figure 6: Innovation Rate. Model and Data



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. Since the regressions also include the count of patents, this indicates that spinouts are more likely to separate after the firms file higher-quality patents. 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.[36]

This finding on higher spinout separation in more technologically advanced firms is also consistent with earlier findings by Klepper and Sleeper (2005) and Franco and Filson (2006) from the rigid disk drive and laser industries. 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 my data focus on innovating firms who are in the very top of the productivity distribution in the economy, my evidence is also consistent with Engbom (2020).[37]

Consistent with the data, the model also generates a largely increasing relationship

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

[37] 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 I 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.

Table 5: Technological Leadership and Spinout Separation

-Panel A: Patent data

	(1) Logit	(2) FE Logit	(3) Neg. Binom	(4) FE Neg. Binom
Log cit-patents (parent)	0.141***	0.155***	0.139***	0.145***
	(0.0123)	(0.0337)	(0.0115)	(0.0299)
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	179313	50292	179547	50606

-Panel B: Patent + Compustat data

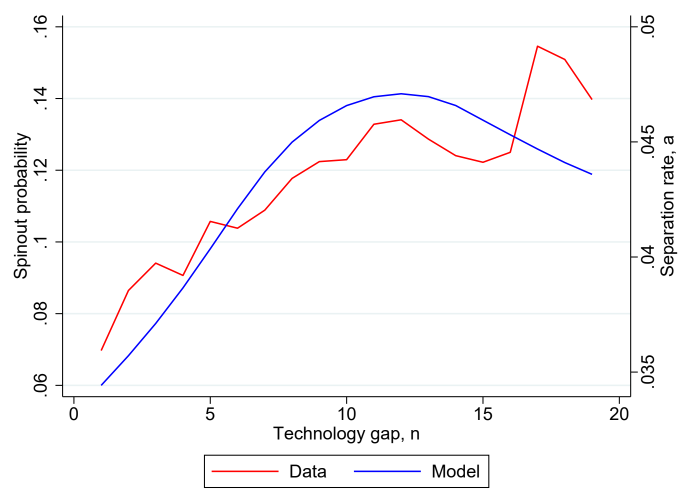
	(1) Logit	(2) FE Logit	(3) Neg. Binom	(4) FE Neg. Binom
Log cit-patents (parent)	0.092*	0.193**	0.158***	0.204***
	(0.0492)	(0.0927)	(0.0392)	(0.0717)
Patents, Inventors, Age, R&D, Sales, Assets, Num. employees	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Industry FE	YES	NO	YES	NO
State FE	YES	NO	YES	NO
Firm FE	NO	YES	NO	YES
Observations	15796	9797	16422	9984

Note: The table presents firm-level regressions of the probability of spinout separation (logit models in columns 1 and 2) and the count of 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. Panel A estimates the results on the sample of all patenting firms. Additional controls are the log number of patents, number of inventors and firm age together with fixed effects. Panel B shows the same kind of estimates for the merged sample with Compustat. Additional control variables are log sales, assets, number of employees, and the log R&D expenditures, log number of employees, sales growth and log assets value. The sample covers the period 1981-2000.

between the technology gap of the employer and the spinout separation rate of R&D managers, a. Interestingly, this separation rate declines at high levels of n. Overall, there are two main forces that drive R&D manager's decisions to form a spinout. The first force – a growing probability $\mu(n)$ of creating a high-type entrepreneurial venture, leads to a positive dependence between n and a.[38] The second force – growing wages, leads to a negative dependence between n and a. For high n, wages still grow (see Figure 5) but learning opportunities subside ($\mu(n)$ is stalling in Figure 4), leading on net to the declining incentives for separation.

Figure 6 compares model-implied separation rate over n and the probability of spawning a spinout by n from the data. In the data, we do not observe the declining tail for spinout probability. However, notice that this part of the technology gap distribution contains very few firms and, as a result, quantitatively plays a little role in aggregate dynamics.

