Entrepreneurial Spillovers from Corporate R&D

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Abstract

How does corporate innovation investment affect employee departures to entrepreneurship (spawning)? Research and development (R&D) investment may generate growth options for the firm or make it a more interesting workplace, which could decrease spawning. Conversely, R&D investment could increase spawning if employees can appropriate some of the new growth options, or if engaging with the R&D process makes them more entrepreneurial. Using U.S. employer-employee matched Census data, we show that R&D investment increases spawning. We identify the causal effect of R&D with changes in federal and state tax incentives. The effect is driven by high-tech parents and by departures to high-growth and venture capital-backed entrepreneurship. Intellectual rather than human capital seems to explain the spawning (i.e., new ideas rather than skills). The effect does not impose observable costs on the parent, leading us to conclude that entrepreneurial spawning is a source of knowledge spillovers from corporate R&D.

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1 Introduction

Investing in innovation yields knowledge spillovers, which are difficult to observe but crucial to explaining economic growth (Marshall 1920, Krugman 1991). Knowledge spillovers are benefits from one firm's innovation efforts that accrue to other firms, and which are not embodied in products and services (Griliches 1992).[1] Despite their incorporeal nature, knowledge spillovers are known to be large in magnitude and seem to decline with geographic distance.[2] However, there is little evidence about their transmission channel. We also do not know much about the identity of spillover recipients; the literature has typically assumed that potential recipients are close in technological or geographic space.

This paper offers a new channel for knowledge to spill from one firm to another: We show that corporate investment in research and development (R&D) increases the rate at which employees depart to launch new firms. This effect is not obvious, as R&D might increase the firm's growth options or make it a more interesting place to work, leading to greater employee retention. Evidence that many successful entrepreneurs are former employees of high-tech, large firms motivates our research (Bhide 2000, Klepper 2001). Especially relevant is Gompers, Lerner & Scharfstein (2005), who observe that around 40 percent of venture capital-backed executive teams previously worked at a public company, often those with entrepreneurial cultures. They note that one limitation of their analysis is that entrepreneurial individuals may select into working at companies with entrepreneurial learning opportunities. We depart from their approach, as well as other prior work, by demonstrating that greater innovation inputs at public companies leads to entrepreneurial spawning.[3]

We measure the propensity of employees to join startups' founding teams using

[1]These pecuniary externalities could in theory ultimately can be measured through hedonic prices, as producer and consumer surplus. For example, after accounting for the improved quality of the R&D-intensive good, a downstream firm will have lower quality-adjusted input costs. Embodied spillovers may be difficult to measure - for example if price indices are not adjusted for quality changes - but they are nonetheless pecuniary externalities (Griliches 1992).

[2]On the first point, see Bernstein & Nadiri (1989), Jones & Williams (1998), Griffith, Harrison & Van Reenen (2006), and Bloom et al. (2013). On the second, see Jaffe et al. (1993) and Greenstone et al. (2010).

[3]Existing work on spawning includes Nanda & Sørensen (2010), Chatterji (2009), Sørensen (2007), Campbell et al. (2012), Babina (2015), and Babina, Ouimet & Zarutskie (2015).

U.S. Census employer-employee matched panel data.[4] There is a robust relationship between firm R&D investment and entrepreneurial spawning. A one standard deviation increase in R&D is associated with a 18.7 percent increase in entrepreneurial spawning, relative to sample mean of 1.3 percent. The model includes firm, state-year, and industry-year fixed effects, as well as a rich array of time-varying firm characteristics, including total investment and establishment-level payroll and employment. Further, the results are robust to including four-digit SIC code fixed effects, suggesting that narrow industries do not explain the result. Finally, they are robust to several measures of entrepreneurial spawning.

Despite these fine controls, our estimate may be biased upwards if an unobserved new technological opportunity leads to both the parent R&D and the spawn. Alternatively, the estimate could be biased downward if the spawning effect leads the parent to underinvest ex-ante in R&D. To address these possibilities, we instrument for R&D using changes in state and federal R&D tax credits, following Bloom et al. (2013). Changes in tax credits affect the firm's tax price of R&D (or equivalently its user cost of R&D capital), and thus its incentives to invest in R&D. We provide exhaustive detail on the sources of within-firm variation for both instruments. The federal tax credit is firm-specific for five reasons, importantly because it depends on firm age, with annual changes for most firms. The state instrument is firm-specific because it is calculated using the time-varying share of the firm's patent inventors located in a given state. The instruments satisfy the relevance condition and are likely to satisfy the exclusion restriction.[5]

The instrumental variables (IV) effect of R&D on spawning is larger than the main effect, and equally robust. This offers strong evidence that the relationship is causal: firm R&D leads to new firm creation. The IV estimate is likely larger because while the OLS strategy measures the effect of an additional dollar of average R&D, the IV strategy approximates increased R&D spending on the margin, capturing the effect

[4] For each public firm establishment-year, we follow departing workers and examine whether they are on the founding team of a new firm (top five earners of a firm founded within three years of when R&D is measured).

[5] To satisfy the relevance condition, we present evidence from the literature that the elasticity of R&D spending to tax credits is at least one. To satisfy the exclusion restriction, we show empirically that there is no relationship between the tax credit and spawning, and present evidence from the legal literature that R&D tax credits are not in general useful to startups.

on spawning of the "last" R&D dollar. This marginal R&D is likely farther from the parent's core focus than average R&D, explaining why the growth options it creates more often optimally reside outside the firm's boundary.[6]

This framing of the IV estimate suggests a specific mechanism. Corporate R&D might increase spawning through an intellectual capital channel. In this channel, R&D leads serendipitously to new project ideas or technologies, some of which are deployed in new firms by departing employees. The alternative is a human capital channel, where learning-by-doing during the R&D process increases employees' entrepreneurial skills. For example, a manager overseeing a new R&D project might learn to guide employees under high uncertainty and become better suited to an innovative startup.

Overall, our cross-sectional evidence is more consistent with the intellectual capital channel. First, this channel should be more associated with the "research" part of R&D. Indeed, we find that firms doing more basic and broad research have higher entrepreneurial spawning effects per dollar of R&D. Also, we find that high-tech parents drive the effect. Second, the intellectual capital channel should be associated with new-to-the-world ideas, rather than "Main Street"-type businesses. Consistent with this, we find that within the population of spawns, higher parent R&D is strongly associated with spawn venture capital backing. Third, we find that spawns tend to be in different industries from parents, suggesting that the spawn has a new idea and is not replicating the parent's business. We present additional cross-sectional evidence that is inconsistent with the human capital channel.

The intellectual capital channel is consistent with the spawning effect of R&D being a new avenue for knowledge spillovers. This requires that the cost to the parent of the R&D-induced spawn does not outweigh the spawns' combined private and social value. The spawning effect of R&D is less likely to be a new source of R&D spillovers if it is very costly to the parent, or if the parent internalizes the spawn's private benefits by investing in or acquiring it.

If R&D-induced spawning is very costly to the parent, the effect should be attenuated in states that strictly enforce non-compete covenants. Instead, the effect persists and is not significantly smaller in these states. Second, the effect should be

[6] A related explanation is that adjustable R&D is less crucial to the the firm, so compliers with the tax shock face lower costs to R&D-induced spawning.

weaker in sectors where intellectual property is easier to protect. We do not find that the effect varies with a measure of industry patentability. Third, costly spawns may compete in product markets with parent. Instead, R&D-induced spawns tend to be in different industries from their parents. Fourth, the IV estimate being larger than the OLS estimate points away from spawning being costly. Finally, we make a revealed preference argument. By virtue of observing the persistent phenomenon of R&D-induced spawning, the parent either chose not to develop the idea in house or chose not to take ex-ante steps to prevent the spawn.

To test whether the parent fully internalizes the spawn's benefits, we conduct an out-of-sample test based on the underlying spawn-parent pair data in Gompers et al. (2005). Of the 9,152 unique parents in their data, just 2.3 percent invest in or acquire their spawns. This small percentage is evidence that parents do not usually internalize spawns by investing in or acquiring them. More generally, the spawn's cost to the parent is unlikely to outweigh its benefits to the rest of the economy given the benefits of new firms found in Kortum & Lerner (2000), Decker et al. (2014), and Glaeser et al. (2015), among others.

Our evidence thus points to the spawning effect of R&D being a new channel for knowledge spillovers. Research on knowledge spillovers at the micro-level has focused on inventor networks, particularly in academia, and exploiting immigration waves or superstar scientist deaths for exogenous variation in (e.g. Waldinger (2012), Azoulay et al. (2010)). By focusing on private firms rather than academics, and a real effect of R&D rather than patent citations, we extend this literature.

Our finding sheds light on how the optimal boundaries of the firm depend on the nature of the growth options it creates (Zingales 2000, Seru 2014, Bernstein 2015). Gromb & Scharfstein (2002) model how growth options with high risk and high potential payoffs benefit from higher-powered incentives, and Robinson (2008) finds that it can be optimal to locate risky projects in joint ventures outside the firm boundary.[7] We show empirically how high-risk, high-reward growth options can be reallocated from large incumbents to startups. For example, venture capital backing implies both a high-growth business and high-powered owner incentives (Metrick & Yasuda 2011).

[7] See also Sevilir (2010).

We find that R&D-induced spawns are much more likely to be venture capital-backed than the average spawn.

Finally, the spawning effect of R&D offers a new source for where ideas for startups come from, a direct channel of absorptive capacity (Cohen & Levinthal 1989, Aghion & Jaravel 2015). We document that R&D is the most important corporate variable that predicts venture capital-backed employee spawns, a fact that contributes to efforts such as Guzman & Stern (2017) to predict which new firms will be high-growth.[8] We show how high-skill R&D labor can be reallocated from incumbents to new firms, which Acemoglu et al. (2013) argue is likely welfare-enhancing. More broadly, our paper is related to work on knowledge diffusion through labor mobility, including Almeida & Kogut (1999), Kim & Marschke (2005), Matray (2015), and Herkenhoff et al. (2018).

2 Data

We use data from five sources: Compustat, Census LBD, Census LEHD, VentureXpert, and the NBER Patent Data Project. This section describes each source of data and explains the key variables we use in analysis. It also discusses concerns with the data and sample.

2.1 Compustat

Our measure of corporate innovation investment is R&D expenditure as reported in 10K filings and provided by Compustat. As R&D expenditure is only available for public firms, they form our universe of firms at hazard of being parents, or spawning entrepreneurs out of their labor force. We primarily use log R&D, but also test whether the results are robust to using R&D divided by total assets. We also obtain balance sheet and income statement data about the potential parents from Compustat.

We consider only firms with positive R&D for two reasons. First, firms that

[8]A one standard deviation increase in R&D increases the probability a spawn is venture capital-backed by 78 percent, at least twice the comparable effect of other corporate variables such as cash or assets.

report R&D are likely qualitatively different from firms that do not in ways that might affect spawning, despite rigorous controls and fixed effects (Lerner & Seru 2017). Second, our primary specification will be focused on the intensive margin; since we use firm fixed effects, firms with zero R&D provide no variation.

2.2 Census LBD

We merge Compustat to the restricted-access U.S. Census Bureau's Longitudinal Business Database (LBD), and establishment-level panel, using the internal Census Compustat/LBD crosswalk. The LBD covers all U.S. business establishments with paid employees beginning in 1976, described in detail in Jarmin & Miranda (2002). We use data for all 50 states from 1990 to 2011.

Establishments and firms are tracked consistently over time. We use data on establishment age, industry, physical location, total employment, payroll, birth, and death. We can therefore identify new employer firms and their future employment growth, payroll, and exit. We define age as the oldest establishment that the firm owns in the first year the firm is observed in the LBD, as in Haltiwanger et al. (2013). A firm birth is thus defined when all of its establishments are new, preventing us from misclassifying an establishment that changes ownership as a startup.

