Not-so-*Dumb Money*: Beating the Competition with Talent Acquisition

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Abstract

The supply of the information technology (IT) entrepreneurial talent, which is an important input to digital innovation, is critically clustered geographically in tech hubs such as Silicon Valley, putting corporations located outside those clusters at a strategic disadvantage. This study focuses on corporate venture capital (CVC) investments, once widely regarded as 'dumb money,' as a mechanism for firms that want to access a 'window of opportunity' to disruptive innovations and a pool of highly-skilled talents. New ventures have the organic structure to coalesce a set of highly-skilled, entrepreneurial-minded, employees that can be a source of rare and hard-to-get talent for the investing firms. While the innovation acquisition benefits of CVC investments, in form of patent adoption, have taken much of the attention in the literature on CVC value, the returns attributed to talent acquisition have remained largely unexplored, arguably due to the difficulty in identifying and measuring talent movements associated with CVC investments. We capitalize on an opportunity to examine over 70 million online resumes to unfold the patterns of talent movement triggered by major CVC investments in digital start-ups and bridge the above-mentioned gap. As such, this study examines how talent acquisition triggered by CVC investments contributes to generating economic returns for firms. In general, our results suggest that firms benefit significantly from CVC activities when IT entrepreneurial talent is acquired from the ventures, especially when such talent is missing inside the investing firm. In economic terms, an otherwise-average firm that can acquire around 23 employees from the target venture can benefit from approximately 3 percent abnormal market return on its strategic CVC investment. More importantly, the results from a difference-in-difference experiment in our sample show that the talent acquisition benefits are significantly higher for firms that are located near IT labor markets with a shortage of entrepreneurial talent (such as those headquartered in non-coastal states). This finding highlights the role of CVC investments in reducing the IT labor disadvantages for firms that operate outside the tech clusters. The results are robust to several variations in measurement and pass placebo tests.

JEL Classification: M00, M20, J44

Keywords: CVC investment, IT talent acquisition, innovation acquisition, CVC returns

Introduction

Digital innovations, fueled by entrepreneurial talent[1], are critical in a firm's growth, advancing in competitions, and upending abysmal performance periods (Nambisan et al. 2017). The digital innovation process is enabled by information technology (IT) entrepreneurial talent who survives in an ecosystem of critically-agglomerated inputs such as entrepreneurial knowledge institutions (e.g., accelerators and incubators), venture capitalists, and deeply embedded networks that facilitate access to those inputs (Kerr et al. 2017, Gleaser and Kerr 2009, Tallman et al. 2004, Rosenthal and Strange 2003, Saxenian 1994). Therefore, the spatial agglomeration of IT entrepreneurial talent and its critical inputs, as famously illustrated in Silicon Valley, creates frictions in the local entrepreneurial labor markets that are not proximate to entrepreneurial clusters, putting established corporations that operate in those frictious labor markets at a disadvantage to adequately supply IT entrepreneurial talent. Moreover, evaluating and hiring entrepreneurial talent in labor markets requires a close assessment of intangible qualities that are usually hard to detect in typical indicators, such as formal education and past experiences listed in professional resumes. The collection of these two issues presents a challenge to firms that strive to keep up with the digital innovation competition while operating distantly from the agglomerated hubs of technological activity.

In response to this challenge, corporate venture capital (CVC) investments[2], with their limited scope and risk of ownership, become an effective means to create a rare opportunity of getting a seat at the table with talented entrepreneurs who are immensely accustomed to the rich face-to-face networks of accessing resources, knowledge, and opportunities (*see* Saxenian 1994). Unlike other forms of investment in the entrepreneurial scene, such as the formal acquisition of promising start-

[1] The labor force that is directly involved in ideation and development of organizational innovations.
[2] Investment by a corporate in the capital of an external start-up or a new venture.

ups, CVC investments cost less (usually below $15 million) and protect the firm from the likely failures of formal acquisitions due to their limited ownership structure. As such, CVC investments have emerged as lucrative options for firms that want to obtain a *'window of opportunity'* to the digital innovation world and a pool of highly-skilled talents. Invested-on ventures provide the investing firm with exposure to their cutting-edge technological innovations, and more critically, have the organic structure to coalesce a set of highly-skilled, entrepreneurial-minded employees that can be a source of rare and hard-to-get talent for the investing firms. In highlighting the role of CVC investments in supplying entrepreneurial talent, Teddy Himler (Forbes 2017) writes:

> *"Indeed, a CVC introduces its parent company to talented entrepreneurs – relationships that would be difficult to foster without an investment tie. Practiced over time, these dynamics spin a virtuous and accelerating CVC flywheel"*