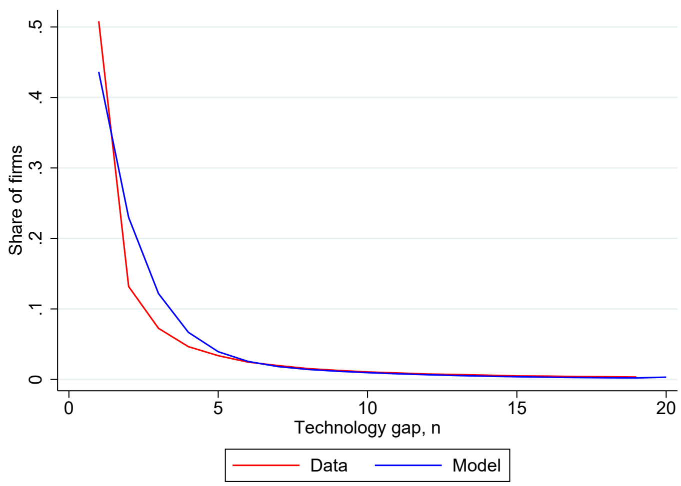
Figure 7: Spinout Separation Rate. Model and Data



Distribution of firms We can also compare the model-implied equilibrium distribution of firms across technology gaps to the distribution in the data. Figure 8 presents the distributions and shows that the entry, innovation, an exit dynamics in the model generate the stationary distribution that matches data well.

[38]Another consideration is also an option value of waiting and increasing the chances of forming a high-type spinout in the next period. This consideration effectively increases the opportunity cost of waiting. Hence, when learning curve is steep, incentives to separate are low.

Figure 8: Distribution of Firms over Technology Gaps. Model and Data



Non-compete laws. Model and Data Lastly, we explore spinout entry as a function of the strength of the non-compete laws both in the data and the model. The 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. I rely on empirical measures of the strength of state-level non-compete laws, *NCL index*, from Garmaise (2011) and Starr (2019).[39]

Table 6 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.

Table 6: Non-Compete Laws and Spinout Separation

	(1) Logit	(2) FE Logit	(3) Neg. Binomial	(4) FE Neg. Binomial
NCL index	-0.623***	-0.077*	-0.425**	-0.101***
	(0.1996)	(0.0416)	(0.1772)	(0.0341)
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	179253	50153	179485	50465

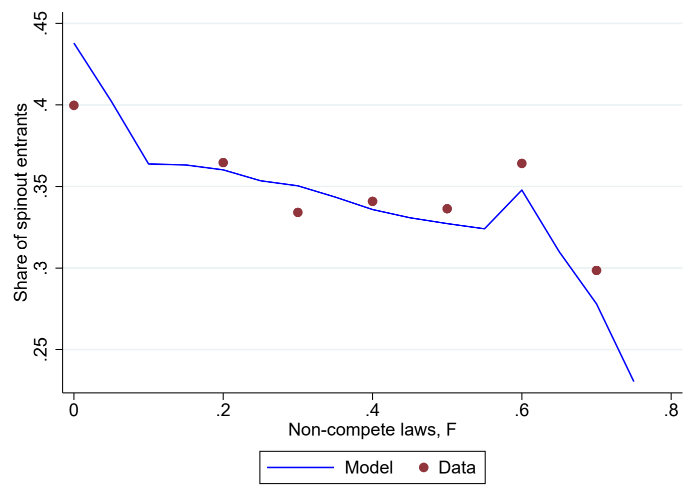
Note: The table presents firm-level regressions of the probability of spinout separation (logit models in columns 1 and 2) and the count of spinouts (negative binomial models in columns 3 and 4) as a function of the NCL index and other firm characteristics. *NCL index* is the non-competition index defined in (31). Other controls are the log number of patents and citation-adjusted patents filed in the last 5 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.