2.3 Census LEHD

A challenge when studying how R&D affects employee departures to entrepreneurship is that we must observe employees and track them from firm to firm. We solve this with the Longitudinal Employer-Household Dynamics (LEHD) program at the U.S. Census Bureau, which provides firm-worker matched data. This permits us to track salaried employees over time and across firms on a quarterly basis. Census builds these data using scrambled social security numbers. In addition to wages, the data contain employees' gender, race, place and date of birth, and citizenship status. Coverage starts in 1990 for several states and increases over time, ending in 2008. We have access to 31 states, shown in Figure 6, in which we observe all spawns. In covered states, the LEHD includes over 96 percent of all private-sector jobs and over 96 percent of total wage and salary civilian jobs (BLS 1997, Abowd et al. 2009). Thus we do not face employee self-selection problems.

The LEHD connects quarterly earnings from the state Unemployment Insurance programs to the Quarterly Census of Employment and Wages Program. Abowd et al. (2009) describe the construction of this data in detail. Workers' employers are identified with State Employer Identification Numbers (SEIN, the state equivalent to EIN), but the data also include the federal employer identification number (EIN), which we use to link the LEHD to the LBD and thus follow employees from firm to firm. The LBD infrastructure is based on physical establishments while the LEHD infrastructure uses reporting units. We match LEHD SEINs to LBD EINs in the first quarter of each year, using an internal Census bridge file. We drop SEINs with less than ten employees, as they tend to have noisy reporting.[9] This yields an annual panel of SEINs of the LBD firms, in which employees are observed as of the first quarter of each year. For ease of exposition, we term SEINs "establishments."

2.3.1 Identifying spawns

The final sample consists of an annual panel of public firm establishments in 31 states between 1990–2005. We follow startup creation from 1990 to 2008. To identify spawns, we begin by observing worker identities at public firm establishments in the first quarter of year t, and the quantity of R&D investment in year year $t-1$. We denote an establishment e. Using longitudinally consistent individual identifiers available in the LEHD data, we follow the establishment e's employees one, two, and three years after year t.

The LEHD data do not designate the founder(s) of a new firm. We proxy for an individual being on the founding team using the highest earners at a young firm. While this is an imperfect measure of entrepreneurship, we believe that it is the best available in administrative data. It also follows Kerr & Kerr (2017), who find that business owners are usually among a firm's top three initial earners. As Azoulay et al. (2017) point out, the W-2 data that is the basis for the LEHD must be filed for all employees, including owners who actively manage the business. Note also that

[9]We obtain similar results if we drop those with less than five or 15 employees.

managers must by law pay themselves reasonable wage compensation.[10]

Founders may not pay themselves the highest wage as they seek to attract high-skill employees. Therefore, using only the highest earner is unlikely to capture all founders. Our definition captures both founders and the early employees who are important to the startup's initial success. It is also in line with prior research focusing on the executive team, including Gompers et al. (2005). Our primary definition of a spawn is a firm founded between t and $t+3$ in which any of the e's employees at year t is among the top five earners as of $t+3$. To arrive at our primary outcome variable – an establishment's spawning rate – we divide the number of spawn founders by e's total number of employees in year t.

There are four other outcomes for e's year t employees. First, they may remain at the firm. Second, they may be employed at a different firm that existed before year t (other incumbents). Third, they may be employed at an institution with unknown age (because some LEHD employers are non-profits, government entities, or non-employer firms not covered by the LBD, which is used to determine employer age). Finally, the employee may no longer be observed in the data. They may have left the work force, no longer earn a wage, or otherwise fail to be covered by the LEHD (see concerns below). We use these outcomes in robustness tests, for example to test whether R&D also leads to greater labor mobility to other incumbent firms.

The LEHD has been widely used in economic research, for example in Tate & Yang (2015) and Goldin et al. (2017). There is nonetheless some concern about its coverage. About 10 percent of workers in year t are not in the LEHD in year $t+3$. This may initially seem high, but the U.S. Current Population Survey (CPS) has a similar attrition rate. The CPS tracks workers for a maximum of 16 months. In the CPS data, among private sector employees who are observed 15 months later, about 9 percent drop out from the employment sample.[11]

A final concern is that parent R&D is correlated with worker mobility to or from uncovered state. If this is the case, then R&D should correlate with the fraction of workers who drop out of sample. We find that this is not the case (Table 1).

[10] See https://www.irs.gov/uac/Wage-Compensation-for-S-Corporation-Officers.

[11] Authors calculations based on IPUMS-CPS data, available at https://cps.ipums.org/cps/.

2.4 Venture capital and patent data

We use a linking between ThomsonOne VentureXpert and the Census Business Register to identify venture capital-backed startups from the bridge constructed by Puri & Zarutskie (2012). We use patent data from the NBER Patent Data Project, which includes patent and citation variables through 2006. The NBER data include Compustat identifiers. We use patent data to construct the instrument for R&D.

We employ several annual patent-based variables at both the firm and industry level. These are the number of patent classes a firm or industry patents in, the number of patents, the number of forward and backward citations, and the average, maximum, and median patent generality and originality. Generality is higher (closer to one than zero) when forward citations are in many classes, and originality is higher when backward citations are in many classes. In analysis, we use indicators for having an above median value for each patent variable within a year.

2.5 Summary statistics

Table 1 panels 1-3 show summary statistics at the parent firm-year, parent establishment-year, and spawn levels, respectively. We show the mean for indicator variables, as well as the quasi-median and the standard deviation for continuous variables.[12] Our main dependent variable, entrepreneurial spawning, is measured at the establishment-year level (panel 2). These are the set of establishments of public firms with positive R&D and at least 10 employees, between 1990 and 2003. On average, 1.3 percent of an establishment's employees separate and are identified as entrepreneurs three years later. Similarly, using the LBD/LEHD matched data Kerr et al. (2015) find that 1.7 percent of workers transition to entrepreneurship over a four-year period.

Panel 3 of Table 1 present summary statistics of the 108,000 spawns identified in the LBD. When we observe a former public firm employee first working at a spawn (three years after R&D is measured), the spawn is on average 1.6 years old and have

[12]Since Census disclosure procedures prohibit disclosure of percentile value, we approximate median with a quasi-median, which is estimated using a 99 percent weight on observations within the interquartile range and a 1 percent weight on the remaining observations. The number of observations and all estimates in the tables are rounded according to the Census disclosure requirements.

14.6 employees. Two percent of spawns ever receive venture capital funding. Kaplan & Lerner (2010) find that over a roughly similar period (1995-2009), 0.16-1 percent of new businesses each year receive first-time venture capital. Thus, the rate of venture capital backing among firm founders who formerly worked at public firms with positive R&D investment is substantially higher than that in the whole population of firm founders.

3 Empirical Approach

This section first describes our primary estimation strategy, a tightly controlled fixed effects regression. In Section 3.2, we explain our instrumental variables strategy.

3.1 Reduced form relationship between R&D and spawning

We estimate variants on Equation 1, where e denotes an establishment, f a firm, i an industry, s state, and t the year. The dependent variable is, as described in Section 2.3.1, is the percent of e_t's employees who are among the top five earners at startups as of $t+3$.

$$\begin{aligned}\text{Pct Entrepreneurs}_{efist+3} = \beta \ln\left(\text{R\&D}_{f,t-t}\right) + \text{Firm FE}_f + \text{Industry-year FE}_{it} \\ + \text{State-year FE}_{st} + \text{Controls}_{ft} + \text{Controls}_{et} + \varepsilon_{efist}.\end{aligned} \tag{1}$$

We employ firm fixed effects to control for time-invariant differences across firms. We expect omitted variables to be correlated within the firm, so we cluster standard errors by firm. Industry-year fixed effects control for changes in investment opportunities, and also subsume industry and year effects. We use SIC four-digit industry codes in our most stringent specifications, and SIC three-digit codes elsewhere. State-year fixed effects control for regional shocks, which may affect investment opportunities at incumbents as well as entrepreneurship.

Time-varying establishment and firm controls address other concerns. First, we control for establishment size, in case, for example, smaller establishments have more focused or autonomous cultures and thus lead to more spawning. Second, we control for the establishment's average wage, in case spawning is driven by higher paid workers rather than R&D. We also include the following firm-level controls, which might correlate with R&D and spawning: return on assets, sales growth, Tobin's Q, asset tangibility (measures as PPE investment divided by total assets), size (log total assets), cash holdings, age, and diversification (indicator for firm having establishments in more than one SIC 3-digit industry).

3.2 Instrument for R&D

The central challenge to Equation 1 is that an unobserved demand shock or new technological opportunity, not captured by our granular industry-year fixed effects, may jointly engender parent R&D and spawning. This is a version of the Manski (1993) reflection problem. The ideal experiment would randomly allocate R&D to firms and observe whether firms assigned to more R&D have more employees that leave to found their own firms. This is infeasible, so we use the best available instrument for R&D expenditure: changes in the tax price of R&D, induced by state and federal R&D tax credits, following Bloom et al. (2013).

This section first describes the motivation for the instrument (Section 3.2.1), and then addresses our expected direction of endogeneity (Section 3.2.2). In Section 3.2.3, we briefly explain the two tax prices of R&D that we use. Appendix Section 6 contains exhaustive details about the federal tax credit and its calculation, the state tax credits, and concerns with instrument validity. While imperfect, we show that the instrumental variables strategy is well-suited to our context and is likely to satisfy the exclusion restriction.

3.2.1 Instrument motivation

We use two instruments: federal tax credit changes, and state tax credit changes. These have been shown to be important drivers of corporate R&D expenditure. First, the federal R&D tax credit has a strong effect on corporate R&D in the short and long term. The elasticity is at least one, such that an extra dollar of federal tax R&D credits stimulates roughly a dollar of additional R&D expenditure (or much more, in some studies). This evidence includes Hall (1993), McCutchen (1993), Mamuneas & Nadiri (1996), Hall & Van Reenen (2000), Billings et al. (2001), Bloom et al. (2002), Klassen et al. (2004), and Clausen (2009).

Buttressing this evidence is the fact that firms claim the tax credit, or expense essentially all of their qualified research expenditures (Guenther 2015). The relative sensitivity to the R&D tax credit may reflect the fact that firms tend to finance R&D out of free cash flows (Brown & Petersen 2011). We are confident that the federal tax price of R&D, if it has adequate firm-level variation, should predict R&D in our sample.

Second, state R&D tax credits increase R&D within the affected state, as shown by Paff (2005), Wu (2008) and Wilson (2009), among others. The most conservative finding is in Wilson (2009), where a one percentage point increase in the state tax credit rate increases R&D by 1.7 percent in the short term and 3-4 percent in the longer term. However, Wilson (2009) also finds that the tax credits cause a reallocation of R&D activity geographically. Since large, multi-state firms are responsible for most R&D expenditure, we expect the state instrument to be generally weaker than the federal one.

3.2.2 Expected direction of endogeneity

There are two major sources of endogeneity that may bias our ordinary least squares (OLS) estimates: 1) technology shocks to the firm's industry would bias the estimates upwards, and 2) the firm's inability to fully appropriate the benefits of R&D would bias the estimates downwards. An example of the first source is a scientific discovery at a university that creates new opportunities for the firm's industry. This may increase both firm R&D and entrepreneurship rates. The second source of endogeneity stems from firms' investment being correlated with their ability to appropriate the investment's benefits. This point is widely used to justify government subsidy of corporate R&D (Feldman & Kelley 2006, Howell 2017). The presence of a spawning effect represents benefits that the parent firm is not appropriating. This second source implies that if firms were randomly assigned R&D expenditures, we would expect a larger fraction of that R&D output to ultimately be developed outside of the firm's boundaries in spawned startups.

In our setting, do we expect that endogeneity biases the OLS result upwards or downwards? While it is possible to tell stories going both ways, we believe it is more likely that endogeneity biases the OLS result down. Two facts suggest that positive bias due to technology shocks is unlikely. First, when we add industry-year fixed effects to specifications with firm fixed effects, our estimates do not attenuate. Second, an opportunity shock in a given sector should lead to both more R&D and more startup formation in that sector. We find that the R&D-induced spawn's line of business tends to be unrelated to the parent's. While it is more difficult to test for the negative bias due to appropriation concerns, the instruments proposed in the following sections will address this concern. The instrumented effect's magnitude relative to the OLS effect will be a test for the direction of bias.

