Innovation and Experimentation in the Entrepreneurial Firm

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Abstract

We ask whether the entrepreneurial firm has an innovative advantage in pursuing radical, experimental innovation and isolate its sources. Using data on a large sample of inventors that move from established firms to founding new firms, we compare innovation activity and outcomes to their former co-workers at the large firm. The difference-in-difference estimation reveals that although the average output and quality of patent production is unchanged for founders, their patents are more likely to end up in the tails of the quality distribution. Founders that shift their innovation to newer ideas and a focused research agenda drive the riskier innovation outcomes. These patterns are consistent with both increased risk-taking after founding and evidence of the entrepreneurial firm's comparative advantage in experimentation.

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Introduction

Since Schumpeter (1942), policymakers and researchers put the small entrepreneurial firm as the main source of radical, disruptive innovation. Similarly, the notion of "heterogeneous innovations" produced by the large and small firm underlies new models of endogenous growth theory (e.g. Akcigit and Kerr (2015)). An empirical literature shows that new firm patents are more likely to reside in the right tail of the quality distribution – often proxied by citations received – than large firm innovations. Several studies also claim that these firms pursue more exploratory innovation. The theoretical literature reconciles these facts with several organizational and incentive frictions, which include agency problems, information asymmetry, narrow product focus and weaker incentives for innovation (Cassiman and Ueda (2006); Klepper and Thompson (2010); Hellmann (2007)).

This paper asks whether the entrepreneurial firm has an advantage in pursuing exploratory, experimental innovation and if so, what are the sources of the advantage. The empirical literature has yet to connect the entrepreneurial firm's higher patent productivity and different innovative strategy to such an advantage. Connecting these two facts can solve confounding empirical issues. Accounting for them requires documenting the full innovation outcome distribution. Moreover, it requires finding that these firms pursue ex-ante riskier ideas that have higher variance outcomes. Addressing the initial characteristics of ideas is important, since a higher likelihood of both right and left tail outcomes is no evidence for any differences in risk. A fatter tailed patent quality distribution could follow from selection of entrepreneurs or the firm developing a combination of very high and very low quality ideas.

This paper provides empirical evidence of the entrepreneurial firm's propensity to pursue radical, experimental innovation. We do so by tracking inventors as they transition from an employee to entrepreneurial firm founder. Incorporating this change into a novel difference-in-difference framework allows us to rule out selection of people and many confounding time trends. Our major contribution is to demonstrate that although the mean quality and output is relatively unchanged for these founders, they produce more patents that have citation counts at both extremes of the distribution. These changes are stronger for founders that shift to relatively newer ideas and a more focused research agenda. Both changes fit a large set of theoretical predictions about the

entrepreneurial firm innovative advantage. Inventors who move between large firms exhibit none of the patterns of patent quality or changes in innovation strategy.

To address our questions, 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.[1] Next, this information is merged with the inventor-level patent data of Li et al. (2014) 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. The final sample of founders is 1,131 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 and at least one patent after founding.

We first explore how the characteristics of individuals choosing to found new firms differ from the ones who rather leave to another established firm. Differences demonstrate the type of selection of individuals into entrepreneurship. Empirical papers (Chatterji (2008); Klepper (2009)) find that entrepreneurial spawns on average perform better than other sets of young firms. Theoretically it is also argued that employers struggle to recognize employees with the best ideas, leading them to offer similar contracts to all employees (Chatterjee and Rossi-Hansberg (2012); Klepper and Thompson (2010)). Consequently, these theories predict better employees being more likely to exit and develop their idea in their own firms. This is indeed what we find: comparing founders to individuals who move to other established firms, founders have been more active, more successful and more original in their patenting activity at the time of their exit. The positive selection of founders from parent firms requires that the final estimation strategy addresses unobserved heterogeneity.

We next assess how entrepreneurial founders' innovation changes as they leave their previous employer to found a firm. Any entrepreneurial firm innovative advantage that stems from a treat-

[1] 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. We focus on the study of founders of these and other non-VC-backed entrepreneurial firms.

ment effect or a time-varying selection of ideas could be reflected in increases in patent output and quality. A standard before-after comparison of means cannot account for confounding trends, so that we match each of our founders to a set of employees with whom they had co-invented in the established firm and who do not change employer. 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 (i.e. quality) as the founder. The final sample has 9-year patenting histories for 1,131 entrepreneurial founders and 2940 matched controls. With this reasonable counterfactual at hand, a standard comparison of means over time for these two groups of individuals shows that patent production and the number of citations received do not significantly change once an employee becomes a founder, albeit them producing slightly more general innovations. The lack of any difference in the *mean* output and quality does not imply the average founder avoids riskier innovation strategy. The next step in the estimation studies how changes beyond the mean innovation quality change.

Empirical evidence for increased risk-taking through experimental or more radical innovation first requires showing that patent quality changes in both the right and left tail of the distribution. Previous empirical work has documented a small firm's innovation being of higher value, but does not document both tails of the distribution. Theoretical predictions about whether risk-taking should increase differ. Conditional on the quality of the founder, she might choose to decrease her risk-exposure due to a smaller cushion of capital and a high cost of failure (Manso (2011)). Alternatively, improved incentives (Anton and Yao (1995)) and less managerial control might lead her to a higher degree of exploration. Using a quantile estimator of the change in citations received, we find that founders are more likely to have extreme tail outcomes on both sides of the quality distribution, compared to employees who stay at the initial employer. This result however, could follow from a combination of very high and very low quality ideas, without any changes in risk-taking over time. For example, a set of founders could simply be fired for poor ideas and others leave to exploit their best ideas in a new firm. To rule out this alternative channel, we rely on the extensive theoretical literature to provide proxies for initial idea characteristics associated with experimentation. We aim to estimate whether the high variance results are driven by a subset of

founders who choose to *switch* do more exploratory research agendas.

The theoretical literature on innovation in the new firm equates riskier innovation strategies to several differences in the ideas pursued. One class of models consider frictions that lead large firms to focus on older ideas in their range of expertise, leading to a reluctance to explore new research avenues (Ferreira, Manso and Silva (2012); Jovanovic and Rousseau (2014); Audretsch (1995)). We use the relative change in the age of patent citations made as a proxy for exploratory research. An alternative proxy for experimentation is focus or the degree to which an inventor is able to explore and deepen knowledge of a specific technological area.[2] Inventors must take decisions about which projects to further pursue in scenarios of incomplete information, a task that becomes even more demanding at higher levels of project exploration and uncertainty (Kerr, Nanda and Rhodes-Kropf (2014)). Expertise and "intuition" (Rajan (2012)) gained through a prolonged exposure to a research field can improve the assessment and evaluation of project potential at an intermediate stage.[3] This, in turn, can make inventors be more willing to pursue riskier projects at the onset. Here, the terms focus, expertise, and experimentation go hand in hand. Finally, we consider investment or research time motivated by the large literature on managerial short-termism (e.g. Stein (1988), Stein (1989) and Graham, Harvey and Rajgopal (2005)).

If these changes truly proxy for experimentation, then two things should hold in the data. First, entrepreneurial founders' innovation should switch to a combination of newer, more focused and longer term patenting strategies. Second, these differences in innovation strategy should predict a founder's propensity to produce innovations in the tails of the quality distribution. A similar tracking of founder's innovation around the founding event shows that indeed innovation choices change towards, newer and more focused innovation. Our second key contribution is to show that the subset of founders who switch to more exploratory projects (understood as younger citations made or greater focus on a given research agenda) end up experiencing innovation outcomes that are more fat-tailed. In other words, there is nothing generic about entrepreneurial firms generating more

[2]Hellmann (2007) and Hellmann and Thiele (2011) study incentives for innovation in a multitask principal-agent model. In the established firm an individual has to perform multiple tasks, therefore losing focus and struggling to devote as much effort as needed to innovation.

[3]Empirically, Lerner, Sorensen and Strömberg (2011) find that private equity firms focus the patenting activity of their portfolio companies.

extreme outcomes; rather, it seems to be driven by the subset of founders exploring. Given these changes to exploratory strategies coincide with high tail risk, they are also signs of experimentation.

To confirm that such a pattern is not a consequence of employee mobility, we return to the sample of employees leaving a parent firm to other large firms. We replicate the previous econometric specifications, including a matching to co-workers who stay at the previous employer. We do not find any change in the likelihood of innovation outcomes in the tails of the quality distribution. More importantly, the average inventor in this sample exhibits none of the changes in innovation strategy such as newness or focus: breaking the sample into those inventors who switch to newer citations or become more focused does not introduce fatter tails in the quality distribution. The lack of similar patterns in these inventors confirms that mobility only cannot explain our main results. The result also reinforces our conclusion that the entrepreneurial firm plays a unique role in the pursuit of experimental innovation. Finally, additional robustness checks confirm that the results are not due to other shocks around the founding event, superstar extinction (Azoulay, Graff-Zivin and Wang (2010)) or the matching methodology.

Our conclusions do not extend to causal claims of the founding event or ideas matched to entrepreneurial firms. Absent a randomization of individuals and/or ideas to entrepreneurial firms, we believe our empirical results nonetheless are the strongest evidence that entrepreneurial firms have a comparative advantage in pursuing riskier, experimental innovations. Randomization in our context is in fact at odds with the assumptions of the entrepreneurship literature and thus may not be a suitable empirical benchmark. This literature treats the founding of a new firm as a choice, either as a consequence of obtaining a certain type of idea, or due to the unwillingness of established firms to pursue certain ideas outside their comfort zone, or as a natural evolution of an inventor's career. It is argued that certain individuals or types are suited for entrepreneurship. Our results improve our understanding of the endogenity of the entrepreneurial choice and innovation strategy that is at the center of theory.

The paper contributes to the literature on public firm innovation such as Bernstein (2014) who shows that going public has strong, negative consequences on innovation. Our work shows that many of these issues may stem from a shift to innovation strategies in ways opposite of what

is observed by the founders in our data (i.e. less exploratory research). It also relates to the emerging heterogeneous innovation literature such as Akcigit and Kerr (2015) and Bena, Garlappi and Grüning (2015) who empirically confirm the higher quality result and theoretically look at innovation from small and large firms. We find evidence for this heterogeneity and tie it to patent outcomes. The conclusions also extend the literature on spinoffs to multiple industries and many years, apart from addressing some econometric concerns in cross-sectional studies (Klepper (2009)). Finally, the paper fits in the literature on venture capital and private equity. The extreme tails of patent production mimics some of the results in Nanda and Rhodes-Kropf (2013) where investment cycles for high-growth entrepreneurial firm generate differences in the tails of both value production and innovation. Last, some of the patterns in founder innovation also mirror those found in post-buyout deals in Lerner, Sorensen and Strömberg (2011).

The paper proceeds as follows. Section 1 describes the data construction and matching process. Section 2 presents the results and Section 3 provides robustness tests. Section 4 concludes.

1 Data

This section details the three major pieces of the data used throughout the paper. The first is the inventor-level data from Li et al. (2014). The second major dataset identifies mobility of inventors to both new and established firms. Finally, we describe the process of creating a matched comparison group for the difference-in-difference estimator.

