The Consequences of Entrepreneurial Firm Founding on Innovation

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Abstract

This paper studies if and how individual-level patenting activity changes as an employee transitions to entrepreneurial firm founder. Using a large database of employment and innovative histories of over 1110 spinoff firm founders, the empirical strategy tracks both founders and her co-inventors who remain at her previous employer. There are significant changes in patenting focus and quality. Founders are relatively more likely to focus on fewer industry patent classes as the lead patent author, while citing their previous work less. Their patent quality increases after spinoff firm founding in several ways. Non-self citations received increase and the types of patent applications point to a move towards longer-term projects. Finally, a higher probability of producing a patent in the extremes of the quality distribution and a move to citations of younger patents suggests that spinoff founders switch to pursuing riskier projects after firm founding.

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Introduction

The employees of large, established firms are a prominent source of new firm founders. These spinoff firms dominate many industries and play an important role in the economy. Extant empirical studies primarily study the firms that have spinoffs or explain the spinoff's superior performance relative to other new firms. This paper uses the patenting and employment history of the spinoff founder to ask how her innovative output changes as she transitions to entrepreneurial firm founder. Our aim is to understand the unique features of entrepreneurial firm innovation.

This paper makes a number of contributions. First, we build a novel database of employee to founder mobility for a representative set of industries over 25 years that tracks patenting activity at the inventor level. The database extends earlier work that mostly relied on firm-level data or alternatively was limited to a few specific industries or short time period. Second, we study if and how patenting changes in its scope and quality after spinoff formation. Understanding such changes informs our understanding of why good employees and their ideas leave established firms. Finally, the paper provides the first large sample evidence that riskier innovative projects leave established firms with mobile employees.

How, if at all, should innovative activity change as an inventive employee transitions to a spinoff firm founder? We consider three classes of changes: focus, quality and risk. The founder's post-spinoff patents could stray away from the core of their past employer (parent) and enter newer industries. Surveys of spinoff founders (Bhide (2000)) and industry case studies (e.g. Klepper and Sleeper (2005)) suggest an alternative. Here, the founder remains in the same industry and patent classes as they were at the parent firm. Evidence for either type of focus change can reveal motivations for the employee to founder decision. The quality of innovations produced can also change. Most models of spinoff formation would predict higher average quality innovations due to selection of employees to entrepreneurs, a small firm effect or signaling to investors. If patenting in the new spinoff is instead defensive, then quality should remain unchanged. The third possibility concerns unexplored predictions about the distribution and types of innovation. In particular, some classes of employee mobility models posit incomplete compensation contracts or managerial time preference as frictions that lead to exit. These models imply changes to tail of the spinoff founder's patent quality distribution and the length of the patent research project. We use rich panel data on spinoff founder patenting to test these focus and quality change predictions.

Any attempt to compare spinoff innovation to that of established firms using firm-level data faces several empirical challenges. The spinoffs we observe are non-random as they are a selected set of all firms which typically outperform other new firms.[1] Next, employee composition differs substantially across types of firms. It is thus difficult to disentangle whether firm-level results are driven by selection of individuals into firms or rather by firm-level characteristics like regulation or management practices. A within-firm analysis can avoid these issues; however, one would need pre-founding data for spinoffs which is obviously non-existent. Fortunately, most theories of new firm formation through spinoffs put the firm's founder at the center of the model.

Analysis of individual-level patenting overcomes some of the empirical challenges as we can track patenting before and after firm founding. However, two new identification concerns arise. First, employees who decide to found a spinoff company are not a random sample of a firm's employees. Second, the timing of exit depends on expectations of future success or poor performance at the established firm. Several models and empirical studies of spinoffs (e.g. Klepper and Sleeper (2005)) show that anticipated or realized changes at the parent or industry impact exit rates. Such trends would bias even a standard fixed effects specification.

To overcome these two issues, we want to observe the spinoff founder's patenting activity in the absence of the spinoff founding. Employment histories and inventor-level patenting data for both founders and non-founders in a firm provides a potential solution to the first issue. Firm-level shocks can help alleviate concerns about certain forms of endogenous exit timing.

Consider a researcher working at an R&D lab at IBM. She has a long patenting history, which includes many patents co-invented with co-workers. She exits IBM to start a new firm and continues to patent. Her past co-workers remain at the IBM lab and continue research. This collection of inventors forms the base of our counter-factual sample and provides a plausible path of innovation the founder would have taken had she remained at IBM. Finally, observables can aid in selecting the best matches on pre-trends of patent outcomes (detailed below). Although this estimation

[1] See Klepper and Thompson (2010).

technique cannot determine the causal impact of the spinoff founding, it can narrow down the real changes and possible mechanisms for such changes.

We build a database of founder employment histories, innovation activity and patent co-inventors that uses a combination of several large datasets. We first identify the founders of the over 21,000 entrepreneurial firms in the venture capital database VentureSource.[2] Next, this information is merged with the inventor-level patent data of Lai et al. (2011) using the entrepreneurial founder's employment history. These employers form the basis for an additional search of spinoffs that do not receive venture capital finance. Our strategy requires estimating changes around the founding event. We therefore measure patent outcomes four years prior and five years after the entrepreneurial firm founding. Additionally, we require patent activity and co-inventorship in the pre-founding period. These restrictions narrow the sample of founders to 3,036 VC- and non-VC-backed founders with at least one patent (with a co-inventor at the same firm) in the four year period prior to the startup event. Next, we find a set of matches for a difference-in-difference specification.

Within the pool of pre-founding co-inventor/co-workers, we select our comparison group to best represent what would have occurred had the founder stayed. These inventors must remain at the firm and continue to patent.[3] The goal is to find past co-inventors and co-workers with similar pre-trends in patenting rate, citations made characteristics, age of patent portfolio and citations received quality as the founder. Using a standard distance metric matching procedure (see Imbens (2004)), we compute the distance between each potential match and the founder (within the same firm and co-inventor network). The final sample has 9-year patenting histories for 1131 entrepreneurial founders and 2929 matched controls. Importantly, the standard matching diagnostics – tests of pre-treatment variables and visual pre-trend analysis – are each satisfied, while the difference-in-difference specification mitigates many of the matching biases issues in such estimators (see Heckman et al. (1998)).[4]

[2]Gompers, Lerner and Scharfstein (2005) use the same data that covered 1987 - 1999 to ask what characteristics of firms explain the exit of employees to spinoffs.

[3]The results are unchanged if we allow matched controls to move to another firm that is not the entrepreneurial firm, however, this setting is not our ideal counter-factual.

[4]Intuitively, if matching bias is time-invariant, we difference it away. Also, Heckman, Ichimura and Todd (1997) and others found improved matching procedures on labor data when matches were constrained to within geography

The difference-in-differences estimates show a strong tendency for spinoff founders to narrow their innovative activity across several dimensions while working away from their patents at the parent firm. The founder invents in fewer patent classes after founding, while increasing the rate at which they use old references. They file fewer patents, but are relatively more likely to be the lead inventor on any applications. We find no evidence that the typical founder enters new areas of research through newer or previously unexplored areas. The major avenue for knowledge diffusion is not through citations of their own patents, but rather an increased intensity of previously cited work. These results are the first suggestion that part of the motivation for employee exit is the ability to focus research and patenting. Next, we investigate how the quality of patents change after spinoff firm founding.

Under this new research approach, the founders perform successfully in multiple dimensions. First, their patents tend to be more fundamental and broad as illustrated by increases in both originality and generality indices. The former captures the diversity of the body of knowledge a patent builds on, while increased generality implies that founders write patents with broad impact across multiple industries. Second, founders shift to a long-term innovation strategy as proxied by an increase in "continuation-in-parts" (CIP) patents. Hegde, Mowery and Graham (2009) show that these patents signal both "pioneering innovations" and projects that are slower to move to the marketplace. We find that the founders with the slowest time to first patent are in fact those inventors with the highest rate of CIP production.

After investigating the mean differences in focus and quality, we ask whether the variability of the patent projects' quality also changes after founding. A quantile regression of changes in non-self citations received reveals a higher propensity for founders to produce patents that end up in the extremes of the quality distribution. Such a fact is consistent with spinoff founders pursuing riskier projects with higher failure rates at the entrepreneurial firm. These ex-post outcomes coincide with an ex-ante change in the types of patents cited and in turn the body of knowledge supporting the average founder. In particular, startup founders cite younger patents after firm founding. The body of results point to a shift in innovation strategy towards riskier, long-term projects built on

or other groupings.

new ideas.

A picture emerges from these results and provides insights into the decision to leave an established firm to form a spinoff. While employed, the typical inventive employee works on multiple projects in several patent classes. She comes upon a new idea while working at the parent firm and must decide how to proceed. The pattern of differences in our sample suggest that founders whose innovation requires a narrow focus, a longer time frame to completion and higher failure tolerance are more likely done outside of the parent and conducted at the spinoff. Although we cannot conclusively show this is the sole reason for exit, the results imply that retention of inventive employees could increase with a longer window for project completion and the high failure tolerance (e.g. Manso (2011) and Nanda and Rhodes-Kropf (2012)).

The results are robust to several alternative explanations. For example, changes in patenting could stem from defensive rather than innovative choices. First, the slower rate of patenting suggests that founders are not aggressively protecting themselves. Further, sub-sample of VC-backed spinoffs that receive capital from their parent firms shows little change in results. An alternative form of patent application called a "continuation" is often used as a way to protect rather than innovate. Spinoff founders do not increase their use of these patent types after founding. Overall, the evidence shows that defensive patenting cannot completely explain the differences in innovative activity.

Next, the exit of the founder could negatively impact her past co-inventors and drive the estimates of the difference-in-difference.[5] In a sub-sample analysis, we recreate the matched sample by re-sorting the best matches by those that have the *least* pre-spinoff interactions with the founder. For example, a past co-inventor may have only written two of her 10 patents with the founder and is thus unlikely to be impacted by the exit. The main results are unchanged with this alternative matching distance criterion. We conclude that the estimates are not driven by a patent version of "superstar extinction."

Next we address some endogenous exit timing concerns. Research shows higher intra-industry spinoff rates around the time of acquisitions and CEO changes.[6] For example, the founder could anticipate worse innovation success after a CEO replacement and leave to maintain her innovative

[5]See Azoulay, Zivin and Wang (2010) for an example in medical publishing.

[6]See Klepper (2009) for a survey and Eriksson and Moritz Kuhn (2006) for an example using Danish firms.

output. We consider a set of founders exits that do *not* occur within a year of an acquisition or CEO change. If the previous results could be explained by these lifecycle effects, this sub-sample should have weaker estimates. The smaller sample limits power, however, generality and the rate of CIP are slightly lower. The results overall suggest that major corporate events are not driving our results. Last, we rule out whether the estimates could have happened by chance with a standard matching falsification test that reassigns founders as non-founders.

The results contribute to a literature on new firms and spinoffs. Gompers, Lerner and Scharfstein (2005) take similar employment histories of entrepreneurial firm executives and show a strong predictor of exit at an established firm was previous VC-backing. Their evidence that spinoffs differ in patent classes from parents relates to our evidence on patent focus for founders. We extend their work by studying the ex-post differences in individual-level innovation around employee exits rather than their antecedents. Our empirical analysis reveals significant differences in patent output with close connections through citations, providing support for the model of Cassiman and Ueda (2006).[7] Singh and Agrawal (2011) also study mobility in the patent data with a focus on movement between existing firms, while Chatterji (2008) studies similar movement in the medical device industry. Our study differs with a focus on new firm formation and inventor-level patent portfolio changes. Importantly, the observed knowledge diffusion occurs between the founder and the non-self knowledge references in her pre-spinoff patent stock.