3.2.3 Summaries of the tax credits

Changes in tax credits affect firm incentives to invest in R&D, because they change the firm-specific tax price of R&D. The lower the user cost of R&D capital, the more likely firms to invest in R&D. The first instrument is the federal tax price of R&D, which we denote ${\rho_{ft}}^F$. The Appendix contains a detailed description of the calculation, which draws from Hall (1993). We explain in the Appendix that the federal tax credit value depends on the firm's qualified research expenditures and, crucially, a fixed base R&D spending. The credit is firm-specific for five reasons, including because it depends on firm age (more specifically, years since the firm's first positive R&D investment), with annual changes for most firms. We find substantial within-industry variation in the tax price of R&D, as well as the necessary variation within firm over time. We ensure that relevant contemporaneous variables do not have strong explanatory power over the tax price of R&D.

The state instrument, also described in more detail in the Appendix, requires two objects: the state tax price component of the R&D user cost of capital, and a measure of the share of a firm's R&D that occurs in a given state. First, we use the state tax price of R&D in Wilson (2009). He incorporated state level corporate income taxes, depreciation allowances, and R&D tax credits into this tax price component, which we call ρ^S_{st}. These credits vary across states and time. To build the second object, θ_{fst}, we follow Bloom et al. (2013). θ_{fst} is a proxy for a firm's R&D share in a given state-year calculated using the share of the firm's patent inventors located in state s. The firm's state-level tax price is then $\rho^S_{ft} = \sum_s \theta_{fst}\rho^S_{st}$.

3.2.4 First stage estimation

Having constructed firm-level federal and state tax prices of R&D (${\rho_{ft}}^F$ and ρ^S_{ft} , respectively), we estimate the following first stage regression:

$$\ln(R\&D_{ft}) = \beta_1 \ln\left(\rho^S_{ft}\right) + \beta_2 \ln\left({\rho_{ft}}^F\right) + \text{Firm FE}_f + \text{Industry-year FE}_{it}. \tag{2}$$

$$+ \text{State-year FE}_{st} + \text{Controls}_{ft} + \varepsilon_{eft} \tag{3}$$

We cluster standard errors by firm. The results are in Table 3. We show all of the specifications that we will show in our main instrumented results table. The instruments are strong, yielding F-statistics of about 25, well above the rule-of-thumb cutoff of ten. The partial R^2 of the two instruments ranges from 2.2 to 3.2 percent, which captures a reasonable amount of variation in R&D (Jiang 2015). The federal instrument is stronger than the state instrument, which in part reflects the fact that the state instrument is identified by firms with patents. As we show below, our main result is not driven by firms with patents, but rather by firms in high-tech sub-sectors.

Note that Bloom et al. (2013) use only firm and year fixed effects. This is equivalent to column 1. In Column 2, we add firm time-varying controls, which reduce the magnitude of the effects somewhat but do not affect their statistical significance. We show a variety of specifications; our preferred specification, with SIC 3-digit industry-year and state-year fixed effects, along with firm time-varying controls and firm fixed effects, is in column 5. The results are also robust to using SIC 4-digit industry fixed effects (column 6).

3.2.5 Concerns

There are four potential concerns, which we describe in detail in the Appendix. Here, we summarize the two more important ones. First, the exclusion restriction is that tax credits cannot affect entrepreneurial spawning. We show empirically that there is no relation between the state tax credits and startup creation. More generally, the legal literature has argued that R&D tax credits are not useful to startups because they usually do not have taxable income (Bankman & Gilson 1999).

The second concern is that changes in state-level R&D tax credits may lead firms to reallocate R&D (or misreport it such that it appears reallocated). Any such reallocation should reduce the power of the instrument. This leads us to expect that the federal instrument will have more power than the state instrument, which is indeed what we find. In sum, R&D tax credits offer the best available source of variation driving corporate R&D, which is plausibly unrelated to technological or demand shocks that could jointly give rise to parent R&D and entrepreneurial spawning.

4 Results

This section first explains our main results. We present the instrument result in Section 4.2. In Section 4.5, we consider reverse causation, and in Section 4.3, we consider alternative outcome variables and potential sources of endogeneity.

4.1 Main results

We present the main results from estimating Equation 1 in Table 2. Our preferred specification in column 5 includes firm, industry-year, and state-year fixed effects. The coefficient of 0.109 implies that a one standard deviation increase in R&D is associated with a 18.9 percent increase in entrepreneurial spawning, relative to sample mean of 1.3 percent. Alternatively, the coefficient implies that a 100 percent increase in R&D is associated with a 6 percent increase in entrepreneurial spawning. The main result is remarkably robust to a wide array of alternative controls and fixed effects as shown across the eight models in panels 1 and 2. For example, the result is robust to using SIC 4-digit industry fixed effects (panel 1 column 4 and panel 2 column 1).

Our baseline set of firm-level controls are reported in Panel 1. We do not report them in further results because we are strictly limited by the Census Bureau in the number of coefficients we may disclose. The controls are at the firm level, except for employment and payroll which are at the establishment level. The only control with any predictive power is employment; spawning is negatively associated with the establishment's number of employees, consistent with the finding in Elfenbein et al. (2010*a*). Some controls are denoted with a lag ($t-1$) and others are not. This is because firm-level controls are measured when R&D is measured (last quarter of year $t-1$), but establishment-level variables are measured when the employee snapshot is taken (first quarter of year t).

We use alternative controls in panel 2 columns 2 and 3. First, column 2 employs establishment employee-level controls. Establishments with a higher share of white workers or foreign-born workers are associated with more spawning. Second, column 3 employs patent-level controls, measured at the firm level. Neither the number of patents nor the two citation measures predict spawning. However, patenting in more classes is associated with spawning. The fact that our estimate does not attenuate in the presence of patent controls shows, as will be discussed further below, that innovation inputs rather than patenting outputs drives spawning. Prior literature on innovation and worker mobility, including Gompers et al. (2005) and Matray (2015), has focused on the role of patents.

4.2 IV Result

The results from the instrumented second stage are in Table 4. (The first stage results are described in Section 3.2.4 and are in Table 3.) We repeat the specifications from Table 2. The coefficients in all models are statistically significant, and they are also uniformly much larger than the OLS results. Our preferred specification, in column 5, implies that a 100 percent increase in R&D is associated with a 36.6 percent increase in spawning, or a one standard deviation increase in R&D is associated with a 100 percent increase.

The larger instrumented effect indicates that the subset of R&D expenditure affected by the tax credits leads to greater spawning than the average increase in R&D. This could reflect endogeneity that biases the OLS result downward, as discussed in Section 3.2.2 above. However, the local average treatment effect for the complier subset may also be larger than the population average treatment effect. As Angrist & Imbens (1995) and Jiang (2015) explain, this can lead an IV strategy to produce larger effects than the true effect, even if the exclusion restriction is satisfied. That is, compliers with the instrument (in our case, the change in the tax price of R&D), may be those firms with a higher causal effect of R&D on spawning.

There are three possible explanations for such a phenomenon. First, there may be a correlation between propensity to spawn and adjustable R&D. That is, firms whose R&D is more sensitive to its tax price may also be doing the sort of R&D that leads to more spawning. Adjustable R&D may tend to be more general or inventive, and thus more often yield new ideas best suited to development outside the firm. It is not obvious why adjustable R&D would be more inventive, but we cannot rule out this possibility.

A second, more plausible explanation is that adjustable R&D is less crucial to the firm. The loss of the innovation output to spawns would then be less costly, implying lower ex-ante incentives to prevent spawning. That is, if the managers making R&D investment decisions are rational and have some information about the expected treatment effect, then costly spawning should lead them to increase R&D less in response to the tax price shock than a firm for which spawning is less costly. If R&D-induced spawning is less costly to compliers with the treatment (the tax shock), we expect the IV estimate to exceed the OLS estimate. To the degree that the spawning effect of R&D represents a knowledge spillover, this interpretation is relevant to policy: the large IV estimate suggests that R&D tax credits stimulate greater R&D-induced entrepreneurial spawning.

The third possibility is that the IV estimate represents the marginal effect of R&D, which is higher than the average effect. Note that OLS estimates the effect of an additional dollar of average R&D. The IV strategy, which uses additional R&D tax subsidies to approximate increased R&D expenditure on the margin, better captures the effect on spawning of the "last" R&D dollar. This marginal R&D is likely farther from the parent's core focus than average R&D, which may make it either less costly to lose or harder to protect.

If endogeneity biases the OLS result down, or if we capture the marginal effect of R&D better in the IV, then the IV estimate better approximates the true effect. Conversely, if the IV strategy isolates those firms whose cost of R&D-induced spawning is especially low, or for which adjustable R&D is otherwise correlated to spawning, then the LATE in the IV is biased upward, and we should assume that OLS yields a better approximation of the true effect. The true economic magnitudes likely lie between the OLS and IV estimates.

4.3 Alternative measures of entrepreneurial spawning and R&D

We consider alternative measures of spawning in Table 5. Panel 1 column 1 considers only spawns founded within one year (by year $t+1$). We continue to find a positive, significant coefficient using this more immediate measure. In the next two columns, we demonstrate why our primary dependent variable (Entrepreneurial spawning rate$_{t+3}$) limits measuring entrepreneurship to three years after the employee snapshot is taken at the parent firm. In panel 1 columns 2-3, the dependent variable classifies employees as entrepreneurs if they depart to a firm that is no more than 1 years old and are among the top five earners at that new firm. The dependent variable is the fraction of an establishment's workers as of first quarter of year zero who are entrepreneurs as of the first quarter of either year two or three. The effect remains positive but becomes insignificant by year three; that is, R&D-induced departures to entrepreneurship occur in the first two years after the increase in R&D.

As a robustness check of our main result, we replicate our main dependent variable using two instead of three years. We continue to find a significant effect (panel 2 column 1). Our primary dependent variable took a snapshot of the workers in year $t+3$. We turn to a different, "flow" measure of spawning in panel 2 column 2. Here entrepreneurs are defined as departed employees who are among the top five earners at a one-year-old spawn in year $t+1$, at a two-year-old spawn in year $t+2$, or at a three-year-old spawn in year $t+3$. That is, we consider cumulative departures. The coefficient in this specification is also positive and significant at the .01 level.

We then examine whether the results are driven by team exits, in which multiple employees leave to found a startup together. This is possible because our definition of "entrepreneur" includes the top five earners at a new firm. In this case, the number of spawns should be less than the number of spawning employees. The dependent variable in panel 2 column 3 is the number of unique startups spawned from an establishment, based on primary spawning dependent variable. We continue to observe a significant effect, albeit significant only at the .1 level, indicating that team exits do not explain the main results.

Our results are robust to alternative measures of R&D, shown in Table 6. When the independent variable is an indicator for the firm having had an above median change in last year's R&D, the effect is .089, significant at the .01 level (column 1). This implies that moving from the bottom to the top half of R&D changes increases the rate of entrepreneurial spawning by 6.9 percent. The effect is naturally stronger using the top 10 percentiles of R&D change (columns 3 and 4). We also find that the effect is robust to using R&D divided by total assets (columns 7-8).

4.4 Alternative explanations: Restructuring & employee turnover

R&D may lead to restructuring, in which many employees depart the firm. This could be an omitted variable causing the correlation between R&D and spawning. Our evidence is inconsistent with this alternative hypothesis. Appendix Table 1 column 1 shows that R&D in year t has no effect on the percent of employees who remain with the parent by year $t + 3$ (the same time period in which we measure spawning). Similarly, columns 2, 3, and 4 show that R&D has no effect on the percent of employees who move to another incumbent firm, drop out of the LEHD sample, or move to organizations whose age is unknown.

