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Funding, Innovation, and Firm Formation: How Entrepreneurs Respond to Investment Booms

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Abstract

This paper examines how the supply of financing impacts entrepreneurial innovation. I present two key findings: First, private-sector funding drives inventors to transition from academia to the private sector, particularly through the creation of new ventures, while also increasing their rate of innovation. Second, greater funding changes the type of innovations being pursued: it leads to shorter-horizon, less-cited, and more narrowly-focused projects. The analysis focuses on the patent output of a panel of potential entrepreneurs: life-science inventors linked to top US universities. Taking advantage of venture-backed IPOs in the same region but in different industries, I identify exogenous variation in life-science venture capital investment, allowing for estimates of causality. Under both OLS and IV specifications, I find that greater funding availability leads to a 10-15\% increase in the rate at which inventors transition from academia to the private sector, and that these transitions lead to a 70\% increase in patenting. At the same time, greater funding also leads to a 19\% reduction in patent citations, reflecting lower scientific value. Further, I find decreases in the scope of innovation and the time horizon of its subsequent impact. The findings of this paper highlight the critical tradeoff between immediate impact and long-term value, and the role that external financing plays in determining both the quantity and the nature of entrepreneurial innovation.

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Funding, Innovation, and Firm Formation: How Entrepreneurs Respond to Investment Booms

Abstract

This paper examines how the local funding environment impacts entrepreneurs? entry decisions and innovative output. I analyze patent filings of a panel of potential entrepreneurs: life-science inventors linked to top US universities. Using venture-backed IPOs in the same location but different industries, I find the causal impact of greater funding to be a 10-15% increase in inventor transitions from academia to the private sector, associated with a 70% increase in post-transition patenting. Greater funding also leads to a 19% reduction in patent citations, reflecting lower scientific value, as well as reductions in the scope of innovation and the time horizon of its impact. These findings highlight the critical role of funding availability in driving the tradeoff between short-term payoffs and long-term value in innovative industries.
Keywords: entrepreneurship, innovation, venture capital, firm formation, patenting.

1 Introduction

Innovation is widely considered to be a critical driver of firm performance, and can offer a defendable advantage in a wide range of competitive markets (Hitt et al., 2001). Indeed, many CEOs view innovation as the most important component of a firm's strategy, and highlight the significance of entrants in developing industry-changing technologies (Hamel, 2000). This implies that individual entrepreneurs, by pursuing strategically important innovations, can not only grow and sustain their own business, but that their decisions can alter the competitive landscape of entire sectors of the economy. Despite its strategic importance, R&D spending is often one of the first budget items to be cut when firms face financial shortfalls (Arrow 1962; Brown, Fazzari, and Petersen, 2009). This challenge is particularly salient at the earliest stages of the firm life cycle, as entrepreneurs often struggle to obtain the startup capital needed to develop and commercialize their ideas (Kortum and Lerner, 2000; Nanda and Rhodes-Kropf, 2013). This paper seeks to develop a comprehensive understanding of how individual entrepreneurs respond to changes in their funding environment, starting with entrepreneurial entry and firm formation, moving through innovation and patenting, and finishing with measures of the impact and utilization of the developed technologies. Specifically, the analysis focuses on a sample of potential entrepreneurs - academics in the life sciences - and takes advantage of local variation in venture-backed IPOs to estimate the causal impact of funding availability on entrepreneurship and innovation.

The main hypotheses analyzed in this paper are that higher levels of funding availability push academic innovators to transition to the private sector, and that shifts in the funding environment will lead to changes in the type of innovations being pursued. Building on theories of control rights and optimal organizational structures in multi-stage innovation (Aghion, Dewatripont, & Stein 2008), I develop the following testable predictions: greater funding availability will lead to increases in (entrepreneurial) transitions to the private sector, and in the quantity of innovation, but decreases in highly-cited innovation, and in the time horizon and scope of its applicability. I test these predictions using the patent output of a sample of potential entrepreneurs: life science researchers from top US universities. This sample is economically meaningful not only because university inventors are directly involved in founding over 600 startups and receive significant angel and venture capital backing each year, but also because they create valuable innovations even when they have only indirect contact with private sector: universities receive over $1.5 billion in royalty flows each year for licensing the innovations of their academic inventors.[1] In order to effectively estimate the causal impact of funding availability on entrepreneurship and innovation, I take advantage of reinvestment dynamics in venture capital as a source of exogenous variation. Specifically, I construct an instrument for venture capital investment by using venture-backed IPOs in the *same* location but in *different* industries.[2] This approach allows me to incorporate both cross-sectional and time-series variation in funding availability, thereby implementing a difference-in-differences estimator comparing high-VC and low-VC regions across "hot" and "cold" funding years.

Using the instrumental strategy described above, I estimate the impact of funding availability on both the decision to engage in entrepreneurship, and on the quantity and type of innovations that entrepreneurs pursue. I find that a one-standard-deviation increase in funding leads to a significant 15% increase in the rate of transitions to the private-sector, and that transitioning inventors experience a highly-significant 70% increase in patent production. However, I also find that greater funding leads to decreases in both the horizon and scope of application for the patents of academic innovators. More significantly, I find that greater funding also leads to a 19% reduction in citations for all inventors, and even greater declines for inventors remaining in academia. These results support the conclusion that the funding environment impacts not only the career trajectory and quantity of innovation for potential entrepreneurs, but that it also changes the type of innovations being developed, promoting less-cited, shorter-horizon, and narrower-scope projects. This implies that

[1]Data from the Association of University Technology Managers (AUTM) U.S. Licensing Activity Surveys for FY2010 and FY2011.

[2]This approach is similar to the one used in Townsend (2012), focusing on funding availability at the local level rather than the level of individual VC firms.

greater funding availability may lead to substitution away from the earliest research stages, where basic-science innovations and the exploration of new ideas is most likely to take place. The paper's main findings therefore highlight a familiar tradeoff in a new context: much like the tradeoff between short-run payoffs and long-run growth for individual firms (Stein, 1989; Levinthal and March, 1993), greater funding availability increases the quantity of entrepreneurial innovation in the short run, but favors shorter-horizon and narrower-scope projects that offer fewer opportunities for long-run growth for the entire technological field. These findings suggest that an adverse funding environment carries even greater costs than those of other forms of entry barriers: in addition to restricting competition from new entrants, a lack of funding can lead to significant shifts in the *composition* of innovative output, with important and long-term consequences for the development of new products and strategies in entire industries.

The rest of the paper is organized as follows. Section 2 outlines the framework of the instrumental-variables empirical strategy, and the details of the inventor-level difference-in-differences estimators used in the second-stage analysis. Section 3 describes the data sources and the construction of measures tracking both funding and innovation. Section 4 presents the empirical results and Section 5 concludes.

2 Empirical Strategy

The primary challenge in examining the impact of funding on both entrepreneurial decisions and innovation is that of endogeneity. Specifically, one would expect investors to be responsive to changes in research and investment opportunities, leading to spurious relationships in OLS specifications. In addition to this, one would expect a wide range of variation in treatment effects, as technologies at different stages of commercialization will have heterogeneous responses to similar changes in funding availability. To address these challenges, I combine an instrumental variables approach with a panel setting, tracking the output of a fixed (but unbalanced) sample of individual inventors over multiple years. Further, I include a full set of fixed effects and a broad range of additional controls helps to limit the scope of uncontrolled determinants. Taken together, these elements combine to offer estimates of the causal impact of funding on entrepreneurship and innovation, as detailed in the following sub-sections.

2.1 Instrument Construction and Validity

As an instrument for the local funding environment faced by the inventors in my sample, I construct measures based on the proceeds of local venture-backed IPOs in unrelated industries. In satisfying the exclusion restriction, this approach relies on three distinct dimensions of separation between the funding environment and investment opportunities.