Fueled by such a prospect, in 2018 alone, the number of new CVCs invested for the first time rose by 35 percent compared to the previous year[3]. This interest in CVC investments is met with academic inquiries. The existing literature on the entrepreneurial activity of established corporations has mainly painted innovation acquisition, in form of patent citations and adoptions, as the driver of value from CVC investments (e.g., Benson and Ziedonis 2009). However, the CVC returns attributed to direct talent acquisition, i.e., recruiting talent from the target venture, and heterogeneity in those returns, have remained largely unexplored, arguably due to the difficulties in identifying and measuring talent movements associated with CVC investments. Unlike innovation patents, which create an official trail of innovation adoption and adaptation and facilitate studying innovation acquisition, talent acquisition is not formally documented, making unfolding the patterns of talent movement and their impacts on CVC investors an enigma. Two recent developments – the rise of online professional networking and job-search platforms as well as advances in machine learning

[3] https://www.cbinsights.com/research/corporate-venture-capital-active-2014/

and analyzing unstructured text corpuses – provide us with a unique opportunity to examine over 70 million online resumes, along with major CVC investments in IT industry, to shed light on how talent acquisition contributes to generating CVC returns. As such, this study answers the broad questions about: a) whether or not talent acquisition is a mechanism through which digital CVC investments create value, and b) what causes the heterogeneity in benefits accrued from such talent acquisitions across various firms.

To empirically address these questions, we start by a population-average model to understand if talent acquisition, above and beyond innovation acquisition, contributes to the buy-and-hold abnormal return benefits of major digital CVC investments. Then, we examine the heterogeneities in the talent acquisition benefits of CVC investments from two distinct, albeit interrelated, angles. First, and considering the internal characteristics of the investing firm, we recognize the importance of the existing pools of talent in the investing firm and examine if the marginal benefits of talent acquisition are higher in cases when the acquired talent has skills that are rare in the investing firm's pool of the existing talent. Second, and considering the characteristics of local IT labor markets in which the investing firms operate, we consider the extent of IT talent supply at local entrepreneurial labor markets and examine if the benefits of talent acquisition are larger in size for firms that operate in disadvantaged (low-supply) local markets.

In understanding the heterogeneities in benefits conditioned on the internal characteristics of the investing firm, we start by building on the theory that an overlap between the firm's innovations and the target venture's innovation enhances the subsequent benefits from innovation acquisition (e.g., patent adoption) in CVC investment (Benson and Ziedonis 2009). We recognize that such overlap is beneficial as it increases the absorptive capacity to adopt innovations from external targets such as a new venture. A firm with prior innovations in a different plane is unlikely to have the readiness and capabilities needed to absorb external innovations in an unfamiliar area and expand on them.

However, the dynamics of overlap are markedly different for talent acquisition. That is, the distinctiveness of the acquired talent, relative to the existing pool of talent in the firm, helps to break the myopia of learning and to reap more benefits from such acquisitions (Song et al. 2003). In other words, the uniqueness of the acquired talent increases its value. Unlike innovation, which is the end-product of the entrepreneurial process, talent is the key input that generates and enacts other required inputs to instigate a process that creates innovation. While the consumption of the innovation outputs, i.e., innovation acquisition, requires absorptive capacities and existing matching processes that allow recycling of that innovation output and building on it, plugging in the key inputs to innovation, i.e., talent, is less dependent on other matching or existing inputs. Entrepreneurial talent is a self-generative input that fosters creation and adaptation. Instead, the existing literature (e.g., Nevo and Wade 2010) highlights that rareness of such key digital inputs increases their value. Especially if IT entrepreneurial talent is rarely supplied by local labor markets, firms successfully completing those talent acquisition moves can reap competitive rents from obtaining a rare and valuable input.

Aside from the internal factors, we also examine the heterogeneities of talent acquisition benefits conditioned on the frictions (shortage or hardship in accessing labor supply) in local IT labor markets. While there is ample empirical evidence supporting the spatial agglomeration of the IT entrepreneurial economy as a whole (see Guzman and Stern (2015) for instance), prior evidence supporting the spatial agglomeration of IT entrepreneurial labor is lacking. However, our pilot analysis based on the bank of 70 million online resumes, mentioned earlier, reveals that while the IT employees with an entrepreneurial background are 23 percent more likely to change jobs in a given year, relative to entrepreneurial employees in other industries, they are 36 percent less likely to change into a new job in another state. With 76 percent of IT entrepreneurial talent being employed at coastal locations in the US, our pilot analysis also shows that the graduates of business schools that are based in coastal states are almost four times more likely to either start their own digital venture or be a part of a digital patent filing, compared to their peers who graduate from business schools located in non-coastal states. Put together, this preliminary descriptive information suggests that the agglomeration of the IT entrepreneurial industry has also created spatially agglomerated IT labor markets with intense activity and limited geographic scope. Therefore, the spatial heterogeneity in the access to IT entrepreneurial talent through local labor markets impacts the heterogeneity in the value of CVC investments because those investments are alternative means of supplying entrepreneurial talent. Hence, we expect that the talent acquisition benefits of CVC investments are higher for firms that primarily operate in IT labor markets with friction (i.e., labor markets with a low supply of IT entrepreneurial talent). In other words, we expect that absent a high supply of IT entrepreneurial talent from local markets, CVC investments play a more valuable role in sustaining the flow of IT entrepreneurial inputs to a firm.