The paper also contributes to the literature on the role of venture capital in innovation. Hellman and Puri (2000) find that venture capitalists select more innovative firms (i.e. products in untested markets) and help those firms move to market quickly. Our founder to employee estimation reveals how these innovative firms distinguish themselves. Kortum and Lerner (2000) study the causal effect of VC financing on patenting rates and find increases in patenting after a random shock to the supply of VC. The current paper provides a lens on the micro-level relationship between VC and innovation and details how the innovation differs from other firms. The changes in innovation around founding are consistent with the Bernstein (2013) study of firm-level innovation and IPOs. Whereas this switch from private to public firm negatively effects innovation, the analysis of established to

[7] Other theories that provide a rational explanation for exits of quality innovation from firms include Hellmann (2007) and Klepper and Thompson (2010).

private (i.e. entrepreneurial firm) here finds the converse. Last, our empirical strategy extends that of Lerner, Sorensen and Strömberg (2011) who study the change in patenting around leveraged buyouts. We investigate new firm formation through spinoffs, while our identification strategy highlights new features about innovative activity in another part of private equity.

1 Data

Our goal is to document the employment and patenting histories of entrepreneurial founders who leave established firms in the U.S. The data construction begins with a rich set of entrepreneurial firms and their founders who are backed by venture capital and extends to a set of firms that do not raise VC. We start with the VentureSource dataset of venture capital financings, entrepreneurs and investors provided by Dow Jones. This database covers a near-population of U.S. venture capital financings from 1990 to the present. The important entrepreneurial firm characteristics for this study are founder(s), founding year, first venture capital financing and industry. We stop tracking founders and entrepreneurial firms were founded after 2007 so we have ample time to track the post-founding characteristics.[8] Entrepreneurial firms also exit the sample when they have an initial public offering, are acquired or failed. This restrictions avoids comparing established firms to others of the same type after ownership changes.

We have the full management and founding team for over 80% of the 21,000 VC-backed entrepreneurial firms in the full sample. From these, we first identify the founder using the firm's website, Capital IQ and web searches we identify 31,160 (co-)founders. The VentureSource data also provides an employment history of these newly identified founders as of the time they start the firm, which we take to the Lai et al. (2011) inventor-level database.[9]

Matching entrepreneurial founder to inventor of a particular patent requires several steps, greatly facilitated by (i) the employment histories and (ii) the unique inventor identifiers in Lai et al. (2011). A fuzzy string match of the unique past employers associated with founders and

[8] We filled in 55% of missing founding years with searches of both the California and Delaware secretary of state websites that list articles of incorporation information. Any remaining missing founding dates were assumed to be at the first VC financing event.

[9] Many were missing, so another data collection exercise similar to the founder identification was required to find employment histories.

company name on the patent application (i.e. assignee) retrieves the firm identifier from the patent data.[10] For example, a founder has an employment history of "Lead engineer, IBM; Software architect, Sun." This identifier in hand, the task of finding the founder's name in the inventor pool is simplified and more accurate by narrowing the search to within the founder's full set of past employers. The weakest matches and all possible false negatives – 17,000 founders – were then hand-checked with Google Patent Search.[11] Some 20% of founders have a patent, although many of these are single patents over a long career. When we focus on the years four years prior to the entrepreneurial firm founding, there are 3,036 founders with at least one patent.

1.1 Non-VC-backed spinoffs

For many of these VC-backed entrepreneurial firm founders, we can identify the employer for which they patented immediately prior to the spinoff firm founding.[12] The pool of these established firms forms the basis of an additional search for non-VC backed spinoffs. The Appendix provides details on the data collection process, which we briefly summarize here. Starting with these "parent" firms, we isolate inventors who switch to other firms (i.e. assignees) in the patent data. Next, these potential founders are required to be on one of the firm's first three patents. We now have a large list of over 11,000 potential spinoffs that spawned from our parent sample. We identify firm founding dates using the Delaware and California Secretary of State websites that list incorporation dates. These two states are very popular locations to incorporate new firms and also provide relatively easy access to firm information online. In the end, we find 6,329 incorporation dates (over 50% of the sample).[13] In the last step, we require that the potential founder patented at most one year prior or two years after the incorporation date. If the inventor satisfies all of these criteria, we label her a founder of the firm and the firm a spinoff or spawn of the parent firm. We find 1,591 non-VC-backed spinoff founders.

[10] A random set of 1000 of these matches were hand-checked manually using the more detailed founder biographies available on websites or in Capital IQ.

[11] An RA searched for the inventor's full name and the employer name. If they found a match, we saved available patent numbers and merged back with Lai et al. (2011). Confirmation of the merge was done using the year of entrepreneurial firm founding to remove false positives.

[12] Some founders have pre-founding patents at firms that lack an identifier in the patent data.

[13] The data is available at: `https://github.com/michaelewens/inventor-data-more`.

Combined with the VC-backed founders, this additional set of founders forms the basis of the major sample of analysis. Section 2 details the construction of this sample, which will end up including 1131 founders and their spinoff firms. Figure 1 shows the rate of spinoff formation in the final sample. At its peak, over 250 firms formed in 2000, while an average of 35 firms were founded each year.

1.2 Parents and analysis timeframe

The top pre-founding employers for all the founders in our final analysis sample are listed in Table 3.[14] The largest source of new entrepreneurial firms is IBM followed by many well-known firms in technology, biotech and communications. For these spinoffs, some 48% founded in California, while Massachusetts and Texas account for 10% and 6% respectively. The time period of interest for each founder and her entrepreneurial firm is four years prior to five years after the founding year.[15] We chose five years after as the average entrepreneurial firm in the VentureSource database exits without failure in approximately five years. The pre-startup period was chosen to balance the matching goals and any age issues with patent variables. The results are insensitive to a choice of five or three years prior to the founding. With the time period set, we then eliminate any patents that are filed with the parent firm after the founding date of the spinoff, which could be due to a lag in patent filing.

1.3 Patent variables

We consider a diverse set of patent characteristics to capture two broad features of the innovation process around spinoff formation. The first set considers how the patents look at the time of application. The first variable "# active patent classes" tracks the unique number of the seven major patent classes an inventor patents in during a period of time. Next, "% repeat cites made" tracks the fraction of an inventor's cites made in year t that were cited by that inventor in the previous two years (including self-cites). This variable measures the use of the same body of

[14]This set of firms is a similar to those used in Gompers, Lerner and Scharfstein (2005), however, they study all managers of entrepreneurial firms who left publicly-held companies.

[15]Again, if the firm has an IPO or other exit this latter interval stops.

knowledge over time. The "# patents" variable counts the total patent applications in a time period, while "% self-cites" computes the fraction of cites made that reference any of the inventor's previous patents. The average patent has at least two inventors and one or many of them can be labeled a "Lead." Over a time period, we calculate the fraction of patents for which the inventor is listed as a lead. Last, we construct a measure of patent technology class age using the original patent classification system in the NBER data.[16] For the major subclasses of the seven patent classes, the age measure is normalized to be zero when they first appear in the database and one at the end (2007). This normalization attempts to capture variation in the speed of a patent class' use over time.

The second set of patent variables broadly capture innovation quality. We start with the standard count on non-self citations received, which we measure year by year for the inventor's patent stock. Citations received are often zero, while a few patents can receive thousands of citations. To address any concerns that the mean cites received is uninformative, we also conduct a quantile regression analysis. Here, we ask whether the relative impact of a founder on citations received differs in the right and left tails of quality distribution. For example, does the founder and founding choice also impact the 90th percentile of the cites received distribution?

The final quality measure captures commercialization activity and long-term research projects. The patent data contains a type of filing called a "continuation-in-part"(CIP) that proxies for this activity. CIPs are often used to build off of an already patented idea that is still in the application process to stake claims to particular commercial uses of an invention. Hegde, Mowery and Graham (2009) also show that CIPs are a good proxy for "pioneering innovation" and are more likely used by R&D-intensive firms. In particular, they cite industry surveys and provide empirical analysis that show continuations help provide additional protections for products that "take a relatively long time to reach the marketplace" (pp 1214). The variable "%CIP" is the fraction of all patents in an inventor's portfolio that have this designation over a given time period.

[16]The patent office often re-classifies existing patents to a new system, making simple patent age difficult.

2 Empirical strategy

To address if and how the patenting activity of entrepreneurial firm founders changes, we first construct a sample of control inventors. We then detail a difference-in-difference strategy to estimate changes after the firm founding.

2.1 Finding controls

Even with knowledge of the full patenting and employment histories of the entrepreneurial founder, any analysis of simple within-founder changes in patenting around spinoff founding is confounded by a host of unobservables. A within-founder analysis centered on the spinoff founding lacks a benchmark or comparison group, particularly if the set of founders are non-random. Fortunately, the co-inventorship and co-worker network in our merged dataset presents a solution. These connections invite an analysis of how the same inventor patents in two different firms. Our goal is to collect inventors that approximate what would have happened had the entrepreneurial founder remained at the firm.

For each of the entrepreneurial founders with a patent around the spinoff founding, we select all co-inventors on patents associated with the last assignee that appears in their patent portfolio the year immediately prior to the founding event. Restricting our potential controls to this set alleviates many issues in matching estimators that have few observables available (see Heckman, Ichimura and Todd (1997)). The final difference-in-difference estimation requires that the "best matches" have parallel trends to that of the founder, so we include pre-trends of our variables of interest. Section 1.3 details the patent variables, many of which are measured years after patent application. We narrow the set of match variables to patenting rate, generality, originality and citations received and calculate their growth rates with the terminal date set to the year prior to the founding event. The final matching procedure uses one year and two year rates. Additionally, we want to ensure that the founders and co-inventors are similar by age and speciality, so we include year they first appeared in the patent data and the share of patents in each patent class.

We follow the common approach in the matching literature and measure the Mahalonobis distance for each potential match.[17] To select the best matches, we use a version of caliper matching, where the distance threshold is set by the full sample mean distance. That is, a potential match is kept if the distance between her and the founder is less than the average distance across all matches. Many inventors collaborate on patents that combine disparate skill sets. For example, a semiconductor is often a combination of software and hardware. Co-inventors on such patents are in fact quite dissimilar in their skill sets and choice of exit decision. Thus, our caliper threshold eliminates some patenting founders whose best matches are quite poor relative to the typical match. If a founder lacks at least one control below the mean threshold, however, we select the closest match if that match's distance is below the 75th percentile of match distance.

Additional requirements of the estimator change the sample. Some founder's controls have insufficient patenting activity in the five years after spinoff, while some founders stop patenting themselves at the spinoff. The matching distance threshold and these two constraints leave us with 1131 founders with at least one matched co-inventor in the pre- and post-spinoff period. There are 2929 non-founder inventors for an average of 2.6 matches per founder.