The first dimension of separation is based on the cyclical nature of venture capital. Specifically, the venture capital industry operates under a model which begins with the funding of early-stage ventures, develops them into more-mature companies, and then exits through an IPO to the public, or a sale to an acquiring firm; this process takes an average of six years (Gompers, 1996). Once an exit occurs, the venture capital firm and its investors seek to re-invest the proceeds into new ventures. While an IPO constitutes a positive signal for the investment opportunities of the exiting firm, it is generally unlikely that newly-founded ventures would have the ability to exploit such opportunities.

While the difference between startups and established firms offers some separation between funding and investment opportunities, spurious correlations can still result from industry-specific shifts to profitability. Thus, the paper's empirical strategy takes advantage of variation across industries by using IPOs in one industry to predict investment in another. While it is true that there is significant overlap across industries for inputs such as corporate real estate, support staff, and general-purpose physical capital, these are provided through relatively competitive markets; by contrast, the main sources of variation in the value of innovative industries tend to be idiosyncratic rather than systemic (Hoberg and

Phillips 2010). As a result, changes in profitability one industry are unlikely to have a significant and persistent relationship with profitability in other industries, after including fixed effects and controlling for observable factors.

The third dimension of separation stems from the importance of local connections in identifying and developing early-stage ventures. Local funding plays a crucial role in early-stage finance, and there are often significant differences in the availability of funding in different locations (Powell et al 2002). In addition, investors such as pension funds tend to prefer funding home-state projects, and their below-average subsequent returns indicate that this preference is not driven by greater knowledge of local investment opportunities (Hochberg and Rauh, 2012). By adding the geographic dimension to the dimensions of industry and lifecycle stage, the empirical analysis therefore rules out a broad range of sources of problematic variation linking funding availability and investment opportunities.

After excluding the sources of spurious correlation described above, the only remaining concern is location-specific, time-varying shocks which impact multiple industries and influence both IPO-stage companies and early-stage ventures. While this source of variation cannot be dismissed *a priori*, I offer a range of robustness tests in the results section to rule out any such variation as a driver behind the results. Combining these robustness tests with the fixed effects and the instrumental strategy described above, I argue that an instrument based on local IPOs in unrelated industries satisfies the exclusion restriction, as it provides a measure of funding availability which is driven by shifts in required returns rather than investment opportunities.

2.2 Impact on Entrepreneurship and Innovation

To estimate the impact of funding on innovation, the empirical analysis takes advantage of both time-series and cross-sectional variation in my panel framework. Specifically, I focus on the output of individual inventors[3] and estimate how the quantity and composition of

[3]The analysis is structured at the level of the individual, because this is the level at which entrepreneurial decisions and tradeoffs take place. It is also possible to focus more broadly, at the geographic level, or more

this output varies in response to local funding availability. In order for this approach to effectively estimate the relationship, it must be the case that inventors cannot costlessly change locations in response to funding availability. For this reason, I focus exclusively on inventors in the life sciences, as their work is performed in capital-intensive research labs which are very difficult to relocate. In the empirical analysis, I confirm that the rate of location-transfers is very low and is almost always limited to one location change in transferring inventors. This persistence of location allows me to construct a difference-in-differences estimator of the impact of the funding environment on entrepreneurial decisions and outcomes. Specifically, because my sample includes locations with both high and low levels of presence by the venture capital industry, and because I cover multiple waves of IPOs and venture capital cycles, I am able to use the low-VC-presence areas as effective controls and contrast them with high-VC-presence locations. This is a conservative approach, as all areas tend to experience a rise in venture capital activity during hot years. For this approach to be valid, it must be the case that inventors at different locations are similar in their baseline innovative ability. To address this concern, I focus on a sample composed of inventors from top US universities, selected based on surveys of quality in graduate programs[4], and control for differences in rankings within this highly-ranked sample. This sample of inventors comprises a relatively homogenous and geographically stable population, allowing for a valid estimate of the impact of funding availability at the local level. Combining this with the instrumental-variables approach described above, I am able to construct estimates of the causal impact of funding on entrepreneurship and innovation.

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narrowly, at the level of specific innovations. However, both of these alternatives are susceptible to bias if there are changes in composition over time: the number of inventors working in a given location may change, as may the quantity of information contained in a given innovation output such as a patent or publication.

[4]The surveys were performed by the American Council on Education (ACE) and the National Research Council (NRC) and were performed approximately once per decade spanning the years from 1964 to 2006.

2.3 Regression Specifications

In this section, I describe the estimated equations of the regression analysis. I do so in broad terms, and move to the specifics of measurement and variable construction in the next section. Because of concerns about endogeneity, I adopt a two-stage least-squares approach through the use of instrumental variables, as described earlier. The first stage seeks to demonstrate a significant relationship between IPOs in unrelated industries and local investment in early-stage ventures in the life sciences. To establish this, I estimate equations of the following format, using observations for region r in year t:

$$\log(VC_{rt}^{LifeSci}) = \alpha \log(IPO_{r(t-1,t-2)}^{NonLifeSci}) + \beta X_{rt} + \gamma_r + \theta_t + \epsilon_{rt}$$

In the above specification, γ_r and θ_t correspond to region and year fixed effects, respectively. I use a log-based specification to focus on proportional shifts, in order to more effectively incorporate observations of different magnitudes when using regions and time periods with a wide range of venture capital activity. In addition, the set of controls X_{rt} includes time-varying region-specific measures; specifically, I use the log of population and the log of income per capita for each region, as well as the average of academic rankings for all top universities in the region. Importantly, I focus the analysis on regions containing at least one of the 30 schools in my sample, in order to best capture the variation in venture capital activity which pertains to regions with a strong presence of academic inventors.

In addition to these control variables, I also use a range of measures of venture capital to capture both exits as an explanatory variable, and investment as a dependent variable. For the right-hand-side variable, my baseline specification is to look at the real value of venture-backed IPOs outside the life sciences which occurred in region r during years $t-1$ and $t-2$. The choice of lags for the baseline case is based on a combination of anecdotal evidence on reinvestment timing in the venture capital industry, and a lag-based where I compare various time horizons and find that the prior two years offer the strongest predictive ability in explaining future investment. For measuring venture capital investment as the dependent variable in the first stage, I focus on the real-dollar value of local venture capital investment in the life sciences during year t. [5] The primary prediction in the first stage is that the coefficient on α will be positive and significant, indicating that cross-industry reinvestment at the local level is an important determinant of future venture capital investment, and offering a viable instrument to evaluate the impact of funding on innovation while excluding channels related to shocks in investment opportunities.

In the second stage of the instrumental variables analysis, I use the fitted values from the first stage to estimate the causal impact on a range of measures of innovation. While I reserve a detailed list of these measures for the following section, the primary dimensions of interest are the quantity of patents produced by inventors, and the value and scope of the underlying innovations. I track these measures at the level of individual inventors, and use log-based or Herfindahl-based specifications to capture the full range of variation across the set of inventors in my sample. In the case of patent quantity, for inventor i at school s in year t, I estimate:

$$InnovativeOutput_{it} = \alpha * \log(VC^{LifeSci}_{r(t-1,t-2)}) + \beta X_{rt} + \lambda Z_{it} + \delta_i + \theta_t + \epsilon_{it}$$

In the above specification, δ_j and θ_t correspond to inventor and year fixed effects, respectively. The control variables in X_{rt} again include population and economic output at the regional level, as well as academic rank at the school level. In addition, in Z_{it}, I include controls for inventor tenure using the natural logarithm of years since the inventor's first patent application, and for citation-based metrics, the average time gap between the application and grant dates of the inventor's patents in year t. This specification applies to both the OLS and IV estimates, varying only by the substitution of actual and instrumented venture capital investment in the life sciences. Further, the specification applies to the full

[5] As robustness tests to the first-stage analysis, I also look at the number of IPOs, and examine the impact of dis-aggregating IPO activity by broad industries. For investment, I also perform tests using only first-round funding, and using the number of investments rather than their real-dollar value.

range of innovation measures I consider, including innovation quality and innovation scope. In addition, by jointly estimating equations for the production of academic and industry patents, I can derive the impact of funding availability on career transitions as inventors move toward or away from the private sector. In these equations, the coefficient of interest is α, and its predicted direction depends on both the attribute being considered, as described in the section on theoretical predictions.