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 (VC) 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 founded after 2007 so we have ample time to track the

post-founding characteristics.[4] Entrepreneurial firms also exit the sample when they have an initial public offering, are acquired or failed. This restriction 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 Li et al. (2014) inventor-level database.[5]

Matching entrepreneurial founder to inventor of a particular patent requires several steps, greatly facilitated by employment histories and the unique inventor identifiers in Li et al. (2014). A fuzzy string match of the unique past employers associated with founders and company name on the patent application (i.e. assignee) retrieves the firm identifier from the patent data.[6] 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.[7] 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.

[4] 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.

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

[6] 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.

[7] 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 Li et al. (2014). Confirmation of the merge was done using the year of entrepreneurial firm founding to remove false positives.

1.1 Non-VC-backed entrepreneurial firms

For many of these VC-backed entrepreneurial firm founders, we can identify the employer for which they patented immediately prior to the firm founding.[8] The pool of these established firms forms the basis of an additional search for non-VC backed entrepreneurial firms. The Internet 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, resulting in over 11,000 potential firms 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).[9] 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 spawn of the parent firm. We find 1,591 non-VC-backed entrepreneurial firm founders.

Combined with the VC-backed founders, this additional set of founders forms the basis of the major sample of analysis. The final sample has 1,131 founders after cleaning and matching (discussed below). Figure 1 shows the rate of entrepreneurial firm 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 Parent firms

The top pre-founding employers for all the founders in our final analysis sample are listed in Table 1.[10] The largest source of new entrepreneurial firms is IBM followed by many well-known firms in technology, biotechnology and communications. For these firms, some 48% were 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

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

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

[10] 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.

founding year.[11] 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 (see Section 1.4) and ensure we use the inventor's recent patent stock. The results are insensitive to a choice of five or three years prior to the founding. We eliminate any patents that are filed with the parent firm after the founding date of the firm, which could be due to a lag in patent filing.

1.3 Patent variables

Our study includes several popular patent measures to capture quantity, quality and changes in innovation strategy. The basic quantity measure is the the count of the number of patents applied for over a given time period. The specifications use either the raw count and estimate a count regression model or use the log of the number of patents.[12] We include two quality measures: non-self citations received and generality. The former captures the external impact of a patent, which we measure up to five years after original patent application. Generality measures the range of industries from which citations are received. A wider set of industries implies a broad impact of the patent. The next set of patent variables are observable at the time of the patent application and under the control of the patent authors. The citations made to other patents represent the body of knowledge on which a inventor builds. The average age of the citations made at the time of the current application captures the "newness" of this body of knowledge. Originality is the backward-looking analogue to generality, here measuring the breadth of industries cited. An inventor can cite her past inventions, leading to a self-citation made. In our sample, the rate of self-citation is low, so we consider a simply indicator for at least one self-citation made. Finally, the set of citations made in an inventor's patent stock can overlap with her previous patents' citation. To proxy for a focused building on a set of patents, we create a variable "% repeat cites" that is the fraction of cites made in the current patent that we also cited in any of the previous patents written by the author.

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

[12] By construction, all the inventors have at least one patent so we do not need to adjust the patent count.

1.4 Finding comparison inventors and matching

We are ultimately interested in studying if and how innovative activity changes around the firm founding event. Any changes inform our understanding of the innovative advantage of the entrepreneurial firm. Consider first a within-founder analysis that tracks changes in her patenting over time. Even with knowledge of the full patenting and employment histories of the entrepreneurial founder, within-founder changes in patenting around the founding date is confounded by a host of unobservables. Here, we lack 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 an observationally similar 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 firm 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 comparison inventors to this set alleviates many issues in matching estimators that have few observables available (see Heckman, Ichimura and Todd (1997)). The final estimator requires that the "best matches" have parallel trends to that of the founder, so we include pre-trends of our variables of interest. 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 specialty, so we include the 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.[13] To select 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

[13]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.

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 comparison coinventors have insufficient patenting activity in the five years after the founding date, while some founders stop patenting themselves at the entrepreneurial firm. The matching distance threshold and these two constraints leave us with 1,131 founders with at least one matched co-inventor in the pre- and post-founding period. There are 2940 non-founder inventors for an average of 2.6 matches per founder.

The matched comparison group allows us to rule out confounding trends while providing a plausible counterfactual for the founder's outcome in the absence of the move. To the former, trends within-industry and over time confound any study of the dynamics of an inventor's patent portfolio. The matched comparison group acts as a plausible benchmark for these trends. Second, the group of former co-inventors who remain at the parent firm represent a possible innovation profile for the founder had she remained at the parent firm. The comparison group's profile mimics what the founder's innovation would have looked like in the absences of either the new idea that led to the exit or any treatment effect from the firm founding. The estimator does not yet allow separation of these explanations. Last, the matching requirement of industry and co-invention mimics other approaches to address trends that normalized patent outcomes by averages within application year and industry (e.g. Lerner, Sorensen and Strömberg (2011)).

Table 2 provides a diagnostic of the matching process for the final sample of founders and co-inventors. The goal of the matching exercise was to ensure that founders and their co-inventors were observably similar in both patent characteristics and growth measures. With the exception of beginning their patenting activity earlier and producing weakly more general patents, the founders and former co-inventors are similar in most observable dimensions. It is important to note that requiring that founders both co-wrote patents and worked at the same parent firm should improve

any matching on unobservables. Heckman, Ichimura and Todd (1997) make similar arguments in their study of matching for policy analysis of job training programs when it was shown that requiring agents to be in the same regional area reduced the matching process bias.

1.5 Movers between established firms

We extend the tracking the movement of individuals founding new firms to also follow inventors at the parent firm moving to other established firms.[14] We use this sample of movers to benchmark the founders' patent characteristics at the time of the move and also test whether any changes to founders are due to the mobility decision alone. The sample of non-founder inventors begins with the parents of all the entrepreneurial firms above. Next, we restrict the set of established firms that these inventors can join. These firms have to be at least five years old at the time of the move, cannot be one of the new entrepreneurial firms in our sample and have to have at a patent stock greater than the bottom quartile of all firms in the patent data. These conditions result in a sample of 13,822 inventors who move from 612 parent firms and join 585 distinct established firms.

2 Results

This section describes the results of our tests concerning the selection of inventors to entrepreneurial firms and the changes that occur after they move.

2.1 What do mobile inventors to new firms look like?

Before understanding any innovative advantage of the entrepreneurial firm, we document the characteristics of their founders. One possible source of their advantage could be positive selection of inventors from large firms. The sample of mobile inventors includes those that start or join entrepreneurial firms and those that move to other large firms. We first ask whether the inventors that leave to join or found new firms differ at the time of their move. A large literature on spinoff formation (e.g. Klepper (2009)) shows that employees that form new firms outperform their denovo

[14] A similar tracking of mobile inventors in done in Singh and Agrawal (2011).

counterparts in profitability and innovation. It is argued that these founders bring additional experience, better networks and knowledge about their product market. Thus we expect regressions with including movers to entrepreneurial firms will suffer from positive selection. To document this, we will compare inventors that move to three different environments: other large firms, new, VC-backed firms and new, non-VC-backed firms.

We predict that inventors that found new firms are of both higher quality and differ in their patenting histories than movers to large firms. Moreover, founders of new firms take on more risk than their salaried position, so we would expect risk-averse founder to be higher quality than those that move to other large firms. Table 3 presents the parent firm fixed effects results for five patent measures used throughout the paper. The regressions take the following form:

$$Y_{ijt} = \beta_0 + \alpha_j + \beta_1 \text{Moved to new firm?}_{it} + \beta_2 \text{VC-backed?}_{it} + \gamma_t + v_{ijt} \tag{1}$$

where α_j is the parent firm fixed effect, γ_t is the year of exit fixed effect and "Moved to new firm?" is a dummy if the inventor moved to an entrepreneurial firm. The last dummy – "VC-backed" – is one if the inventor moved to a new entrepreneurial firm that also received venture capital. The excluded category is those inventors that moved to other large firms. This specification compares the characteristics of inventors that leave to the three types of firms, within each parent firm. The dependent variables Y_{ijt} are patent characteristics measured at the time of the inventors exit.

Column (1) asks whether the inventor's stock of cited patents have different age profiles by the choice of exit. The dependent variable is the log of the citation age of cites made by the inventor (excluding the examiner). A negative coefficient implies that movers are more likely to have cited relatively younger patents than other exiting inventors from the parent at the time of their exit. Inventors who join entrepreneurial firms exhibit no difference in this patent measure. Column (2) shows that movers to new firms are more prolific patenters at the time of the move, while columns (3) and (4) show that their patents are both more general and original. The coefficients on "Move to VC-backed" imply that founders of VC-backed firms have higher levels of each of these measures. Finally, Column (5) demonstrates that at the time of exit, the patent stocks of inventors to new firms are of higher quality as shown by greater non-self citations received than their counterparts

who moved to large firms. Perhaps unsurprisingly, entrepreneurial firm founders differ in their experience and innovation quality compared to movers to large firms. This positive selection will be an important issue to address in the analysis below.

2.2 Changes after new firm founding

We next ask what happens to the entrepreneurial firm founder's innovation outcomes as she transitions from an employee to founder. Any changes in quality, patenting rate and other patent measures can reveal either a treatment effect of founding or evidence of the impetus for the mobility choice. The analysis of parent-level mobility choices in Section 2.1 shows that the founders of entrepreneurial firms differ in several dimensions from employees of the same parent firm that move to other large firms. Studying changes over time invites differencing out the time-invariant selection or unobserved heterogeneity. What remains is a suitable comparison group that acts as a plausible counterfactual. We address this by comparing the entrepreneurial founders to their former co-workers at co-inventors at the parent firm who remain employed as detailed in Section 1.4.

2.2.1 Empirical model

The main specification is a difference-in-difference estimator with a founder-matched co-inventor group. The number of comparison co-inventors 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 comparison inventors where the weight is the inverse of the calculated match distance.[15] Let P_{it} be one of the patent variables described in Section 1 where the event time is defined in the range $t \in [-4, 5]$:

$$P_{ilt} = \gamma_0 + \text{Founder}_i + \sum_{t=-4,t\neq-1}^{5} \beta_t T_t + \sum_{t=-4,t\neq-1}^{5} \rho_t \text{Founder}_i T_t + \epsilon_{it} \tag{2}$$

[15] Results are similar when we have one observation per inventor, however, this approach gives relatively more weight to founders with more co-inventors.

where i indexes inventor.[16] 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 (2) 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 2 and Table 2). Our main estimation uses a variant of (2) 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 comparison co-inventors, 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. The new estimator becomes:

$$P_{it} = \beta_0 + \beta_1 * \text{Post-founding}_{it} + \beta_2 \text{Founder}_i + \beta_3 \text{Founder}_i * \text{Post-founding}_{it} + \epsilon_{it} \qquad (3)$$

where indices are as in (2), $t \in \{0, 1\}$ for the pre- and post-founding periods and "Post-founding" is a dummy equal to one for the latter. The parameter of interest is β_3, which measures the difference between the founder and matched comparison inventors after the firm founding. This empirical specification of pre-regression matching and averaging ensures that we compare founders to their past co-inventors. The model (3) mimics the difference-in-difference matching estimator detailed in Heckman, Ichimura and Todd (1997).