Diagnostics

How well do the matches perform? Table 2 presents the means of the match inputs and other observables, where the mean is computed across all groups. As the differences and t-tests demonstrate, the samples are statistically similar in the pre-startup period. Founders entered the patent data approximately one year prior to the average control and had more general patents as of the founding year. Second, Figure 3 previews one of the main empirical estimates and demonstrates the efficacy of the match. The figure shows the coefficients and 95% confidence intervals of the nine interaction terms of years around spinoff founding and a founder dummy variable. The estimates exhibit no strong trend (the excluded category is the year prior to startup). Plots for other variables are similar in a lack of pre-trends. The strong match on observables is encouraging and perhaps not surprising given our narrow focus within the co-inventorship and co-worker group. These matched founder-co-inventor groups (hereafter, cohorts) can now address our questions.

[17] This distance behaves like a Euclidean norm, but assigns weights to variables that are inverse to their variances. The results are insensitive to using the Abadie and Imbens (2006) distance metric.

2.2 Empirical model

The main specification is a difference-in-difference estimator with a founder-matched co-inventor group. The number of controls vary for each founder, so we follow Abadie, Diamond and Hainmueller (2010) and create a "synthetic control." Simply, each variable of interest (e.g. patenting rate) is averaged across controls where the weight is the inverse of the calculated match distance.[18] Let P_{it} be one of the patent variables described in Section 1 where the event time is defined in the range $t \in [-4, 5]$:

$$P_{ilt} = \gamma_0 + \text{Founder}_i + \sum_{t=-4,t\neq-1}^{5} \beta_t T_t + \sum_{t=-4,t\neq-1}^{5} \rho_t \text{Founder}_i T_t + \epsilon_{it} \tag{1}$$

where i indexes inventor.[19] The dummy Founder$_i$ is one if inventor i a founder and T_t are the event time dummies with T_{-1} the excluded categories. If the average founder differs from her matched co-inventors after startup, then we expect $\hat{\rho}_s \neq 0$ for $s \geq 0$.

Estimates from equation (1) provide a test of the parallel trends assumption of the matching algorithm. As discussed, patenting rate and other measures demonstrate a good pre-founding match (Figure 3 and Table 2). Our main estimation uses a variant of (1) because disaggregation of patenting variables by year results in noisy estimates, while the long time series raises serial correlation issues (see Bertrand, Duflo and Mullainathan (2000)).

For each founder and group of controls, we calculate averages of the patent variables in two intervals. The first is four years prior to the firm founding ($[-4, -1]$) and the second is the startup year up to five years after ($[0, 5]$). The averages are weighted by the number of patents applied in each year (if relevant). The new estimation becomes:

$$P_{it} = \beta_0 + \beta_1 * \text{After}_{it} + \beta_2 \text{Founder}_i + \beta_3 \text{Founder}_i * \text{After}_{it} + \epsilon_{it} \tag{2}$$

where indices are as in (1), $t \in \{0, 1\}$ for the pre- and post-founding periods and "After" is a dummy equal to one for the latter. The parameter of interest is β_3, which measures the difference

[18] Results are similar when we have one observation per control, however, this approach gives relatively more weight to founders with more controls.

[19] An inventor i may be matched with multiple founders for the control sample.

between the founder and matched controls after the spinoff founding. This empirical specification of pre-regression matching and averaging ensures that we compare founders to their past co-inventor controls. The model (2) mimics the difference-in-difference matching estimator detailed in Heckman, Ichimura and Todd (1997). The object of interest takes the form:

$$\alpha_{DDM} = \frac{1}{N}\sum_{i,j}(P_i1 - P_{i0}) - \sum_{j\neq i} w_{ij}(P_{j1} - P_{j0})$$

where i indicator founders, j indicate possible co-inventor controls, and w_{ij} is the normalized distance metric from the matching algorithm. Such an estimate mimics the $\hat{\beta}_3$ from equation (2).

3 Analysis

The results and analysis will come in three parts. In Section 3.2, we ask how patenting changes in its focus and scope after the spinoff firm founding. Motivated by the observed differences, we then ask in Section 3.3 if and how the quality of the innovation differs after the employee becomes a founder. Next, we attempt to determine whether observed changes are driven by a shift in the types of projects undertaken, particularly in their risk profile (Section 3.5).

3.1 Focus: industry classes

A spinoff founder can change the classes of patents in which she invents.[20] Such changes can signal new requirements of producing innovation in spinoffs versus established firms. Importantly, changes in industry focus of founders could confound any difference-in-difference estimates if industries are on different trends. For each inventor and patent class, let D_{ilk} define whether the inventor decreased her patenting in class k after the founding year:

$$D_{ilk} = \begin{cases} 1 & \text{if } f_{ilk1} < f_{ilk0} \text{ where } f_{ilk0} > 0 \\ 0 & \text{if } f_{ilk1} \geq f_{ik0} \text{ where } f_{ilk0} > 0 \end{cases} \tag{3}$$

[20]This analysis is similar to the comparison of parent and spinoff patent classes in Gompers, Lerner and Scharfstein (2005). We extend it by using founder-level data and the difference-in-difference specification.

where f_{ilkt} if the fraction of inventor i's patents in cohort l where the pre-($t = 0$) or post-founding ($t = 1$) periods. We estimate a conditional logit model where the unit of observation is the inventor and patent class for all inventors with $f_{ik0} > 0$:

$$D_{ilk} = \beta_0 + \beta_1 \text{Founder}_{il} + \beta_2 X_{il0} + \alpha_l + \rho_k + \epsilon_{ilk}. \tag{4}$$

The indices are as in (1) and ρ_k is a patent class fixed effect. The controls X_{il0} include the share of patents in class k in the pre-founding period and the change in total patents between the pre- and post-founding. If founders are more likely to decrease patent rates in the patent classes where they have experience, then $\hat{\beta}_1 > 0$. The coefficient's sign does not help us separate the focus strategy from one where they enter whole new patent classes. We thus construct a variable in the same spirit as (3) but captures whether an inventor shifts from zero patenting to positive patenting in class k. A positive difference in this regression combined with one in (4) implies a shift out of classes with experience and into new classes, while the opposite signals a narrowing of patent class focus.

Table 4 presents the results.[21] Each column reports the estimated odds ratios (exponentiated coefficients) of the conditional logit estimator of (4) where the fixed effect is the founder cohort and standard errors are clustered at the cohort level. An inventor has one observation for each patent class for which see has a pre-founding patent, so we also include patent class fixed effects.

Column 1 shows that compared to the match set of co-worker/authors, spinoff founders are more likely to shift out of one of their pre-spinoff patent classes. The odds ratio implies an approximately 60% higher likelihood of decreasing the rate of patenting in the patent class. Column (2) presents the estimates from a similar estimation where the dependent variable captures whether, post-spinoff, the inventor entered a patent class where they had no pre-spinoff experience. Founders are no more likely to shift to a patent class where they lack experience. Combined with the results in column (1), we conclude that founders are on average focusing their patenting in fewer classes relative to their cohort.

The founder's exit decision may depend on the strength of her state's covenant to not compete

[21] The patent classes are generally, "Biotech," "Chemicals," "Software," "Computer Networks," "Semiconductors," "'Transportation" and "Mechanical Engineering."

laws (see Marx, Strumsky and Fleming (2009)). That is, these laws' strength increase the likelihood a new firm starts in an industry that differs from the parent firm. Although the results go in the opposite direction of what such restrictions would predict, columns (3) and (4) repeat these regressions on the subset of states that have weak covenant to not compete laws (see Malsberger (2008) for the index). The robustness check illustrates these legal restrictions are not a first-order concern. Overall, we find no evidence of a shift to new industries, but rather a focus on patent classes that are connected to both the founder and established firm's past. Additional analysis of the other patent characteristics will help us understand the changes at founding.

3.2 Focus: patenting activity

We next study if and how the scope of patenting activity changes for the entrepreneurial firm founders after they exit the parent firm. We consider two basic scenarios. In the first, the spinoff and its founder work on ideas and innovations that are closely tied to the parent firm. The Bhide (2000) survey of small firm founder showed that the vast majority used ideas that they arrived at while working at their parent firm. Similarly, research shows that in both the laser and semiconductor industry, spinoffs are likely to enter the same industry and produce product similar to those of the parent firm (see Klepper (2009) for a review). Alternatively, the spinoff founder could have an idea at the parent firm that is tangential to the parent's product space and innovation capabilities. Here, the spinoff founder's patents will enter new, possibly younger patent classes while her post-spinoff patents build off of a different knowledge base than what she used at the parent.

Table 5 presents estimates from equation (2) for the six focus variables discussed in Section 1.3. There is no evidence that the founder moves into newer patent classes after the startup ("# active patent classes") as found in Table 4. The rate of citing the founder's early work falls relatively more after founding, however, she increasingly uses the same body of references that are not her own. Simply, it appears that founders do not build directly on their old work, but rather increase their focus in the same area of research. This result extends that of Chatterji (2008) who finds the superior performance of spinoffs in the medical device industry is not driven by parent-to-spinoff diffusion. Next, the rate of patenting falls and founders are relatively more likely to be lead authors.

Last, consistent with the decrease in active patent classes, founders do not focus their energies on relatively younger patent sub-class areas.

This collection of results reveals that founders increasingly exploit the same knowledge base that they used at their parent firm, while simultaneously focusing on a more narrow range of ideas. We find no evidence of the average founder innovating in newer industries or shifting to relatively unknown areas. The lack of dramatic change in industry class or focus ensures that the diff-in-diff results discussed below are not primarily driven by new industry trends after spinoff founding. A simple explanation for these changes is the shift from a large to small firm, where the latter has fewer resources such as co-workers. Alternatively, the spinoff firm provides the opportunity to work on a new, single project is familiar areas. We next ask if and how this more focused innovative translates into higher quality and more impactful patents.

3.3 Quality hypotheses

Our sample of entrepreneurial founders likely choose to exit their parent firm and did so with an expectation that their innovative activity would improve. Nonetheless, there are a range of predictions about if and how innovation quality should change. Nearly all stories of the spinoff founding choice involve a new, high quality idea. Independent of any effects of moving to a new firm with this idea, it is clear that innovation would increase. We call this the "good ideas leaving" scenario. This prediction is consistent with a large body of work that shows spinoffs are of higher quality than other new entrants. Models of patents as signals for investors (e.g. VCs) also predict a higher level of innovation quality after founding (see Hsu and Ziedonis (2007)). Patent quality does not necessarily have to increase. For example, the patenting activity of spinoffs could be primarily driven by legal concerns or the employee could have proposed a new product that would simply cannibalize the parent's revenues. In these scenarios, it is plausible that no change in quality occurs. More nuanced predictions about innovation quality stem from reasons why the parent let the invention leave.