3 Data and Variables

3.1 Data Sources and Sample Selection

The empirical analysis of the relationship between funding availability and entrepreneurial innovation brings together a wide range of disparate data sources. My starting point is to identify a sample of high-quality inventors with readily identifiable locations. To do so, I take advantage of a series of five surveys of academic quality among graduate programs in the life sciences, performed by the American Council on Education and National Research Council and spanning the years from 1964 to 2006. Through these surveys, I identify the top thirty academic life-science research institutions across the US, and obtain information on their relative academic rankings across the time period above. I then categorize the schools based on the average level of the natural log of venture capital investment activity in their metropolitan area over the full set of years in my sample, arriving at the following lists of schools:

- **High-VC:** (11) Berkeley, Brandeis, Columbia, Cornell Medical, Harvard, MIT, NYU, Rockefeller, Stanford, UCSF, Yeshiva

- **Medium-VC:** (9) CalTech, U. of Chicago, Johns Hopkins, U. of Pennsylvania, Princeton, UCLA, UCSD, U. of Washington, Yale

- **Low-VC:** (10) Cornell, Duke, Illinois, Iowa, Michigan, North Carolina, Utah, Vanderbilt, Washington U. in St Louis, Wisconsin

Next, I then obtain the list of all patents assigned to them from 1975 through 2010 using data from the NBER Patent Data Project and the IQSS Patent Network Dataverse[6] From the patent data, I identify inventors and their geographic locations, and arrive at my sample of inventors by focusing on those with *three or more* life-science patents linked to the 30 schools I track. I then add in all other life-science patents assigned to these inventors, and continue to track inventors' locations as listed on their patent applications. This gives the full set of patents I consider in my analysis, though I often focus on the set of patents linked to regions containing the 30 schools in my sample, or to inventors who remain in a single location for the duration of their careers. For each entry in this set of patents, I obtain further information on assignees, patent classes, claims, and patent citations, and the patent class distributions of both citing and cited patents through the IQSS Patent Network Dataverse, which runs from 1975 through 2010[7]. This range of information forms the foundation of my measures of entrepreneurship and innovation.

The remaining data sources I employ are focused on measuring funding availability and related economic indicators. All variables are collected at the geographical level of Metropolitan Statistical Areas, or MSAs, as defined by the US Office of Management and Budget, and tracked by the US Census Bureau. From the Bureau of Economic Analysis, I obtain population and economic output levels by MSA from 1969 to 2009. Next, I collect data on venture capital investment at the MSA level from Thomson Financial's Private Equity Investments Screener database. I collect information on all investments defined as "Venture Capital Deals"[8], including the stage of the investment, the location of both the investing

[6]These data are described in detail in Hall, Jaffe, and Trajtenberg (2001), and Li et al (2014).

[7]This extended range of data is particularly helpful in tracking citations, as it takes multiple years before innovations based on a previously-published patent can work their way through the patent application process.

[8]This is a broad measure covering deals at the venture stage and also include and any non-venture-stage deals made by traditionally venture-focused firms. These are then sub-divided by Thomson Financial into startup/seed, early-stage, expansion, and late-stage deals.

firm and the receiving company, the industry of the receiving company, and the value of the investment. In addition to investments, I also collect information on venture capital exits, including both IPOs and acquisitions; for exits, I again collect information on location, industry, and deal value, and link all exits to the database of venture capital investments. This set of variables enables me to construct the necessary measures of funding availability, which I match at the MSA-year level to the data on innovation described above.

3.2 Regional Measures and Funding Availability

The first measures I construct focus on the first stage of the instrumental-variables strategy: the variables that capture funding availability. The dependent variable $\log(VC_{rt}^{LifeSci})$, which is the natural log of the value of all venture-capital investment in life-science companies, occurring in region r during year t. In the Thomson Financial database, this measure is denominated in millions of dollars, rounded to the nearest $10,000. Using CPI data, I convert values from all years to 2005 dollars.[9] To highlight both the levels and volatilities of venture capital investment across my sample, I plot the average level of investment over time across the high-, medium- and low-VC regions in my sample in Figure 1. The pattern of investment flows indicates that not only do the high- and medium-VC areas have a higher baseline level of VC investment, but that they also have much more volatility in their investment flows. This is the basis for my difference-in-differences approach, as the low-VC regions effectively function as a control group while the high- and medium-VC regions experience the bulk of shocks to funding availability.

FIGURE 1 HERE

Next, I take a similar approach to the measure of venture-backed exits. I construct the variable $\log(IPO_{rt}^{NonLifeSci})$ as the natural log of the value of all venture-backed IPOs

[9] In most regression specifications, I adopt a log-log format, for which I take the natural logarithm of all dollar values, after adding the first percentile of non-zero investments (appriximately $200,000) to all observations in order to avoid undefined values when no investment was observed.

outside the life sciences undertaken by portfolio companies in region r in year t.[10] I track this measure not only at the aggregation level of all industries outside the life sciences, but also by dividing it between the categories of "Information Technology" and "Non-High-Technology" industries[11]. Further, I track this not only for the regions which contain the schools I investigate, but also for adjacent regions, and nationwide.

Finally, because general measures of population and economic activity may not correspond exactly to specific field of life-science innovation, and because fixed effects at the region- and year-levels may not capture all relevant forms of variation, I include the variable $SchoolReputation_{rt}$, which captures the academic quality of graduate programs in the life sciences within region r during year t. This measure is based on previously-described surveys of graduate program quality performed by the ACE and NRC. However, these surveys occurred approximately once per decade, with the first survey taking place in 1964 and the most recent in 2006. Further, schools are ranked on multiple departments in each survey. To address these issues, I run a set of school-specific regressions fitting a quadratic time-trend to the reported ranks across all surveys. I use the fitted values from these school-specific regressions to measure the academic rank of school s in year t, and take the average of these fitted log-rank values (i.e. the geometric mean of the actual ranks) when aggregating this measure at the regional level.

3.3 Measures of Entrepreneurship and Innovation

In the second stage of the analysis, I examine the impact of funding on innovation. Beginning with explanatory variables, OLS specifications use the actual values of $\log(VC_{rt}^{LifeSci})$ to measure funding availability, while IV specifications use the fitted values from the first-stage regressions. All specifications continue to use the measures of population, personal income, and school rank described above. In addition to these controls, I introduce a measure of

[10] As with funding measures, I again scale all observations to 2005 dollars, and add the first percentile of non-zero IPO valuations to avoid undefined logarithms.

[11] These classifications are based on the Venture Economics Industry Codes (VEICs) present in Thomson Financial databases.

inventor tenure, $\log(Tenure_{it})$, which equals the natural log of the number of years between year t and the application year of the first patent on which inventor i is listed as an inventor[12]. Further, I track the total number of inventors, and whether inventor i is listed as the first (and therefore most prominent) inventor on the patent. I also track the number of assignees listed on the patent, and take advantage of assignee classifications to determine whether a given patent is assigned to only academic or non-profit institutions, or whether the private sector is involved in the research.

Moving to the dependent variables, my first measure deals directly with the theoretical prediction along the extensive margin: transitions of inventors between academia and the private sector. I measure these transitions through the variable $Transition_{it}$, which is defined as an indicator for whether any of the patents that inventor i applies for in year t include a private-sector assignee. For this measure to be meaningful, I restrict the sample to years in which the inventor applies for at least one patent of any kind, and focus on inventors who have applied for an academic patent in the past three years. These restrictions make sure that my results are not biased by inventors who are not producing any patents, or inventors who have left academia. The second dependent variable I construct is the $\log(Patents_{it})$ measure, which tracks the number of patent applications submitted in year t which list inventor i as an inventor[13]. I also dis-aggregate this measure into academic and industry linked patent production in the same manner, tracking these outputs through the variables of $\log(Patents_{it}^{Acad})$ and $\log(Patents_{it}^{Ind})$, respectively.