2.2.2 Differences in patent outcomes

The first measure we study is the number of patents applied for in the pre- and post-founding period. Patent counts are often used in the literature to measure innovation activity and increased patenting is treated as a positive sign of innovation. Next, we track the changes in the major patent quality measure: non-self citations received. The last outcome measure captures the impact of a patent across patent classes, "generality." If there is in an entrepreneurial firm innovative

[16] An inventor i may be matched with multiple founders for the comparison sample.

advantage, then we predict each of these measures will increase. However, if the existing literature's conclusions about higher quality are driven by a selection of better individuals to these firms, then the difference-in-difference approach will find no changes in quality. Similarly, if the main advantage of the entrepreneurial firm is the production of riskier, experimental innovation, then the mean differences in any estimator could be zero. In this case, the higher risk increases both failed and successful patents such that the mean quality is unchanged.

Consider first the univariate differences presented in Table 4, which presents differences in three patent measures: total patents applied for, non-self cites received and the average age of patents cited. Each cell reports the mean of founders and the comparison group co-inventors for both periods around the founding event. The bottom row of each panel reports the within-inventor difference across the two periods, while the last column reports the difference in means within each period. Both the comparison co-inventors and the founders exhibit meaningful changes in these measures. Patent counts weakly increase, citation counts fall and citation age increases around the founding event. The bottom right estimates are equivalent to a difference-in-difference coefficient estimate, which we now present.

Table 5 extends the univariate analysis in Table 4 into the standard difference-in-difference setup in model (3). Column (1) regresses a founder and comparison group's total patent rate before and after founding on the main controls. As evidenced by the coefficient on "Post-founding" there is an increase in patenting on average. The coefficient on "Founder X Post" is statistically and economically small, suggesting little relative change in the patents applied for by founders. Note that the simple within difference from Table 4 showed an increase in patenting after founding, something the main estimator rules out. The next two columns present dependent variables that measure innovation quality. Column (2) presents the log of total non-self cites received (one if no cites) for the pre and post-period. The average founder exhibits no change in the level of cites received. Column (3) considers the ratio of total cites received to total patents. Founder patents receive relatively more citations per patent on average. However, the economic significance of the estimates is small at approximately 2% of the mean cites received. The final column shows that the generality of patents filed in the post-founding period by founders is significantly larger. Post-

founding patents are no more likely to receive increase citations, however, those cites arrive from a wider set of patent classes.

2.3 Differences in citations received: tails

Table 5 shows that the average entrepreneurial firm founder exhibits little difference in mean output and innovation quality after firm founding. A major goal of this study is to determine whether the entrepreneurial firm in fact pursues radical, disruptive innovation. Despite the lack of differences in mean output and quality, it is possible that entrepreneurial firms engage in relatively more radical innovation strategies. The pursuit of such innovation strategies is often tied to the notion of *experimentation* (e.g. Manso (2011) and Kerr, Nanda and Rhodes-Kropf (2014)). Theorists model experimental projects with some action that allows the agent to learn about project feasibility, but has some probability of initial, costly failure. Conditional on success, the expected value of the project is larger than the non-experimental path alternative. Simply, agents who pursue experiment, risky projects face a higher probability of failure, which is offset by a non-negligible probability of a large, positive outcome. In the context of patent data, experimentation should lead to a pattern of quality outcomes where conditional on low quality, experimentation is relatively worse and conditional on high quality (i.e. success), the observed patent quality is relatively higher.

To test for these patterns, we estimate a quantile estimator on the log of non-self citations received. The data is first-differenced so that we are left with a dependent variable that is the difference in the log of non-self cites received around the founding event.[17] The regressions include controls for the change in total patents filed because the average cites per patent differs around founding. Table 6 presents the results. Column (1) of Table 6 repeats the estimation in Column (2) of Table 5 showing no difference in mean patent cites received. The remaining five columns demonstrate that any differences in patent quality between founders and their comparison former co-inventors comes from both tails of the quality distribution. The estimates from the "10th perc." illustrate that the differences in the change log non-self cites received is lower for founders in the left tail of the outcome distribution. That is, founders have relatively lower 10th percentile

[17] Differencing the data eliminates some of the issues around estimation and interpretation of interaction effects in non-linear models as shown in Ai and Norton (2003).

outcomes than the comparison group, suggesting the low quality patents are *worse* when produced by founders. The coefficients in columns (2) and (3) confirm that for low levels of citations received, founders' patents are relatively worse. Moving to the right tails estimates of the 75th and 90th percentile, we see the opposite holds: the predicted impact of a founder on patent quality is relatively larger for high-cite patents.

A comparison of column (1) in Table 6 with the quantile estimates show that the founders in the sample produce patents that are relatively worse in the left tail and better in the right tail of patent quality, which balances in a comparison of means. Such a pattern is consistent with increased risk-taking or experimentation at the time of founding. The evidence, however, is necessary but not sufficient to form this conclusion. For example, the quantile estimates could also be explained by a set of low quality entrepreneurial founders (e.g. fired from parent firm) and a set of high-quality inventors leaving to form new entrepreneurial firms. To determine whether the outcomes are changes in innovative strategy, we next study changes in ex-ante patent behavior around founding.

2.4 Are these changes experimentation?

If the quantile estimates represent a shift to more experimental innovation and such a strategy is an advantage of the entrepreneurial firm, then we expect several additional empirical patterns to hold. Thus far we have measured outcomes measured after patent application (up to five years). Patent characteristics at the time of application provide a view of whether and how founders change their experimentation strategy. First, most models of entrepreneurial firm innovation involve a sorting of ideas to firms. New firms and established firm face different frictions in management and incentives that leads to a matching of ideas to firm type. Thus, we predict that founder's innovation strategy will change around the founding event. A large theoretical literature on new firm innovation motivates the search for innovative changes. Next, if the selection of ideas is an important source of the advantage in experimental innovation, then the founders that exhibit such changes should drive the quantile estimates in Table 6. The results should be confined to those founders who also change their innovation strategy in line with predicted frictions at established

firms. Finally, a fully accounting of any innovative advantage requires showing large firms pursue the ideas at a lower rate and when they do, the tails of the quality distribution are unchanged. Such a breakdown of the sample will also show the degree to which the increased tail outcomes are a general phenomenon to entrepreneurial firms (i.e. a treatment effect).

2.4.1 Changes in patenting

To begin, Table 7 asks whether founders are relatively more likely to change their ex-ante innovation strategy compared to their former co-inventors. Column (1) considers the average age of citations made by the inventor. The coefficient estimate implies that founders cite relatively younger patents after founding (around six months younger). Column (2) counts the unique number of patent classes filed in all the inventor's patents around founding for inventors with at least two patent classes prior to founding. If founders are more likely to increase or broaden their innovation scope, then we would expect a positive coefficient. We find a significant decrease in the number of unique classes in the founder's patents. Columns (3) and (4) consider the focus of the patents by measuring the fraction of cites repeated over the previous 5 year period and the fraction of cites to one's own work. The estimates in Column (3) suggest that founders are relatively more likely to repeatedly build off of the same patents, though not necessarily their own. Finally, the last column asks whether founders' patents change in their originality, a measure often used to signify more basic, fundamental research. Founders' patents are weakly more original after founding. Overall, there is evidence that the founding event coincides with changes in innovation strategy. Such changes could be a "treatment" effect or the result of a new idea moving to the entrepreneurial firm at founding (i.e. idea selection).

2.4.2 Tail outcomes and changes in patenting

To isolate whether the changes in tail outcomes are consistent with experimentation, we search for changes in innovation strategy that map to the frictions at the center of models of large firm innovation. The first class of frictions concerns the established firm's propensity to invest in incremental innovation. The work of Cohen and Klepper (1996*a*) and Cohen and Klepper (1996*b*) show

that large, established firms have an advantage in incremental innovation. This advantage stems from the ability to spread R&D costs which leads to differential returns to product versus process innovation across the firm size distribution. Models of employee mobility often have product focus as a key assumption. For example, Hellmann (2007) shows that firms optimally choose to reject projects outside their core areas and allow employees to exit to new firms. Akcigit and Kerr (2015) argue that the heterogeneity in innovation across the firm size distribution is observed through the propensity to produce "external" patents. An external patent is one that does not cite previous work of the firm. Small, new firms are argued to produce relatively more of these patents. Our focus on new firms limits this metric because entrepreneurial firms have no history of patents to cite. We consider instead the age of the citations made to other patents. Such patents can be to their own work, their parent's patents or patents by other firms. Patent citations to younger patents signal a willingness to work with relatively untested ideas, while citing relatively older patents implies the inventor builds off of established ideas. If the advantage in experimentation or risk-taking in innovation stems from the entrepreneurial firm's advantage to incorporate newer ideas, then we would predict much of the increased tail events will reside in those founders who shifted to newer ideas.

For each founder, we calculate the change in age of cited patents for themselves and their comparison group. The sample is then split by the median of this measure, where being below the median equates to moving to relatively younger ideas than the comparison group. This "newness" proxy is based on a within-founder and comparison group outcomes. Figure 5 first plots the kernel densities of the two samples for each group. The left panel belonging to those founders moving to younger citations made exhibits weakly fatter tails. Table 8 splits the sample of founders and comparison inventors into two groups based on the relative age of the patents cited. The quantile regressions are then estimated for each sample. Comparing the estimates in Panel A and B of Table 8 shows some evidence that founders who move to newer ideas exhibit a higher propensity to be in both tails of the citations received distribution. The 75th and 90th percentile in Panel B are both economically smaller and statistically weaker than that in Panel A. Figure 6 plots these quantile estimates for the founder coefficient. Here the stronger right tail for the sample that moved to

newer ideas is apparent. Founders that shift to a relatively newer body of knowledge also generate more failed and high-quality patents.

The second class of frictions considers the large firm's product diversity and avoidance or projects that require failure tolerance. Manso (2011) separates experimental projects from other projects using the "exploration" versus "exploitation" distinction. Similarly, experimentation and risk-taking often require an inventor(s) to devote both resources and time to a single project. Kerr, Nanda and Rhodes-Kropf (2014)'s' review of the literature on experimentation and innovation argues that large firms may not terminate projects quickly enough, leading the firm to avoid longer-term innovation.[18] New, small firms thus take on projects that require more patience. Lerner, Sorensen and Strömberg (2011) show that private equity investors focus the patent strategy of their portfolio firms, leading to higher impact patents. The ability to specialize on a core technology rather than a large portfolio or products and innovation is one possible source of the entrepreneurial firm innovation advantage. For the founder of the entrepreneurial firm, the move from the parent firm should weaken these constraints. Table 7 shows that the average founder is relatively unchanged in self-citations, but does increase focus on the same citations made. We define a founder as "Increased focus" if she is above the sample median change in repeated citations, decreases her patent classes or has least one self citation. Of the 1,131 founders, 651 are in this group.

Figure 7 presents the kernel densities of the change in cites received for founders that increased and decreased focus. The former sample distributions are quite distinct, with those subset of founders having fatter left and right tails. These differences manifest themselves clearly in the quantile regression estimates in Table 9 and their visual representation in Figure 8. The sample of founders who either move to patent in more technology classes and do not repeatedly build off of earlier cited patents exhibit no difference in the tails of the cites received distribution. Only for those founders that have increased the focus of their innovation do we observe both an increase in the left and right tail of the quality distribution. The relative strength of the quantile estimates in the increased focus sample implies that such a strategy drives fatter tails and is better suited for

[18] For example, focus can increase the ability to learn faster (Jovanovic and Rob (1990); JOVANOVIC and NYARKO (1996); Aghion (2002)) and extract useful information from a signal at early or intermediate stages of the project.

the entrepreneurial firm.