A major change when an employee becomes a founder is the simultaneous change from employer- to employee-owned innovations. Ownership of innovation plays a role in many models of employee spinoffs (e.g. Hellmann (2007)). Further, Anton and Yao (1995) and Manso (2011) provide additional justification employee exit from the parent firm with a new idea. An idea may require a very long research period and have a high failure rate. As Manso (2011) frames the problem, there are often differing mechanisms available to motivate and contract on *exploitative* versus *exploratory* innovation. These agency explanations for spinoff formation provide some predictions on additional dimensions for quality changes. Pioneering, long-term research – exploration – is more likely to suffer contracting problems. Recall that CIPs have been shown to be good proxies for "pioneering innovations" and used by R&D-intensive firms with slow-to-market projects (see Hegde, Mowery and Graham (2009)). Large, established firms are often burdened by short-term financial goals, while typical compensation contracts are limited in their ability to incentivize employees to exert effort towards these innovations. The small firm with inventor-owned patents can potentially solve this problem and lead to exit. Next, high failure rate innovative projects may be too risky for large parent firms. If these risk conflicts are a source of spinoffs, then we would expect both the right and left tail of patent quality distribution to change. An analysis of the relative impact of founding on the upper and lower parts of the cites received distribution can help answer this question. We take these predictions to the data.

3.4 Quality results

Table 6 presents the innovation quality results. First, we find that the non-self citations received increases significantly after the founding event, by approximately 25%. These higher quality innovations are also cited by a larger set of patent classes – higher generality – and build off of a more broad base of patent classes (originality). These latter two results are consistent with the result of Bernstein (2013) who finds that these measures of fundamental research fall after a firm goes public. Such changes are the opposite of our employee to founder transitions. We also find that these innovations are more likely to be applied as a CIP, which is an additional signal that the founder shifts to a different type of research agenda. Relative to their past co-inventors, spinoff founders use CIPs at a 40% higher rate. In unreported regressions, we confirm the conclusion of Hegde, Mowery and Graham (2009) and find that CIPs are primarily driven by the founders who take the longest to complete their first patent. Overall, the average founder is as predicted: higher quality.

3.5 Changes in innovation risk

Now that we have documented real changes in the focus and quality of a founder's patent portfolio, it is natural to ask what is the underlying source of such changes. Of course, many features of the innovation environment change in the switch from employee to founder, including firm size, ownership structure, compensation, co-workers and management practices. The results in Table 5 indicate that on average the changes in this switch are not industry shifts or moves to radically new patent areas. Several recent theoretical and empirical papers have highlighted differences in firm capacity for innovation through failure tolerance or risk-taking (e.g. Manso (2011) and Nanda and Rhodes-Kropf (forthcoming)). Here, small new firms have the proper incentives, structure and contracts to take on riskier projects. Thus, we would expect to see both more failures and more outcomes in the right tail of the quality distribution for entrepreneurial firms. Nanda and Rhodes-Kropf (forthcoming) find just these features in VC financing behavior as measured by valuations or patent counts. We test whether the choices and outcomes of the founders in our sample are consistent with a story of riskier projects being produced outside of the established firm.

Measuring the riskiness of the founder's innovative project is challenging without observing all inputs. Beyond the originality and patent class measures in Table 5, we next consider the age of the patents cited. Innovation strategies that work off of a younger base of patents are presumably exploiting relatively less tested ideas. Consider the age of a cited patent as measured by the application year of the citing patent minus the application year of the cited patent. If founders switch to a riskier innovation path, then the patents they cite should be younger after the founding event. Column 1 of Table 7 show the coefficient estimate for the dependent variable defined as the change in age of citations made between $[-4,-1]$ and $[0,5]$. The estimates imply that founders decrease the age of patents cited 27% more relative to the average non-founder. The story mimics that of the patenting rate results; the change is driven by a slowing of the increase in patent cite age rather than a dramatic shift in the average. Nonetheless, on average founders cite relatively younger patents after founding than their past co-inventors.

Finally, we ask whether the ex-post quality differences reflect a change in riskiness. We already observed in Table 6 that founders produce patents that are of a higher average quality through an increase in non-self citations received. A change in patent portfolio or innovation riskiness also implies that there should be a higher propensity for founders to produce quality in both the left and right tail. The predicted increase in extreme success and failure can be estimated with a quantile regression. Here we ask whether the relative difference in founders and controls also differs in quantiles of the changes in citations received distribution. For example, if founders are relatively more likely to produce lower quality patents, then the lower quantiles of the quality distribution should be smaller for founders. First, Figure 4 reports the distribution of changes in log non-self citations received for founders and controls. The figure makes clear that founders have more changes in both the left and right tail. The quantile regression estimates in columns 2 - 5 of Table 7 reinforce this conclusion. For example, the coefficient for the 90th percentile implies that, all else equal, the impact of a founder on changes in cites received is even larger in the right tail of the quality distribution. Figure 5 plots the coefficient estimates from a wide range of quantiles, showing that the extremes of the distribution differ from the OLS estimate for founders. Overall, the ex-ante and ex-post patent measures are suggestive of a switch to riskier innovative projects after spinoff founding.

4 Robustness

This section address several potential concerns about the diff-in-diff strategy and inference about patents as innovation measures.

4.1 Superstar extinction?

The matching algorithm matches the pre-founding trends in the major patent variables. Figure 3 and Table 2 confirm it achieved this goal. However, the founding event and exit of the inventor could itself signal a change at the established firm that could explain the main difference-in-difference results. Simply, the founder may have timed her exit expecting a fall in her co-inventor patenting activity or her exit could have caused such a fall. The latter concern mimics the setting of Azoulay, Zivin and Wang (2010) who study the effects of unexpected deaths of star researchers in medical publishing on their co-authors.

To address this concern, we look at the pool of co-workers who are the least likely to be affected by the exit. Let x be the fraction of a co-workers' patents in $[-4, -1]$ that were co-written with the founder. The average control had the founder on 30% of her patents as a co-inventor. We take the distances from the matching algorithm and re-scale them by $1 - x$, effectively shrinking the distance between the least connected co-inventors, while maintaining the benefits of the match distance. Note that co-inventors who only patented with the founder will have an undefined rescaled difference and be dropped. Tables 9 and 8 repeat the main estimator with the new match set. The results are basically unchanged. We conclude that the patent version of "superstar extinction" is not a major driver of our results.[22]

4.2 Corporate change

The exit of employee from established firm to new firms is often precipitated by major corporate changes. These include CEO transitions, acquisition events or IPOs.[23] The difference-in-difference estimates could be driven by a downward trend at the established firm in innovative activity rather than a positive change at the spinoff founding. We address this concern by identifying all the parent firms in the data that had a CEO change or a large M&A transaction (target or acquirer) at least two years prior to the spinoff founding.[24] We use the executive compensation data Execucomp that covers on public firms and SDC which covers the universe of most merger and acquisition activity.[25] A large transaction is an acquisition with a reported value of at least 10% of the firm's market capitalization. Some 16% of the spinoff foundings in our sample occur after a CEO change

[22]It is plausible that the founder hires away her past co-inventors after the spinoff firm founding and we are capturing this impact. However, our matching algorithm requires that the co-inventor remain at the past employer for the post-founding period. Thus, only if the founder depletes the entire talent pool do we think this will drive the results.

[23]Klepper (2009) reviews the empirical literature that demonstrates the positive correlation between these corporate changes and employee exits to new firms. Also see Bernstein (2013) for inventor mobility around IPOs.

[24]Results are insensitive to using 1 year as a cutoff.

[25]If the established firm is private, we will not identify a CEO change. Only if the firm is public or is a private *target* firm, will be identify M&A.

or large M&A transaction.

This robustness test assumes that founders who do not leave after major corporate change are less likely to be timing an exit before falling innovation. We divide the sample into those firms with and without corporate changes for which we could find a public firm identifier. If the results are driven by major corporate changes, then the sub-sample without such changes should have weaker or non-existent results. Tables 10 and 11 repeat the main regressions for these two subsamples. The "No change" columns exhibit no strong differences from the main results in Table 5 and 6, which an unreported triple difference confirms. This result supports our claim that the major conclusions above are not driven by corporate changes.

4.3 Defensive patenting

A large literature shows that some patenting activity by large and small firms is done for defensive reasons (e.g. Hall and Ziedonis (2001)). A concern, therefore, is that the set of differences found in our sample are not measures of innovation, but rather consequences of a legal environment. Similarly, small firms may have a greater incentive or propensity to patent ideas, rather than say, use trade secrets. To start, defensive patenting should result in a relative increase in the rate of patenting, which we do not find. Next, the legal literature and case law also demonstrates that the threat of parents suing spinoffs is relatively low. Merges (1999) discusses the legal issues surrounding mobility of employee-inventors. The major conclusion is that it is actually quite difficult for past employers to successfully restrict inventive employees from starting new firms. Third, in unreported regressions we estimate the propensity of spinoff founders to use standard "continuation applications." Hegde, Mowery and Graham (2009) find that these applications are more likely used for defensive purposes. Founders are no more likely to use this patent strategy than their past co-inventors. The sub-sample of VC-backed founders provides a final test of the defensive patenting explanation.

We attempt to address this concern empirically with a partition of the VC-backed spinoffs sample into those who received equity capital from their parent firm and those that did not. Of the 715 that received VC, 41 received corporate venture capital (CVC). These spawned firms presumably have much less concern for being sued by their parent firm and can therefore help us isolate defensive patenting behavior. In unreported regressions, we split the VC-backed sample into non-CVC and CVC. Given the small size of the latter sample, we focus on any changes in sign from the main specification. Only two changes stand out. First, CVC-backed firms have relatively fewer CIP patents and do not decrease their rate of self-citation. One could interpret the self-citation difference as a consequence of the parent firm's investment: IBM invests in ideas that are related to their inventors' past work. Alternatively, the fall in self-citations for the non-CVC is a consequence of defensive patenting and an attempt to avoid strong connections with a potential legal foe. This ambiguity and lack of other differences lead us to conclude that defensive patenting cannot fully explain our results.

4.4 Matching process

Conditional on finding a match distance between a past co-worker and the founder, we consider only the set of all matches that are below the full sample mean distance and if none are found, take the best match if it is below the 75th percentile. The general results are insensitive to altering the cutoff to the median distance, however, we lose power with a smaller sample. The main specification of below mean distance appears to be a good choice for the tradeoff between precision and bias.

4.5 Falsification tests

What are the chances that our matching process and estimation resulted purely from chance? We address this concern in two ways. In the first, we consider the full set of founders and co-inventors with the required patenting around the founding event. A non-founder co-inventor and founder are randomly switched. We then rerun the matching algorithm with these false founders and co-inventors. In unreported tables, the main results from the difference-in-difference estimator disappear. In the second robustness check, we perform the matching algorithm on the true founder and co-inventor inventors and instead randomly reassign the founder to one of the matched co-inventors. Again, the results nearly all disappear.[26] The collection of evidence suggests that the

[26] One would expect one out of 20 to have a p-value of 5%, so some may be significant.

results are not driven by chance or a misspecification in the matching process.

4.6 VC vs. non-VC-backed spinoffs

Recall that the sample of founders includes both VC and non-VC-backed firms. This paper focuses on the entrepreneurial firm founding decision and its consequences, however, there are some interesting differences between the two samples of founders worth discussion. Table 12 details the characteristics of founders at the time of founding for these two sub-samples. VC investors back founders that are younger, have more patents and are significantly more likely to be a lead author on their patents. In an unreported set of regressions, the focus and quality estimates for these two sub-samples differ in several ways, but neither sample drives the major conclusions.