A second possible source of endogeneity is that when a firm undertakes R&D, it may hire new research employees, who are inherently more likely to start their own ventures than the average worker. In this case, workers with relatively short tenures would drive the effect. In fact, we find that the effect of R&D on spawning is positive and significant among employees with above-median tenure, suggesting that workers hired specifically for the new R&D project do not drive the spawning effect.[13]

Finally, it would be concerning if our effect were driven by employees who are

[13]Regressions are unreported due to disclosure limitations.

unlikely to be engaged in R&D activities or who are unlikely to start their own ventures. Unfortunately, we do not observe worker occupations. However, we do find that the effect is larger for employees in the top half of the establishment's wage distribution. Further, the effect is driven by workers with above median age.[14] This is consistent with the peak age for entering any type of entrepreneurship, high-tech entrepreneurship, and VC-backed or high-growth entrepreneurship being at least 40 (Jones 2010, Ozkal 2016, Azoulay et al. 2017).

4.5 Reverse causation

If R&D has a causal effect on spawning, it cannot be the case that spawning predicts R&D. To ensure this is the case, we project current-year R&D (in year t) on past spawning in Appendix Table 2. In column 1, we include one year of spawning, from year $t-2$ to year $t-1$. In columns 2 and 3, we include two years ($t-3$ to $t-1$) and three years ($t-4$ to $t-1$), respectively. In all cases, the coefficient is insignificant. This provides strong evidence for causality of our main effect, beyond the instrumental variables approach. In particular, it allays the primary endogeneity concern, which is that a technological opportunity jointly causes R&D and spawning. The very nature of a startup is to be adaptable and responsive to new opportunities. We would thus expect startup founding to respond to the new opportunity faster than corporate R&D. In contrast, we find that the entrepreneurial spawning occurs after the R&D.

5 Mechanism

This section considers two not mutually exclusive ways that corporate R&D might increase entrepreneurial spawning. One is intellectual capital, or new ideas generated by R&D, which an employee takes to his new firm. The other is human capital, or entrepreneurial skills that make employees more likely to launch their own ventures.

[14]Regressions are unreported due to disclosure limitations but are available upon request.

5.1 Intellectual capital

Our cross-sectional evidence supports the intellectual capital channel, as it satisfies three hypotheses. R&D induced spawning is associated with (a) the "research" part of R&D; (b) new-to-the-world ideas; and (c) R&D generating some ideas that are too far afield for the firm to benefit from.

5.1.1 "Research" part of R&D

We expect that the intellectual capital channel will be more associated with the "research" part of R&D, rather than the "development" part. Indeed, we find that high-tech establishments and more firms that do more general-purpose innovation are responsible for the spawning effect of R&D. These are less well associated with the commercialization, or development, aspect of R&D.

First, Table 7 shows that high-tech establishments drive our result. We interact R&D with a parent firm-level cross-sectional variable. An establishment is "high-tech" if its four-digit SIC code corresponds to high-tech manufacturing or R&D.[15] The effect is 0.083 larger for high-tech establishments than non-high-tech establishments. The effect for non-high-tech establishments (the coefficient on Log R&D) is small and insignificant, indicating that despite having positive R&D, non-high-tech establishments do not generate a spawning effect of R&D.

Second, the effect is driven by firms with patents that are more valuable because they are more general-purpose; used by a wider array of fields (Hall & Trajtenberg 2004). We interact R&D with an indicator for the firm having above-median patent generality, which means that future cites of its patents are from a wider array of patent classes. The effect is significantly higher for these firms (Table 7 column 4). Also, recall that firms that patent in more classes tend to have higher spawning rates (Table 2 panel 2 column 5). Thus, it seems that firms doing more basic and broad research have higher entrepreneurial spawning effects per dollar of R&D.

It is important to note that patenting does not drive our results, and there is no significant interaction between parent R&D and the number of patents or patent citations. R&D investment is an input, producing innovation in a highly uncertain,

[15] We identify high-tech SIC codes as 3200-3299, 3500-3599, 3700-3899, and 8732-8734.

serendipitous manner. Patents represent outputs that the firm has chosen to appropriate and sufficiently values the intellectual property right conferred by patents to make the necessary disclosure worthwhile. To our knowledge, we present the first evidence that R&D inputs lead to entrepreneurial spawning.

5.1.2 New-to-the-world ideas

The intellectual capital channel should yield spawns with new-to-the-world ideas, rather than "Main street" type businesses. If R&D stimulates restaurants or plumbing companies, it seems unlikely that ideas and inventions created by the R&D investment are the mechanism. We find that within the population of spawns, more parent R&D is associated with high-tech and venture capital-backed spawns. We examine in Table 8 whether parent R&D is associated with certain spawn characteristics.

Venture capital-backed startups are widely thought to be strongly associated with new-to-the-world ideas. Gornall & Strebulaev (2015) show that among U.S. public companies, those with venture capital are responsible for 44 percent of research and development expenditure, and Kaplan & Lerner (2010) show that over 60 percent of IPO issuers have venture capital backing. The dependent variable in Table 8 panel 1 column 1 is one if the spawn receives venture capital, which is the case for two percent of spawns (recall from Section 2.5 that this is high relative to the rate in the overall population of new firms). The coefficient on R&D is 0.007, significant at the .01 level. This implies that a one standard deviation increase in R&D leads to a 78.8 percent increase in venture capital-backed spawns. While there are other firm variables that are weakly associated with spawning, such as investment, R&D is the most economically important variable that predicts venture capital-backed spawns.

In panel 2 column 3, the dependent variable is one if the spawn is in a high-tech industry, and zero if it is not. Parent R&D is strongly associated with spawns being high-tech, consistent with the R&D-induced spawns being driven by new ideas. In column 4, we show that R&D induces spawns with higher wages than the average spawn. In unreported analysis, we do not find that R&D induces spawns with more initial employees. Thus R&D seems to induce spawns with high-skill labor, but that do not start at a larger than average size. The last outcome is the rate of exit, which we view as a proxy for risk. We assume the vast majority of exits are firm failures, but a small minority may be acquisitions, which could be a very successful exit. In column 5, the dependent variable is one if the startup exits within five years (starting from year $t + 3$, where t is the year in which we measure R&D). We find a positive, significant effect of R&D. In sum, relative to the average spawn, R&D-induced spawns are more likely to be high-tech, high-impact, and high-risk.

5.1.3 R&D generates some ideas that are too far afield for the firm to benefit from

We expect that the intellectual capital channel reflects R&D generating many new ideas, some of which are far from the parent's ken, and are easily appropriated by an employee. If the spawns are simply replicating the parents' business models, then they likely do not have a new idea. Instead, we find that spawns tend to be in different industries from parents, and more parent R&D makes it less likely that the spawn is in same industry as the parent. This suggests that the spawn has a new idea and is not replicating the parent's business.

In column 1 of Table 8, the dependent variable is one if the spawn is in the same 2-digit SIC classification as its parent (examples of 2-digit industries are "Business Services" and "Coal Mining"). The coefficient is negative and significant; more parent R&D reduces the chances that a spawn is in the same industry as its parent. Only 16.8 percent of spawns are in their parent's 2-digit industry.

Thus, our effect is driven by high-tech parents and high-tech spawns, while the R&D-induced spawns tend to be in different industries from their parents. The intellectual capital channel can reconcile these facts. The parent firm R&D creates growth options far from its core focus, which the employee can deploy in a new firm. The intellectual capital mechanism also fits well with our interpretation of the IV results. The ideas generated by R&D that wind up in departing employees' startups are much more likely to come from the last dollar of R&D than the first. In this light, the IV strategy yields an effect that isolates the driving mechanism: marginal R&D generates ideas, some of which spill over into startups founded by employees.

5.2 Human capital

In the human capital channel, R&D induces employee learning, which makes the employee more productive as an entrepreneur. In this channel, R&D leads to spawning not because of new ideas that it generates, but rather because of new skills that it generates. We cannot rule out that this channel plays a role, but three pieces of cross sectional evidence are inconsistent with it.

First, in a human capital channel, we would expect R&D-induced spawns to come from small parents. This is because small firm employees tend to have a broader scope of work (Stuart & Ding 2006, Sørensen 2007). Instead, large firms – defined as having above-median total assets within a given year – drive the effect (Table 7 column 2). Also note that the independent indicator for being a large firm has a negative coefficient that is slightly more than twice the positive coefficient on the interaction with R&D. While R&D-induced spawning is driven by large firms, on average small firms tend to have more spawns. This is consistent with Elfenbein et al. (2010*b*), who find using survey data on scientists that entrepreneurs are more likely to be spawned from small firms. Second, we might also expect that there is more opportunity for entrepreneurial learning at young firms. However, when we interact R&D with an indicator for being young (below median age), we find no effect.

Third, we would expect that capital expenditure would have a similar effect on spawning if the channel were skills, because new capital investment seems likely to create similar project management skills as R&D projects. Instead, Table 2 panel 1 shows that there is no effect of total investment or PPE investment on spawning. In sum, our evidence strongly supports the intellectual capital channel and is inconsistent with the human capital channel.

5.3 Control rights and spillovers

The intellectual capital channel implies that the spawning effect of R&D is a new avenue for knowledge spillovers. While knowledge spillovers have long been known to exist, it has been challenging for the literature to identify the channel of transmission (Jaffe et al. 1993, Greenstone et al. 2010). For the spawning effect of R&D to be a knowledge spillover, the cost to the parent of the R&D-induced spawn cannot outweigh the spawns's combined private and social value. Its private value is to the entrepreneur and other equity holders. Its social value comes from new jobs created or unpriced benefits from commercializing a new idea.

The effect might not be a knowledge spillover if either: 1) The spawn is very costly to the parent; or 2) The parent fully internalizes the spawn's benefits, implying no ex-ante underinvestment relative to the social optimum. In the subsections below, we consider each of these in turn. Note, however, that the ex-post split between the parent and the spawn of the surplus from the new idea is not relevant from a social welfare perspective. Strictly speaking, to be a positive externality it is only necessary that the spawning effect of R&D implies greater ex-ante underinvestment in R&D relative to the social optimum.

It is also worth emphasizing that a strong argument for the R&D effect on spawning being a source of knowledge spillovers is that R&D induces high-growth new firms. Young firms are more productive and grow faster than incumbents, as shown by a voluminous literature including Acs & Audretsch (1990), Kortum & Lerner (2000), Akcigit & Kerr (2010) Decker et al. (2014), and Glaeser et al. (2015). These social benefits suggest that even in the presence of some costs to the parent firm, the effect may still be a knowledge spillover.

5.3.1 Is spawning costly to the parent?

We find no evidence of large costs to parent. One test comes from non-compete covenants, which restrict employees from working for a competing firm within the state for a specified period of time. Literature has found that non-compete enforcement reduces local knowledge spillovers (Belenzon & Schankerman 2013, Matray 2015), and reduce within-state inventor mobility (Marx et al. 2015). We expect that if the R&D effect on spawning is very costly to the parent, it should be attenuated in states that enforce non-competes. Instead, the main result persists in states that enforce non-competes, and there is no significant effect on an interaction between R&D and an indicator for being in a weak enforcement state. A second test is that if R&D-induced spawning were costly to parent, it should be less feasible in sectors where intellectual property is easier to protect. We do not find that the effect varies with a measure of industry "patentability". Third, costly spawns may compete in product markets with the parent. Instead, we found that spawns tend to be in different industries from parents. This helps explain why the parent does not value the idea enough to keep it in-house.

Finally, we make a revealed preference argument. By virtue of observing the persistent phenomenon of R&D-induced spawning, the parent either chose not to develop the idea in house or chose not to take ex-ante steps to prevent the spawn. These steps could include increasing the employee's compensation to retain him, or even not conducting R&D at all.

It is possible that the parent does not possess the option to prevent the spawn. For example, the employee may fear expropriation and not disclose ideas, or he may be able to steal an idea that the firm deems valuable.[16] In the case of such contracting frictions, the parent firm should predict the loss of some innovative employees to spawning. It might price this cost into their compensation ex-ante. Regardless of these considerations, by virtue of observing spawning, any costs of preventing it must exceed the benefits.