In addition to measures of career trajectory and the quantity of innovation, I construct several measures to capture the type of innovation being pursued. I measure the scientific value of an innovation by tracking the citations to the patents in my sample: I construct the variable $log(Citations_{it})$, which is calculated as the natural log of (one plus) the number of

[12]I set tenure equal to one in the year that the first patent application is submitted to avoid undefined values when taking logs.

[13]Note that there can be a significant lag between a patent's application year and its grant year. To minimize the potential for truncation bias, I only include patent applications published through 2005, which would almost certainly be granted (or rejected) by 2010, the final year of my dataset of granted patents.

citations that accrue to the patents that inventor i applies for in year t.[14] Because these are forward-looking measures, I designate fixed time horizons in order to create a valid metric for patents across a broad range of vintages. For my primary measure, I track all citations occurring within ten years of the patent's application. I also divide the citations I observe into short-term and long-term citations, with a range of zero to five years for the former and six to ten years for the latter. Further, I include a measure of robustness by constructing the number of citations to the single most-cited patent applied for by inventor i in year t, to differentiate between changes to marginal-quality research and changes to inventors' most important innovations.

4 Results

4.1 First Stage: Reinvestment in the Venture Capital Industry

The results begin with Table 1, which illustrates the reinvestment dynamics of venture capital within the life-science sector and identifies the appropriate lag structure for the first-stage analysis in Table 2. The dependent variable is $\log(VC_{rt}^{LifeSci})$: the log of venture capital investment in the life sciences for a given MSA in a given year. Specifications (1) and (2) include all venture capital investment in the life sciences, while specifications (3) and (4) focus exclusively on venture capital investments into first-round financing of portfolio companies. The key explanatory variables consist of lags and cumulative sums of venture-backed IPOs outside the life sciences occurring in the same MSA. Specifically, I take the log of the combined value of all local IPOs over a given year or set of years. All specifications include each lag separately, from one to four years; specifications (2) and (4) also include the contemporary measures for venture-backed IPOs both within and outside the life sciences. Because I employ standardized right-hand-side variables, the economic significance of the results is

[14] In aggregating citations to a inventor's patents, I only count each citing patent once, even if it cites multiple patents applied for by inventor i in year t.

easily interpreted: a one-standard-deviation rise in local non-life-science IPO activity leads to an approximately 11% increase in local life science investment lagged at a two-year horizon; the same increase in IPOs leads to a larger 27% increase in local life science investment. In all specifications, I also report the impact of MSA population, income per capita, and school reputation. While only the coefficient on population is consistently significant after accounting MSA fixed effects, all coefficients point in the expected direction: more populous regions, more prosperous regions, and those containing higher-quality schools all attract higher levels of investment.

The lag-structure results line up well with the mechanics of capital redeployment in the VC industry, falling in the middle of the one-to-three-year range described by Nanda and Rhodes-Kropf (2012). This supports the interpretation that cross-industry reinvestment dynamics can offer a source of variation which is uncorrelated with investment opportunities. Note that specifications (2) and (4) provide a relatively direct test of whether cross-industry IPOs are conditionally uncorrelated with the prospects of new ventures, by including the contemporary life-science IPO measure alongside my measures of IPOs outside the life sciences. I find that adding this explanatory variable has a negligible impact on the explanatory power of (two-year) lagged IPOs outside the life sciences. This lends credence to the argument that lagged cross-industry IPOs offer a source of potentially exogenous variation in funding availability for life-science investment.

TABLE 1 HERE

Building on the two-year lag structure detailed above, Table 2 focuses the first-stage analysis on the complementary dimension of geographic proximity, in order to evaluate the degree to which local variation drives funding availability. I again divide my analysis between all venture capital investments and first-round investments, and examine the former in specifications (1) and (2). These regressions seek to explain local investment in life-science ventures by comparing the relative impact of same-MSA, adjacent-MSA, and national (venture-backed) IPO levels outside the life sciences. I continue to focus on local life-science investment as the dependent variable, captured by $\log(VC_{rt}^{LifeSci})$. In this analysis, I focus on explanatory variables covering a progressively more distant set of non-life-science IPOs, using same-MSA, adjacent-MSA, and nationwide measures. Based on the results in Table 3, I focus on a cumulative measure of the past two years of local life-science IPOs.

In specification (1), I find that the same-MSA effect is strongest in both economic and statistical significance, leading to a 15% rise in life-science investment. With the inclusion of calendar-year fixed effects in specification (2), the impact of local cross-industry IPOs becomes stronger in both statistical and economic significance. This result indicates that variation at the metropolitan level is the most effective predictor of subsequent investment, as IPOs in adjacent MSAs have a near-zero contribution. I find a similar pattern of results when focusing on first-round venture capital investment as the dependent variable: a one-standard-deviation increase in cross-industry IPO activity leads to an approximately 35% rise in first-round investment. The relative strength of the first-round investment effect indicates that earlier-stage funding is even more sensitive to financing constraints than the venture capital industry in general. The controls of academic rank and local MSA population and income continue to point in the expected directions, as in Table 1. Specifications (2) and (4) combine all three dimensions of separation described earlier: they take advantage of venture capital cycles by targeting lags that match reinvestment horizons, incorporate cross-industry effects to avoid alternative channels of influence, and target geographically-concentrated effects which correspond to the local nature of the VC industry. By combining these dimensions, my specifications presents evidence for a measure of funding availability that is uncorrelated with investment opportunities in the life sciences. I therefore use these regression to construct my instrumented measure of local VC investment, and bring the fitted values to the second stage to evaluate the impact of funding availability on innovation.

TABLE 2 HERE

4.2 Second Stage: Entrepreneurship and Innovation

This section describes the second stage of the empirical analysis, where I investigate the impact of funding availability on entrepreneurship and innovative output. I focus on four specific measures: career transitions, and the quantity, value, and scope of innovation. The results are presented in Tables 3 through 5, and I describe them in detail below.

4.2.1 Career Transitions

The second-stage results begin with Table 3, which analyzes the career transitions potential entrepreneurs (i.e. inventors) in my dataset. As described in the previous section, the dependent variable $IndustryTransitionIndicator_{it}$ tracks whether inventor i applies for an "industry patent" in year t. The explanatory variables of focus are measures of local VC investment in the life sciences, either by using $\log(VC_{rt}^{LifeSci})$ directly in OLS specifications or using the fitted values resulting from the first stage to instrument for the same variable. I also include a full set of fixed effects at the calendar-year, school, and inventor level, and controls based on academic rank, MSA population and income, and inventor tenure. In specification (1), I find a significant positive impact of funding on career transitions under OLS, with a magnitude of just over 7% relative to the baseline industry transition rate of 0.20. However, this estimate is potentially biased: if the level of investment is responding to an increase in the value of innovation, this is likely to correlate with increases in the attractiveness of both academia and the private sector for inventors. This will mitigate the differential effect between the two, and reduce the estimated impact on career transitions.

To address the shortcomings of the OLS approach, specification (2) incorporates instruments for local investment levels into the above framework, calculated from specification (2) of Table 2. The point-estimates for the impact of lagged investment increases substantially. The increase in effect relative to specification (1) matches expectations based on the shortcomings of the OLS approach. This supports a causal interpretation for the IV estimates, which indicate that a one-standard-deviation increase in local investment leads to a 13.8%

rise in the likelihood of transition. Specifications (3) and (4) repeat the analysis using Probit and IV-Probit frameworks, respectively. As in the linear regressions, results for both the direct and instrumented effects are positive and significant, with the IV estimate being the larger of the two. Specifically, I find an 11.9% increase under a direct Probit specification, and a 14.9% rise in transition rates under IV-Probit. These results indicate that the inventors in my sample are responsive to shifts in funding, and are consistent with the theoretical predictions along the extensive margin: inventors are more likely to transition into the private sector when funding availability is greater.