5 Conclusion

The founding of a spinoff firm coincides with many changes to innovative activity. Founders focus their research, take the lead on patenting and are no more likely to enter new, unexplored industries. The quality of innovative output follows this change in focus. The increase in the average patent quality confirms the predictions of many models of spinoff formation. An analysis of the tails of the patent quality around the spinoff founding reveal these founders also change their extreme success and failure rates. Such changes coincide with the founder switching to a younger body of knowledge relative to her past co-inventors. Overall, a picture emerges – thus far undocumented across industry or time – about the entrepreneurial firm founding decision.

The spinoff firm appears to excel at implementing long-term, riskier innovative projects than their parent firms. Where these advantages stem from is an open question. We believe one mechanism suggested by the results are incentive structures and firm investment policies that limit the parent firm's ability to accept high failure rate, but potential right-tail innovations.

There are several interesting areas for future research. Richer detail on the post-spinoff connections between the parent and spinoff through relationship such as strategic alliances could improve the analysis. With new ideas in the spinoff firm, one could follow the path of Furman and Stern (2011) to ask whether ideas in the spinoff have differing impacts than those inside the parent firm.

Finally, it would be interesting to study how the entrepreneurial founder builds an team to produce innovation.

References

Abadie, A., and G.W. Imbens. 2006. "Large sample properties of matching estimators for average treatment effects." *Econometrica*, 74(1): 235–267.

Abadie, Alberto, Alexis Diamond, and Jens Hainmueller. 2010. "Synthetic control methods for comparative case studies: Estimating the effect of California's tobacco control program." *Journal of the American Statistical Association*, 105(490).

Anton, James J, and Dennis A Yao. 1995. "Start-ups, spin-offs, and internal projects." *Journal of Law, Economics, & Organization*, 362–378.

Azoulay, Pierre, J. Graff Zivin, and Jialan Wang. 2010. "Superstar Extinction." *The Quarterly Journal of Economics*, 125(2): 549–589.

Bernstein, Shai. 2013. "Does Going Public Affect Innovation?"

Bertrand, M., E. Duflo, and S. Mullainathan. 2000. "How Much Should We Trust Differences-in-Differences Estimates?" *The Quarterly Journal of Economics*, 119(1): 249–275.

Bhide, Amar. 2000. *The origin and evolution of new businesses.* Oxford University Press.

Cassiman, Bruno, and Masako Ueda. 2006. "Optimal Project Rejection and New Firm Start-ups." *Management Science*, 52(2): 262–275.

Chatterji, Aaron K. 2008. "Spawned with a silver spoon? Entrepreneurial performance and innovation in the medical device industry." *Strategic Management Journal*, 30(2): 185–206.

Eriksson, T., and J. Moritz Kuhn. 2006. "Firm spin-offs in Denmark 1981–2000—patterns of entry and exit." *International Journal of Industrial Organization*, 24(5): 1021–1040.

Furman, Jeffrey L, and Scott Stern. 2011. "Climbing atop the Shoulders of Giants: The Impact of Institutions on Cumulative Research." *The American Economic Review*, 101(5): 1933–1963.

Gompers, Paul, Josh Lerner, and David Scharfstein. 2005. "Entrepreneurial Spawning: Public Corporations and the Genesis of New Ventures, 1986 to 1999." *Journal of Finance*, 60(2): 577–614.

Hall, Bronwyn H., Adam B. Jaffe, and Manuel Trajtenberg. 2001. "The NBER Patent Citation Data File: Lessons, Insights and Methodological Tools."

Hall, Bronwyn H, and Rosemarie Ziedonis. 2001. "The patent paradox revisited: an empirical study of patenting in the US semiconductor industry, 1979-1995." *RAND Journal of Economics*, 101–128.

Heckman, James, Hidehiko Ichimura, Jeffrey Smith, and Petra Todd. 1998. "Characterizing Selection Bias Using Experimental Data." *Econometrica*, 66(5): 1017–1098.

Heckman, James J, Hidehiko Ichimura, and Petra E Todd. 1997. "Matching as an Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Programme." *Review of Economic Studies*, 64(4): 605–54.

Hegde, Deepak, David C Mowery, and Stuart JH Graham. 2009. "Pioneering Inventors or Thicket Builders: Which US Firms Use Continuations in Patenting?" *Management Science*, 55(7): 1214–1226.

Hellmann, Thomas. 2007. "When do employees become entrepreneurs?" *Management science*, 53(6): 919–933.

Hellman, T., and M. Puri. 2000. "The interaction between product market and financing strategy: The role of venture capital." *Review of Financial Studies*, 13(4): 959–984.

Hsu, D.H., and R.H. Ziedonis. 2007. "Patents as quality signals for entrepreneurial ventures." *Unpublished working paper, University of Michigan.*

Imbens, Guido W. 2004. "Nonparametric Estimation of Average Treatment Effects Under Exogeneity: A Review." *The Review of Economics and Statistics*, 86(1): 4–29.

Klepper, S. 2009. "Spinoffs: A review and synthesis." *European Management Review*, 6(3): 159–171.

Klepper, Steven, and Peter Thompson. 2010. "Disagreements and intra-industry spinoffs." *International Journal of Industrial Organization*, 28(5): 526–538.

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

Kortum, Samuel, and Josh Lerner. 2000. "Assessing the Contribution of Venture Capital to Innovation." *RAND Journal of Economics*, 31(4): 674–692.

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

Lerner, J., M. Sorensen, and P. Strömberg. 2011. "Private Equity and Long-Run Investment: The Case of Innovation." *The Journal of Finance*, 66(2): 445–477.

Malsberger, Brian. 2008. *Covenants Not to Compete : A State-by-State Survey.* BNA Books.

Manso, Gustavo. 2011. "Motivating innovation." *The Journal of Finance*, 66(5): 1823–1860.

Marx, M., D. Strumsky, and L. Fleming. 2009. "Mobility, skills, and the Michigan non-compete experiment." *Management Science*, 55(6): 875–889.

Merges, Robert P. 1999. "The Law and Economics of Employee Inventions." *Harvard Journal of Law and Technology*, 13: 1.

Nanda, Ramana, and Matthew Rhodes-Kropf. 2012. "Innovation and the Financial Guillotine." Harvard Business School.

Nanda, R., and M. Rhodes-Kropf. forthcoming. "Financing risk and innovation." *Journal of Financial Economics.*

Papke, Leslie E., and Jeffrey M. Wooldridge. 2008. "Panel data methods for fractional response variables with an application to test pass rates." *Journal of Econometrics*, 145(1-2): 121–133.

Singh, Jasjit, and Ajay Agrawal. 2011. "Recruiting for Ideas: How Firms Exploit the Prior Inventions of New Hires." *Management Science*, 57(1): 129–150.

Tables and figures

Figure 1: Spinoffs over time

The figure reports the number of spinoffs founded per year in our final sample of 1131 firms. Section 2 details the construction of the sample.

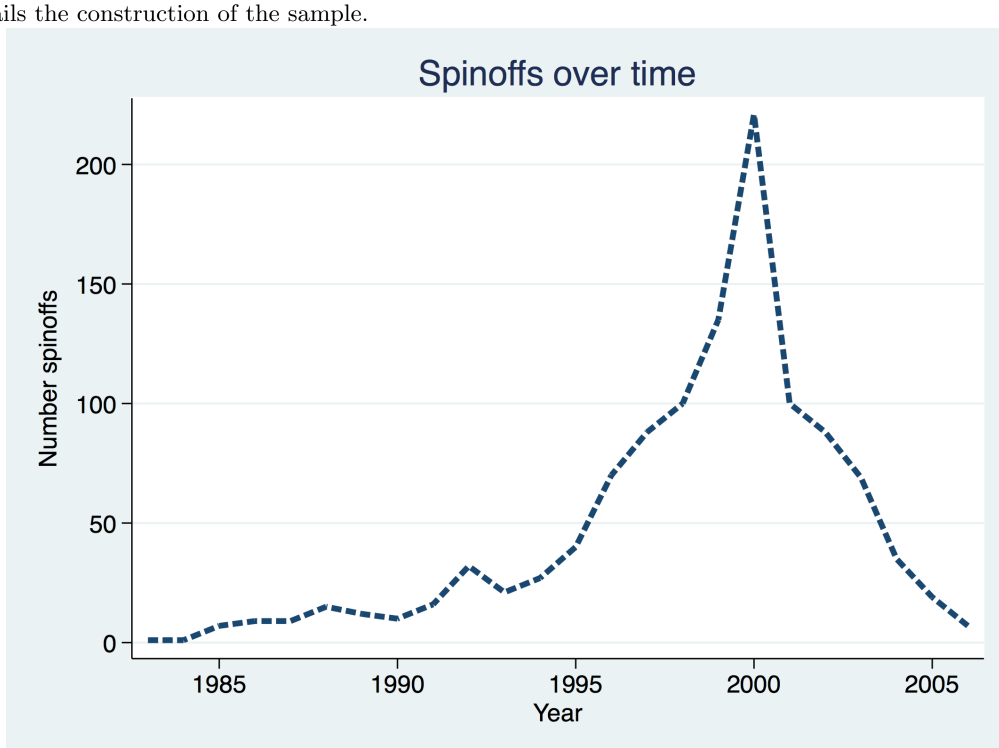

Figure 2: Patent applications around spinoff founding

The figure reports the average number of patents applied for in each year around the spinoff founding event for the entrepreneurial founders in the sample. Year 0 is the founding year. The bars represent the average patent rates across founders. The dashed line presents the empirical cumulative distribution function for the average fraction of patents applied for between $t = 0$ and $t = 5$. For example, the average spinoff applied for 20% of their total patents in the first founding year.

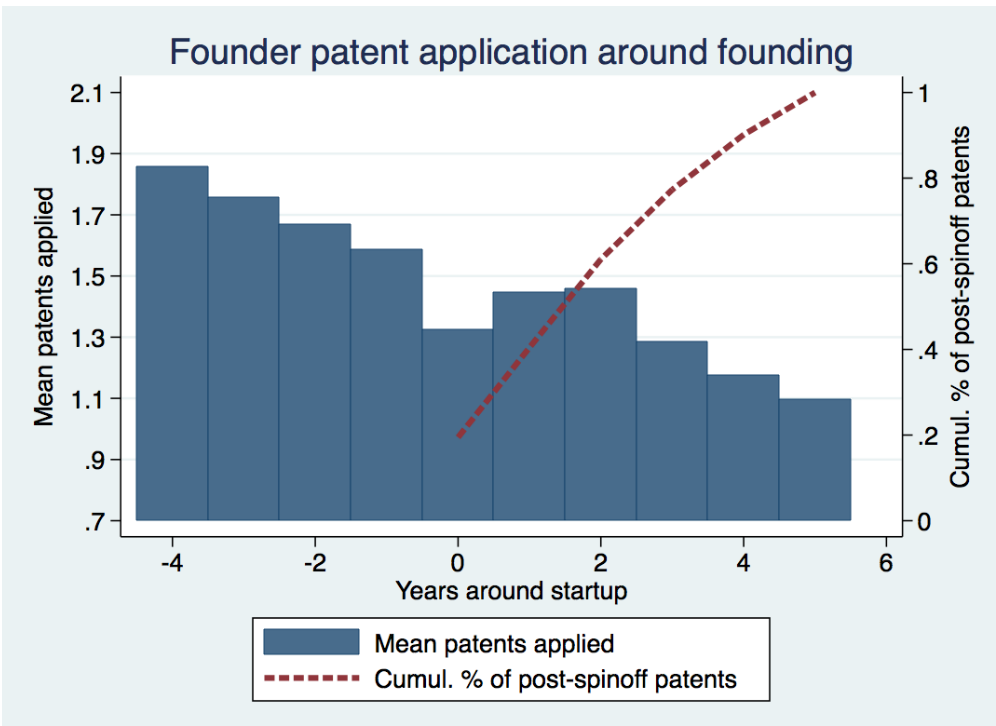

Figure 3: Trends of patenting over time

The figure reports the coefficients of the interaction terms of event time and the founder dummy for the main sample. The dependent variable is the number of patents applied for in a given year. Estimation is poisson with standard errors clustered at the founder-cohort level. Graph shows the point estimate and 95% confidence interval.