5.3.2 Do parents internalize the benefits of the spawn?

The spawning effect of R&D would be less obviously a new source of R&D spillovers if the parent internalizes, or appropriates, the spawn's private benefits. This might occur if the parent invests in or acquires the spawn. Two pieces of cross-sectional evidence make this unlikely. First, we find that firms with corporate venture capital programs are not more responsible for spawning. Second, we expect parent-supported spinoffs to start at a larger scale than a typical bootstrapped startup. We find no relation between initial spawn size and parent R&D. That is, in specifications similar to those in Table 8, we find no effect of parent R&D on initial spawn employment. Also, spinoffs or parent

[16] The low costs of information and resource sharing (including teamwork) are reasons the firm exists in the first place. Giving employees the right incentives to innovate – that is, high-powered incentives – would make it impossible to manage the larger R&D process. For example, the firm will find it difficult to figure out ex-post exactly who is responsible for the innovation, and individuals will have incentives to hoard information. Note that the contracting challenges arise in large part from the inalienability of human labor (no slavery). This relates to the property rights literature associated with Grossman and Hart (1986).

reorganization would be expected to at least in some cases use the same establishment as before. Startups are defined in our data as firms with no prior activity at any of their establishments;

To provide more concrete evidence, we directly assess the possibility that parents internalize spawns' benefits using an out-of-sample test based on the underlying data in Gompers et al. (2005). They connected all venture capital-backed startup executives in the VentureOne database between 1986 and 1999 to their prior employers.[17] We hypothesize that this data should provide an upper bound on possible internalized spawning; since these spawns by definition received external investment, they are more likely than the average spawn to have received investment from their former employer. We begin with 13,612 entrepreneur-parent pairs. The entrepreneurs are founders of 6,499 unique spawns. There are 9,152 unique parents. In most cases spawns have multiple parents (that is, there are multiple executives with prior jobs). We linked all of the spawn parents to VentureXpert acquisition and investment data. We successfully matched 4,786 unique spawns to at least one investor or acquirer, a match rate of 74 percent. There are 20,478 unique spawn-investor pairs.[18]

A merge of these investors and acquirers to the parents yields 266 unique spawns where the parent matches an investor or acquirer, out of 4,786 spawns that we matched to VentureXpert, or 5.6 percent.[19] Of these, 192 are investment deals, and 74 are acquisitions. There are 208 unique parents that are matched to investors/acquirers. Note that some parents have multiple spawns, such as IBM and Highland Capital Partners, so the parent and spawn numbers do not match. Some parents that invested in or acquired their spawns are corporates, including Seagate, Xerox, Monsanto, Johnson &

[17] This time period overlaps with our primary Census data (1990 to 2005).

[18] Note that the underlying dataset, from Dow Jones Venture Source, is of venture capital-backed startups. In theory, if we used VentureSource, we should match 100 percent to initial investors. However, as Kaplan & Lerner (2016) and Maats et al. (2011) explain, VentureXpert's coverage is much better than Venture Source (more than 40 percent more investments). VentureXpert also has superior acquisition data, and Venture Source's data quality has declined over time. We are most interested in whether parents ultimately invested in (and especially acquired) spawns, so VentureXpert seems like the optimal data set to use. If there is any bias, it should be the case that the spawns that do not match have lower rates of subsequent investment and acquisition, since the commercial databases often backfill based on exit events.

[19] We matched on the company's first word, which yielded 275 matches. This enables successful matches such as "Xerox Venture Capital" to "Xerox." We then manually removed obviously wrong matches, erring on the side of leaving the match to be conservative in ambiguous cases.

Johnson, and Microsoft. Others are asset managers, including Accel Partners, Softbank, and Equus Capital. Still others are non-corporates, including Boston University. We identified 41 spawning parents that are clearly venture funds or other asset managers. This leaves 167 parents that are plausibly corporates, though this is generous as we retained financial services companies such as Goldman Sachs.

To interpret this exercise, we return to the total parent population. Of the 9,152 unique parents in the original Gompers et al. (2005) data, just 2.3 percent (208) invest in or acquire their spawns. This small percentage is evidence that parents do not usually internalize spawns by investing in or acquiring them. One concern may be that perhaps many corporate parents are not covered as investors or acquirers in VentureXpert. We can match 2,617 of the parents to investors or acquirers in VentureXpert. The most conservative framing of our results, then, restricts the parent population to firms that ever invested in or acquired a startup in VentureXpert. In this case, 7.9 percent of parents (208 out of 2,617) invest in or acquire their spawns. This extreme upper bound is still small and confirms that it is unlikely that parents generally internalize the benefits of their spawns.

The parent could also appropriate the spawn's benefits through technology licensing deals. We cannot assess this possibility with our data, but we think it unlikely that the parent can fully internalize the spawn's social benefits through such arms-length contracts.

Consistent with the out-of-sample test, within our data we find no interaction effect on spawning between R&D and the parent having a corporate venture capital program. These results are consistent with Ma (2016), who finds that public firms launch corporate venture capital programs when internal innovation is poor, invest in startups in their own industries, and invest in geographically distant startups. That is, corporate venture capital is a way to outsource innovation. This is the opposite of the corporate environment that yields R&D-induced spawning. Instead, when corporate R&D increases at innovative firms, it seems to serendipitously produce "extra" growth options, and spawning is an unintended consequence.

In sum, it appears likely that R&D-induced spawning is a direct form of knowledge spillover. We document that a remarkable 88 percent of spawns are located in the same state as the parent. The literature on knowledge spillovers has focused on their ability to explain industrial agglomeration, or the spatial concentration of firms. Knowledge spillovers have been found to be quite local and to decline with distance (e.g. Jaffe et al. 1993, Belenzon & Schankerman 2013, Kantor & Whalley 2014).

Our result offers another channel for the link between industrial agglomeration and knowledge spillovers, which is often attributed in part to the importance of tacit information (Audretsch & Feldman 1996, Glaeser 1999, Duranton & Puga 2001). Since spawns tend not to be in the same industry as their parents, our data suggest another reason for the connection between spillovers and agglomeration, more along the lines found in Ellison et al. (2010): moving may be privately costly to the spawned entrepreneur, or he may have relevant networks in the location of his former firm.

6 Conclusion

This paper shows that corporate R&D investment leads to entrepreneurial spawning, in which employees depart to launch their own firms. We do this both in tightly controlled fixed effects regressions and in an instrumental variables approach, where we instrument for R&D using federal and state R&D tax credits. We find that for the parent firm, the spawning effect of R&D yields no obvious contractual benefits, nor is it observably costly. Our evidence is consistent with corporate R&D being a new channel for knowledge spillovers, as well as a new source of high-tech startups.

Our results have two policy implications. First, the spawning effect of R&D implies greater corporate underinvestment in R&D relative to the social optimum than previously thought. Second, the presence of knowledge spillovers are one motivation for offering firms tax credits that lower their cost of R&D investment. The spawning effect of R&D is much larger in the instrumental variables model than in the fixed effects regression. This suggests, albeit in a partial equilibrium sense, that R&D tax credits are effective in that they lead to greater R&D-induced entrepreneurial spawning, which is likely a form of knowledge spillover.

Our finding also speaks to the theory of the firm. Zingales (2000) writes that

> "Entrepreneurship is the process by which new firms are created. But new firms are created to exploit growth options existing firms cannot or do not want to exploit. Thus, a theory able to explain what growth options existing firms are willing and able to exploit will also identify the opportunities for entrepreneurial activity."

We offer a concrete mechanism tying entrepreneurship to the growth options that an incumbent does not to exploit.

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Table 1: Summary Statistics

Panel 1: Firm-year level variables

	Mean	Quasi-median	Standard deviation
Made corporate VC investments$_t$	0.038		
Had $\geq$ 1 patent$_{t-10,t}$	0.601		
Diversified$_t$	0.789		
R&D/Total Assets$_{t-1}$	0.085	0.052	0.102
Log R&D$_{t-1}$	2.53	2.45	2.25
Tobin's Q$_{t-1}$	2.12	1.65	1.59
Age$_t$	20.03	21.03	6.18
Total Assets$_{t-1}$ ('000s)	3,483	529	12,630
Employment$_{t-1}$	6,107	1,987	12,690

Panel 2: Establishment-year level variables

	Mean	Quasi-median	Standard deviation
Weak non-compete enforcement (state)	0.613		
In high-tech industry	0.641		
Entrepreneurial spawning rate$_{t+3}$	1.31	0.82	2.43
# spawned firms$_{t+3}$	1.15	0.78	1.91
Stayers$_{t+3}$	47.77	52.30	25.98
Movers to old firms$_{t+3}$	26.29	22.51	18.10
Depart LEHD coverage$_{t+3}$	12.39	11.11	7.78
Movers to firms of unknown age$_{t+3}$	9.73	6.65	12.28
Average worker quarterly wage$_t$	17.53	15.50	10.56
Average worker age$_t$(years)	40.08	40.27	4.76
Average employee tenure$_t$(years)	2.69	2.40	1.88
Share employees female$_t$	0.333	0.313	0.192
Share employees white$_t$	0.795	0.835	0.171
Share employees foreign$_t$	0.062	0.031	0.098
Number employees$_t$	329	122	1,698

Note: Panel 1 shows summary statistics at the firm-year level (10,500 observations), and Panel 2 at the establishment-year level (36,000 observations). We do not show the median or standard deviation for indicators. Since Census disclosure procedures prohibit disclosure of percentile value, we approximate median with a quasi-median, which is estimated using a 99% weight on observations within the interquartile range and a 1% weight on the remaining observations. R&D, assets, and wages are in real 2014 dollars.

Panel 3: Spawn level variables

	Mean	Quasi-median	Standard deviation
	(1)	(2)	(3)
Same industry (SIC2) as parent	0.168		
Same state as parent	0.876		
High-tech industry	0.494		
Ever received VC	0.020		
Employee female	0.331		
Employee white	0.799		
Employee foreign	0.077		
Employee born in state	0.475		
Spawn employment$_{t+3}$	14.59	5.92	39.48
Spawn age$_{t+3}$	1.59	1.99	1.01
Spawn payroll$_{t+3}$ ('000s)	511	126	1,603
Employee age$_t$	35.16	34.64	10.94
Employee education	13.66	14.36	2.49
Employee tenure (years)$_t$	2.07	1.58	2.25
Employee wages (at parent firm)$_t$	57.80	39.12	71.70
Employee wages (at spawn)$_{t+3}$	51.84	33.60	60.99

Note: Panel 3 shows summary statistics at the spawn level. All variables are indicators and have 108,000 observations. Variables through "Employee born in state" are indicators, and the rest are continuous. "Employee" refers to individuals who left the parent firm to join the startup's founding team. Payroll and wages are in real 2014 dollars.