The final class of frictions concerns the time devoted to innovative projects. A large literature on managerial short-termism (e.g. Stein (1988), Stein (1989) and Graham, Harvey and Rajgopal (2005)) argues that the large, established firm manager passes on positive NPV projects because the project takes too long to complete. Experimental project are often modeled as taking relatively longer and require multiple investment decisions. If part of the entrepreneurial firm innovative advantage stems from the firm's willingness to pursue longer-term projects, then we expect the quantile estimates to differ by project length. For the sample of founder innovation inputs, we cannot directly observe the time from initial conception to project completion. In its place, we separate founders by the time from the firm founding to the intial patent application. Founders above the median time to first patent are labeled "Long term." Table 10 presents the two samples, where Panel A includes founders and their comparison co-inventors who were relatively quick to their first patent. The breakdown of the sample into these two groups has no impact on the quantile estimates. Insofar as this is a good proxy for investment time, we thus find no evidence that the risk-taking observed in entrepreneurial firms rests on a shift to longer-term research.

2.5 Are changes simple due to mobility?

We show that inventors that leave the established firm to start a new firm produce more patents in the tails of the outcome distribution and such changes are stronger for inventors that also become more focused and move to newer ideas. The results suggest that any entrepreneurial firm innovative advantage in experimentation requires a specific change in strategy. In particular, we find that founders that work on newer ideas in a more focused research approach drive the differences in the tails. These differences are still not necessarily an advantage of the entrepreneurial firm. An alternative explanation remains: perhaps the changes are simply a consequence of the mobility event itself. To address this issue, we return to the full sample of mobile inventors and study those that moved from the parent firm to another large, established firm. If the choice to leave the established firm alone explains the results, then we should find that the tail results will hold in the movers to other large firms. We should also find that their ex-ante patent characteristics move in

similar ways in terms of citation age and focus. Tables 11 and 12 tackle this issue.

Table 11 repeats the quantile regression of the change in log non-self cites received using the inventors who moved between large firms. These inventors have a relatively larger right tail of the patent quality distribution than their former co-inventors, however, there is no evidence of an increase in lower quality patent production. Next, Table 12 asks whether these inventors shift their strategy in terms of citation age, focus or originality. Despite the significantly larger sample of inventors (3178 vs 1075), there is no evidence of meaningful changes in ex-ante innovation strategy of movers between large firms. Perhaps the average mobile inventor does not shift innovation strategy, but those that do exhibit the change in tail outcomes? In the Internet Appendix and unreported tables we repeat the three-subsample quantile regressions of newness, focus and investment time. In none of the sub-samples do we find that the two tail differences emerge. Overall, the collection of evidence reveals that the changes in both patent quality and innovation strategy are unique to the inventors that found entrepreneurial firms. These results confirm that the patterns found in entrepreneurial firms are not due solely to mobility and more importantly, suggestive the changes in innovation strategy are unique to these new firms.

3 Robustness

We have shown that founders' innovation quality does not change on average, but does exhibit fatter tails. The differences in tails is partially confined to the set of founders whose innovation strategy moves to a more focused, newer set of research. This section addresses several alternative explanations for the difference-in-difference estimator, matching and sample selection.

3.1 Corporate change

The exit of an employee from an established firm to an entrepreneurial firm is often precipitated by major corporate changes. These include CEO transitions, acquisition events or IPOs.[19] The difference-in-difference estimates could be driven by a downward trend at the established firm in

[19] Klepper (2009) reviews the empirical literature that demonstrates the positive correlation between these corporate changes and employee exits to new firms. Also see Bernstein (2014) for inventor mobility around IPOs.

innovative activity rather than a positive change at the entrepreneurial firm 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 founding date.[20] We use the executive compensation data Execucomp that covers on public firms and SDC which covers the universe of most merger and acquisition activity.[21] A large transaction is an acquisition with a reported value of at least 10% of the firm's market capitalization. Some 16% of the foundings in the sample occur after a CEO change or large M&A transaction.

This robustness test assumes that founders who do not leave after a 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. In the Internet Appendix, we repeat the main regressions – patent outcomes and quantile regressions – for these two subsamples. The sample of founders that left public firms outside of major corporate events shows the same patterns in patent output, quality and ex-ante changes as those found above. Thus, we conclude that such confounding events cannot explain our main results.

3.2 Superstar extinction?

The matching algorithm matches the pre-founding trends in the major patent variables. Figure 2 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, Graff-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-inventors who are the least likely to be

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

[21]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.

affected by the exit. Let x be the fraction of a co-inventors patents in $[-4, -1]$ that were co-written with the founder. The average comparison inventor 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 coinventors who only patented with the founder will have an undefined rescaled difference and be dropped. Table 13 repeats the main quantile estimator with the new match set and the Internet Appendix presents regressions of the changes in ex-ante and ex-post patent characteristics. The results are basically unchanged. We conclude that the patent version of "superstar extinction" is not a major driver of our results.[22]

3.3 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.

3.4 VC vs. non-VC-backed firms

The sample of founders includes both VC and non-VC-backed firms. The former could drive the average results as such firms are higher quality and fail in different ways than other entrepreneurial firms (e.g. Puri and Zarutskie (2012)). The Internet Appendix presents the regressions of changes in patenting around founding and the quantile regressions for the VC and non-VC-backed entrepreneurial firms. The typical concern is that VC-backed firms are driving the results of patent quality, patenting rates and tail outcomes. The main differences between the changes in ex-post outcomes is that VC-backed founders are more likely to slow down patenting. The quantile estimates are similar across the two entrepreneurial firm samples. Overall, we conclude that the sample

[22] It is plausible that the founder hires away her past co-inventors after the entrepreneurial 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.

of VC-backed firms is not the driver of the main results.

3.5 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.[23]

4 Conclusion

This paper asks whether the entrepreneurial firm pursues more experimental, radical innovation and if so, studies the source of their advantage. In a comparison of founders to their former co-inventors over time, we found that, perhaps surprisingly, average patent quality and patenting rates are unchanged. The empirical strategy rules out basic time-invariant differences between founders of entrepreneurial firms and other inventors and also addresses confounding trends. Documenting a propensity to pursue more experimental innovation requires documenting the quality distribution beyond the mean. We find that differences in patent quality manifest themselves in the tails of the citations received distribution. The average founder in the sample not only produces more patents that end up in both the left and right tail of the quality distribution, but they also switch *how* they patent after founding the new firm. Such changes suggest that the entrepreneurial firm matches with specific types of innovation. To study this hypothesis, we analyze the tails of the distribution across sub-samples of changes in innovation strategy. We compare founders who move to relatively newer ideas, shift to a more focused innovation path and take relatively longer to complete projects. In the first two samples, the tail outcomes are stronger. A similar comparison

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

of mobile inventors between established firms exhibits none of these patterns. These results are consistent with entrepreneurial founders switching to a riskier, experimental innovation strategy.

To our knowledge, this is the first empirical evidence that shows an increased propensity for risk-taking in entrepreneurial firms. Prior work shows that the entrepreneurial firm or small firm produce better patents and those patents differ in several dimensions. Our contribution is unique in that we find both increased production of high and low-quality patents which stem from changes in innovation strategy tied to theoretically motivated advantages of the entrepreneurial firm. Importantly, the empirical strategy rules out selection of people as the main cause of the results. We do not claim to have identified either the causal effect of founding or employee mobility. Two explanations remain.

One possibility is that the changes we observe are treatment effects of the founding event. Alternatively, the changes are consistent with new ideas optimally moving from the parent firm to new firm. Treatment effects are possible, however, the importance of the ex-ante patent characteristics implies a complicated match between the entrepreneurial firm and idea. Moreover, most entrepreneurial firms are founded with an idea rather than ideas follow firm formation. We thus believe that a new idea matched to the entrepreneurial firm is more likely an explanation. The entrepreneurial firm has an innovation advantage to pursue experimental, radical innovation which stems from its ability to attract newer ideas that demand a focused research approach.

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Tables and figures

Figure 1: Startup founding over time

The figure reports the number of entrepreneurial firms founded per year in our final sample of 1075 firms. The dashed line represents the non-VC-backed firms, while the solid line the VC-backed firms. Section 1 details the construction of the sample.

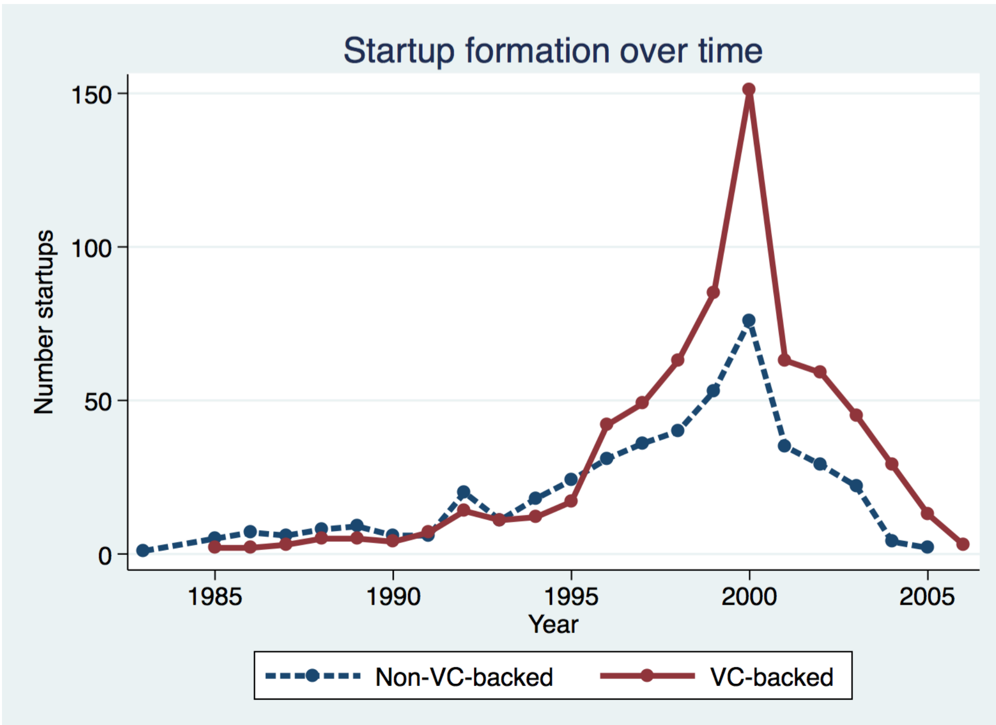

Figure 2: Trends of patenting over time

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.