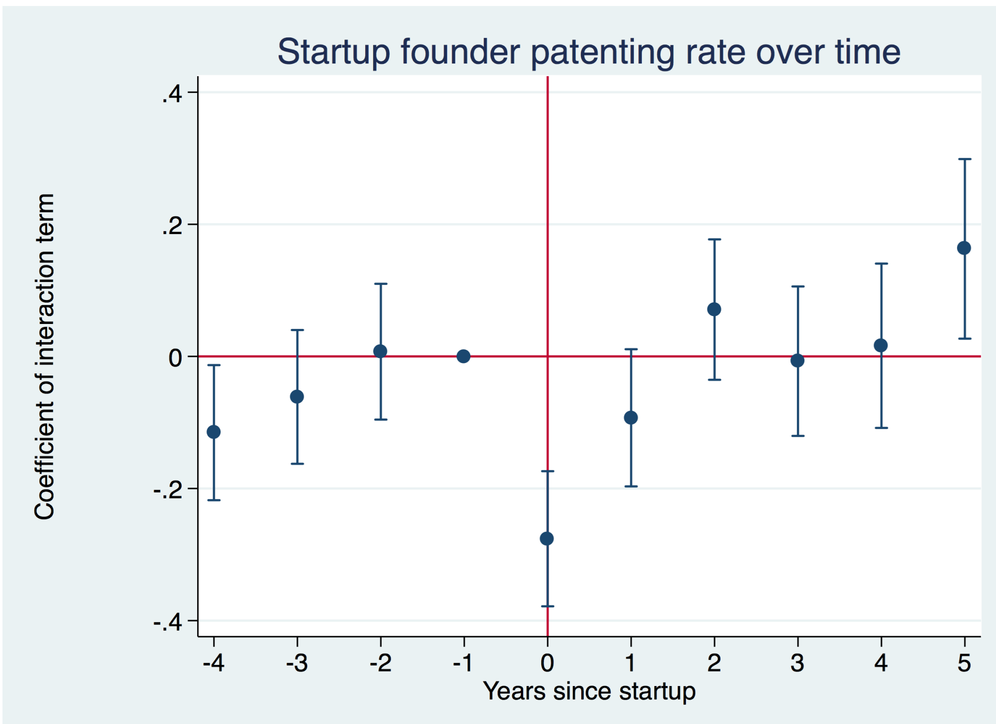

Figure 4: Distribution of changes in non-self cites received: founders vs. controls
The figure displays the kernel density for the change in citations received before and after the startup event for all controls and all founders.

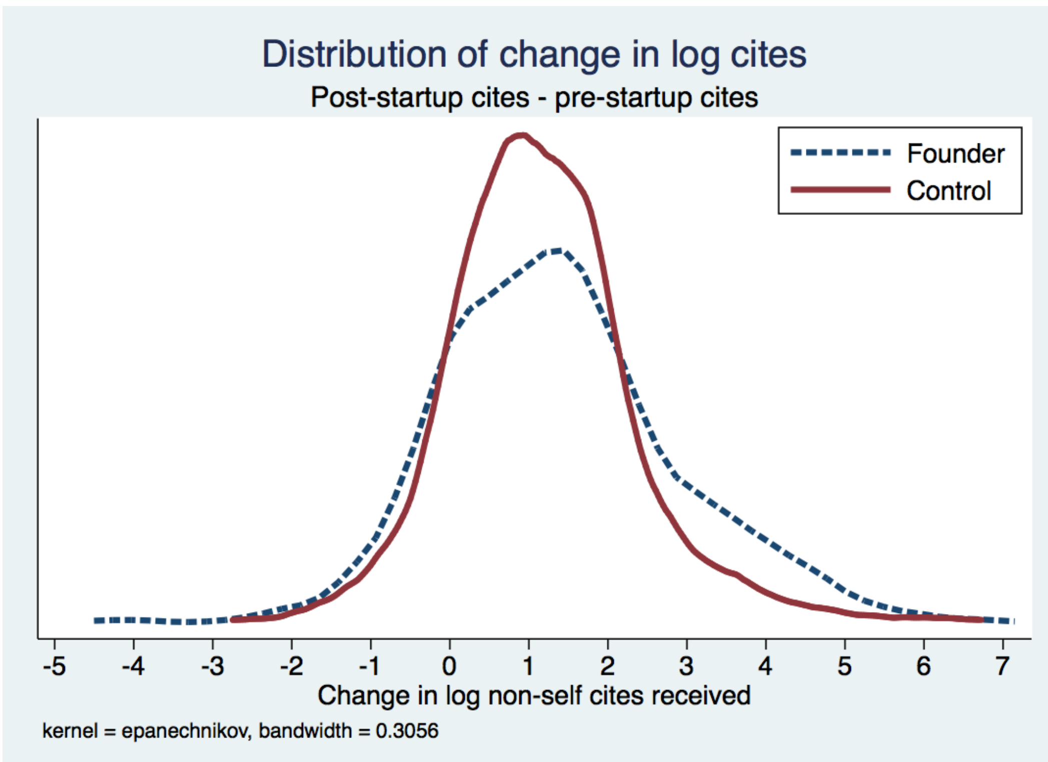

Figure 5: Quantile regression estimates for non-self cites received: founder dummy coefficient

The figure displays the OLS coefficient and quantile regression estimates for a regression of change in log non-self citation received on a dummy for a founder. The horizontal line with dashed boundaries is the OLS estimate, while the solid line and grayed bars are the quantile estimates and their 95% confidence intervals.

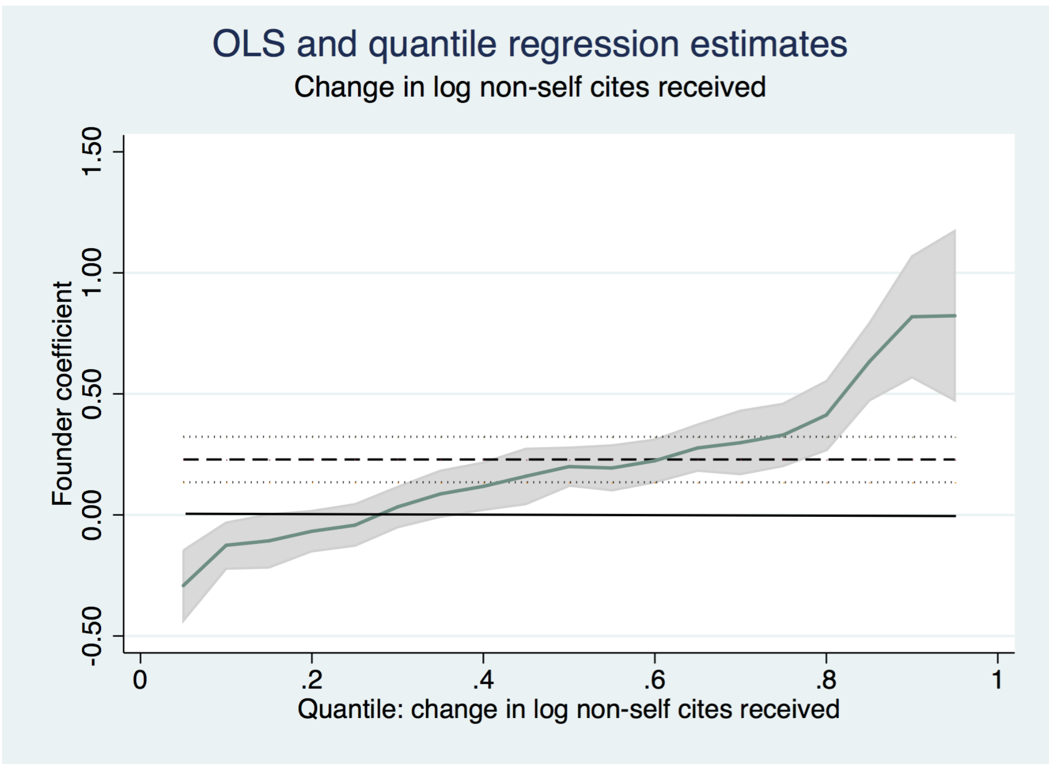

Table 1: Variable description

Notes: Description of the main patent dependent variables used throughout the paper.

Variable	Description
# Patents	The number of patents applied for each year in the windows $[-4, 0)$ and $[0, 5]$.
Originality	The originality (adjusted) measure using the sub-class of patents cited in an inventor's patents in each window. Patents that cite a larger set of sub-classes are more original. The adjustment (see Hall, Jaffe and Trajtenberg (2001)) addresses the inherent bias in the standard measure.
Citations received (non-self)	For the pre-spinoff patents, the total number of non-self citations received at $t = -1$ for all patents applied for in $[-4, 0)$. For the post-spinoff patents, the total number of citations received at $t = 5$ for all patents applied for in $[0, 5]$.
Generality	The generality (adjusted) measure using the sub-class of patents citing the patent in each window. As in "Citations received," this variable is measured for the two sets of patent stocks at $t = -1$ and $t = 4$. Patents with higher generality are cited by a larger set of patent sub-classes. The adjustment (see Hall, Jaffe and Trajtenberg (2001)) addresses the inherent bias in the measure related to citations counts.
% Winners	For each patent sub-class and year, we calculate the number of citations received 5 years after patent grant. A patent is a "winner" if it is in the top 10% this citation count within the same application year and patent classification.
Patent cite age	The average age of patents cited by a given patent as of the application year.
% self citations made	A number in $[0, 1]$ that measures the fraction of a patents citations made that are self-citations. A self-citation is defined at the inventor-level, so a patent with multiple inventors can have different values of "% self-citations made."
CIP	A continuation-in-part (CIP) creates a relationship of a "parent" and "child" patent. A patent is a (CIP) if it references itself as a continuation-in-part of an already applied for patent. A CIP typically adds new claims to the parent patent while the latter is still pending grant. CIPs are often used to add commercial application/uses to an existing technology and proxies for "pioneering inventors" (see Hegde, Mowery and Graham (2009)).
Patent Age	The NBER patent data includes the original patent class/sub-class (OCL) category recorded at the time of patent application. For the full history of each OCL, we calculate the cumulative fraction of the within-sub-class patents have been applied for as of year t. Patents filed in the final year of the sample (2006) each have a value of 1.
Lead inventor	A dummy variable equal to one if the inventor was referenced as the lead or first inventor on the patent.
# patent classes	The number of patent classes the inventor patents in during a given time period.
% repeat cites made	The fraction of the cites made in an inventor's patent that were also cited by any of the inventor's patents in the previous two years.