Figure 9 shows a similar evidence at the macro level: in the states with stricter enforcement, the share of spinout entrants among all entrants is lower (red dots in the figure). In the model (blue line), the entry of spinouts decline, too. An important caveat in this comparison between the model and the data is that the model treats different states with different strength of laws as separate economies, but in the data the mobility across states

[39]See Appendix F for more details about data.

may affect the relationship between state-level laws and entry. Despite these considerations, the quantitative magnitudes of the decline in the share of spinout entrants over F are very similar. In addition, Appendix Figure 12 illustrates that the model also generates an interesting empirical observation highlighted by previous studies (e.g. Starr et al., 2018): although fewer spinouts enter in states with stricter a non-compete enforcement, the average quality of these entrants is higher. The model has a simple selection mechanism that accounts for this result: when cost of entry is higher, R&D managers wait longer on the job[40] to find a better-quality idea and separate only when in expectation this idea covers higher entry costs.

Figure 9: The Share of Spinout Entrants over Non-compete Laws. Model and Data



6 Growth Decomposition and Policy Counterfactuals

6.1 Growth Decompositions

I now use the structure of the model to analyze sources of aggregate productivity growth. From equation (1), we can decompose growth into productivity improvements coming from entrants and incumbents. Decomposing growth into these two margins in Table 7 shows that entry accounts for 23% of aggregate growth. This share is large given the overall low fraction of entrants. This number, however, is comparable to the estimates from recent studies showing large contribution of entrants to growth (Foster et al., 2008; Lentz and Mortensen, 2008; Acemoglu et al., 2018). Spinouts account for about the third of this contribution by entrants, resulting in 7% aggregate growth contribution. Table 7 also shows

[40] See Balasubramanian et al. (2017) for the evidence on longer job attachments of high-tech workers with stricter NCL.

that 46% of aggregate growth is accounted for by high-type firms, while the low-type firms contribute 31% of growth.

These direct growth contributions by spinouts and high-type firms are not taking into account dynamic effects. The high-type firms tend to achieve higher technological gaps and spawn more spinouts; these spinouts are in turn more likely to be high-type themselves. This sort of the proliferation effect is an important dynamic characteristic of this problem and increases the indirect contribution of spinout formation to growth. In the following section, we will see a more nuanced analysis of growth contribution of spinouts via channels of knowledge diffusion, firm composition, and incumbents' innovation. Finally, smaller firms (here, defined as $n \leq 5$) contribute more to growth compared to larger firms.

Table 7: Growth Decomposition

Aggregate growth: $g = 3.08\%$			
Entrants 23%		Incumbents 77%	
		High-type firms 46%	Low-type firms 31%
Spinout entrants 7%	Regular entrants 16%	Small firms ($n \leq 5$) 59%	Large firms ($n > 5$) 18%

6.2 Policy Analysis

This section considers the effect of non-compete laws on industry dynamics and exploits optimal non-compete policies.

The first column of Table 8 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, I 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 (25). 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 10 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 (28) shows that $F = 0$ also maximizes the consumer welfare.

Next, I 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 8, 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 8 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, I 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. I 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, I consider F as a function on n. The last column of Table 8 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. 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 aggre-