Building on the above analysis, specifications (5) through (8) divide the career transitions into two groups: "startup transitions" and "established-firm transitions," and compare the impact of funding on these sub-cagetories in Table 4. I define these categories based on the length of time since the first patent grant of the industry assignee to which the inventor transitions: assignees with a patent history of two years or less are defined as startups, while all other assignees are defined as established firms. I find that while funding increases transitions to both startups and established firms, the impact on startup transitions is more than twice as large: 16.3% vs. 7.8%. This offers confirmation that the transitions I identify are closely linked to the venture capital industry, where one would expect the vast majority of funding to flow to newly-formed ventures.

TABLE 3 HERE

4.2.2 Quantity of Innovation

In Table 4, I explore the impact of funding availability on the quantity of innovative output. This analysis addresses two important theoretical predictions: first, that stronger incentives and greater access to funding will increase innovative output for all inventors, and that this increase will be particularly strong for inventors transitioning from academia to the private sector. The dependent variable in this table is $\log(PatentQuantity_{it})$, representing the log of one plus the number of patents applied for by inventor i in year t. The main explanatory variables are the same as in Table 3: local life-science VC investment and its instrument, with the latter calculated from specification (2) of Table 2. I again include a full set of fixed effects and a range of controls based on school, MSA, and inventor characteristics. The sample in these regressions is unrestricted: because an observation of no patents is meaningful, I include all years between the first and last observation of a patent application for each inventor.[15]

Specifications (1) and (2) present the OLS results, which indicate a small positive effect of funding on the quantity of innovation. While specification (1) indicates that increased funding leads to a 1.3% increase in patenting, specification (2) shows that more than half of this effect is driven by transitions to the private sector. This result seems to favor the interpretation that inventors remaining in academia have significant alternatives to patenting which also increase in value when investment opportunities improve. This interpretation is supported by the positive results under an IV approach in specifications (3) and (4). I find significant effects both unconditionally and when controlling for the effect of transitioning inventors, with a 4.6% increase in the former case and a 3.3% increase in the latter. In addition to identifying the impact of funding availability, I also estimate that transitioning to the private sector leads to a very large 72% increase in patent output. These findings lend support to the prediction that increased funding availability differentially promotes patent-focused innovation relative to the alternative activities in which inventors might choose to engage.

TABLE 4 HERE

4.2.3 Scientific Value of Innovation

Having presented evidence for a rise in the quantity of innovation in response to funding availability, I now turn to the results in Tables 5, which highlights the impact of funding on the type of innovations being pursued. The first dimension I explore is that of the "scientific

[15] As noted earlier, however, I restrict my analysis to inventors with at least three lifetime patents.

value of innovation," as measured by the number of citations a given patent receives from subsequent innovations. The first four columns of Table 5 focus primarily on this dimension, and present results based on citations occurring in the first ten years following the patent's application. The second dimension of interest is the time horizon of a given innovation, i.e. the duration of its relevance to emerging technologies. This aspect of the composition of innovative output is the focus of columns five through eight, which divide the decompose the dependent variable between short term (0-5 year) and long-term (6-10 year) citation totals. For all specifications, I control for whether or not the inventor is in academia based on the assignees of prior patents. This means that at least one patent is necessary for the identification, so I restrict the sample to the years after a given inventor's first patent. Further, in order to highlight a different dimension from that of patent quantity, I exclude all years in which a given inventor does not produce any patents, as these years would mechanically lead to a lack of subsequent citations.

Specifications (1) and (2) present the OLS results, and indicate a consistent positive effect of academia on citation rates, in line with the theoretical prediction that academia focuses on earlier-stage innovations that are likely to offer a foundation for future research. In evaluating the impact of funding availability using an OLS approach, I find that the effect is strongest for academic inventors: the interaction between funding and academia has a significant negative impact. Specifically, Ia one-standard-deviation increase in funding availability is associated with a 5.7% decrease in citation rates, implying that the output of academic inventors is less valuable as a foundation for future inventions when funding availability is high. Specifications (3) and (4) show that this pattern continues to hold under an instrumental-variables approach, with the interaction term between academia and local life-science investment leading to a significant 5.6% decline in citation rates. More importantly, the IV results also show a strong unconditional impact of funding availability: specifications (3) and (4) both show that a one-standard-deviation increase in funding leads to an unconditional 19% drop in citation rates. This is a very large effect, and is significantly different from the OLS estimates. This difference is not surprising: it indicates that the endogenous variation in funding availability is positively correlated with the scientific value of innovative projects, as one would expect if venture capital investment were responsive to investment opportunities. Given this relationship, the finding of a zero net effect in the OLS specifications and a strong negative result under IV indicates that holding investment opportunities constant, greater funding leads inventors in both academia and the private sector to pursue significantly lower-value projects.

In specifications (5) through (8), I break down the citation rates described above between short-term (0-5 year) and long-term (6-10 year) citations. As in the results above, greater funding has a zero net effect under OLS, and a strong negative effect when controlling for investment opportunities under IV. Beyond this robustness check, the division between short-run and long-run citations yields several new insights. First, the unconditional effect of the academia indicator differs significantly between the short-run and long-run horizons: in terms of short-run citations, there is no difference between inventors in academia and in the private sector. By contrast, in the six-to-ten year range of the long-run specifications, patents created by academic inventors receive approximately 10% more citations than those of private-sector inventors. In addition, comparing the short-run and long-run effects of funding, I find that its unconditional impact is negative for both horizons, but that the decline is almost twice as strong for long-run citations. Specifically, while a one-standard-deviation increase in funding availability leads to a 14% decline in short run citations in specification (2), the same change in funding leads to a 25% drop in long-run citations. These results indicate that while innovations with a long impact horizon are more often observed in academia, it is precisely these innovations which are neglected when private-sector funding dominates in a given location. In sum, Tables 4 and 5 demonstrate that while funding availability increases the quantity of innovation with relatively minor short-run costs, it also undermines the early-stage innovations that form the foundation for future development.

TABLE 5 HERE

5 Conclusion

In this paper I argued that fluctuations in funding availability have a significant impact on not only the quantity but also the type of innovation that entrepreneurs pursue. Based on theories of multi-stage innovation and commercialization, I generate the predictions that greater funding pushes inventors to transition to the private sector and to engage in a greater number of shorter-horizon, narrower-scope projects. I test these hypotheses using a panel of potential entrepreneurs: life-science inventors linked to top US universities, and their patent output from 1975 through 2005. To identify the causal relationship between funding and innovation, I adopt an instrumental-variables approach based on venture-backed IPOs outside the life sciences but occurring in the inventor's metropolitan area. In the first stage, I find that local variation is an important driver of venture capital reinvestment, and that cross-industry effects persist even after controlling for own-industry conditions. Using this source of conditionally uncorrelated variation in funding availability, I examine the impact of funding on early-stage innovation. In line with theoretical predictions and previous studies, I find that greater funding availability leads to an increase in transitions from academia to the private sector, and an increase in the quantity of innovation, particularly for transitioning inventors. However, I also present evidence for three novel dimensions of funding impact: I find that greater funding availability leads to a decrease in citation rates, citation horizons, and the scope of applicability for innovative output. These findings imply a tradeoff between focused, high-output development of existing technologies under high funding levels, and earlier-stage exploration of new technologies when funding is lower.

References

Aghion, P., Dewatripont, M., & Stein, J. C. (2008). Academic freedom, private?sector focus, and the process of innovation. The RAND Journal of Economics, 39(3), 617-635.