Table 2: Match diagnostics

Notes: Table reports the differences between the average founder and matched control from the matching procedure described in Section 2.1.

	Control	Founder	Diff/s.e.
Total patents	7.167	7.698	-0.531
			0.347
First year patent	1987.9	1988.9	-1.036***
			0.278
Growth in patent stock $(T-1, T)$	-0.420	-0.451	0.0314
			0.0409
Growth in patent stock $(T-2, T)$	-0.167	-0.176	0.00848
			0.0528
Growth in cites received $(T-1, T)$	-0.418	-0.451	0.0330
			0.0430
Growth in cites received $(T-2, T)$	-0.145	-0.176	0.0303
			0.0544
Total non-self cites received	82.51	86.30	-3.789
			8.619
Avg. Originality (adj.)	0.536	0.538	-0.00181
			0.00917
Generality pre-startup patents	0.747	0.721	0.0257*
			0.0102
Number active classes	1.681	1.706	-0.0250
			0.0339
Fraction patent is CIP	0.00574	0.00571	0.0000354
			0.00164
Fraction self-cites made	0.0338	0.0373	-0.00349
			0.00309
Fraction winners	0.133	0.146	-0.0132
			0.00935
Fraction losers	0.0372	0.0395	-0.00222
			0.00456
Avg. age of patent class	0.610	0.605	0.00473
			0.00691
% cite made again	0.0587	0.0636	-0.00483
			0.00320

Table 3: Sources of entrepreneurial founders with patents

Notes: Tabulation of the assignees associated with the entrepreneurial firm founders who have a matched co-inventor and at least one patent before and after the spinoff founding event who have at least 4 employee exits to spinoffs.

Parent firm	Count
International Business Machines Corporation	53
Intel Corporation	36
Lucent Technologies Inc	30
Sun Microsystems Inc	27
Microsoft Corporation	24
3Com Corporation	16
General Electric Company	14
Motorola Inc	14
Xerox Corporation	14
Advanced Micro Devices Inc	13
Cisco Technology Inc	13
National Semiconductor Corporation	12
Apple Inc	11
Applied Materials Inc	11
Hewlettpackard Company	11
Lsi Logic Corporation	10
Agilent Technologies Inc	9
Att Corp	9
Hoechst Celanese Corporation	7
Hughes Electronics Corporation	7
Micron Technology Inc	7
Polaroid Corporation	7
Affymetrix Inc	6
Broadcom Corporation	6
Silicon Graphics Inc	6
Texas Instruments Incorporated	6
Advanced Cardiovascular Systems Inc	5
Agere Systems Inc	5
Baxter International Inc	5
Ciena Corporation	5
Cirrus Logic Inc	5
Compaq Computer Corporation Inc	5
Eastman Kodak Company	5
Genentech Inc	5
Heartport Inc	5
Kopin Corporation	5
Medtronic Inc	5
Synopsys Inc	5
Unisys Corporation	5
Abbott Laboratories	4
Alza Corporation	4
Cabletron Systems Inc	4
Digital Equipment Corporation	4
Gilead Sciences Inc	4
Headway Technologies Inc	4
Hughes Aircraft Company	4
Human Genome Sciences Inc	4
Juniper Networks Inc	4
Koninklijke Philips Electronics Nv	4
Litton Systems Inc	4
Merck Co Inc	4
Nexabit Networks Inc	4
Nortel Networks Limited	4
Pfizer Inc	4
Scimed Life Systems Inc	4
Sdl Inc	4
Seagate Technology Llc	4
Silicon Image Inc	4

Table 4: Changes in patent classes around startup

Notes: Table characterizes the changes in patenting activity by industry class for startup founders and their co-inventor controls. The estimation specification is found in equation (4) using the conditional logit. Odds ratio (i.e. exponentiated coefficients) reported, where greater than 1 implies relatively higher probabilities. Each set of columns – (1)/(3) and (2)/(4) – present conditional logit estimates of two dummies variables. For each of the seven patent classes, an inventor can have a defined "Decrease" dummy if she (i) had positive patenting in that class pre-startup. The dummy is 1 if the fraction of patents in that class post-startup falls. The dummy is undefined if not pre-startup patenting occurs in that class. An inventor has multiple observations if she has multiple pre-startup patent classes with positive patenting. The "New?" dependent variable is defined for all inventors-classes where the inventor had zero patents in the pre-startup period. The dummy is 1 if there is an increase in patenting from 0 in the post-startup period. The group fixed effect is the founder-co-inventor controls. Columns 3 and 4 repeat the regressions on the sub-sample of firms that are have low covenant not to compete (CNC) states (i.e. below the median index measure in Malsberger (2008)) in the pre-period. The index comes from the survey of laws in Malsberger (2008). The control "Founder" is equal to 1 if the inventor was a founder and the coefficient reports the relative higher or lower probability the founder decreased her patenting in that patent class. "Change in patents" is the difference in total patents between the pre- and post-period (pre minus post). "Share at $t = -1$" is the share of patents in the given patent class for this stock of patents. "Class N" are dummy variables for each of the seven patent classes (the excluded class is class 1). The patent class definitions are found in Section 3.1. "Cohort FE" are fixed effects for each founder-co-inventor group, where co-inventors are chosen according to the matching process described in Section 2.1. Standard errors clustered at the founder-co-inventor group shown in parentheses. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Decrease?	New?	Decrease?	New?
	All		Low CNC States	
	(1)	(2)	(3)	(4)
Founder	1.244***	0.988	1.206**	0.934
	(0.0770)	(0.0810)	(0.102)	(0.113)
Share $t-1$	0.700***		0.803	
	(0.0849)		(0.128)	
Change in patents	0.978***	0.975***	0.969***	0.954***
	(0.00572)	(0.00694)	(0.00470)	(0.00636)
Class 2	1.343*	1.592***	1.234	1.483**
	(0.223)	(0.224)	(0.262)	(0.293)
Class 3	1.034	1.394**	1.133	1.839***
	(0.194)	(0.208)	(0.276)	(0.374)
Class 4	0.711*	2.612***	0.663*	2.760***
	(0.131)	(0.399)	(0.155)	(0.587)
Class 5	0.811	3.950***	0.754	4.168***
	(0.136)	(0.580)	(0.167)	(0.890)
Class 6	1.758**	1.276*	1.453	1.166
	(0.390)	(0.172)	(0.464)	(0.216)
Class 7	0.961	1.191	0.796	1.253
	(0.178)	(0.160)	(0.193)	(0.230)
Observations	5198	8536	2852	4657
Pseudo-R^2	0.0299	390.0499	0.0372	0.0703
Total founders	823	598	430	312

Table 5: Patent portfolio focus around the spinoff event

Notes: Estimates from regressions with a spinoff founder before and after the spinoff founding event. A founder is included in the sample if she has at least one patent before and after the founding and we found a matched co-inventor as described in Section 2.1. See Table 1 for definitions. For all dependent variables, the weighted means are computed in the intervals $[-4, -1]$ and $[0, 5]$ using the number of patents applied in each event year. Then the set of controls' values of each variables are averaged with weights equal to the match distance with the founder. Columns 1 and 3 use the poisson regression. The remaining columns use the Papke and Wooldridge (2008) panel method for fractional response dependent variables that have significant values on the boundaries. "Cohort FE?" is the fixed effect for each founder-co-inventor group using the matching process described in Section 2.2.Robust standard errors, which cluster at the founder cohort, are in parentheses. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	# active patent classes	% repeat cites made	# patents	% self-cites	% lead author	Patent class age
Founder X Post	-0.0346	0.160***	-0.958**	-0.147*	0.103*	0.00659
	(0.0336)	(0.0308)	(0.389)	(0.0863)	(0.0626)	(0.0248)
Post-startup	-0.0432*	0.0237	0.578*	-0.0139	0.970***	0.715***
	(0.0246)	(0.0245)	(0.311)	(0.0635)	(0.0475)	(0.0250)
Founder	0.0290	0.0413*	0.826***	0.112*	0.0427	-0.0208***
	(0.0250)	(0.0213)	(0.228)	(0.0579)	(0.0574)	(0.00639)
Constant	1.677***	-1.567***	7.188***	-3.363***	-2.032***	0.448***
	(0.0217)	(0.0185)	(0.235)	(0.0574)	(0.0493)	(0.0206)
Observations	4524	4524	4524	4524	4519	4524
Founders	1131	1131	1131	1131	1131	1131
R^2	0.00150	0.0209	0.000828	0.000790	0.118	0.166

Table 6: Patent portfolio quality around the spinoff founding

Notes: Estimates from regressions with a spinoff founder before and after the spinoff founding. A founder is included in the sample if she has at least one patent before and after the founding and we found a matched co-inventor as described in Section 2.1. See Table 1 for definitions. For all dependent variables, the weighted means are computed in the intervals $[-4,-1]$ and $[0,5]$ using the number of patents applied in each event year. Then the set of controls' values of each variables are averaged with weights equal to the match distance with the founder. Columns 1, 3 and 4 use the standard fixed effects. The remaining columns use the Papke and Wooldridge (2008) panel method for fractional response dependent variables that have significant values on the boundaries. "Cohort FE?" is the fixed effect for each founder-co-inventor group using the matching process described in Section 2.2.Robust standard errors, which cluster at the founder cohort, are in parentheses. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Non-self cites received (log)	Generality	Originality	CIP
Founder X Post	0.234***	0.0227***	0.0165*	0.204**
	(0.0352)	(0.00698)	(0.00885)	(0.0963)
Post-startup	1.154***	0.0837***	0.0221***	0.690***
	(0.0347)	(0.00557)	(0.00655)	(0.0634)
Founder	-0.450***	-0.0293***	-0.00446	0.00126
	(0.0414)	(0.00757)	(0.00568)	(0.0852)
Constant	3.503***	0.715***	0.543***	-2.531***
	(0.0412)	(0.00651)	(0.00583)	(0.0565)
Observations	4517	4524	4524	4524
Founders	1131	1131	1131	1131
R^2	0.182	0.0573	0.00581	0.0423

Table 7: Patent portfolio risk: changes in ex-ante and ex-post

Notes: OLS and quantile regressions of the change in the log non-self citation received and change in citation made age. Column 1 presents the OLS coefficient estimates with the dependent variable as the change in the average age of non-examiner citations made in the pre- and post-startup patent portfolio. A lower value over time suggests that the inventor is building off of relatively younger patents. In columns 2 - 5 we report the OLS coefficient and three estimates from quantile regressions of the 10th, 50th and 90th percentile of the change in log non-self citations received dependent variable. There is one observation per founder and control because the data is differenced. "Year startup FE" are dummies for the founding year of each startup firm. Bootstrapped standard errors reported in parentheses (for Columns 2 - 5) and robust standard errors are reported in Column 1. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Δ Citation age	Change in log cites received			
	OLS	OLS	10th perc.	Median	90th perc.
Founder	-0.313**	0.252***	-0.146***	0.216***	0.663***
	(0.125)	(0.0341)	(0.0454)	(0.0484)	(0.111)
Constant	0.505***	0.520***	0.156	0.186	0.436
	(0.0634)	(0.0187)	(0.861)	(0.587)	(0.514)
Observations	2262	2255	2255	2255	2255
Founders	1131	1131	1131	1131	1131
R^2 / psuedo-R^2	0.0563	0.326	0.285	0.321	0.302
Year startup FE?	Y	Y	Y	Y	Y