In examining our research questions, we utilize a multi-sourced longitudinal dataset of CVC investments in IT ventures, which are announced publicly and are over $5 million from 2000 to 2017. Data about the investments, characteristics of the investors (corporate) and targets (venture), and innovation acquisitions (in form of patent acquisition) are collected from *Lexis-Nexis*, *COMPUSTAT*, *CrunchBase*, *VentureXpert*, *US Patent and Trademark Office (USPTO)* databases, respectively. Finally, data from over 70 million job resumes, obtained from a major online recruiting website, is utilized to shed light on the movements of IT entrepreneurial talent. Our analysis based on 3,282 CVC investments on IT start-ups shows that: a) talent acquisition increases the CVC investments returns with a magnitude almost twice as high as the impact that innovation acquisition makes, b) the returns from acquired talent *decrease* with the extent of acquired talent overlapping with the investing firm's existing pool of talent, and c) the returns from acquired talent are higher for firms which are in local IT labor markets with friction. In economic terms, an otherwise-average firm that acquires around 23 employees from its target venture benefits from approximately 3 percent abnormal market return from its investment.

We believe that this study is among the first empirical attempts to evaluate the economic impacts of IT entrepreneurial talent and to document the boundary conditions that moderate its value. While innovation acquisition has been the predominantly-assumed value mechanism for CVC investments, our study highlights the critical role of these investments in overcoming the frictions in local IT labor markets. Below, we preface the description of our empirical study with some background information about CVC investments and their purposes and discuss our study's focus. Then, we present the details of our empirical study and conclude with discussing the implications of our findings for corporations who seek to join the lucrative CVC scene.

Strategic CVC Investments in the Digital Scene

For long, scholars have been interested in understanding the process of innovation production in firms, with an ample focus on internal innovation processes (Dushnitsky and Lenox 2005) where formal R&D expenditures and new product development teams drive the advent of new ideas and concepts. This interest in strategic management literature is also matched in studies specific to digital innovations (e.g., Yoo et al. 2010; Nambisan et al. 2017). More recently, the focus on the internal modes of innovation production has shifted to external modes, such as alliances, acquisitions (e.g., Ceccagnoli et al. 2012; Rai et al. 2012; Han et al. 2012), and particularly, CVC investments (e.g., Dushnitsky and Lenox 2005; Titus and Anderson 2018).

CVC investments in the digital scene embody a wide range of purposes, from purely driven by financial equity management reasons, where the primary purpose of investment is earning financial benefits by investing in up-and-coming digital businesses that are thought to embark disruptive digital transformations, to more strategic intents of stifling competition (catch-and-kill) and more importantly, acquiring external innovations. Especially the strategic purpose of innovation acquisition has received much of the attention (Benson and Ziodnis 2009) in the existing body of literature. In this study, similar to the previous literature, we focus on CVC investments with the strategic intent of innovation production, although, as we earlier discussed, our primary intent is to understand the value of talent acquisition from the targets of investment and compare such benefits with the more conventional means of benefiting from CVC investments, i.e., innovation acquisition. Below, we discuss the settings to our study.

Sample

In designing our, study, we start with a systematic search to identify a set of strategic CVC investments in the digital scene. We focus on the period from 2000 to 2017 and compile a list of digital new ventures relying on information from VentureXpert and CrunchBase database. Then, we use the search services of Lexis-Nexis and Factiva to search for CVC investments in these digital new ventures. From an initial set of 6,231 digital CVC investment announcements by public firms, we eliminate those with explicitly-mentioned financial purposes. Moreover, we eliminate the investments made by IT-producing firms with a shared market with the investment target, since those firms may be in direct competition with the invested-on digital ventures, therefore, the investment purpose could be purely driven by competition stifling. Moreover, we eliminate investments with a value below $5 million, since those smaller investments may not have the economic size to impact the bottom-line value in investing firms. Finally, we eliminate firm-year observations with two or more announcements per year, since our method of estimating the value of the investment cannot tease apart the conflating impact of multiple investments. After the elimination process, we retain 4,112 firm-year announcements belonging to 872 firms. Since our estimate of benefits from CVC investments considers a 2-year window post investment, we further eliminate observations from the same organization that overlap in the 2-year window in which the benefits of the CVC investment is estimated. This results in 3,282 CVC announcements made by 780 firms (with no more than one announcement per firm per year).