Arrow, K. (1962). Economic welfare and the allocation of resources for invention. In The rate and direction of inventive activity: Economic and social factors (pp. 609-626). Princeton University Press.

Azoulay, P., Graff Zivin, J. S., & Manso, G. (2011). Incentives and creativity: evidence from the academic life sciences. The RAND Journal of Economics, 42(3), 527-554.

Brown, J. R., Fazzari, S. M., & Petersen, B. C. (2009). Financing innovation and growth: Cash flow, external equity, and the 1990s R&D boom. The Journal of Finance, 64(1), 151-185.

Brown, S. L., & Eisenhardt, K. M. (1995). Product development: Past research, present findings, and future directions. Academy of management review, 20(2), 343-378.

Chesbrough, H. W. (2006). Open innovation: The new imperative for creating and profiting from technology. Harvard Business Press.

Gans, J. S., Murray, F. E., & Stern, S. (2013). Contracting over the disclosure of scientific knowledge: Intellectual property and academic publication (No. w19560). National Bureau of Economic Research.

Gompers, P. A. (1996). Grandstanding in the venture capital industry. Journal of Financial economics, 42(1), 133-156.

Gompers, P., & Lerner, J. (2000). Money chasing deals? The impact of fund inflows on private equity valuation. Journal of financial economics, 55(2), 281-325.

Grant, R. M. (1996). Toward a knowledge-based theory of the firm. Strategic management journal, 17(S2), 109-122.

Hall, B. H., Jaffe, A. B., & Trajtenberg, M. (2001). The NBER patent citation data file: Lessons, insights and methodological tools (No. w8498). National Bureau of Economic Research.

Hamel, G. (2002). Leading the revolution: How to thrive in turbulent times by making innovation a way of life. Boston: Harvard Business School Press.

Hitt, M. A., Ireland, R. D., Camp, S. M., & Sexton, D. L. (2001). Strategic entrepreneurship: Entrepreneurial strategies for wealth creation. Strategic management journal, 22(6?7), 479-491.

Hoberg, G., & Phillips, G. (2010). Real and financial industry booms and busts. The Journal of Finance, 65(1), 45-86.

Hochberg, Y. V., & Rauh, J. D. (2012). Local overweighting and underperformance: evidence from limited partner private equity investments. Review of financial studies, hhs128.

Holmstrom, B., & Tirole, J. (1997). Financial intermediation, loanable funds, and the real sector. the Quarterly Journal of economics, 663-691.

Kortum, S., & Lerner, J. (2000). Assessing the contribution of venture capital to innovation. RAND journal of Economics, 674-692.

Laursen, K., & Salter, A. (2006). Open for innovation: the role of openness in explaining innovation performance among UK manufacturing firms. Strategic management journal, 27(2), 131-150.

Levinthal, D. A., & March, J. G. (1993). The myopia of learning. Strategic management journal, 14(S2), 95-112.

Li, G. C., Lai, R., D?Amour, A., Doolin, D. M., Sun, Y., Torvik, V. I., ... & Fleming, L. (2014). Disambiguation and co-authorship networks of the US patent inventor database (1975?2010). Research Policy, 43(6), 941-955.

Murray, F., Aghion, P., Dewatripont, M., Kolev, J., & Stern, S. (2015). Of Mice and Academics: Examining the Effect of Openness on Innovation. Forthcoming in *American Economic Journal: Economic Policy.*

Nanda, R., & Rhodes-Kropf, M. (2013). Investment cycles and startup innovation. Journal of Financial Economics, 110(2), 403-418.

Nelson, R. (1959). The Simple Economics of Basic Scientific Research. Journal of Political Economy, 67(3), 297-306.

Powell, W. W., Koput, K. W., Bowie, J. I., & Smith-Doerr, L. (2002). The spatial clustering of science and capital: Accounting for biotech firm-venture capital relationships. Regional Studies, 36(3), 291-305.

Salter, A. J., & Martin, B. R. (2001). The economic benefits of publicly funded basic research: a critical review. Research policy, 30(3), 509-532.

Scotchmer, S. (1991). Standing on the shoulders of giants: cumulative research and the patent law. The Journal of Economic Perspectives, 29-41.

Spender, J. C. (1996). Making knowledge the basis of a dynamic theory of the firm. Strategic management journal, 17, 45-62.

Stein, J. C. (1989). Efficient capital markets, inefficient firms: A model of myopic corporate behavior. The Quarterly Journal of Economics, 655-669.

Stern, S. (2004). Do scientists pay to be scientists?. Management science, 50(6), 835-853.

Townsend, R. R. (2012). Propagation of financial shocks: The case of venture capital. Available at SSRN 2021310.

Trajtenberg, M., Henderson, R., & Jaffe, A. (1997). University versus corporate patents: A window on the basicness of invention. Economics of Innovation and new technology, 5(1), 19-50.

Von Hippel, E. (2007). The sources of innovation. Gabler.

Figure 1
Local Venture Capital Investment by Region

This figure plots the average level of the natural log of gross venture capital investment ($M) across the high-, medium-, and low-VC regions in my sample from 1975 through 2010. Venture capital investment is tracked in millions of constant 2005 dollars, and is aggregated across all industries for each MSA in my sample. MSAs are sorted into the three levels of venture capital intensity based on the average level of log-investment across the entire sample period.