Table 8: Patent portfolio focus around the spinoff founding: superstar extinction

Notes: Estimates from regressions with a spinoff founder before and after the spinoff founding. The table repeats the regressions in Table 5 on a re-matched sample of controls. The distance metric between a founder and past co-inventor is first rescaled by the fraction of patents done together out of the controls whole portfolio. This rescaled distance is then used to create the average value of the control's dependent variable. Robust standard errors, which cluster at the founder cohort, are in parentheses. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	# active patent classes	% repeat cites made	# patents	% self-cites	% lead inventor	Patent class age
Founder X Post	-0.0321	0.136***	-0.978**	-0.142	0.0135	0.00708
	(0.0338)	(0.0308)	(0.392)	(0.0878)	(0.128)	(0.0251)
Post-startup	-0.0443*	0.0473*	0.600*	-0.0186	2.016***	0.715***
	(0.0248)	(0.0244)	(0.313)	(0.0640)	(0.0993)	(0.0253)
Founder	0.0156	0.0468**	0.718***	0.106*	0.207*	-0.0205***
	(0.0255)	(0.0216)	(0.231)	(0.0591)	(0.120)	(0.00655)
Constant	1.690***	-1.571***	7.303***	-3.365***	-2.897***	0.450***
	(0.0219)	(0.0189)	(0.236)	(0.0569)	(0.101)	(0.0207)
Observations	4504	4504	4504	4504	4504	4504
Founders	1126	1126	1126	1126	1126	1126
R^2	0.00141	0.0203	0.000701	0.000785	0.143	0.166

Table 9: Patent portfolio quality around the spinoff founding: superstar extinction

Notes: Estimates from regressions with a spinoff founder before and after the spinoff founding. The table repeats the regressions in Table 6 on a re-matched sample of controls. The distance metric between a founder and past co-inventor is first rescaled by the fraction of patents done together out of the controls whole portfolio. This rescaled distance is then used to create the average value of the control's dependent variable. Robust standard errors, which cluster at the founder cohort, are in parentheses. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Non-self cites received (log)	Generality	Originality	CIP
Founder X Post	0.240***	0.0257***	0.0169*	0.196**
	(0.0356)	(0.00707)	(0.00896)	(0.0967)
Post-startup	1.146***	0.0804***	0.0215***	0.699***
	(0.0347)	(0.00550)	(0.00653)	(0.0635)
Founder	-0.481***	-0.0330***	-0.00393	-0.00243
	(0.0419)	(0.00768)	(0.00579)	(0.0854)
Constant	3.536***	0.719***	0.543***	-2.526***
	(0.0411)	(0.00636)	(0.00580)	(0.0560)
Observations	4497	4504	4504	4504
Founders	1126	1126	1126	1126
R^2	0.183	0.0573	0.00574	0.0424

Table 10: Comparing spinoffs founded after corporate events: patent focus

Notes: Estimates from regressions with a spinoff founder before and after the spinoff founding. The table repeats the regressions in Table 5 for two sub-samples. The sub-sample "No change" include all founders who left parent firms that have a matched Compustat identifier and reported no major corporate change (CEO or large M&A) before the founding event. The sub-sample "CEO/M&A" only includes those firms that did have such a change. Robust standard errors, which cluster at the founder cohort, are in parentheses. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	# active patent classes		% repeat cites made		# patents	
	No change	CEO/M&A	No change	CEO/M&A	No change	CEO/M&A
Founder X Post	-0.0171	-0.313**	0.148***	0.0534	-0.372	-3.409*
	(0.0599)	(0.120)	(0.0530)	(0.137)	(0.723)	(1.812)
Post-startup	-0.0433	-0.0332	0.0379	0.135	0.490	1.943
	(0.0417)	(0.0760)	(0.0434)	(0.102)	(0.643)	(1.451)
Founder	0.00283	0.181**	0.0853**	0.0424	0.762**	0.333
	(0.0442)	(0.0825)	(0.0358)	(0.112)	(0.346)	(0.615)
Constant	1.711***	1.739***	-1.599***	-1.524***	8.210***	6.974***
	(0.0359)	(0.0929)	(0.0312)	(0.0821)	(0.529)	(0.844)
Observations	1524	300	1524	300	1524	300
Founders	381	75	381	75	381	75
R^2	0.00103	0.0229	0.0281	0.0182	0.000712	0.0116
	% self-cites		% lead inventor		Patent class age	
	No change	CEO/M&A	No change	CEO/M&A	No change	CEO/M&A
Founder X Post	-0.265*	-0.572	0.233	0.233	0.0254	-0.0385
	(0.152)	(0.371)	(0.530)	(0.530)	(0.0409)	(0.116)
Post-startup	0.163	-0.263	2.019***	2.019***	0.665***	0.774***
	(0.109)	(0.232)	(0.300)	(0.300)	(0.0445)	(0.118)
Founder	0.202*	0.183	-0.481	-0.481	-0.0267**	-0.0157
	(0.108)	(0.235)	(0.496)	(0.496)	(0.0107)	(0.0325)
Constant	-3.482***	-3.707***	-3.341***	-3.341***	0.424***	0.728***
	(0.0794)	(0.193)	(0.350)	(0.350)	(0.0364)	(0.0582)
Observations	1524	300	300	300	1524	300
Founders	381	75	75	75	381	75
R^2	0.00133	0.0244	0.144	0.144	0.152	0.221

Table 11: Comparing spinoffs founded after corporate events: patent quality

Notes: Estimates from regressions with a spinoff founder before and after the spinoff founding. The table repeats the regressions in Table 6 for two sub-samples. The sub-sample "No change" include all founders who left parent firms that have a matched Compustat identifier and reported no major corporate change (CEO or large M&A) before the founding event. Robust standard errors, which cluster at the founder cohort, are in parentheses. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Non-self cites rec. (log)		Generality	
	No change	CEO/M&A	No change	CEO/M&A
Founder X Post	0.279***	0.197	0.0206*	-0.0523**
	(0.0588)	(0.156)	(0.0122)	(0.0234)
Post-startup	1.120***	1.079***	0.0641***	0.151***
	(0.0624)	(0.137)	(0.00860)	(0.0312)
Founder	-0.439***	-0.536***	-0.0200	0.0371
	(0.0686)	(0.172)	(0.0123)	(0.0262)
Constant	3.673***	3.676***	0.744***	0.666***
	(0.0730)	(0.147)	(0.00997)	(0.0319)
Observations	1522	298	1524	300
Founders	381	75	381	75
R^2	0.168	0.202	0.0438	0.0807
	Originality		CIP	
	No change	CEO/M&A	No change	CEO/M&A
Founder X Post	0.0323**	0.0536	0.0277	0.215
	(0.0150)	(0.0350)	(0.160)	(0.212)
Post-startup	0.00608	0.0461	0.721***	0.637***
	(0.0101)	(0.0277)	(0.106)	(0.140)
Founder	-0.000620	-0.0315	0.228*	-0.298
	(0.00954)	(0.0249)	(0.136)	(0.204)
Constant	0.554***	0.551***	-2.603***	-2.153***
	(0.00925)	(0.0262)	(0.0893)	(0.178)
Observations	1524	300	1524	300
Founders	381	75	381	75
R^2	0.00649	0.0342	0.0419	0.0710

Table 12: Comparing VC and non-VC-backed spinoff founders

Notes: Table reports the characteristics of founders in two sub-samples as of the founding date. Column 1 shows the means of founders that eventually raise venture capital and the second column shows the same means for the non-VC-backed founders. The third column reports the difference in means and the stars are from a two-sided t-test. Variables are defined in Table 1. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	VC-backed	Non-VC-backed	Diff/s.e.
Total patents	9.454	5.972	3.482***
			0.740
Percentile rank at parent	0.466	0.460	0.00598
			0.0166
Years patented at parent	5.652	5.170	0.481
			0.338
Years between last parent/first startup	3.304	2.884	0.420**
			0.157
First year patent	1989.7	1987.2	2.516***
			0.446
Total non-self cites received	3.316	2.564	0.752***
			0.110
Avg. Originality (adj.)	0.547	0.522	0.0252
			0.0140
Generality ($t = -1, 4$)	0.700	0.646	0.0538**
			0.0176
Fraction patent is CIP	0.00518	0.00142	0.00376*
			0.00182
Fraction self-cites made	0.0405	0.0375	0.00305
			0.00550
Fraction winners	0.270	0.195	0.0749***
			0.0184
% patents as lead author	0.0786	0.0167	0.0619***
			0.0128
Avg. age of patent class	0.622	0.556	0.0653***
			0.0103
% cite made again	0.0696	0.0543	0.0152**
			0.00506

6 Appendix

6.1 Finding non-VC-backed spinoffs

As discussed in Section 1.1, we supplement the set of VC-backed spinoffs with a collection of firms that were plausibly formed by inventors leaving the same parent firms as those from the main sample. Some of these parent firms lack an identifier in the patent data (pdpass), which we have to ignore for this sample creation. For each of these parent firms, we isolate all the inventors – not in the VC sample – that switch firms and where the switch occurs after 1984.[27] Later steps in this process will require a unique firm identifier, so we cannot study inventors that leave to start firms that do not have a "pdpass." Many potential switches are in fact inventors patenting in their own name or under a subsidiary of the parent firm. So we have to restrict the sample of switches to those that are persistent: the potential spinoff has to have at least 4 patents in the data. We are ultimately interested in identifying both new firms and their founders, so consider only inventors who leave these parent firms are patent at new firms in one of the firms first three patents. Of course, this is not enough to identify a founder because we do not know when a firm is founded.

Private firm founding dates are difficult to find. Those firms that decide to incorporate in either Delaware or California provide some useful information. Delaware is a very popular location to incorporate because of the friendliness of its courts, quick bureaucracy and typical corporate lawyer's familiarity with the state's institution. From the patent data, we have potentially several versions of the firms name. We take these strings to one of these two state's secretary of state websites.[28] A combination of manual searches and a web scraping script searched for the 11,000 potential new firm founding dates on these websites. If the Delaware site had a perfect match, then it was assumed to be the correct date, while the California result was only used if the Delaware return zero or multiple results. This data collection recovered over 60% of the potential spinoffs incorporation dates. These dates are imperfect measures of *founding* dates, which informs the final step to identify founders.

[27] This date restriction is simply to ensure the time of the VC and non-VC-backed firm foundings is approximately the same.

[28] Delaware: `https://delecorp.delaware.gov/tin/GINameSearch.jsp`. California: `http://kepler.sos.ca.gov/`.

We now have a collection of potential spinoffs, potential founders and incorporation dates. Labeling an inventor as a founder requires the incorporation date occur within one year prior to two years after the first observed patent at the firm. This condition will of course eliminate some firms that patent many years after founding, however, we are interested in mapping to both spinoff and its founder. Further, this condition helps rule out some incorrect incorporation date results where the date occurs many years after the first patent. For the set of inventors that have one of a firm's first three patents in this $[-1, 2]$ year window around the incorporation date, we label them as founders. The final sample includes 1,319 unique firms and 1,529 unique founders. Future work could take this process to all potential new firms in the patent data.