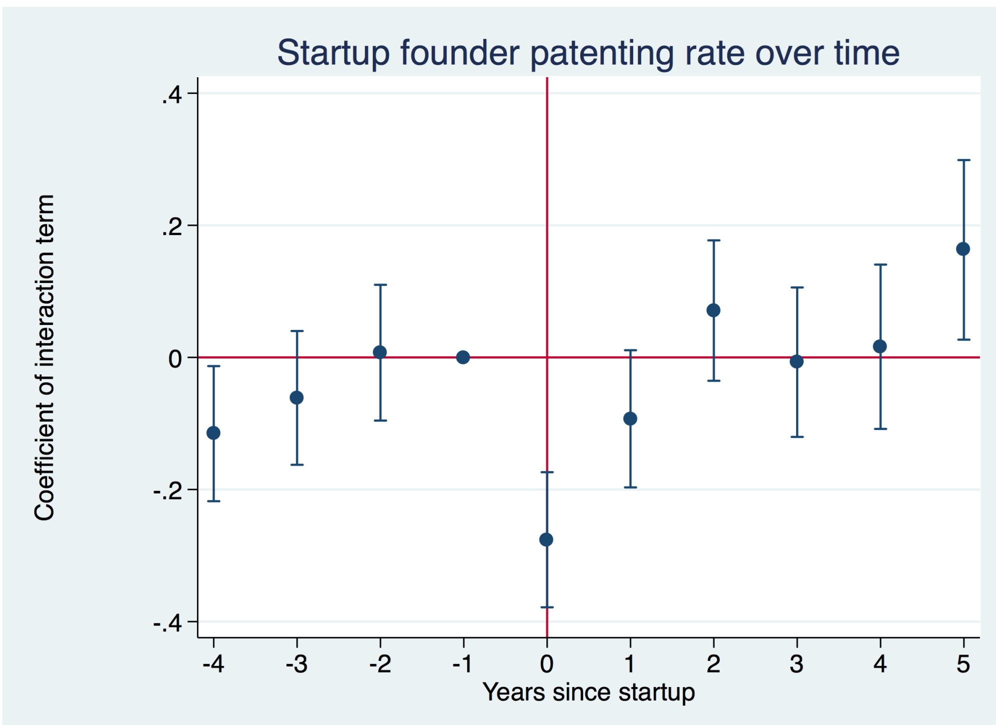

Figure 3: Distribution of changes in non-self cites received: founders vs. comparison co-inventors

The figure displays the kernel densities for the change in citations received before and after the startup event for all comparison co-inventors and all founders. The variable of interest is the log of the total non-self cites received for patents applied for in the four years prior to the startup and five years after. The final variable logs these two measures and takes the difference. The dashed line summarizes this difference for the founder inventors, while the dashed line presents the density of the control inventors.

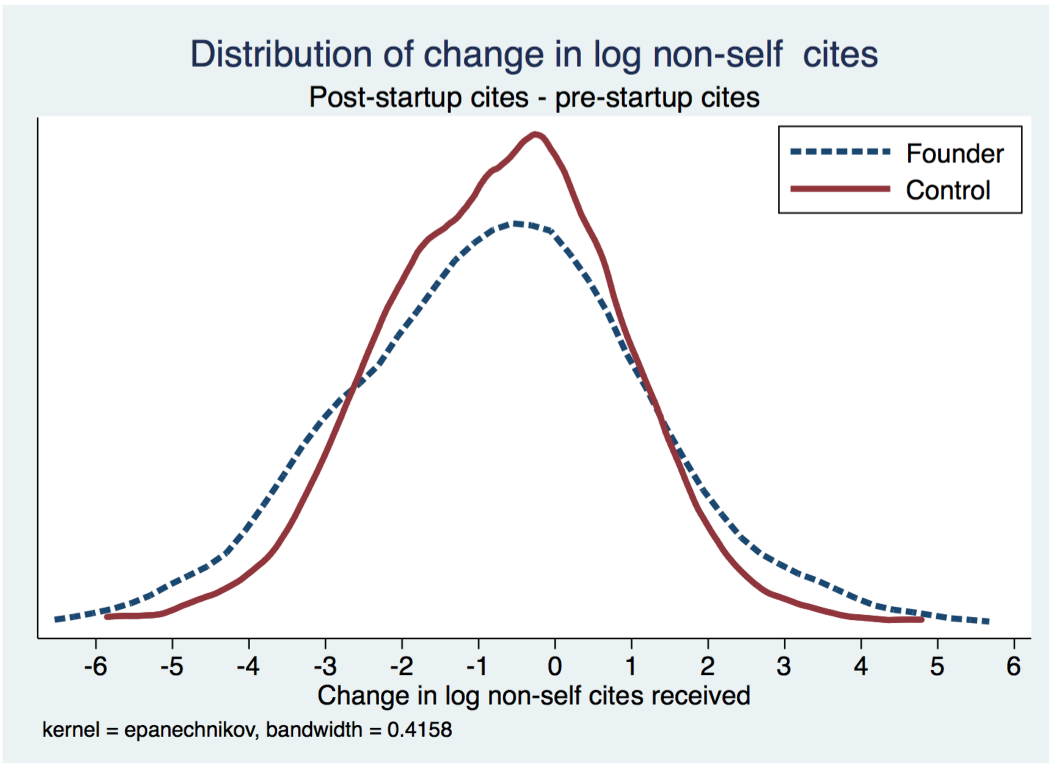

Figure 4: Quantile regression estimates for non-self cites received: founder dummy coefficient

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 estimates for quantiles is found in Table 6. 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.

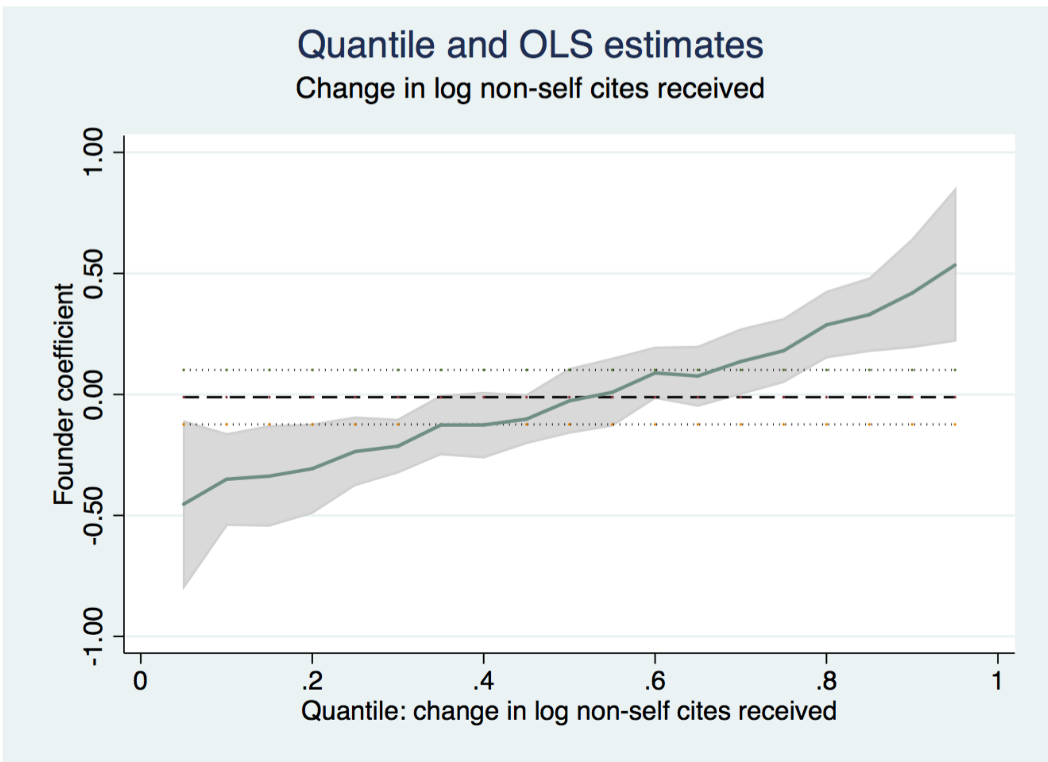

Figure 5: Differences in change in cites received by founder's age of cites made

The figure presents two sets of kernel densities for two sub-samples of founder-control pairs. The left panel includes those founders (and their respective comparison coinventors) where the founder cites relatively newer patents than her comparison coinventors after the founding event. The panel then presents densities for the founder (dashed) and control (solid). The right panel includes all those founders that moved to relatively older cited patents after founding. The variable graphed is as defined in Figure 3.

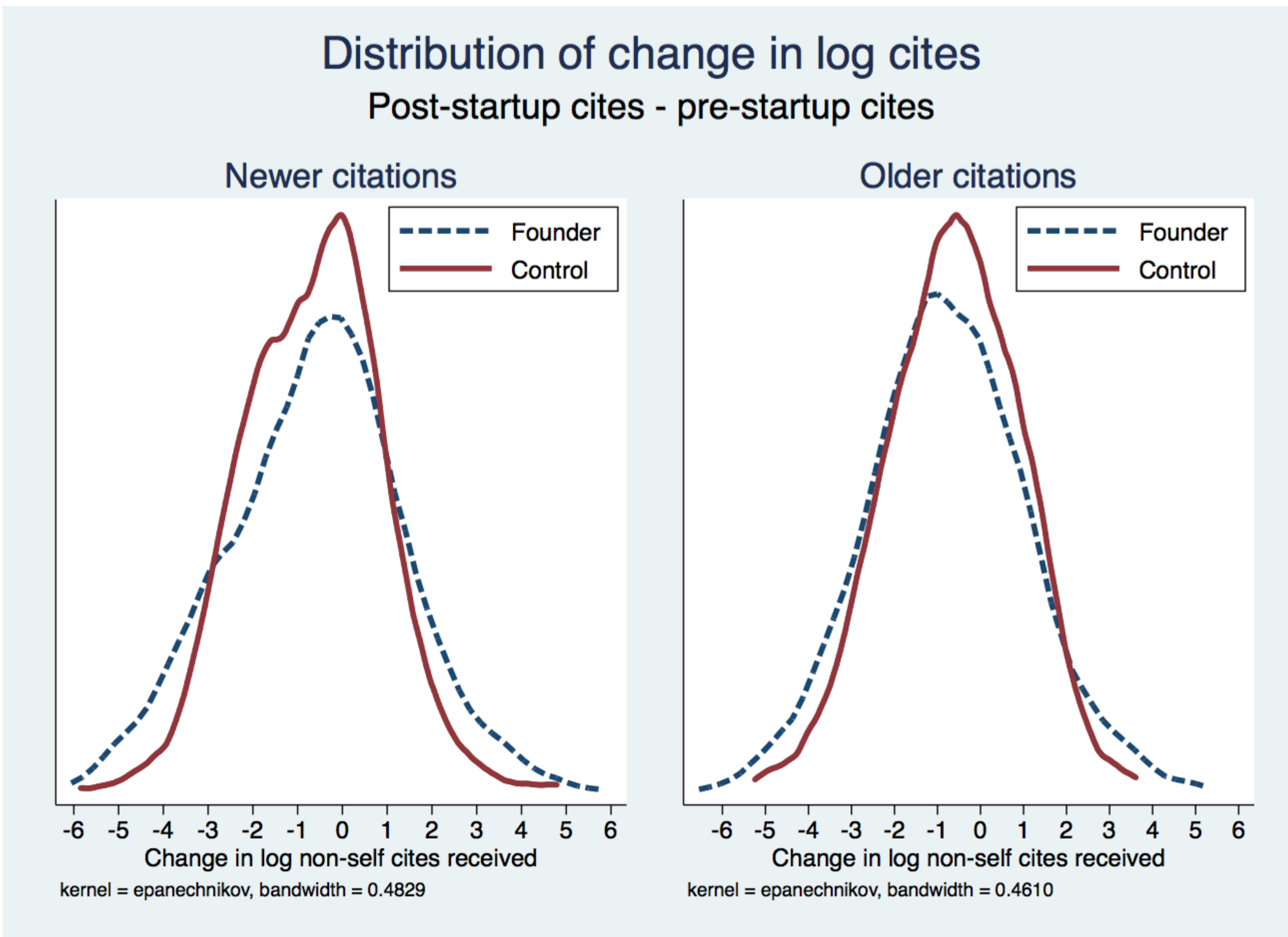

Figure 6: Quantile regression estimates: newer vs. older citations

The figure plots the quantile coefficient estimates for the "Founder" dummy in the regression of change in log cites for the sub-sample of founders that have below median change in citation age (i.e. moved to relatively newer citations).