General financial and expenditure characteristics, as well as market information about these firms, are then obtained from COMPUSTAT and CRSP databases. Information about the Characteristics of the targets of the investments is then collected from CrunchBase, VentureXpert, and Angel.co. Further, information about patented innovations (filed patents) in both the investor and the target of investment is collected from the existing US Patent and Trademark Office (USPTO) databases. Finally, we access a unique set of 70 million online resumes, form a major online job search platform, which is used to obtain information about IT talent and its movement across firms. The investing firms in our sample are rather large firms with an average annual sales of $16 billion. The digital venture targets are on average 3 years post establishment with a rather considerable cumulated financial capital of $150 million prior to the CVC investment, indicating that the targets are rather successful and stable ventures. Most of the investing firms in our sample belong to retail, manufacturing, transportation, banking and financial services, telecommunication, IT, insurance, and healthcare industries. Table 1 summarizes the demographic information about investors (Panel A) and the targets (Panel B).

---Insert Table 1 Here---

Estimation and Measurement

We start our estimation by forming a regression model that assesses the impact of talent acquisition and innovation acquisition on the returns from a CVC investment:

(EQ.1) $$CVC\_Returns_{it} = \alpha + \beta_1 * Talent\_Acquisition_{it} + \beta_5 * Innovation\_Acquisition_{it} + Controls + Year + c_i + \epsilon_{it}$$

where subscripts *it* signify the extent of a variable for *i*th firm-announcement at year *t*, and *Controls* represents a matrix of control variables including CVC investment size (natural log of the $ value), R&D and capital expenditure by the firm, financial growth, financial leverage, firm size, and cumulative positive sentiment of other news about the investing firm in the window of time in which the CVC returns are estimated. Also, c_i captures the time-invariant firm-specific (investing firm) unobserved heterogeneity, Year is a time dummy which removes the fixed effect of the year in which the investment happens, and ϵ_{it} is the idiosyncratic error.

To remove the time-invariant firm-specific unobserved heterogeneity, we estimate EQ. 1 utilizing a fixed-effect regression. In the regression, ***CVC returns*** are estimated as the 2-year buy-and-hold abnormal return (BHAR) following the announcement, Following Barber and Lyon (1997). The 2-year buy-and-hold abnormal return estimates return on an investment based on daily market returns, where the abnormal return is the difference between the return on a stock and return on an appropriate benchmark. To build proper benchmark portfolios, firms are first sorted into deciles based on their market value of equity with the smallest decile further broken into quantiles, composing 14 size portfolios. Each portfolio is further divided into quintiles according to their market-to-book ratio of equity, resulting in 70 portfolios. Each of these 70 portfolios is further divided into 3 portfolios based on the stock price performance of firms in that portfolio over the previous year, resulting in 210 portfolios for each of the 216 months covered in the study. Then, each of the sample's firm-year announcements is assigned to a portfolio that best matches its characteristics in the month of announcement. Then, the combined daily returns on its stock value in a 500 business days after the announcement deducted by the combined daily returns on its portfolio is used as the measure of the CVC return.

Innovation acquisition is measured as the natural log of a firm's citations to the invested-on venture's patents within 500 business days after the announcement. ***Talent acquisition*** is measured as the natural log of a firm's employee recruits from the venture within 500 days after the investment. To obtain the employee movement information from the bank of online resumes, a select set of online resumes were first text-mined to identify the header keywords used to list previous and current job positions. Then, a bag of header keywords was formed to identify the details of job positions, and the identified sections of available resumes were searched to find matches with the set of investing firms and the target ventures in the samples. A talent move from the venture to the investing firm was identified if the focal employee: a) was employed at the venture at the time of investment, and b) departs the venture after the date of investment to start a position at the investing firm.

Because CVC investments are strategic choices for the investing firm, the firms in our sample self-select into the observed announcements. Building on the literature that has specified factors driving the strategic choice to invest in CVCs (i.e., Dushnitsly and Lenox 2005), we use Heckman's procedure to control for the hazard of selection in EQ. 1. To do so, the self-selection equation is specified as:

$$\text{(EQ.2)}\ Selection_{it} = \alpha + \beta_1 * CashFlow_{it} + \beta_2 * Patent\_Stock_{it} + Year + c_i + \epsilon_{it}$$

Cash flow and patent stock (natural log of the number of awarded patents to date) are measured from COMPUSTAT and USPTO databases. Tech opportunity and IP Protection are industry level covariates in Dushnitsly and Lenox's work, which are absorbed by estimating EQ. 2 via a fixed-effect regression. Moreover, since the extent of talent acquisition may depend on time-variant unobserved factors that simultaneously contribute to the BHAR of the investment, we instrument this variable by considering the presence of angel tax credits in the state where the firm is headquartered at the time of investment as well as by considering the average talent acquisition by firms in the same state but in a different industry[4]. For a better interpretation of coefficients, all independent variables are standardized. Table 2 presents descriptive statistics about the variables of the study. On average, the return on the CVC investment is 1.412 percent although this number fluctuates in a wide range between -8.37 and 12.64 percent. Moreover, average talent acquisition is around 16 employees.