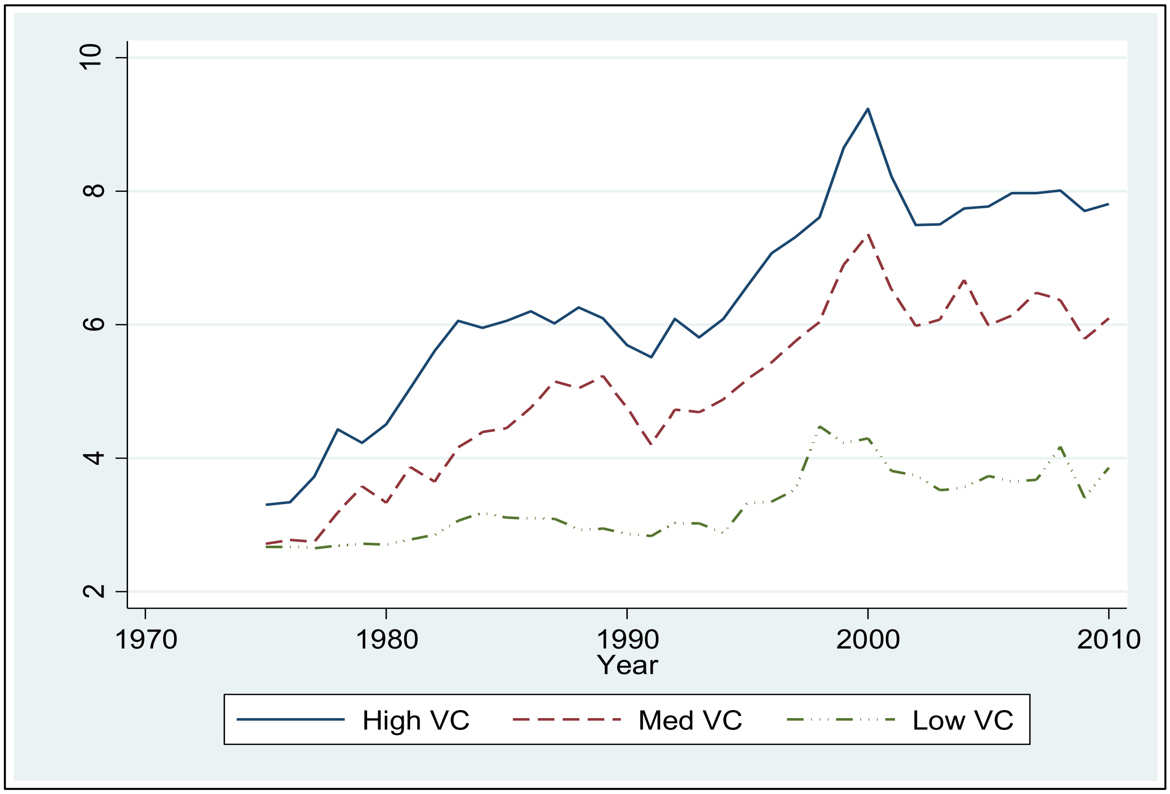

Table 1

Cross-Industry Reinvestment Dynamics

This table reports OLS regressions, and is based on a sample of venture capital transactions from Thomson Financial, covering both investments and exits. The transactions are aggregated together into units of observation at the MSA-year level. The dependent variable is the natural logarithm of gross investment into life-science ventures based in the MSA during the given year, tracked in millions of real 2005 dollars. The first two columns analyze the outcome of all venture capital investment, while the last two columns look at only first-round investments. The main explanatory variable of interest is Log(Local Non-Life-Science IPOs), which aggregates the IPO valuations of venture-backed companies outside the life sciences but located in the MSA and going public during the given year, tracked in millions of 2005 dollars. Full sets of fixed effects for calendar years and MSAs are included for all specifications. All right-hand-side variables are standardized to facilitate interpretation of economic significance.

	Dep. Var. = Log(Local Life-Science VC Investment)			
	ALL VC INVESTMENT		FIRST-ROUND VC INVESTMENT	
Independent Variables	(1)	(2)	(3)	(4)
Log(Local Non-Life-Science IPOs)				
IPO Lag: 1 year	0.057	0.019	0.048	0.018
	(0.060)	(0.061)	(0.068)	(0.071)
IPO Lag: 2 years	0.114**	0.109*	0.274***	0.272***
	(0.052)	(0.055)	(0.066)	(0.063)
IPO Lag: 3 years	0.047	0.021	0.154	0.136
	(0.055)	(0.051)	(0.109)	(0.108)
IPO Lag: 4 years	0.060	0.043	0.060	0.049
	(0.064)	(0.064)	(0.106)	(0.103)
Contemporary IPOs				
Log(Local Non-Life-Science IPOs)		0.104*		0.139
		(0.051)		(0.089)
Log(Local Life-Science IPOs)		0.139**		0.022
		(0.053)		(0.048)
Log(MSA Population)	4.371**	4.231**	4.510***	4.491***
	(1.653)	(1.665)	(1.147)	(1.108)
Log(MSA Income Per Capita)	0.754	0.670	0.854**	0.802**
	(0.479)	(0.464)	(0.382)	(0.380)
Average School Reputation	0.188	0.177	0.292*	0.290*
	(0.237)	(0.230)	(0.156)	(0.156)
Calendar-Year Controls	FE	FE	FE	FE
MSA Controls	FE	FE	FE	FE
Level of Observation	MSA-Year	MSA-Year	MSA-Year	MSA-Year
N. of Observations	770	770	770	770
N. of MSAs	22	22	22	22

Standard errors clustered by Region in parentheses. Significance: * 10% ** 5% *** 1%

Table 2

2SLS Stage 1 Analysis: Cross-Industry Local Reinvestment Effects

This table reports OLS regressions, and is based on a sample of venture capital transactions from Thomson Financial, covering both investments and exits. The transactions are aggregated together into units of observation at the MSA-year level. The dependent variable is the natural logarithm of gross investment into life-science ventures based in the MSA during the given year, tracked in millions of real 2005 dollars. The first two columns analyze the outcome of all venture capital investment, while the last two columns look at only first-round investments. The measure Log(Non-Life-Science IPOs) aggregates the IPO valuations of venture-backed companies outside the life sciences, located either in the MSA of the dependent variable, adjacent MSAs, or nationwide, and going public in the two years prior to the observation of the dependent variable, tracked in millions of 2005 dollars. A full set of fixed effects for MSAs is included for all specifications, and fixed effects for calendar years are also included when Nationwide IPOs are excluded, specifically, in specifications (2) and (4). All right-hand-side variables are standardized to facilitate interpretation of economic significance. Note that specification (2) is the basis for the instrumental variables used in the second-stage analysis.

	Dep. Var. = Log(Local Life-Science VC Investment)			
	ALL VC INVESTMENT		FIRST-ROUND VC INVESTMENT	
Independent Variables	(1)	(2)	(3)	(4)
Log(Local Non-Life-Science IPOs)				
Same MSA, past 2 years	0.154*	0.177**	0.360***	0.343***
	(0.087)	(0.082)	(0.080)	(0.080)
Adjacent MSAs, past 2 years	0.055	0.032	0.147	0.130
	(0.144)	(0.135)	(0.120)	(0.106)
Nationwide, past 2 years	0.103		0.117	
	(0.086)		(0.103)	
Log(MSA Population)	4.315**	4.392**	4.476***	4.572***
	(1.588)	(1.667)	(1.162)	(1.225)
Log(MSA Income Per Capita)	1.003**	0.787	0.924***	0.913**
	(0.357)	(0.481)	(0.322)	(0.361)
Average School Reputation	0.163	0.184	0.262	0.267
	(0.216)	(0.217)	(0.159)	(0.158)
Calendar-Year Controls	Polynomial	FE	Polynomial	FE
MSA Controls	FE	FE	FE	FE
Level of Observation	MSA-Year	MSA-Year	MSA-Year	MSA-Year
N. of Observations	770	770	770	770
N. of MSAs	22	22	22	22

Standard errors clustered by Region in parentheses. Significance: * 10% ** 5% *** 1%

Table 3
Career Transitions

This table reports OLS and Probit regressions and their IV equivalents, and is based on the patent output of a sample of inventors linked to top US research universities. The patent output is aggregated into units of observation at the inventor-year level, with years based on the application dates of a given inventor's patents. In specifications (1) through (4), the dependent variable is an indicator which equals one in any year in which the inventor's patent output includes a patent with an industry assignee. In specifications (5) and (6), only industry assignees with a patent history of up to two years are included, while specifications (7) and (8) focus on the complementary set of industry assignees with a patent history of more than two years at the time of the patent application. The sample is restricted to inventors with at least one patent in the previous five years to focus on a sample of potential entrepreneurs. To facilitate comparison between the OLS and Probit results, the dependent variable is scaled to have a mean of one in the OLS specifications. The measure Log(Life-Science Investment) aggregates the value of gross investments by venture capital funds into companies within the life sciences, located in the MSA of a given inventor, and tracked in millions of 2005 dollars. The measure Instrumented Log(Life-Science Investment) uses the fitted values from specification (2) in Table 2, with exogenous variation stemming from shocks to local venture-backed IPOs outside the life sciences. Full sets of fixed effects for schools and calendar years are included for all specifications, and fixed effects at the inventor level are also present in specifications (1) and (2). All right-hand-side variables are standardized to facilitate interpretation of economic significance.