Table 2: Effect of R&D on Entrepreneurial Spawning

Panel 1

Dependent variable: Entrepreneurial spawning rate$_{t+3}$

	(1)	(2)	(3)	(4)	(5)
Log R&D$_{t-1}$	0.096**	0.105**	0.106**	0.099*	0.109*
	(0.045)	(0.050)	(0.051)	(0.052)	(0.060)
Log employment$_t$			-0.181***	-0.174***	-0.179***
			(0.019)	(0.018)	(0.019)
Log payroll$_t$			-0.057	-0.082	-0.033
			(0.054)	(0.056)	(0.054)
Firm age$_t$			-0.033	-0.021	-0.003
			(0.033)	(0.028)	(0.030)
Firm diversified$_t$			-0.130	-0.135	-0.141
			(0.095)	(0.095)	(0.100)
Sales growth$_{t-1}$			0.130	0.124	0.129
			(0.090)	(0.091)	(0.099)
EBITDA$_{t-1}$			0.127	0.155	-0.112
			(0.260)	(0.261)	(0.294)
Investment/Total assets$_{t-1}$			0.811	0.731	0.508
			(0.543)	(0.553)	(0.617)
Log Tobin's Q$_{t-1}$			0.032	0.027	0.044
			(0.067)	(0.067)	(0.077)
Log Total Assets$_{t-1}$			-0.033	-0.054	-0.001
			(0.069)	(0.070)	(0.066)
PPE investment/Total assets$_{t-1}$			-0.058	-0.050	-0.063
			(0.385)	(0.393)	(0.424)
Cash$_{t-1}$			-0.502	-0.506	-0.521
			(0.307)	(0.315)	(0.320)
Debt$_{t-1}$			0.052	0.069	0.187
			(0.220)	(0.225)	(0.203)
Controls		Yes			
Year FE	Yes	Yes	Yes	Yes	
Firm FE	Yes	Yes	Yes	Yes	Yes
State FE			Yes	Yes	
Industry (SIC3) FE			Yes		
Industry (SIC4) FE				Yes	
Industry-year FE					Yes
State-year FE					Yes
N	36,000	36,000	36,000	36,000	36,000
Adj. R^2	0.156	0.167	0.176	0.184	0.180

Panel 2

Dependent variable: Entrepreneurial spawning rate$_{t+3}$

	(1)	(2)	(3)
Log R&D$_{t-1}$	0.102**	0.104**	0.101**
	(0.052)	(0.051)	(0.051)
Average employee age$_t$		-0.036***	
		(0.007)	
Share employees female$_t$		-0.084	
		(0.165)	
Share employees white$_t$		0.713***	
		(0.169)	
Share employees foreign$_t$		0.508**	
		(0.251)	
Average employee education$_t$		-0.055	
		(0.043)	
Average employee tenure$_t$		-0.023*	
		(0.013)	
Average employee experience$_t$		0.004	
		(0.017)	
Log patent classes			0.227*
			(0.120)
Log patents			-0.137
			(0.091)
Log forward citations			-0.006
			(0.022)
Log backward citations			-0.005
			(0.038)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
State FE		Yes	Yes
Industry (SIC3) FE		Yes	Yes
Industry (SIC4) FE	Yes		
N	36,000	36,000	36,000
Adj. R^2	0.181	0.179	0.176

Note: This table shows the effect of corporate R&D on entrepreneurial spawning. The sample is an establishment-year panel of public firms. The dependent variable is the fraction of an establishment's workers as of first quarter of year zero who are entrepreneurs as of 1st quarter of year 3. An entrepreneur is defined as a person at a firm no more than 3 years old who is among the top 5 earners at that new firm. In panel 2, controls are the same as in panel 1. Standard errors are clustered by firm. $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% levels.

Table 3: First Stage IV Results

Dependent variable: Log R&D$_{t-1}$

	(1)	(2)	(3)	(4)	(5)	(6)
Federal R&D tax price	-2.020***	-1.504***	-1.504***	-1.470***	-1.363***	-1.424***
	(0.295)	(0.231)	(0.231)	(0.225)	(0.168)	(0.199)
State R&D tax price	-1.158*	-0.950**	-0.956**	-0.978**	-0.303	-0.947**
	(0.691)	(0.476)	(0.476)	(0.471)	(0.375)	(0.420)
Controls		Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes		Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE			Yes	Yes		Yes
Industry (SIC3) FE				Yes		
Industry-year FE					Yes	
State-year FE					Yes	
Industry (SIC4) FE						Yes
N	36,000	36,000	36,000	36,000	36,000	36,000
R^2 (partial for the IV instruments)	0.032	0.027	0.026	0.026	0.022	0.025
F-test (instruments)	24.70	22.23	22.25	22.37	34.11	27.64

Note: This table shows the first stage of the instrumental variables analysis (Table 4). The sample is an establishment-year panel of public firms. We predict parent firm R&D using firm-level federal and state tax prices of R&D, which are partially determined by tax credits that change across time, states, and depending on firm age. The federal R&D tax price is the log firm-level tax price of R&D, based on the federal tax credit, and following Hall (1993) and Bloom et al. (2013). The state R&D tax price is the log state-level tax price of R&D, following Bloom et al. (2013). See Section 3.2 and Appendix Section 1 for details. Establishment controls are size and average wage. Firm controls are return on assets, sales growth, Tobin's Q, asset tangibility (PPE investment/total assets), size (log total assets), cash holdings, age, and diversified (establishments in more than one SIC 3-digit industry). Standard errors are clustered by firm. $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% levels.

Table 4: Second Stage IV Results: Effect of R&D on Entrepreneurial Spawning

Dependent variable: Entrepreneurial spawning rate$_{t+3}$

	(1)	(2)	(3)	(4)	(5)	(6)
Instrumented log R&D$_{t-1}$	0.577***	0.719***	0.659**	0.648**	0.587*	0.598**
	(0.207)	(0.274)	(0.271)	(0.270)	(0.317)	(0.276)
Controls		Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes		Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE				Yes		Yes
Industry (SIC3) FE			Yes	Yes		
Industry-year FE					Yes	
State-year FE					Yes	
Industry (SIC4) FE						Yes
N	36,000	36,000	36,000	36,000	36,000	36,000

Note: This table shows the effect of instrumented R&D on entrepreneurial spawning. The sample is an establishment-year panel of public firms. The first stage predicting R&D is shown in Table 3. The dependent variable is the fraction of an establishment's workers as of first quarter of year 0 who are entrepreneurs as of 1st quarter of year 3. An entrepreneur is defined as a person at a firm no more than 3 years old who is among the top 5 earners at that new firm. We do not display controls because we are limited by Census in the number of coefficients we may disclose. Establishment controls are size and average wage. Firm controls are return on assets, sales growth, Tobin's Q, asset tangibility (PPE investment/total assets), size (log total assets), cash holdings, age, and diversified (establishments in more than one SIC 3-digit industry). Standard errors are clustered by firm. $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% levels.

Table 5: Effect of R&D on Alternative Measures of Entrepreneurial Spawning

Panel 1

Dependent variable:	Entrepreneurial spawning rate to... 1-yr old startups$_{t+1}$	1-yr old startups$_{t+2}$	1-yr old startups$_{t+3}$
	(1)	(2)	(3)
Log R&D$_{t-1}$	0.055**	0.057*	0.036
	(0.025)	(0.033)	(0.032)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Industry (SIC3) FE	Yes	Yes	Yes
N	36,000	36,000	36,000
Adj. R^2	0.090	0.097	0.106

Panel 2

Dependent variable:	Entrepreneurial spawning rate to 1-or 2-yr old startups$_{t+2}$	Flow entrepreneurial spawning rate$_{t+3}$	Number of spawned firms$_{t+3}$
	(1)	(2)	(3)
Log R&D$_{t-1}$	0.076*	0.89***	0.067*
	(0.042)	(0.070)	(0.037)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Industry (SIC3) FE	Yes	Yes	Yes
N	36,000	36,000	36,000
Adj. R^2	0.131	0.209	0.154

Note: This table shows the effect of R&D on alternative measures of entrepreneurial spawning. The sample is an establishment-year panel of public firms. For a detailed description of the dependent variables, see Section 4.3. Controls are the same as in Table 2 Panel 1. Standard errors are clustered by firm. $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% levels.

Table 6: Effect of Alternative Measures of R&D on Entrepreneurial Spawning

Dependent variable: Entrepreneurial spawning rate$_{t+3}$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Above median Δ R&D$_{t-1}$	0.089***	0.078**						
	(0.033)	(0.032)						
Top 10 pct Δ R&D$_{t-1}$			0.132**	0.157**				
			(0.067)	(0.070)				
Bottom 10 pct Δ R&D$_{t-1}$					-0.105**	-0.114*		
					(0.053)	(0.060)		
R&D/Total Assets$_{t-1}$							1.020**	0.887*
							(0.495)	(0.529)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes		Yes		Yes		Yes	
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry (SIC3) FE	Yes		Yes		Yes		Yes	
State FE	Yes		Yes		Yes		Yes	
Year-industry FE		Yes		Yes		Yes		Yes
Year-state FE		Yes		Yes		Yes		Yes
N	36,000	36,000	36,000	36,000	36,000	36,000	36,000	36,000
Adj. R^2	0.176	0.180	0.176	0.180	0.176	0.180	0.175	0.180

Note: This table shows the effect of alternative measures of R&D on entrepreneurial spawning. The sample is an establishment-year panel of public firms. Change (Δ) in R&D is defined as: $\frac{R\&D_{t-1}-R\&D_{t-2}}{.5\cdot(R\&D_{t-1}+R\&D_{t-2})}$. Top 10 pct Δ R&D$_{t-1}$ is 1 if the firm had a change in R&D that is in the top 10 percentiles (relative to all firm-years), and 0 if in the bottom 90 percentiles. Bottom 10 pct Δ R&D$_{t-1}$ is defined analogously. The dependent variable is the fraction of an establishment's workers as of first quarter of year zero who are entrepreneurs as of 1st quarter of year 3. An entrepreneur is defined as a person at a firm no more than 3 years old who is among the top 5 earners at that new firm. Controls are the same as in Table 2 Panel 1. Standard errors are clustered by firm. $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% levels.

Table 7: Parent Variation in Effect of R&D on Entrepreneurial Spawning

Dependent variable: Entrepreneurial spawning rate$_{t+3}$

	(1)	(2)	(3)	(4)
Log R&D$_{t-1}$	0.048	0.016	0.035	0.099*
	(0.057)	(0.062)	(0.066)	(0.052)
Log R&D$_{t-1}$·High Tech	0.083***			
	(0.029)			
High Tech	1.378***			
	(0.351)			
Log R&D$_{t-1}$·Large		0.130**		
		(0.056)		
Large		-0.333**		
		(0.149)		
Log R&D$_{t-1}$·Old			0.098	
			(0.067)	
Old			-0.315	
			(0.491)	
Log R&D$_{t-1}$·High patent generality				0.027*
				(0.016)
High patent generality				-0.093
				(0.076)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Industry (SIC3) FE	Yes	Yes	Yes	Yes
N	36,000	36,000	36,000	36,000
Adj. R^2	0.176	0.176	0.176	0.176

Note: This table shows how the effect of corporate R&D on entrepreneurial spawning varies by parent firm characteristics. The sample is an establishment-year panel of public firms. High Tech is 1 if the parent establishment is in a high-tech industry, and 0 if not. Large is 1 if the parent has above-median total assets (calculated at the firm-year level), and 0 if below-median. Old is 1 if the parent is of above-median age (calculated at the firm-year level), and 0 if below-median. High patent generality is 1 if the parent has above-median patent generality (calculated at the industry-year level), and 0 if below-median. The dependent variable is the fraction of an establishment's workers as of first quarter of year zero who are entrepreneurs as of 1st quarter of year 3. An entrepreneur is defined as a person at a firm no more than 3 years old who is among the top 5 earners at that new firm. Controls are the same as in Table 2 panel 1. Standard errors are clustered by firm. $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% levels.

Table 8: Effect of R&D on Entrepreneurial Spawning by Spawn Characteristics

Panel 1: What predicts venture capital-backed spawns?