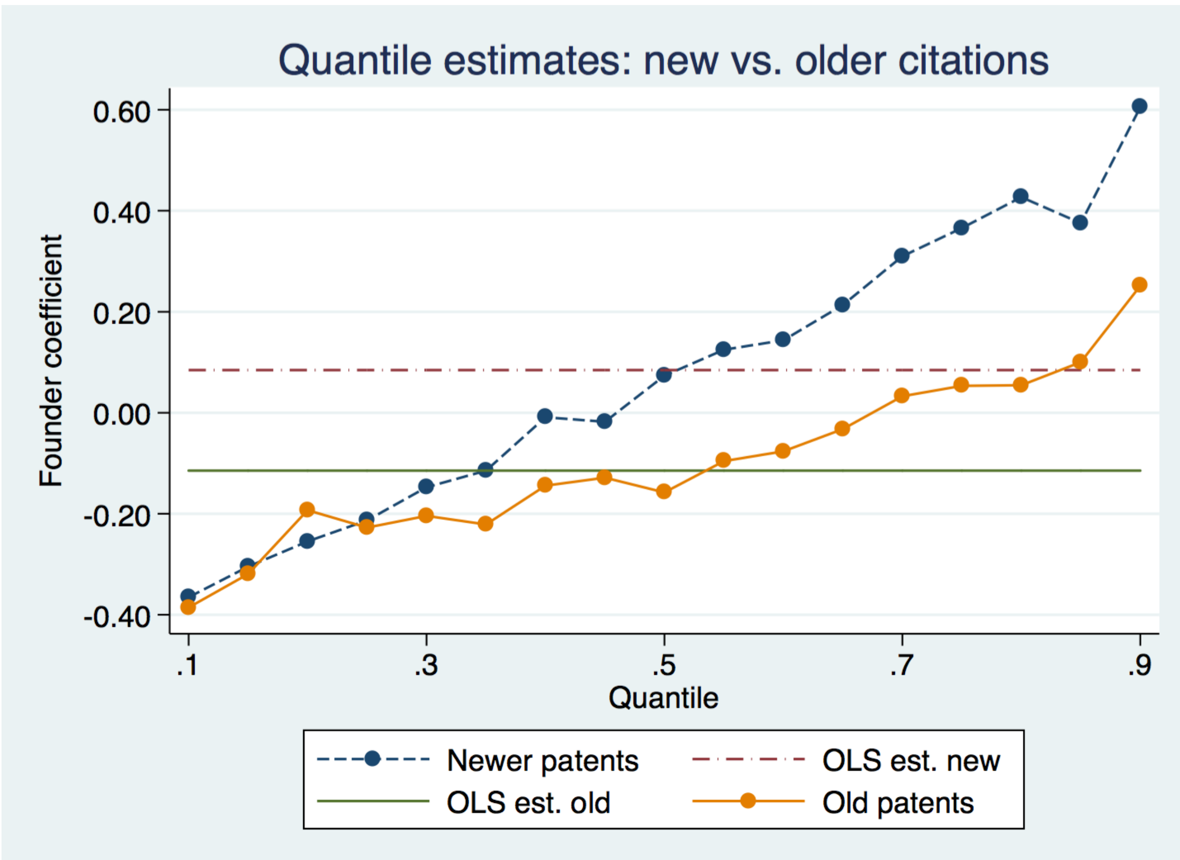

Figure 7: Differences in change in cites received by founder focus

The figure presents two sets of kernel densities for two sub-sample of founder-control pairs. The left panel includes those founders (and their respective comparison co-inventors) where the founder patenting has an increased focus. Increased focus is defined as one of the following: they patent in fewer patent classes, they self cite at least once or they increase citation of previous cites. The panel then presents densities for the founder (dashed) and control (solid). The right panel includes all those founders that decreased focus in their patenting after founding. The variable graphed is as defined in Figure 3.

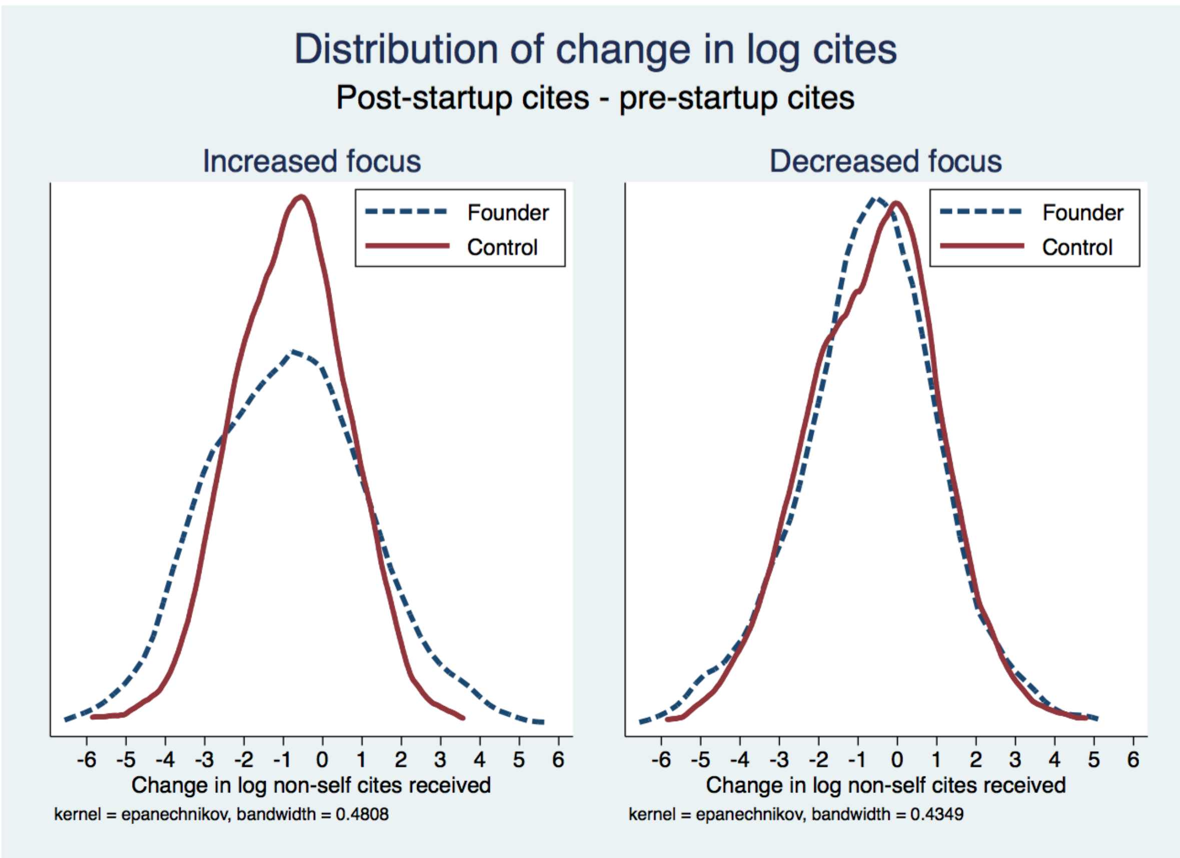

Figure 8: Quantile regression estimates: differences by founder focus

The figure plots the quantile coefficient estimates for the "Founder" dummy in the regression of change in log cites for the sub-sample of founders that differ in their change of inventive focus. See Figure 7 for more details.

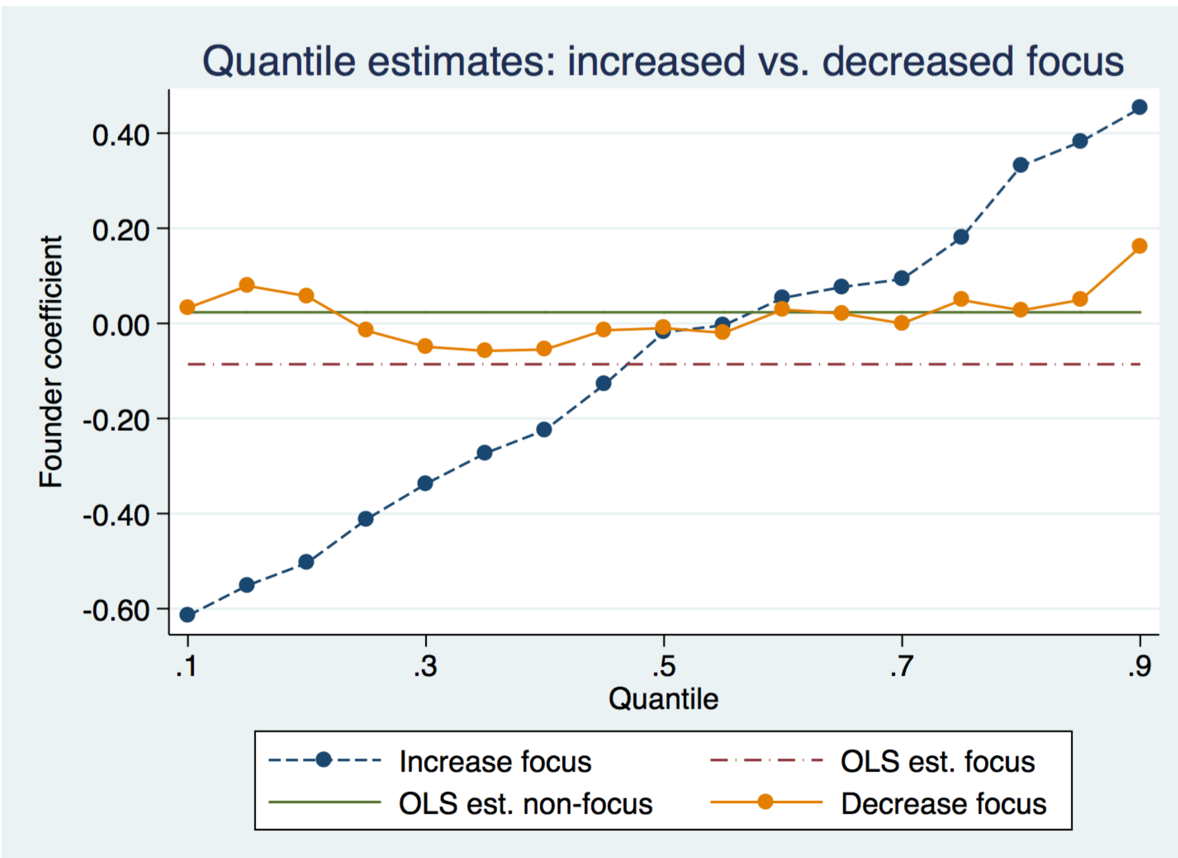

Table 1: Sources of entrepreneurial founders with patents

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

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

Table 2: Match diagnostics

Notes: Table reports the differences between the average founder and matched control from the matching procedure described in Section 1.4. Variables are as defined in Section 1. The third column presents the difference in means and the significance from a two-sided t-test. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Control	Founder	Diff/s.e.
Total patents	7.235	7.708	-0.473
			0.359
First year patent	1987.8	1988.8	-0.946***
			0.283
Growth in patent stock $(T-1, T)$	-0.406	-0.440	0.0341
			0.0426
Growth in patent stock $(T-2, T)$	-0.148	-0.159	0.0108
			0.0551
Growth in cites received $(T-1, T)$	-0.412	-0.440	0.0282
			0.0452
Growth in cites received $(T-2, T)$	-0.157	-0.159	0.00191
			0.0565
Total non-self cites received	83.33	87.27	-3.944
			8.997
Avg. Originality (adj.)	0.538	0.535	0.00364
			0.00938
Generality pre-startup patents	0.749	0.725	0.0237*
			0.0104
Number active classes	1.687	1.715	-0.0280
			0.0348
Fraction patent is CIP	0.00513	0.00479	0.000334
			0.00157
Fraction self-cites made	0.0337	0.0372	-0.00354
			0.00317
Fraction winners	0.134	0.147	-0.0129
			0.00963
Fraction losers	0.0382	0.0402	-0.00197
			0.00475
Avg. age of patent class	0.608	0.604	0.00461
			0.00699
% cite made again	0.0599	0.0634	-0.00347
			0.00338
Observations	2940	1,131	