Table 8: 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

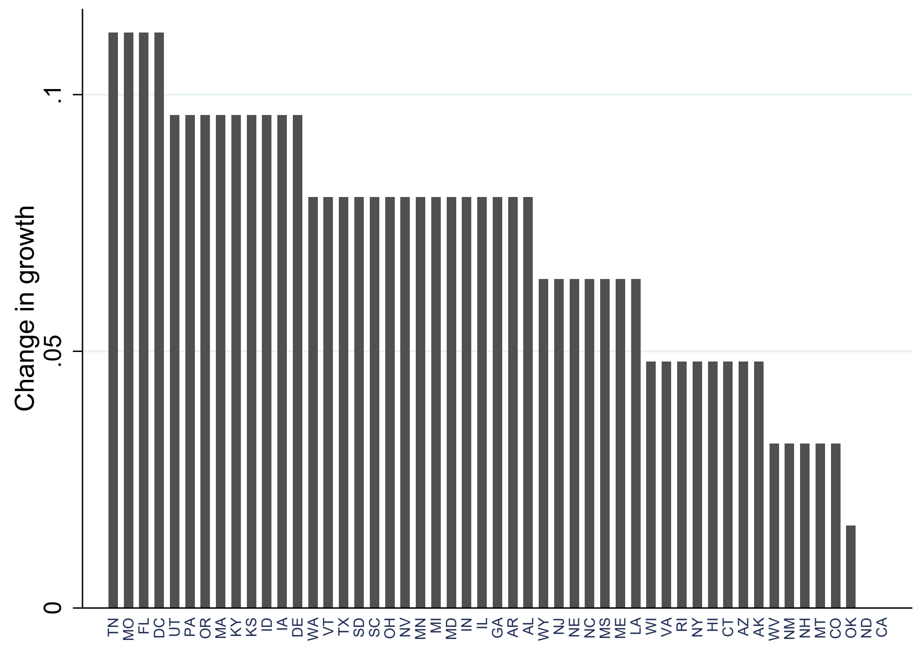
gate growth. However, notice that while maximizing growth, this policy reduces welfare relative to no-protection case. This largely happens because giving protection to technological leaders shifts firm's distribution to the right, and higher markups are associated with welfare losses for consumers.

7 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, I 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, I 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. I find that it is welfare improving to abolish existing non-compete restrictions; however, the policy protecting firms with high technological leadership is 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.

Figure 10: Gains from the Optimal Uniform Policy Adoption across States



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Theoretical Appendix

A Derivation of Bellman Equation (13)

As an example, I 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

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

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:

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

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

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

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,

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

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:

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

where we used the fact that $\frac{\dot{V}_t^{manager}(n,\tau)}{Y(t)} = g v^{manager}$ and by Euler equation, $\rho = r - g$. This gives us equation (13).

B Proof of Equation (28)

Expanding the expression for the welfare (26) and taking into account that in the steady state equilibrium Y_t grows at rate g, we get

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

Now, let us expand $\ln Y_0$:

$$
\begin{aligned}
\ln Y_0 &= \int_0^1 \ln y(j,0) dj \\
&= \int_0^1 \ln q(j,0) dj + \int_0^1 \ln l(j,0) dj \\
&= \ln Q(0) + \int_0^1 \ln \frac{1}{\omega^u \lambda^{n_j}} dj \qquad (30) \\
&= \ln Q(0) - \ln \lambda \int_0^1 n_j dj - \ln \omega^u \\
&= \ln Q(0) - \ln \lambda \sum_{n,\tau} n \xi(n,\tau) - \ln \omega^u
\end{aligned}
$$

The second line used (3) and the third line used labor demand (23). Hence, we arrived at equation (28).

C Proof of Proposition 1

Similar derivation as above gives us that $\ln Y_t = \ln Q(t) + \textit{constant terms}$ in steady state. Hence, growth in output is the same as 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 comes from successful innovation by incumbents, spinout entry, or entry by outsiders. In a time interval Δt, probability of a successful innovation by incumbents is equal to $\Delta t \sum_{n,\tau} \xi(n,\tau) z(n,\tau)$, while probability of a successful spinout entry is equal to $I^s \Delta t$ and probability of a successful entry by outsiders is $I^o \Delta t$. All these innovations improve productivity by λ.

Hence,

$$\begin{aligned}
g &= \frac{\Delta t(I^s + I^o + \sum_{n,\tau} \xi(n,\tau)z(n,\tau)) \ln \lambda Q(t) + (1 - \Delta t(I^s + I^o + \sum_{n,\tau} \xi(n,\tau)z(n,\tau)) \ln Q(t) - \ln Q(t)}{\Delta t} \\
&= (I^s + I^o + \sum_{n,\tau} \xi(n,\tau)z(n,\tau)) \ln \lambda Q(t) - (I^s + I^o + \sum_{n,\tau} \xi(n,\tau)z(n,\tau)) \ln Q(t) \\
&= (I^s + I^o + \sum_{n,\tau} \xi(n,\tau)z(n,\tau)) \ln \lambda
\end{aligned}$$

D Computational Algorithm

To quantitatively solve for the steady state equilibrium of the model, I use the following computational algorithm.