Table 3 presents the results of estimating EQ. 1. Model 1 presents the results for the main period of 2 years. This model shows that while high levels of innovation acquisition contribute to 1.023 percent increase in the BHAR of a CVC investment, high levels of talent acquisition (one standard deviation above mean) contribute to a 2.267 percent increase in BHAR. Models 2 and 3 present the results of estimation when the window of BHAR estimation is 18 months and one year, respectively. Although the coefficient estimates of talent acquisition remain significant across models 2 and 3, the effect sizes subside. This points to the importance of the time required to integrate the acquired talent in order to reap economic benefits from it. Model 4 presents the results when the extent of talent acquisition is estimated by assigning weights to each recruit based on the number of patents that recruit has been involved in prior to the investment. Similarly, Model 5 presents the results when the weights to each recruit is determined based on the number of years of IT entrepreneurial activity as listed in their professional resumes. The results of Models 4 and 5 converge with those of Model 1, however, both models show a higher effect size when talent is weighted. Given this finding, the rest of the estimations in the study are based on a weighted measure of talent (based on the measure used in Model 4 since it shows the highest effect size).

Heterogeneity in Benefits from Talent Acquisition

[4] We believe both instruments are relevant to talent acquisition because they pertain to legislative incentives and normative institutional patterns that value entrepreneurial talent. Moreover, the instruments are determined exogenously to the locus of control in a focal firm, reducing their likelihood of being derivative from the same firm-specific time variant [unobserved] factors that influence talent acquisition.

Talent Overlap

To unfold the heterogeneities of talent acquisition benefits, we first adopt a control function approach to understand if the extent of overlap between the acquired talent and the existing pool of talent at the firm controls the extent of benefits reaped from talent acquisition following CVC investments. To remain consistent, we also model the extent of innovation overlap and assume it moderates the impact of innovation acquisition. In our control function approach, EQ.4 and EQ.5 model the levels of talent and innovation as dependent on talent and innovation acquisition, respectively. Each control function equation (4 and 5) also includes other proper covariates as identified in the relevant literature. As such, we test the following system of equations 3-5:

$$\text{(EQ.3)}\quad CVC\_Returns\ (BHAR)_{it} = \alpha + \beta_1 * Talent\_Overlap_{it} + \beta_2 * Talent\_Acquisition_{it} + \beta_3 * Talent\_Acquisition_{it} * Talent\_Overlap_{it} + \beta_4 * Innovation\_Overlap_{it} + \beta_5 * Innovation\_Acquisition_{it} + \beta_6 * Innovation\_Acquisition_{it} * Innovation\_Overlap_{it} + Controls + Year + c_i + IMR_{it} + \epsilon_{it}$$

Controls: CVC investment size, R&D and capital expenditure by the firm, financial growth, financial leverage, firm size, and cumulative positive sentiment of other news about the investing firm in the BHAR window

$$\text{(EQ.4)}\quad Talent\_Acquisition_{it} = \alpha' + \beta'_1 * Talent\_Overlap_{it} + Instruments\ Controls' + Year + c'_i + IMR_{it} + \epsilon'_{it}$$

Controls': CVC Investment size, External ownership, attainment discrepancy, average tenure of employees; Instruments: passage of state –wide angel credit tax, avg. talent acquisition by firms in same state but in a different 2-digit SIC code

$$\text{(EQ.5)}\quad Innovation\_Acquisition_{it} = \alpha'' + \beta''_1 * Innovation\_Overlap_{it} + Instruments\ Controls'' + Year + c''_i + IMR_{it} + \epsilon''_{it}$$

Controls": CVC Investment size, R&D, patent stock, industry's patent stock; Instruments: passage of state –wide angel credit tax, avg. innovation acquisition by firms in same state but in a different 2-digit SIC code

Garen (1984) suggests the following control-function specification to estimates the system of equations mentioned above:

$$\text{(EQ.6)}\quad CVC\_Returns\ (BHAR)_{it} = \alpha + \beta_1 * Talent\_Overlap_{it} + \beta_2 * Talent\_Acquisition_{it} + \beta_3 * Talent\_Acquisition_{it} * Talent\_Overlap_{it} + \beta_4 * Innovation\_Overlap_{it} + \beta_5 * Innovation\_Acquisition_{it} + \beta_6 * Innovation\_Acquisition_{it} * Innovation\_Overlap_{it} +$$

$$\beta_7 * \eta_{it} + \beta_8 * \eta_{it} * Talent\_Acquisition_{it} + \beta_8 * \eta'_{it} + \beta_9 * \eta'_{it} * Innovation\_Acquisition_{it} + Controls + Year + c_i + IMR_{it} + \epsilon_{it}$$