Table 3: Characteristics of exiting inventors by exit type: parent fixed effects

Notes: Table reports firm fixed effects regressions where the dependent variables are various patent measures of inventors at large firm at the time of their move to either other large firms or to a new firm. A unit of observation is an inventor at the parent firms defined in Section 1 in the year of their exit. Column (1) uses the dependent variable that is the log of the mean citation age of patents applied for by the parent in the current year. Column (2) uses the log of the number of patents filed in the previous 5 years.Column (3) uses the average generality of the patents applied for by the inventor over the previous 5 years and column (4) is the same structure, but uses patent originality. Column (5) uses the log of the number of non-self citations received in the next five years for patents applied for in the previous five year. “Moved to new firm” is a dummy variable equal to one if the inventor moved to any entrepreneurial firm (VC-backed or otherwise). “Move to VC-backed” is a dummy variable equal to one if the inventor moved to a new, VC-backed firm. The excluded category is thus those inventors that moved to another established firm. All regressions include parent firm fixed effects and year of exit fixed effects. Robust standard errors clustered at the parent firm reported in parentheses. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Citation age	# patents	Generality	Originality	Non-self cites rec.
	(1)	(2)	(3)	(4)	(5)
Move to new firm	0.0298	3.995***	0.0465***	0.0668***	0.212*
	(0.0272)	(0.591)	(0.0176)	(0.0175)	(0.111)
Move to VC-backed	-0.00936	2.757***	0.0879***	0.0630***	0.596***
	(0.0318)	(0.711)	(0.0226)	(0.0214)	(0.175)
Constant	0.928*	3.127**	0.241***	0.298*	0.986***
	(0.550)	(1.298)	(0.0674)	(0.163)	(0.254)
Observations	14953	15199	15199	15199	15199
R^2	0.0345	0.0592	0.124	0.0241	0.0254
Number Parents	612	617	617	617	617
Number inventors	14953	15199	15199	15199	15199
Year founding FE?	Y	Y	Y	Y	Y
Parent firm FE?	Y	Y	Y	Y	Y

Table 4: Univariate differences: founders and co-inventors

Notes: Each panel report univariate differences between inventors and across time for several patent measures. The differences are tested against a two-sided t-test. Panel A reports the differences in total patents applied for around the founding event (i.e. in the $[-4,5]$ time period). "Before startup" is the time in $[-4,0)$ prior to firm founding and "After startup" are patents filed in $[0,5]$. The bottom row of each column reports the difference in means within founders and matched co-inventors, while the last column reports differences within each time period. Panel B considers differences in the total non-self cites received over the five years after patent application. Panel C presents the mean age of cites made by the inventors (i.e. excluding the examiner). Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Panel A Total number of patents		
	Co-inventor	Founder	Difference
Before startup	7.057	7.654	.597
	(.235)	(.333)	(.408)
After startup	7.88	7.939	.059
	(.335)	(.361)	(.493)
Total	.823**	.285**	-.538
	(.409)	(.492)	
	Panel B Non-self cites received		
	Co-inventor	Founder	Difference
Before startup	99.898	108.004	8.105**
	(6.19)	(8.27)	(10.333)
After startup	67.2	69.743	2.545**
	(4.471)	(5.86)	(7.371)
Total	-32.701***	-38.261***	-5.56
	(7.638)	(10.137)	
	Panel C Average age citations made		
	Co-inventor	Founder	Difference
Before startup	6.508	6.426	-.084***
	(.06)	(.08)	(.099)
After startup	7.75	7.268	-.482***
	(.079)	(.086)	(.117)
Total	1.241***	.843***	-.398
	(.102)	(.114)	

Table 5: Changes in patenting rates and output

Notes: Table reports regression estimates for several patent characteristics. The specification throughout is

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

Column 1 counts the number of patents applied for in the periods $[-4, 0]$ and $(0, 5]$ around startup founding. Column 2 presents OLS regression estimates for the log of non-self cites received for patents in the two periods up to 5 years after the patent application. Column 3 uses a dependent variable that is the average non-self cites received per patent. The last column has the dependent variable generality, which captures the breadth of industries that characterize the cites received by the patent. All dependent variables are averaged within the pre- and post-period. For the comparison co-inventors, these are collapsed across all comparison co-inventors using a weighted average. The weights are the inverse of the match distance from the matching procedure. "Year founded FE?" are dummy variables for the year of the startup's founding. Standard errors clustered at the founding year. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	# Patents	Log cites rec.	Cites per patent	Generality
	(1)	(2)	(3)	(4)
Founder X Post	-0.0737	-0.0392	0.288***	0.0472***
	(0.0824)	(0.0883)	(0.0954)	(0.0130)
Post-startup	0.110**	-0.713***	-0.655***	0.0932***
	(0.0535)	(0.0599)	(0.0507)	(0.00764)
Founder	0.0811	-0.141**	-0.0482	-0.0642***
	(0.0544)	(0.0606)	(0.0478)	(0.0114)
Observations	4532	4532	4532	4532
R^2		0.130		0.114
Psuedo R^2	0.0186		0.107	
Year founded FE?	Y	Y	Y	Y
Model	Poisson	OLS	OLS	OLS

Table 6: Patent portfolio risk: differences in the tails

Notes: OLS and quantile regressions of the change in the log non-self citation received. Column 1 presents the OLS coefficient estimates with the dependent variable as the change in the log non-self cites received (analogous to Column (2) of Table 5). In columns 2 - 6 we report the OLS coefficient and three estimates from quantile regressions of the 10th, 25th, 50th, 75th 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 (500 replications) reported in parentheses (for Columns 2 - 6) and robust standard errors are reported in Column 1. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Change in log cites received					
	OLS	10th perc.	25th perc.	Median	75th perc.	90th perc.
	(1)	(2)	(3)	(4)	(5)	(6)
Founder	-0.0117	-0.349***	-0.219***	-0.0227	0.210***	0.433***
	(0.0576)	(0.106)	(0.0696)	(0.0680)	(0.0691)	(0.121)
Change # patents	0.0511***	0.0512***	0.0572***	0.0684***	0.0617***	0.0630***
	(0.00684)	(0.00987)	(0.00670)	(0.00405)	(0.00672)	(0.00893)
Constant	0.389***	0.256	0.286	0.342***	0.309***	0.315**
	(0.0999)	(0.299)	(0.213)	(0.105)	(0.0543)	(0.127)
Observations	2266	2266	2266	2266	2266	2266
Founders	1133	1133	1133	1133	1133	1133
R^2 / psuedo-R^2	0.381	0.153	0.181	0.371	0.207	0.350
Year startup FE?	Y	Y	Y	Y	Y	Y

Table 7: Differences in patent characteristics at founding

Notes: This table describes the characteristics of patents at the time of application. Column 1 compares the average age of non-examiner citations made by the patents of founders and control around startup founding for founder and comparisons with at least one cite made (excluding the examiner). Column 2 counts the number of patent classes patented in (between 1 and 7) before and after founding. A founder and comparison group is in this sample only if both had at least two patent classes in the pre-founding period (so we can have a decrease in classes). Column 3 uses the dependent variable that is the fraction of cites made in each subsequent patent that cites the same patents in the inventor's previous patent stock (through four years prior to founding) for founder and comparisons with at least one cite made (excluding the examiner). Column 4 estimates a model where the dependent variable is the average fraction of cites made that cite the inventor's previous patents. The final column compares the originality of patents before and after founding, which captures the breadth of patent classes cited. Standard errors clustered at the founding year. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Citation age (1)	# classes (2)	% cite again (3)	% self cites made (4)	Originality (5)
Founder X Post	-0.449***	-0.225***	0.192***	0.105	0.0375*
	(0.157)	(0.0381)	(0.0385)	(0.0840)	(0.0227)
Post-startup	1.220***	-0.267***	0.0292	0.0224	0.0618***
	(0.105)	(0.0533)	(0.0271)	(0.0539)	(0.0169)
Founder	-0.0398	0.293***	0.0238	0.132**	-0.0110
	(0.103)	(0.0390)	(0.0269)	(0.0570)	(0.0147)
Constant	6.533***	1.633***	-1.573***	-2.242***	0.0920***
	(0.0661)	(0.0266)	(0.0187)	(0.0368)	(0.0149)
Observations	4148	2460	4532	4148	4532
Founders	1037	794	1133	1037	1133
R^2 / psuedo-R^2	0.0417	0.0806	0.0260	0.00556	0.00602
Model	OLS	OLS	GLM	GLM	GLM

Table 8: Quantile regression subsample: move to relatively newer ideas

Notes: This table repeats the quantile regressions in Table 6 for sub-samples defined by the characteristics of patents at the time of application. For each founder, one can calculate average change in age of cited patents (e.g. the patents cite four year old patents). For each founder's difference around founding, we compare that to the same difference for their control inventors. The sample is split between those whose relative difference is negative (i.e. they move to relatively newer patents cited). Panel A considers the founders who move to newer cites (Panel B, older cites). The specifications in each are as described in Table 6. Bootstrapped standard errors (500 replications) reported in parentheses. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Panel A Founder moved to relatively newer cites					
	OLS	10th prec.	25th perc.	50th perc.	75th perc	90th perc.
Founder	0.0845	-0.365**	-0.213**	0.0734	0.366***	0.605***
	(0.0810)	(0.149)	(0.0986)	(0.0918)	(0.104)	(0.179)
Change # patents	0.0572***	0.0607***	0.0640***	0.0725***	0.0586***	0.0617***
	(0.00777)	(0.0118)	(0.00646)	(0.00693)	(0.0115)	(0.0123)
Constant	-0.143	-1.593***	-1.575***	-1.509***	-1.605***	-1.588***
	(0.255)	(0.218)	(0.141)	(0.0759)	(0.161)	(0.244)
Observations	1036	1036	1036	1036	1036	1036
Founders	518	518	518	518	518	518
R^2 / psuedo-R^2	0.439	0.385	0.195	0.433	0.422	0.395
Year startup FE?	Y	Y	Y	Y	Y	Y