Dependent variable: Spawn ever received VC

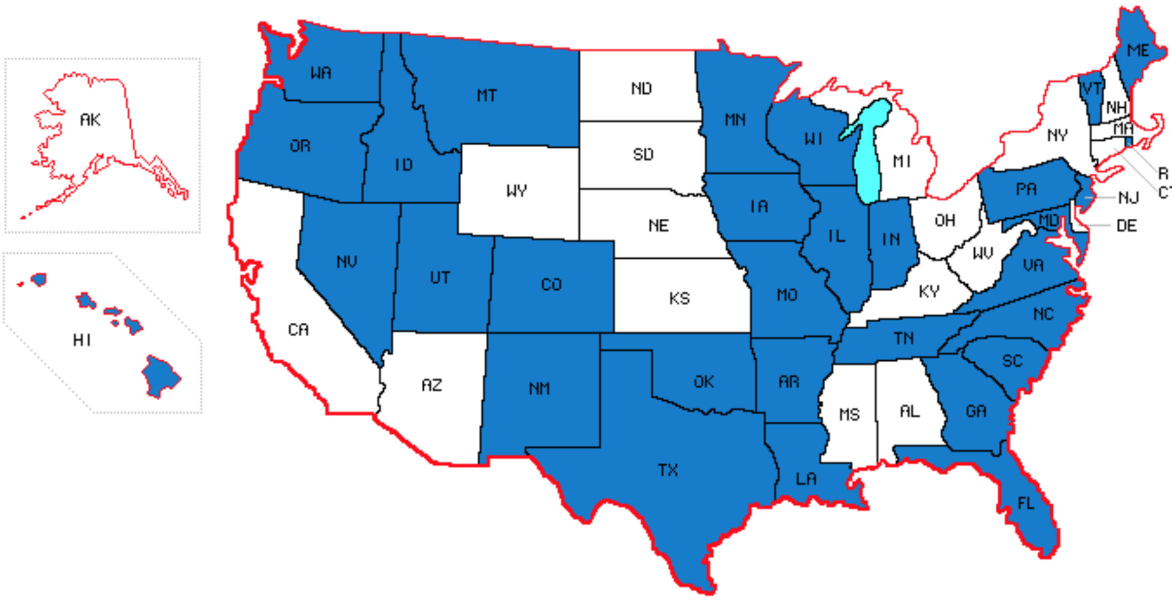
	(1)
Log R&D$_{t-1}$	0.007***
	(0.001)
Employee age$_t$	0.001**
	(0.000)
Employee age$^2{}_t$	-0.000**
	(0.000)
Employee female	-0.013***
	(0.002)
Employee white	0.003**
	(0.001)
Employee foreign	-0.002
	(0.004)
Employee born in state	-0.007***
	(0.001)
Employee education	0.001***
	(0.000)
Employee experience$_t$	-0.000
	(0.001)
Employee tenure$_t$	-0.000
	(0.000)
Employee log earnings$_t$	0.008***
	(0.002)
Spawn age$_{t+3}$	0.007***
	(0.001)
Spawn initial employment	0.008***
	(0.002)
Continued...	
...Continued	
Establishment Log Employment$_t$	0.001
	(0.001)
Establishment average employee wage$_t$	0.012***
	(0.003)
Firm Age$_t$	-0.002***
	(0.001)
Firm Diversified	-0.003
	(0.006)
Firm Sales growth$_{t-1}$	0.004
	(0.006)
Firm EBITDA$_{t-1}$	-0.008
	(0.016)
Firm Investment/Total$_{t-1}$	-0.013
	(0.041)
Firm Log Tobin's Q$_{t-1}$	0.002
	(0.004)
Firm Log Total Assets$_{t-1}$	-0.006***
	(0.002)
Firm PPE Investment/Total Assets$_{t-1}$	-0.004
	(0.012)
Firm Cash$_{t-1}$	0.076***
	(0.015)
Firm Debt$_{t-1}$	0.009
	(0.007)
Year-state FE	Yes
Year-industry (SIC3) FE	Yes
N	108,000
Adj. R^2	0.079

Panel 2: Other spawn characteristics

Dependent variable:	Spawn in same industry (SIC2) as parent est.	Spawn in same state as parent est.	Spawn in a high-tech industry	Spawning employee's log wages$_{t+3}$	Spawn exit$_{t+5}$
	(1)	(2)	(3)	(4)	(5)
Log R&D$_{t-1}$	-0.007**	0.002	0.009***	0.028***	0.007**
	(0.003)	(0.002)	(0.004)	(0.006)	(0.003)
Controls	Yes	Yes	Yes	Yes	Yes
Year-state FE	Yes	Yes	Yes	Yes	Yes
Year-industry (SIC3) FE	Yes	Yes	Yes	Yes	Yes
N	108,000	108,000	108,000	108,000	108000
Adj. R^2	0.206	0.053	0.102	0.318	0.083

Note: This table shows the effect of R&D on types of entrepreneurial spawning. The sample is at the spawn level, and consists of all spawns of public firms. Based on the main variable used in Table 2, "Entrepreneurial spawning rate$_{t+3}$", we identify whether the new firm associated with the spawning employee has a given characteristic. The dependent variable in panel 1 column 1 is 1 if the spawn ever received VC backing (either before or after the spawn is identified in year $t + 3$), and 0 if not. The "Employee..." controls in panel 1 column 1 refer to the spawning employee who left the parent. The dependent variable in panel 2 column 1 (2) (3) is 1 if the spawn is in the same 2-digit SIC code as the parent establishment (is in the same state as the parent establishment) (is in a high-tech industry), and 0 if not. The dependent variable in panel 2 column 4 is the spawning employee's log wages at the new firm in the 1st quarter of year 3. An entrepreneur is defined as a person at a firm no more than 3 years old who is among the top 5 earners at that new firm. The dependent variable in panel 2 column 5 is 1 if the spawn exited (failed, though a small minority may be acquisitions) by year 5, and 0 if not. Controls are the same as in Table 8 Panel 1, except that we include the indicator for being VC-backed as an additional control in panel 2 columns 1-5. Standard errors are clustered by parent firm. $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% levels.

Figure 1: Map of States with LEHD (spawn) Data



Note: This figure shows the 31 LEHD states that we have access to. We observe all spawns located in these states.

Appendix

(for online publication)

Instrumental variables calculation and discussion

A.1. The Federal R&D tax credit

The first instrument is the federal tax price of R&D, which we denote ${\rho_{ft}}^F$. Implemented in 1981, the federal "Research and Experimentation" (R&E) tax credit permits firms to reduce their corporate income tax liability by the value of the credit. The credit was extremely complex to calculate (leading to a substantial simplification in 2009), and has changed over time. In the early 2000s, the total value of the federal credits was about $5 billion per year (Wilson et al. 2005).

In this description, we focus on the calculation of the credit between 1990 and 2005, which is the sample period for which we need to predict public firm R&D.[20] The general formula for the R&E tax credit is as follows, for tax year t and firm f:

$$R\&E\ Tax\ Credit\ Value_{tf} = 20\% \cdot [QRE_{tf} - Base_{tf}] + 20\% \cdot [Basic\ Research_{tf}] \quad (4)$$

The last element, basic research expenditures, must be paid to a qualified organization, which is either a research university or tax-exempt scientific organizations. The other, more complex type of research costs are qualified research expenditures (QRE). These must occur within the U.S., and have three categories: salaries and wages, supplies, and contract research. The law is quite specific about what counts and what does not count as QRE. For example, QRE must be technological in nature and relate to new or improved function, performance, reliability, or quality. Among other excluded types, research after commercial production of a component, survey research, and social science research do not count.[21]

[20] The calculation was quite different before 1989. In practice, we draw heavily from code originally written for Hall (1993).

[21] The complete legal text is here: https://www.law.cornell.edu/uscode/text/26/41.

The "base" amount is by far the most complicated element. It is constructed using the following equation:

$$Base_{tf} = Fixed\ Base\ \%_{tf} \cdot Sales_t$$

The complexity lies in the fixed base percentage, which varies by a firm's "startup" status. This term, which is used in the legislation and in Hall (1993), refers to the number of years since the firm's first instance of QRE. It is calculated as follows (firm index omitted for simplicity):

$$Fixed\ Base\ \% = \begin{cases} \max\left[\frac{\sum_{t=1984}^{1988}\frac{QRE_t}{Sales_t}}{5},\ 0.16\right] & if\ QRE_{1983} > 0\ \&\ Sales_{1983} > 0 \\ 0.03 & if\ QRE_{t-6} \in \{0, \emptyset\} \\ \frac{1}{6}\left[\frac{\sum_{t=-2}^{-1}\frac{QRE_t}{Sales_t}}{2}\right] & if\ QRE_{t-7} \in \{0, \emptyset\}\ \&\ QRE_{t-6} > 0 \\ \frac{1}{3}\left[\frac{\sum_{t=-2}^{-1}\frac{QRE_t}{Sales_t}}{2}\right] & if\ QRE_{t-8} \in \{0, \emptyset\}\ \&\ QRE_{t-7} > 0 \\ \frac{1}{2}\left[\frac{\sum_{t=-3}^{-1}\frac{QRE_t}{Sales_t}}{3}\right] & if\ QRE_{t-9} \in \{0, \emptyset\}\ \&\ QRE_{t-8} > 0 \\ \frac{2}{3}\left[\frac{\sum_{t=-4}^{-1}\frac{QRE_t}{Sales_t}}{4}\right] & if\ QRE_{t-10} \in \{0, \emptyset\}\ \&\ QRE_{t-9} > 0 \\ \frac{5}{6}\left[\frac{\sum_{t=-5}^{-1}\frac{QRE_t}{Sales_t}}{5}\right] & if\ QRE_{t-11} \in \{0, \emptyset\}\ \&\ QRE_{t-10} > 0 \\ \min\left[\frac{QRE_t}{Sales_t}\right]_{t-6}^{t-1} & if\ QRE_{t-x} \in \{0, \emptyset\}\ \&\ QRE_{t-x-1} > 0\ \forall\ \text{x}\geq 12 \end{cases}$$

In words, the first row is interpreted in the following way. For firms that had positive QRE and sales in 1983, the fixed base percentage is the maximum of 16% and the average of R&D intensity over the five years between 1984 and 1988. All the subsequent rows in the above equation pertain to what the law terms "startups." For example, for the first five taxable years after the first year in which a firm has positive QRE, the fixed base is 3%. In the 6th such year, it is one-sixth the average of the R&D intensity over the previous two years. The following rows are similarly calculated. Starting in the eleventh such year, firm may choose the percentage from any of the prior fifth through tenth years.

A few other details bear mention. The expense deduction for R&D is recaptured, reducing the effective credit rate from 20% to about 13.5%. Also, in the fiscal year 1995-6, the credit lapsed entirely. Additionally, when the credit value is larger that taxable profits, it can be carried forward for ten years. Finally, between 1990 and 1996, the only option was the R&E tax credit. Starting in 1996, firms could elect the alternative incremental credit (AIC), in lieu of the R&E tax credit. This has 3 tiers depending on R&D intensity (QRE relative to sales); if intensity is 1-1.5% (1.5-2%) (>2%), the AIC rate is 2.65% (3.2%) (3.75%), respectively. These rates have varied over time; they were lower in the late 1990s, and have increased in recent years.

The credit is firm-specific for a number of reasons. First, it depends on firm age, with annual changes for most firms. Second, the "base" amount of R&D is calculated using a firm's past R&D and current-year sales. Third, the base amount of the tax credit is the difference between realized R&D and the base. Fourth, there is a lower implicit value of the credit among tax exhausted firms because the value of the carry forward must be discounted. Finally, the lapse in 1995-96 generates additional within-firm variation, only for firms with R&D expenditures that year.

The R&E tax credit (denoted ERC_t) is in practice considerably more complicated to calculate than Equation 4, and follows Equation 7 in Hall (1992) and underlying equations not shown in her paper; these are available in Stata code on request. Calculating ERC_t begins with the tax credit rate (constant across firms), and multiplies by a categorical variable derived from QRE. This is then deducted from corporate tax liability. Then, a 3-year carry-back and a 15-year carry-forward are added in cases of no taxable income this year. Once this tax credit is arrived at, the tax price of R&D

is calculated following Equation 6 in Hall (1992). This is:

$$\rho_{ft}{}^{F} = \rho_t^R \left[1 - T_t \left(1 + r\right)^{-Jt} \tau \right] - \eta ERC_t \tag{5}$$

Here, ρ_t^R is an R&D deflator divided by a GDP deflator, or the "price" of R&D investment in the absence of taxes, T_t is an indicator for whether the firm has taxable income in the current year, J_t is the number of years until loss carry-forwards will be exhausted, τ_t is the corporate tax rate, and η_t is QRE. If $\rho_{ft}{}^{F} = 1$, then the firm should not treat R&D differently than other expenditure. If $\rho_{ft}{}^{F} < 1$, R&D is less expensive than other expenditure because of the tax credit.