Where:

η_{it}: *above-expectation talent acquisition (residual from EQ. 4)*

η'_{it}: *above-expectation acquisition (residual from EQ. 5)*

In the above estimations, the degree of similarity between the keywords used in the filed patents of the venture and the investing firm prior to the investment is treated as the ***innovation overlap***. To estimate ***talent overlap***, we start by first identifying a set of keywords that different individuals use to list their IT skillset (e.g., MapReduce programming, NoSQL). Then, a comprehensive list of 358 unique skills is used to form vectors of technical skills (with 358 elements) at the individual level. From the individual skill vectors, aggregated vectors of skills for both the incoming labor and the investing firm's current employees are formed and the inverse value of the Mahalanobis distance between these two vectors is treated as the extent of *talent overlap*. Model 1 in Table 4 shows the results of this estimation for a 2-year BHAR estimation. Models 2 and 3 present the results for 18-month and one-year windows of BHAR estimation. Consistent with our expectations, the results of these models show a negative interaction between talent acquisition and the talent overlap, suggesting that firms benefit more by recruiting talent which is distinct from its existing pool. This finding stands in sharp contrast to the results pertaining to the interaction between innovation overlap and innovation acquisition where we find that increasing innovation overlap enhances the value of innovation acquisition post-CVC investments.

Labor Market Frictions: A Difference-in-Difference Estimation

While our previous analysis sheds light on the heterogeneities in benefits accrued from talent acquisition contingent upon internal characteristics of the firm, we also test for heterogeneities that are caused by external factors. Specifically, given the agglomerated nature of IT labor markets, we strive to understand if firms located in disadvantaged markets (with low IT entrepreneurial labor supply) benefit more from talent acquisition. To conduct this analysis, we seek to form a nearexperimental setting. In doing so, we start by categorizing firms based on being located (headquartered) in states with high or low IT entrepreneurial labor activity (Low_Supply dummy). This categorization is done based on the number of jobs accepted by IT entrepreneurs in that state in a given year. Then, we look for observations about firms with CVC investments in back-to-back years wherein year t-1 the investment was not followed by talent acquisition, whereas in the next year (year t), the investment is followed by talent acquisition (pool A). From pool A, we further eliminate firm observations that cannot be matched with at least one counterfactual observation in states with an opposite designation in terms of IT entrepreneurial labor activity[5]. Then, the following equation was estimated:

$$BHAR_{it} = \alpha + \beta \cdot Post_t * Low\_Supply_i + \gamma \cdot W_{it} + YEAR + c_i + \epsilon_{it}$$

The key variable of interest in this specification is the interaction term, *Post × Low_Supply*, where both Post and Low_Supply are dummy variables, indicating the year in which and the firm's investment in CVC is followed by talent acquisition (year t) and the firm is located in states with low IT entrepreneurial labor supply, respectively. The individual terms for Post and Low_Supply are not included in the regressions independently because their direct impacts are absorbed by date and firm fixed effects, respectively. β is a difference-in-difference (DID) estimate, with a positive (negative) value indicating that the BHAR (12-month) increases (decreases) in year t when the CVC investment is followed by talent acquisition in firms with low IT entrepreneurial labor market supply, relatively to those located in states with high IT entrepreneurial labor market supply. W_{it} represents a set of firm-level control variables which include the controls listed in EQ.1 in addition to the level of innovation acquisition. Model 1 in Table 5 presents the result of this DID estimation. The results indicate that adjusted for the baseline differences between the BHAR of CVC

[5] A coarsened exact matching (CEM) process based on size (employees), market share, and industry was performed to find counterfactuals.

investments in low- and high-supply states, talent acquisition in low-supply states is associated with an additional 1.26 percent increase in BHAR. Model 2 presents a similar estimation with the exception that instead of Post indicating a year with talent acquisition (after a year with no talent acquisition), it indicates a year with high levels (based on a median split) of talent acquisition (after a year with low levels of talent acquisition). The results remain robust to this variation. The results also remain robust when the categorization of firms into regions is simply based on coastal versus non-coastal states (Model 3).

To ensure that the observed heterogeneity in talent acquisition benefits across the low- and high-supply regions is actually due to talent acquisition and not caused by other time-variant factors that coincide with talent acquisition in year t, we conduct a placebo test. In this test, the settings are the same as the main DID design with the exception that we focus on observations where both in year t and t-1 low levels of talent acquisition (based on median split) occur after the CVC investment[6]. Model 4 in Table 5 reports the results of this estimation and shows a non-significant interaction term. This further increases the confidence in attributing the increase in BHAR of low-supply region firms to (high levels of) talent acquisition.