Step 1. Guess the firm's and manager's value functions $v^{firm}(n,\tau)$ and $v^{manager}(n,\tau)$.

Step 2. Given $v^{firm}(n,\tau)$ and $v^{manager}(n,\tau)$, compute optimal policies $z(n,\tau)$ and $a(n,\tau)$ using the first-order conditions in (14) and (16).

Step 3. Find v^{entry} and optimal entry rate ν using the value function definition in (9). This reduces to solving a quadratic equation in v^{entry} unknown. The resulting solution is:

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

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 (10).

Step 4. 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 (19), (20), (21), and (22). Compute spinout entry rate I^s from equation (22).

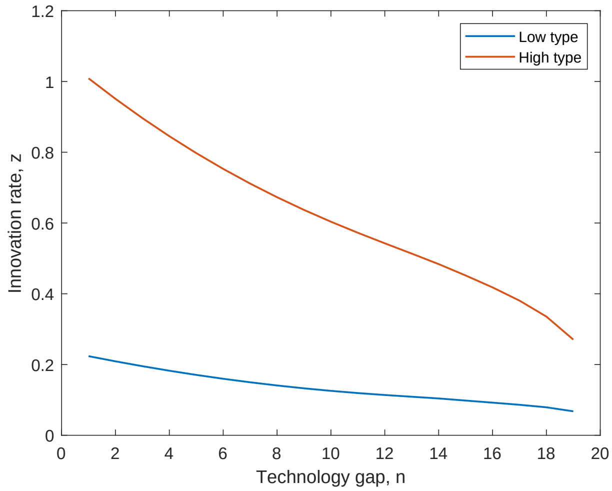
Step 5. Solve for $v^{firm}(n, \tau)$, $v^{manager}(n, \tau)$, and wages $\omega(n, \tau)$ using equations (12), (13), (15), (17), and (18). Use the fact that v^{work} is equal to v^{entry}, which has already been calculated.

Step 6. Compare $v^{firm}(n, \tau)$ and $v^{manager}(n, \tau)$ to the previous guesses. Iterate this algorithm until both value functions converge.