	Panel B Founder moved to relatively older cites					
	OLS	10th prec.	25th perc.	50th perc.	75th perc	90th perc.
Founder	-0.115	-0.386**	-0.227**	-0.158	0.0533	0.251*
	(0.0856)	(0.186)	(0.107)	(0.111)	(0.0890)	(0.151)
Change # patents	0.0431***	0.0430***	0.0491***	0.0600***	0.0578***	0.0640***
	(0.00956)	(0.0166)	(0.00855)	(0.00728)	(0.00603)	(0.0122)
Constant	0.0364	-2.085***	-2.032***	-0.689	-0.920*	-1.061**
	(0.484)	(0.656)	(0.591)	(0.614)	(0.508)	(0.431)
Observations	1038	1038	1038	1038	1038	1038
Founders	519	519	519	519	519	519
R^2 / psuedo-R^2	0.356	0.330	0.150	0.345	0.341	0.319
Year startup FE?	Y	Y	Y	Y	Y	Y

Table 9: Quantile regression subsample: changes in patent focus

Notes: This table repeats the quantile regressions in Table 6 for sub-samples defined by the characteristics of patents at the time of application. For each founder. A founder is labeled as increasing their patent focus if one of the following holds. If they have at least two patents before and after, then they increase focus if the number of patent classes falls after founding. Alternatively, if the founder cites any of their previous patents (i.e. self cite) then the focus increases. Finally, if the founder increases the rate of re-citing previous cites (compared to the median), then patent focus increases. If all of these conditions fail, then the founder decreases focus (Panel B). The specifications in each are as described in Table 6. Bootstrapped standard errors (500 replications) reported in parentheses. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Panel A Founder increase focus: less classes or has self-cite					
	OLS	10th prec.	25th perc.	50th perc.	75th perc	90th perc.
Founder	-0.0858	-0.615***	-0.412***	-0.0181	0.180*	0.453***
	(0.0723)	(0.134)	(0.0993)	(0.0886)	(0.101)	(0.138)
Change # patents	0.0512***	0.0536***	0.0609***	0.0698***	0.0776***	0.0705***
	(0.0105)	(0.0112)	(0.00718)	(0.00570)	(0.0104)	(0.0141)
Constant	-0.476	-1.621***	-1.566***	-1.033***	-1.169***	-1.492***
	(0.818)	(0.486)	(0.381)	(0.263)	(0.165)	(0.144)
Observations	1302	1302	1302	1302	1302	1302
Founders	651	651	651	651	651	651
R^2 / psuedo-R^2	0.425	0.382	0.189	0.414	0.399	0.387
Year startup FE?	Y	Y	Y	Y	Y	Y

	Panel B Founder decrease focus: more classes or no self-cite					
	OLS	10th prec.	25th perc.	50th perc.	75th perc	90th perc.
Founder	0.0231	-0.0198	-0.0107	-0.00599	0.0492	0.160
	(0.0969)	(0.185)	(0.125)	(0.107)	(0.117)	(0.201)
Change # patents	0.0501***	0.0447**	0.0564***	0.0609***	0.0591***	0.0530***
	(0.00747)	(0.0174)	(0.0123)	(0.00836)	(0.00802)	(0.0105)
Constant	0.369***	0.224	0.282**	0.304**	0.462***	0.350**
	(0.0984)	(0.173)	(0.141)	(0.133)	(0.129)	(0.157)
Observations	890	890	890	890	890	890
Founders	445	445	445	445	445	445
R^2 / psuedo-R^2	0.317	0.270	0.144	0.310	0.295	0.282
Year startup FE?	Y	Y	Y	Y	Y	Y

Table 10: Quantile regression subsample: time from founding to patent

Notes: This table repeats the quantile regressions in Table 6 for sub-samples defined by the characteristics of patents at the time of application. In contrast to the sample used in earlier tables, the sample includes startups founded before 2004 to allow time for patenting. For each founder, one can calculate the time between the founding date and the first patent application date. We first split the sample by the median of this distance. Panel A considers the founders who are below the median time to first patent, while Panel B considers those at or above the median. The specifications in each are as described in Table 6. Bootstrapped standard errors (500 replications) reported in parentheses. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Panel A					
	Below median time from founding to patent					
	OLS	10th prec.	25th perc.	50th perc.	75th perc	90th perc.
Founder	0.0174	-0.375**	-0.210**	0.0113	0.145	0.577***
	(0.0810)	(0.172)	(0.0974)	(0.0938)	(0.103)	(0.175)
Change # patents	0.0463***	0.0523***	0.0631***	0.0688***	0.0653***	0.0617***
	(0.00953)	(0.0160)	(0.00923)	(0.00855)	(0.0110)	(0.0142)
Constant	-0.323	-3.360***	-2.782***	-1.762***	-0.997***	-0.505
	(0.243)	(0.429)	(0.173)	(0.246)	(0.158)	(0.359)
Observations	1080	1080	1080	1080	1080	1080
Founders	540	540	540	540	540	540
R^2 / psuedo-R^2	0.357	0.141	0.342	0.342	0.338	0.318
Year startup FE?	Y	Y	Y	Y	Y	Y
	Panel B					
	Above median time from founding to patent					
	OLS	10th prec.	25th perc.	50th perc.	75th perc	90th perc.
Founder	-0.0351	-0.469***	-0.270**	-0.0868	0.187*	0.494***
	(0.0852)	(0.146)	(0.129)	(0.105)	(0.111)	(0.142)
Change # patents	0.0573***	0.0576***	0.0555***	0.0671***	0.0619***	0.0582***
	(0.00676)	(0.0109)	(0.00910)	(0.00583)	(0.00860)	(0.0103)
Constant	0.416***	0.288	0.277	0.598***	0.324***	0.291**
	(0.103)	(0.336)	(0.253)	(0.163)	(0.0822)	(0.131)
Observations	1084	1084	1084	1084	1084	1084
Founders	542	542	542	542	542	542
R^2 / psuedo-R^2	0.372	0.0826	0.359	0.366	0.360	0.331
Year startup FE?	Y	Y	Y	Y	Y	Y

Table 11: Patent portfolio risk: differences in the tails for large-to-large mobility

Notes: OLS and quantile regressions of the change in the log non-self citation received. The sample includes the set of inventors that moved from the parent firms in the main data to other non-new, established firms detailed in Section 1. The specification is otherwise identical to that reported in Table 6. Column 1 presents the OLS coefficient estimates with the dependent variable as the change in the log non-self cites received (analogous to Column (2) of Table 5). In columns 2 - 6 we report the OLS coefficient and three estimates from quantile regressions of the 10th, 25th, 50th, 75th 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 move FE" are dummies for the the year the inventor moved to the large firm. Bootstrapped standard errors (500 replications) reported in parentheses (for Columns 2 - 6) and robust standard errors are reported in Column 1. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Change in log cites received					
	OLS	10th perc.	25th perc.	Median	75th perc.	90th perc.
	(1)	(2)	(3)	(4)	(5)	(6)
Founder	0.120***	-0.0639	-0.00587	0.132***	0.237***	0.276***
	(0.0281)	(0.0487)	(0.0345)	(0.0310)	(0.0412)	(0.0522)
Change # patents	0.111***	0.113***	0.114***	0.117***	0.118***	0.110***
	(0.00394)	(0.00481)	(0.00402)	(0.00424)	(0.00497)	(0.00679)
Constant	-0.382	-1.030**	-1.089**	0.172	0.170	0.676
	(0.416)	(0.448)	(0.536)	(0.752)	(0.705)	(0.619)
Observations	6366	6366	6366	6366	6366	6366
Movers	3183	3183	3183	3183	3183	3183
R^2 / psuedo-R^2	0.384	0.202	0.227	0.383	0.256	0.376
Year move FE?	Y	Y	Y	Y	Y	Y

Table 12: Differences in patent characteristics at move: large to large mobility

Notes: The table describes the characteristics of patents at the time of application. The sample includes the set of inventors that moved from the parent firms in the main data to other non-new, established firms detailed in Section 1. Column 1 compares the average age of non-examiner citations made by the patents of founders and control around startup founding. The sample is smaller than the other columns because many patents have no citations made by the author (i.e. only the patent examiner). Column 2 counts the number of patent classes patented in (between 1 and 7) before and after founding. Column 3 uses the dependent variable that is the fraction of cites made in each subsequent patent that cites the same patents in the inventor's previous patent stock (through four years prior to founding). Column 4 estimates a model where the dependent variable is the average fraction of cites made that cite the inventor's previous patents. The final column compares the originality of patents before and after the move to the large firm, which captures the breadth of patent classes cited. Standard errors clustered at the founding year. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Citation age (1)	# classes (2)	% cite again (3)	% self cites made (4)	Originality (5)
Founder X Post	-0.138	-0.0218	0.0167	-0.00458*	-0.0106
	(0.119)	(0.0222)	(0.0288)	(0.00239)	(0.0146)
Post-startup	1.329***	-0.0727***	-0.0163	0.00216	0.0226*
	(0.0768)	(0.0163)	(0.0196)	(0.00172)	(0.0119)
Founder	-0.127*	-0.0906***	-0.115***	-0.00163	-0.0232**
	(0.0744)	(0.0164)	(0.0195)	(0.00150)	(0.00906)
Constant	7.395***	1.462***	-1.761***	0.0145***	0.00895
	(0.0489)	(0.171)	(0.0131)	(0.000975)	(0.0104)
Observations	12036	12732	12732	12732	12732
Movers	3178	3183	3183	3183	3183
R^2 / psuedo-R^2	0.0378	0.0172	0.00435	0.00113	0.000665
Model	OLS	Poisson	OLS	OLS	OLS

Table 13: Patent portfolio risk: differences in the tails: superstar extinction

Notes: OLS and quantile regressions of the change in the log non-self citation received. Model and variables as defined in Table 6. The sample of comparison co-inventors here is the weighted average of those who worked the least with the founder (to address issues of impacting their former collaborators over time). Bootstrapped standard errors (500 replications) reported in parentheses (for Columns 2 - 6) and robust standard errors are reported in Column 1. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Change in log cites received					
	OLS	10th perc.	25th perc.	Median	75th perc.	90th perc.
	(1)	(2)	(3)	(4)	(5)	(6)
Founder	0.00915	-0.313**	-0.207***	-0.00280	0.188***	0.412***
	(0.0576)	(0.123)	(0.0705)	(0.0673)	(0.0708)	(0.107)
Change # patents	0.0564***	0.0539***	0.0577***	0.0676***	0.0617***	0.0612***
	(0.00527)	(0.00825)	(0.00588)	(0.00422)	(0.00652)	(0.00756)
Constant	0.502***	0.824***	0.718***	0.514***	0.323***	0.0991
	(0.0576)	(0.123)	(0.0705)	(0.0673)	(0.0708)	(0.107)
Observations	2135	2135	2135	2135	2135	2135
Founders	1070	1070	1070	1070	1070	1070
R^2 / psuedo-R^2	0.403	0.196	0.222	0.399	0.253	0.372
Year startup FE?	Y	Y	Y	Y	Y	Y