	Dep. Var. = Industry Transition Indicator				Dep. Var. = Startup Transitions		Dep. Var. = Established Firm Transitions	
	OLS	IV	Probit	IV Probit	Probit	IV Probit	Probit	IV Probit
Independent Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(Life-Science Investment)								
Same MSA, past 2 years	0.074**		0.119***		0.142***		0.052**	
	(0.032)		(0.022)		(0.023)		(0.024)	
Instrumented Log(Life-Science Investment)								
Same MSA, past 2 years		0.138*		0.149***		0.163***		0.078***
		(0.081)		(0.015)		-0.018		-0.019
Log(Tenure)	0.324***	0.322***	0.210***	0.211***	0.170***	0.171***	0.167***	0.168***
	(0.055)	(0.055)	(0.017)	(0.009)	(0.017)	(0.011)	(0.018)	(0.012)
Log(MSA Population)	0.045	0.033	-0.089***	-0.099***	-0.054***	-0.060***	-0.099***	-0.108***
	(0.076)	(0.075)	(0.018)	(0.009)	(0.018)	(0.011)	(0.019)	-0.012
Log(MSA Income Per Capita)	-0.102	-0.134*	-0.032	-0.043***	-0.083***	-0.091***	0.039	0.029
	(0.078)	(0.079)	(0.029)	(0.015)	(0.028)	(0.017)	(0.030)	-0.018
School Reputation	0.033	0.016	0.009	0.000	-0.001	-0.008	0.017	0.01
	(0.051)	(0.052)	(0.015)	(0.008)	(0.015)	(0.010)	(0.017)	-0.01
School Controls	FE	FE	FE	FE	FE	FE	FE	FE
Calendar-Year Controls	FE	FE	FE	FE	FE	FE	FE	FE
Inventor Controls	FE	FE	-	-	-	-	-	-
Level of Observation	Inventor-Year	Inventor-Year	Inventor-Year	Inventor-Year	Inventor-Year	Inventor-Year	Inventor-Year	Inventor-Year
N. of Observations	53042	53042	53042	53042	53042	53042	53042	53042
N. of Inventors	6799	6799	6799	6799	6799	6799	6799	6799

Standard errors clustered by Inventor in parentheses. Significance: * 10% ** 5% *** 1%

Table 4

Patent Quantity

This table reports OLS and IV regressions, and is based on the patent output of a sample of inventors linked to top US research universities. The patent output is aggregated into units of observation at the inventor-year level, with years based on the application dates of a given inventor's patents. The dependent variable is the natural logarithm of one plus the numer of patents applied for by a given inventor in a given year. The measure Log(Life-Science Investment) aggregates the value of gross investments by venture capital funds into companies within the life sciences, located in the MSA of a given inventor, and tracked in millions of 2005 dollars. The measure Instrumented Log(Life-Science Investment) uses the fitted values from specification (2) in Table 2, with exogenous variation stemming from shocks to local venture-backed IPOs outside the life sciences. The measure Industry Transition Indicator is identical to the dependent variable in Table 3, and is an indicator which equals one in any year in which the inventor's patent output includes a patent with an industry assignee. Full sets of fixed effects for inventors, schools, and calendar years are included for all specifications. All right-hand-side variables except Industry Transition Indicator are standardized to facilitate interpretation of economic significance.

	Dep. Var. = Log(Patent Quantity)			
Independent Variables	(1)	(2)	(3)	(4)
Log(Life-Science Investment)				
Same MSA, past 2 years	0.013**	0.006		
	(0.006)	(0.005)		
Instrumented Log(Life-Science Investment)				
Same MSA, past 2 years			0.046**	0.033*
			(0.019)	(0.017)
Industry Transition Indicator		0.725***		0.725***
		(0.006)		(0.006)
Log(Tenure)	-0.180***	-0.160***	-0.181***	-0.160***
	(0.005)	(0.005)	(0.005)	(0.005)
Log(MSA Population)	0.001	-0.002	-0.008	-0.010
	(0.018)	(0.016)	(0.017)	(0.015)
Log(MSA Income Per Capita)	-0.024	-0.007	-0.036**	-0.017
	(0.018)	(0.014)	(0.018)	(0.015)
School Reputation	0.010	0.004	0.003	-0.002
	(0.012)	(0.010)	(0.012)	(0.010)
School Controls	FE	FE	FE	FE
Calendar-Year Controls	FE	FE	FE	FE
Inventor Controls	FE	FE	FE	FE
Level of Observation	Inventor-Year	Inventor-Year	Inventor-Year	Inventor-Year
N. of Observations	73979	73979	73979	73979
N. of Inventors	7070	7070	7070	7070

Standard errors clustered by Inventor in parentheses. Significance: * 10% ** 5% *** 1%

Table 5
Patent Citations

This table reports OLS and IV regressions, and is based on the patent output of a sample of inventors linked to top US research universities. The patent output is aggregated into units of observation at the inventor-year level, with years based on the application dates of a given inventor's patents. In specifications (1) through (4), the dependent variable is the natural logarithm of one plus the total number of patent citations accruing in the first ten years to the patents applied for by a given inventor in a given year. In specifications (5) and (6), only citations accruing in years zero to five are included, while specifications (7) and (8) focus on the complementary set of citations accruing in years six through ten. The sample is restricted to years in which a given inventor applies for at least one patent, and years no later than 2000. The measure Academia Indicator is an indicator variable equal to one for inventors who have not worked on a patent with an industry assignee at any prior point in their career. The measure Log(Life-Science Investment) aggregates the value of gross investments by venture capital funds into companies within the life sciences, located in the MSA of a given inventor, and tracked in millions of 2005 dollars. The measure Instrumented Log(Life-Science Investment) uses the fitted values from specification (2) in Table 2, with exogenous variation stemming from shocks to local venture-backed IPOs outside the life sciences. Full sets of fixed effects for inventors, schools, and calendar years are included for all specifications. All right-hand-side variables except Academia Indicator are standardized to facilitate interpretation of economic significance.

	Dep. Var. = Log(Citations)				Dep. Var. = Log(Short-Run Citations)		Dep. Var. = Log(Long-Run Citations)	
Independent Variables	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Academia Indicator	0.054	0.053	0.053	0.052	0.008	0.007	0.106***	0.109***
	(0.037)	(0.037)	(0.037)	(0.037)	(0.035)	(0.035)	(0.035)	(0.036)
Log(Life-Science Investment)								
Same MSA, past 2 years	0.001	-0.001			0.006		0.003	
	(0.028)	(0.028)			(0.025)		(0.026)	
Academia X Log(Life-Science Investment)		-0.057*			-0.038		-0.025	
		(0.029)			(0.027)		(0.027)	
Instrumented Log(Life-Science Investment)								
Same MSA, past 2 years			-0.190**	-0.187**		-0.138*		-0.246***
			(0.088)	(0.088)		(0.076)		(0.086)
Academia X Inst. Log(Life-Science Investment)				-0.056*		-0.039		-0.007
				(0.031)		(0.028)		(0.029)
Application-to-Grant Gap	-0.245***	-0.245***	-0.245***	-0.245***	-0.301***	-0.301***	-0.095***	-0.095***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.009)	(0.009)	(0.010)	(0.010)
Log(Tenure)	-0.208***	-0.202***	-0.206***	-0.199***	-0.178***	-0.175***	-0.135***	-0.134***
	(0.042)	(0.042)	(0.042)	(0.042)	(0.039)	(0.039)	(0.039)	(0.039)
Log(MSA Population)	-0.003	0.004	0.037	0.043	-0.002	0.029	0.008	0.058
	(0.078)	(0.077)	(0.081)	(0.080)	(0.072)	(0.074)	(0.072)	(0.072)
Log(MSA Income Per Capita)	-0.051	-0.060	0.003	-0.011	-0.001	0.036	-0.164**	-0.091
	(0.069)	(0.069)	(0.071)	(0.072)	(0.063)	(0.066)	(0.065)	(0.068)
School Reputation	0.001	-0.002	0.034	0.030	-0.027	-0.002	0.022	0.066
	(0.061)	(0.061)	(0.063)	(0.063)	(0.053)	(0.055)	(0.055)	(0.057)
School Controls	FE	FE	FE	FE	FE	FE	FE	FE
Calendar-Year Controls	FE	FE	FE	FE	FE	FE	FE	FE
Inventor Controls	FE	FE	FE	FE	FE	FE	FE	FE
Level of Observation	Inventor-Year	Inventor-Year	Inventor-Year	Inventor-Year	Inventor-Year	Inventor-Year	Inventor-Year	Inventor-Year
N. of Observations	19958	19958	19958	19958	19958	19958	19958	19958
N. of Inventors	5546	5546	5546	5546	5546	5546	5546	5546

Standard errors clustered by Inventor in parentheses. Significance: * 10% ** 5% *** 1%