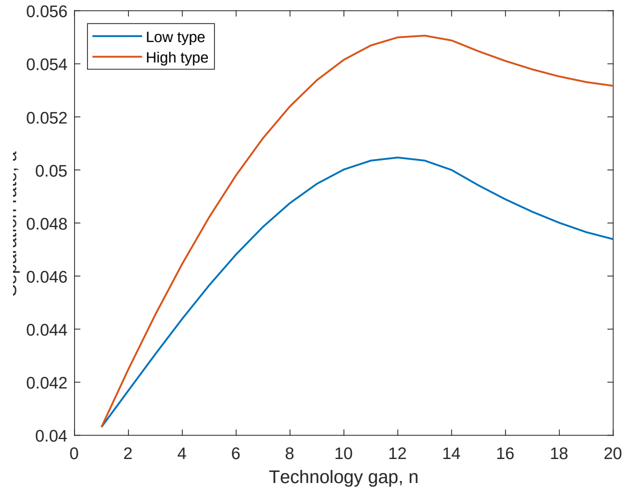
E Additional Results from the Model

Figure 11: Innovation, Separation, and Firm Size Distribution in the Model

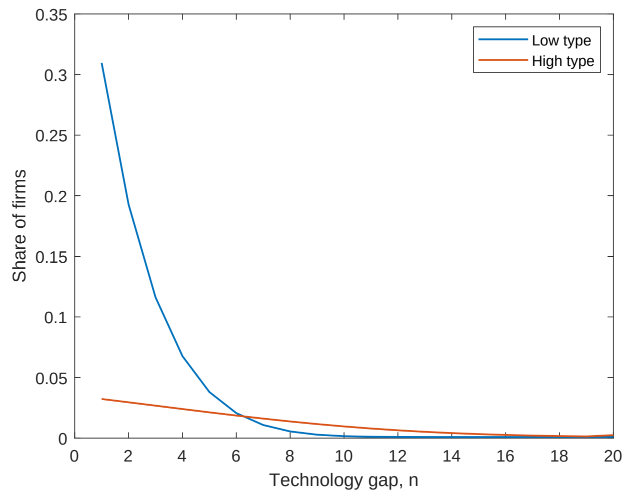
(a) Innovation rate of the firm



(b) Spinout separation rate

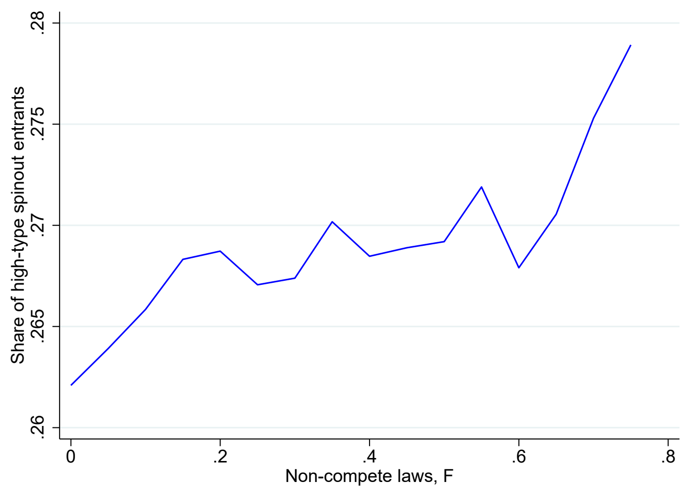


(c) Firm size distribution



Notes: Equilibrium solution of the model given the calibrated parameter values.

Figure 12: The Share of High-type Spinouts among Spinout Entrants



Notes: The figure plots the equilibrium share of H-type entrants among all spinout entrants over different values of F correnponding to the *NLC index* range across the U.S. states.

F 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, I use this index as the benchmark in the regression analysis. More specifically, I combine the 1991 and 2009 versions of the index and define the final index over time as

$$NCL(t) = NCL_{1991} + \frac{NCL_{2009} - NCL_{1991}}{18}(t - 1991) \tag{31}$$

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.

G 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
Hawaii	3	-0.83	-0.17	Oregon	6	0.14	0.14
Idaho	6	-0.01	0.77	Pennsylvania	6	-0.14	0.14
Illinois	5	0.55	0.95	Rhode Island	3	-0.67	-0.33
Indiana	5	0.7	0.7	South Carolina	5	-0.2	-0.27
Iowa	6	0.19	1.01	South Dakota	5	0.37	1.02
Kansas	6	0.69	1.21	Tennessee	7	0.22	0.45
Kentucky	6	0.61	0.85	Texas	5	-0.04	-0.28
Louisiana	4	-0.7	0.5	Utah	6	1	1
Maine	4	0.06	0.41	Vermont	5	0.3	0.6
Maryland	5	0.15	0.6	Virginia	3	0.09	-0.29
Massachusetts	6	0.87	0.48	Washington	5	0.64	0.34
Michigan	5	0.07	0.46	West Virginia	2	-0.8	-0.8
Minnesota	5	-0.07	-0.07	Wisconsin	3	0.16	-0.09
Mississippi	4	-0.2	0.04	Wyoming	4	-0.65	0.23

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

Appendix Table 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 truncated-adjusted citations are above the 90th percentile of the citations distribution of patents filed in the same year and technology class. Control variables include the log number of parents, parents' log number of patents, log number of citations-weighted patents, technological lead percentiles, and log number of top patents. Technological lead percentile is a categorical variables with 20 quantiles of the patent quality distribution based on the citations-weighted patent counts in the last 5 years in the technology class (*cat-ocl*) of the firm. 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.