Conclusions

In summary, this study utilizes the power of new analytics platforms to analyze a corpus of over 70 million unstructured resumes and highlights the role of talent acquisition – in the form of talent recruitment, which has not been, hitherto, established as a mechanism – in creating value from strategic CVC investments. In doing so, the study unfolds two factors that contribute to the heterogeneities in reaping value from talent acquisition. First, the study unfolds that in sharp contrast

[6] We could not match enough firms with two consecutive year CVC investment and no talent acquisition in both years.

with the case of innovation acquisition, talent acquisition becomes more valuable when there is less overlap between the incoming talent and the pool of existing talent in the firm. Moreover, our study unravels the critical value of talent acquisition through CVC investments in regions that are far from IT entrepreneurial hubs and face a shortage in the supply of IT entrepreneurial talent. Put together, the study has two important implications for firms that strive to compete in the digital innovation scene. First, the unfolded role of talent acquisition as a viable value-creating path calls for further involvement of the human resources development function in the CVC process. This function has not been traditionally a part of CVC explorations. Second, the abnormal value of talent acquisition for firms based around local IT labor markets with a shortage of entrepreneurial talent suggests that CVC investments may be low-risk and low-cost solutions that can help a firm reduce its search frictions when targeting competition in the digital scene while operating far from the tech hubs. Despite the increasing interest in CVC, still, less than 1,000 firms in the US engage in frequent CVC investments. The findings of this study can add to the incentives that contribute to the growth of these types of investments in the external sources of digital innovation. Moreover, the findings stress that firms may need to look beyond patent acquisition prospects of a possible CVC investment and actively consider the benefits that can be accrued from an access to a pool of otherwise unavailable IT talent.

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Table 1. Demographics

	Mean	Median	S.D.	Max	Min
Panel A- Investing firms					
Sales (US$ Million)	16354.83	10784.22	8845.73	172314.7	824.23
Total Assets (US$ Million)	20673.41	10333.52	9203.76	433917.2	7129.93
Equity Market Value (US$ Million)	24375.83	16702.64	8801.26	425918.8	8205.34
Employment (thousands)	33.78	24.62	67.23	715.62	2.34
Panel B- Target ventures					
Funds Raised (US$ Million)	150.72	135.89	124.25	4004.19	22.35
Years since Establishment	3.76	2.18	4.33	8	1
# Fundraising Rounds	3.14	2.04	3.33	8	1
Employment	35.23	42.51	38.64	1218	5

Table 2. Descriptive Statistics

Variable	Mean	Std.	Min	Max
BHAR	1.412	1.982	-8.37	12.64
Innovation overlap	1.654	2.233	1	2.77
Innovation acquisition	0.751	1.214	1	2.89
Talent overlap	0.161	3.091	0	0.742
Talent acquisition	2.799	2.180	1	4.836
CVC investment	2.107	2.008	0	7.09
R&D expenditures	3.341	1.982	0	9.22
Capital expenditures	4.221	2.034	0	7.38
Growth	0.176	3.982	-1	214
Leverage	0.144	0.122	0	4.47
Firm size	3.114	3.451	0	7.74
Positive sentiment	0.126	0.231	0	0.87

Table 3. Main Analysis

	Model 1	Model 2	Mode 3	Model 4	Model 5
DV= Buy-and-Hold abnormal return (24-month)	24-month	18-month	12-month	Weighted Talent (patents)	Weighted Talent (Experience)
Constant	1.295***	1.005*	0.974*	1.373***	2.456***
	(0.347)	(0.5)	(0.406)	(0.252)	(0.643)
Innovation acquisition	1.027*	0.872#	0.762#	1.048**	0.977*
	(0.422)	(0.478)	(0.405)	(0.385)	(0.469)
Talent acquisition	2.267***	1.587***	1.023*	2.831***	2.533***
	(0.38)	(0.332)	(0.442)	(0.569)	(0.514)
Investment size	0.941*	0.887#	0.95*	0.95*	0.878#
	(0.441)	(0.487)	(0.408)	(0.417)	(0.452)
R&D expenditures	1.094**	1.137**	1.052**	1.127**	1.03*
	(0.382)	(0.369)	(0.369)	(0.361)	(0.434)
Capital expenditures	0.135	0.136	0.134	0.127	0.127
	(0.12)	(0.116)	(0.082)	(0.083)	(0.079)
Growth	0.021	0.021	0.02	0.022	0.022
	(0.013)	(0.014)	(0.012)	(0.019)	(0.016)
Leverage	0.371	0.401	0.356	0.356	0.398
	(0.326)	(0.241)	(0.235)	(0.271)	(0.295)
Window_Sentiment_Other_News	3.057***	2.821***	2.851***	3.086***	3.086***
	(0.477)	(0.472)	(0.516)	(0.563)	(0.672)
Adj. R^2	*0.67*	*0.62*	*0.53*	*0.78*	*0.072*
Firm-year observations	*3,282*	*3,814*	*4112*	*3,282*	*3,282*
Number of unique firms	*789*	*844*	*872*	*789*	*789*