In practice, we find substantial within-industry variation in $\rho_{ft}{}^{F}$, especially in manufacturing and services. The median tax price is well below 1 on average, so that R&D is cheaper than other spending. Within industries, the distributions have negative skew (i.e., a longer right tail). We also ensure that relevant current year variables, including R&D, do not have strong explanatory power over the tax price of R&D. Within firms, we find small positive correlations (all less than 0.1) between $\rho_{ft}{}^{F}$ and employment, assets, and R&D. In regressions, we verify substantial firm-level variation in the tax price of R&D. Firms in high tech areas such as pharmaceuticals and electronics, tend to have the most variation.

A.2 State R&D tax credits

State R&D tax credits have been generally modeled on the federal one. The first state R&D tax credit was implemented in 1982 by Minnesota; by the end of our sample period, forty states had some sort of R&D tax credit. The calculation of the base amount, and the definition of qualified R&D, can vary across states (Wilson et al. 2005). According to Miller & Richard (2010), manufacturing-intensive states, and those with one-party political control, are more likely to pass R&D tax credits. They argue that the tax credits primarily support incumbent R&D-conducting firms.

The state instrument requires two objects: the state tax price component of the R&D user cost of capital, and a measure of the share of a firm's R&D that occurs in a given state. For both, we follow Bloom et al. (2013). First, we use the state tax price of R&D in Wilson (2009). He incorporated state level corporate income taxes, depreciation allowances, and R&D tax credits into this tax price component, which we call ρ^S_{st}.[22] These credits vary across states and time. They allow a firm to offset its state-level corporate tax liabilities, and they are calculated by weighting total firm profits according to the location of the firm's sales, employment, and property. Thus firms with R&D activities in the state will likely both have tax liability and R&D tax credit eligibility there.

The second object, θ_{fst}, is a proxy for a firm's R&D share in a given state-year. It is the 10-year moving average of the share of the firm's patent inventors located in state s.[23] The firm's state-level tax price is then $\rho^S_{ft} = \sum_s \theta_{fst}\rho^S_{st}$.

A.3 Concerns

There are four potential concerns. Most importantly, the exclusion restriction is that tax credits cannot affect entrepreneurial spawning. We show empirically that there is no relation between the state tax credits and state-level startup creation, or the federal tax credit and national startup creation. We do this using two data sources, each of which have limitations. The first is the Business Dynamics Statistics (BDS), which contains firm entry by state for our entire sample period, but does not have state-industry data.[24] The second is the Quarterly Workforce Indicators (QWI), a publicly available dataset derived from the LEHD. While the QWI has state-industry level data, its coverage is poor in the early years of our data, with counties being added over time.[25]

At the state level, using the BDS sample, we regress either the log number of new firms or the change in firm entry rates year to year on the tax price of R&D, as well as state and year fixed effects. The results are in Table 3. We cluster errors by state. Regardless of the fixed effects or standard error assumptions, we find that the tax credits have no correlation with startup entry (panel 1). Using the QWI sample,

[22] Specifically, it is roughly: $\frac{1-(tax\ credits+depr.\ allowances)}{1-tax\ rate}$.

[23] The data is from NBER patent data, available at https://sites.google.com/site/patentdataproject/Home/downloads.

[24] This public version of the LBD is available at https://www.census.gov/ces/dataproducts/bds/data_firm.html.

[25] We used a transformed version of the data used in Adelino et al. (2017), courtesy of Song Ma.

our dependent variable is either the logged new jobs created in new firms in the past two years, or the change in the number of new jobs created in new firms in the past two years. We consider only R&D-intensive industries.[26] Again, regardless of whether we use year and/or state fixed effects, and regardless of the standard error assumptions, we find no effect of the tax price of R&D on these measures. This is in Table 3 Panel 2.

At the federal level, we regress either the log number of new firms or the change in firm entry rates on the statutory federal R&D tax credit. This is, of course, very different from the firm-specific tax price of R&D that is calculated per the description in Section A1.1. This reflects baseline changes in the rate, which is then applied to a firm's specific situation. There are very few observations, and we do not use robust standard errors. The results, in Table 3 Panel 3, again show no correlation.

More generally, the legal literature has argued that R&D tax credits are not useful to startups, as they have no or little taxable income against which to offset losses from failed R&D efforts (Bankman & Gilson 1999).[27] Perhaps in response to this, a few states have recently made their R&D tax credits transferable, so that firms without revenue can potentially derive value from them. However, these policies occurred after the end of our sample period.

The second concern is that changes in state-level R&D tax credits may lead firms to reallocate R&D (or misreport it such that it appears reallocated). For studies evaluating how a state-level R&D tax credit affects national R&D, this is a central concern. In our case, however, such reallocation will simply reduce the power of the instrument. As long as the combined instruments have adequate power, some degree of reallocation should not bias our findings. It does lead us to expect that the federal instrument will have more power than the state instrument, which is indeed what we find. This is because it should have a larger effect on firms that only operate in the affected state, but most firms with positive R&D operate in multiple states.

[26]NAICS codes 31-33, 51, and 54.

[27]Bankman & Gilson (1999) note that "the U.S. tax code subsidizes R&D by existing successful companies by allowing losses from failed attempts at innovation to offset otherwise taxable income from other activities. Since startups have no other income against which their losses from a particular project may be set off, the government in effect gives established companies with a stable source of income an R&D tax subsidy that is not available to a startup entity."

The third concern is that the tax credits may not be large enough to affect R&D. The above sections pointed to substantial literature finding R&D responses to R&D tax credits that are large in economic magnitude and quite robust, especially for the federal instrument. The literature examining the state instrument finds large within-state elasticities, but also finds evidence of reallocation across states.

Finally, the fourth concern is that state decisions to adopt R&D tax credits could be endogenous, reflecting recent declines in R&D. Bloom et al. (2013) consider this possibility at length, and show that the results are robust to lagging the tax credit instruments one and two periods. They also point out that cross-sectional variation in the state R&D tax credit rates is very large relative to the average rate within states, and also large relative to the secular increase in the tax credit generosity that has occurred over time. Finally, Chirinko & Wilson (2008), Chirinko & Wilson (2011), and Bloom et al. (2013) show that the level and timing of R&D tax credit adoption is uncorrelated with local economic observables like state R&D expenditure or per capita GDP, once year and state fixed effects are included.

In sum, we believe that R&D tax credits offer the best available source of variation driving corporate R&D that is plausibly unrelated to technological opportunities that could jointly give rise to parent R&D and entrepreneurial spawning.

Table 1: Effect of R&D on Non-entrepreneurial Employee Outcomes

Dependent variable:	Stayers_{t+1}	Movers to old firms_{t+3}	Depart LEHD coverage_{t+3}	Movers to firms of unknown age_{t+3}
	(1)	(2)	(3)	(4)
Log $\text{R\&D}_{t-1}$	-1.133	0.485	-0.004	0.506
	(0.715)	(0.608)	(0.133)	(0.452)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Industry (SIC3) FE	Yes	Yes	Yes	Yes
N	36,000	36,000	36,000	36,000
Adj. R^2	0.385	0.356	0.222	"0.207

Note: This table shows the effect of R&D on alternative employee outcomes. The sample is an establishment-year panel of public firms. In column 1, the dependent variable is the fraction of an establishment's workers in the 1st quarter of year zero who remain at the firm in the 1st quarter of year 3. In column 2, the dependent variable is the fraction of an establishment's workers in the 1st quarter of year zero who move to a firm that is more than 3 years old by the 1st quarter of year 3. In column 3, the dependent variable is the fraction of an establishment's workers in the 1st quarter of year zero who drop out of the employment sample by the 1st quarter of year 3 (note they may have moved to an uncovered state). In column 4, the dependent variable is the fraction of an establishment's workers in the 1st quarter of year zero who move to an organization whose age is unknown by the 1st quarter of year 3. Controls are the same as in Table 2 Panel 1. Standard errors are clustered by firm. $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% levels.

Table 2: Reverse Causality Test (Effect of Entrepreneurial Spawning on R&D)

Dependent variable: Log R&D$_t$

	(1)	(2)	(3)
One-year entrepreneurial spawning rate$_{t-2,\ t-1}$	0.008		
	(0.005)		
Two-year entrepreneurial spawning rate$_{t-3,\ t-1}$		0.001	
		(0.006)	
Three-year entrepreneurial spawning rate$_{t-4,\ t-1}$			-0.005
			(0.003)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Industry (SIC3) FE	Yes	Yes	Yes
N	36,000	36,000	36,000
Adj. R^2	0.879	0.879	0.879

Note: This table shows that current entrepreneurial spawning does not predict corporate R&D. The sample is an establishment-year panel of public firms. The independent variables are lagged variations on our main entrepreneurial spawning rate measures used as the dependent variable in Tables 2 and 4. The one-year entrepreneurial spawning rate$_{t-1}$ is the fraction of an establishment's workers as of first quarter of year $t-1$ who are entrepreneurs as of 1st quarter of year t, which is the year that R&D is measured (the dependent variable). The two-year entrepreneurial spawning rate$_{t-2}$ is the fraction of an establishment's workers as of first quarter of year $t-2$ who are entrepreneurs as of 1st quarter of year t. The three-year entrepreneurial spawning rate$_{t-3}$ is the fraction of an establishment's workers as of first quarter of year $t-3$ who are entrepreneurs as of 1st quarter of year t. An entrepreneur is defined as a person at a firm no more than 3 years old who is among the top 5 earners at that new firm. Controls are the same as in Table 2 Panel 1. Standard errors are clustered by firm. $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% levels.

Table 3: Relationship between state tax price of R&D and state startup formation

Panel 1: Quarterly Workforce Indicator (LEHD) data

Dependent variable	2-year employment growth		Log 2-year employment growth		Change in 2-year employment growth	
	(1)	(2)	(3)	(4)	(5)	(6)
State tax price of R&D	-20068	4754	-.74	.33	-117	-6.5
	(21295)	(9035)	(.59)	(.36)	(7912)	(57677)
State f.e.	Y	Y	Y	Y	Y	Y
Year f.e.	Y	N	Y	N	Y	N
N	449	449	449	449	448	447
R^2	.21	.2	.44	.43	.11	.11

Panel 2: Business Dynamics Statistics Data

Dependent variable	2-year employment growth		Log 2-year employment growth		Change in 2-year employment growth	
	(1)	(2)	(3)	(4)	(5)	(6)
State tax price of R&D	-1650	-493	-.11	.036	188	-583
	(3570)	(756)	(.37)	(.084)	(1619)	(981)
State f.e.	Y	Y	Y	Y	Y	Y
Year f.e.	Y	N	Y	N	Y	N
N	1530	1530	1530	1530	1529	1529
R^2	0.1585	0.0016	.24	0.0012	0.0204	0.0005

Note: This table shows estimates of the relationship between last year's state tax price of R&D (from Wilson), and employment growth at new firms. Panel 1 uses data from the QWI, courtesy of Song Ma. Firms are limited to R&D-intensive (high tech) sectors. Panel 2 uses data from the BDS, where all firms are used as the data do not include industry information. Errors are clustered at the state *** indicates p-value$<$.01.

Panel 3:

Data source:	Quarterly Workforce Indicator (LEHD) data		Business Dynamics Statistics Data	
Dependent variable	Log 2-year employment growth	Change in 2-year employment growth	Log 2-year employment growth	Change in 2-year employment growth
	(1)	(2)	(3)	(4)
Federal R&D credit	4.4	-39912	-.19	-377227
	(7.3)	(885697)	(.16)	(274243)
N	16	15	30	37
R^2	.026	.00016	.05	.051

Note: This panel shows estimates of the relationship between last year's federal tax price of R&D, and employment growth at new firms. *** indicates p-value$<$.01.