	(1) Logit	(2) FE Logit	(3) Neg. Binom	(4) FE Neg. Binom
-Panel A: Patent data				
Log top patents	0.259***	0.127***	0.219***	0.076***
	(0.0151)	(0.0343)	(0.0125)	(0.0275)
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	184009	50660	184213	50978

	(1) Logit	(2) FE Logit	(3) Neg. Binom	(4) FE Neg. Binom
-Panel B: Patent + Compustat data				
Log top patents	0.230***	0.174**	0.182***	0.092*
	(0.0357)	(0.0685)	(0.0262)	(0.0478)
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	15796	9797	16422	9984

Note: The Table repeats the analysis in Table 5, but using the log top patents as measure of parent's technological leadership. Panel A of the table shows annual panel estimates of the probability of an entrant firm being a spinout as a function of various firm characteristics in different rows for all firms in the patent data, for the time period 1981-2000. Patents and top patents are the total number of all patents and top patents granted to the firm during the last 5 years for each year, respectively. Inventors is the total number of inventors of the firm during the last 5 years for each year. Panel B shows the same kind of estimates of Panel A for the merged databases between Patents and Compustat. Control variables in Panel B are firm's annual log R&D expenditures, log number of employees, sales growth and log assets value.

Appendix Table A.6: Probability of spinout separation. Contemporaneous measure of parent's technological leadership.

-Panel A: Patent data

	(1) Logit	(2) FE Logit	(3) Neg. Binom	(4) FE Neg. Binom
Log cit-patents yr	0.111***	0.055***	0.104***	0.037**
	(0.0107)	(0.0178)	(0.0099)	(0.0156)
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	175352	48983	175632	49285

-Panel B: Patent + Compustat data

	(1) Logit	(2) FE Logit	(3) Neg. Binom	(4) FE Neg. Binom
Log cit-patents yr	0.022	0.058	0.077***	0.046
	(0.0353)	(0.0479)	(0.0280)	(0.0378)
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	15796	9797	16422	9984

Note: The Table repeats the analysis in Table 5, but using the contemporaneous (instead of last 5-year) quality-adjusted patent count of parent firms. Panel A of the table shows annual panel estimates of the probability of an entrant firm being a spinout as a function of various firm characteristics in different rows for all firms in the patent data, for the time period 1981-2000. "Patents yr" and "cit-patents yr" are the total number of all patents and adjusted citation patents granted to the firm for each year, respectively. Inventors is the total number of inventors of the firm for each year. Panel B shows the same kind of estimates of Panel A for the merged databases between Patents and Compustat. Control variables in Panel B are firm's annual log R&D expenditures, log number of employees, sales growth and log assets value.

Appendix Table A.7: Non-compete Laws and Spinout Formation. Alternative NCL index.

	(1) Logit	(2) Logit	(3) Neg. Binomial	(4) Neg. Binomial
NCL index	-0.037*	-0.056***	-0.027	-0.046***
	(0.0196)	(0.0203)	(0.0175)	(0.0156)
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	179253	50153	179485	50465

Note: The table repeats the regressions in Table 6 but using a different measure of non-compete laws from Garmaise (2011). Other controls are the log number of patents and citation-adjusted patents filed in the last 5 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.

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

-Panel A-

	Within-state spinouts			
	(1)	(2)	(3)	(4)
	Logit	Logit	Neg. Binomial	Neg. Binomial
NCL index	-0.403	-0.223***	-0.396	-0.169**
	(0.3260)	(0.0728)	(0.3062)	(0.0665)
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	168908	23264	170599	23402

-Panel B-

	Within-industry spinouts			
	(1)	(2)	(3)	(4)
	Logit	Logit	Neg. Binomial	Neg. Binomial
NCL index	-0.236	-0.173***	-0.129	-0.168***
	(0.2772)	(0.0611)	(0.2586)	(0.0536)
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	170673	26993	170673	27120

Note: The table repeats the regressions in Table 6 but only considering the within-industry spinouts (Panel A) and within-industry spinouts (Panel B). *NCL index* is the non-competition index defined in (31). Other controls are the log number of patents and citation-adjusted patents filed in the last 5 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.