Notes: $^{\#}$, p<0.10; *, p<0.05; **, p<0.01; ***, p<0.001. BHAR portfolios are built based on assets, size, and book-to-market ratio. All models are estimated with a fixed-effects specification, with year fixed effects, as well as inverse-mills ratio of CVC self-selectivity in the sample accounted for. The self-selection to sample is explained by firm's cash flow and patent of stock.

Table 4. Control Function Estimation

	Model 1	Model 2	Model 3
DV= BHAR	*24-month*	*18-month*	*12-month*
Constant	1.239***	1.073**	0.999*
	(0.215)	(0.402)	(0.485)
Talent overlap	0.011	0.011	0.012
	(0.008)	(0.007)	(0.007)
Talent acquisition	2.388***	2.224***	1.972***
	(0.418)	(0.408)	(0.318)
Talent overlap * talent acquisition	-0.99*	-0.909#	-0.758
	(0.429)	(0.515)	(0.564)
Innovation overlap	0.658	0.609	0.535
	(0.519)	(0.426)	(0.438)
Innovation acquisition	1.074**	0.894#	0.889#
	(0.338)	(0.51)	(0.479)
Innovation overlap * Innovation acquisition	0.948*	0.871#	0.849#
	(0.441)	(0.494)	(0.486)
Above-expectation talent acquisition	0.765	0.742	0.665
	(0.603)	(0.466)	(0.472)
Above-expectation talent acquisition *	1.234***	1.27***	1.031*
talent acquisition	(0.374)	(0.343)	(0.406)
Above-expectation innovation acquisition	1.108**	0.929*	0.778
	(0.415)	(0.416)	(0.596)
Above-expectation innovation acquisition* innovation	0.213	0.174	0.172
acquisition	(0.14)	(0.148)	(0.138)
Wald's χ^2	*0.82*	0.64	0.53
Firm-year observations	*3,282*	*3,814*	*4112*
Number of unique firms	*789*	*844*	*872*

Notes: #, p<0.10; *, p<0.05; **, p<0.01; ***, p<0.001. BHAR portfolios are built based on assets, size, and book-to-market ratio. All models are estimated with a fixed-effects specification, with year and industry fixed effects, as well as inverse-mills ratio of CVC self-selectivity in the sample accounted for. The self-selection to sample is explained by firm's cash flow and patent of stock. The coefficient estimates for control variables are excluded for brevity. The first-stage estimations (equations (2) and (3)) of Garen's approach are excluded for brevity.

Table 5. Difference-in-Difference Estimation

	Model 1	Model 2	Mode 3	Model 4
DV= Buy-and-Hold abnormal return (24-month)	Main	Median Split	Coastal/non-Coastal	Placebo
Constant	1.282***	1.36***	1.334***	1.282***
	(0.338)	(0.359)	(0.319)	(0.22)
Post * Low_Supply	1.192***	1.357***	1.306***	0.151
	(0.206)	(0.293)	(0.36)	(0.106)
Innovation acquisition	0.857#	0.893#	0.875#	0.902#
	(0.447)	(0.529)	(0.483)	(0.524)
Investment size	1.007*	0.96*	0.932*	0.95*
	(0.44)	(0.414)	(0.422)	(0.416)
R&D expenditures	1.017*	1.083**	1.083**	1.171**
	(0.474)	(0.415)	(0.357)	(0.362)
Capital expenditures	0.142	0.132	0.140	0.138
	(0.106)	(0.083)	(0.116)	(0.083)
Growth	0.021	0.022	0.021	0.022
	(0.018)	(0.019)	(0.016)	(0.013)
Leverage	0.349	0.364	0.349	0.352
	(0.208)	(0.249)	(0.265)	(0.25)
Window_Sentiment_Other_News	2.214***	2.304***	2.101***	2.349***
	(0.431)	(0.368)	(0.378)	(0.39)
Adj. R^2	*0.67*	*0.73*	*0.62*	*0.53*
Firm-year observations	*384*	*564*	*408*	*776*

Notes: #, p<0.10; *, p<0.05; **, p<0.01; ***, p<0.001. BHAR portfolios are built based on assets, size, and book-to-market ratio. All models are estimated with a fixed-effects specification, with year and industry fixed effects, as well as inverse-mills ratio of CVC self-selectivity in the sample accounted for.