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Who creates jobs? Venture capital, research grants, and regional employment in the U.S.

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ABSTRACT

We build on the exploratory and exploitative learning literature that suggests that venture capital and governmental research grants may impact regional employment in a different manner. Using a regional employment dataset in the U.S. (United States) medical device sector, our analysis reveals that research grants contribute to create a greater level of regional employment compared with venture capital funding. Furthermore, the positive effects of both funding sources are more salient when intellectual capital is abundant in the region. More specifically, the interaction effect of research grants and intellectual capital is gradually increased in the long term and eventually becomes greater than that of venture capital and intellectual capital, which is relatively constant. These findings highlight the heterogeneous motivations and consequences of two funding sources that should be considered in the future resource allocation policy accordingly.

KEYWORDS

Employment; venture capital; research grant; intellectual capital; medical device

JEL CLASSIFICATION

G24; L26; O38; R10

1. Introduction

In the last two or more decades, a key concern of the U.S. (United States) federal and local governments turns on whether and how they create quality jobs in a timely and cost-efficient manner. This issue is also critical for company strategists to determine how to allocate their resources because the local economy is an important part of their business ecosystems. This concern is particularly true to technology-intensive industries, where the pace of technology development is fast, the expense of updating human capital is high, and the ripple effect on other industries is profound (Griffin 2002). In response to these pressures, public and private sectors often seek an efficient strategy to create regional jobs. To do so, it is important to understand the motivations and consequences of financial capital because financial capital is easier to control compared with other resources, and impacts the performance of organizations that have utilized it.

While prior studies have provided ample evidence that financial capital is critical to enhance the local employment (e.g., Easterly and Sergio 1993; NVCA 2009), relatively...
little is known as to how each funding source impacts regional employment in a different manner. Indeed, most prior studies have typically focused on a single source of financial capital or have treated distinguishable funding sources in a holistic perspective. Given that each funding source has its own motivation and investment pattern, it is needed to examine how heterogeneous funding sources impact regional employment in a different way. For example, venture capital and governmental research grants have been recognized as the important sources of financial capital in the literature. While the former is private capital that pursues capital gains through supporting start-ups, the latter is public capital that often fulfills societal objectives. These two funding sources may affect regional employment in a different manner due to the heterogeneous motivations and investment patterns. The lack of comparative analysis in the existing literature raises two interesting and interrelated research questions, including (1) how venture capital and research grants impact regional employment, respectively, and (2) what contextual factors shape these relationships. In particular, we explore the distinct roles of research grants and venture capital with regard to the level of regional employment.

Understanding the different roles of capital type allows us to avoid a serious misestimation regarding the effect of financial capital on the level of employment. The consequence of misestimation can be a sub-optimal decision that generates unnecessary costs to governments and companies. The first source of misestimation is the lack of appropriate typology for financial capital. Given that research grants and venture capital funding pursue different objectives, the drawback of adopting a holistic perspective is that it essentially provides an aggregate analysis of two components that cannot be aggregated simply. The second source of misestimation is the lack of proper dissection of interactions between both funding sources and other types of capital, which can impact the level of employment. Anecdotal evidence suggests that financial capital often contributes to create intellectual capital, and vice versa (e.g., Kortum and Lerner 2000; Hellmann and Puri 2002; Agrawal and Henderson 2002; Freeman 2010; Samila and Sorenson 2010, 2011). These two factors may interact with each other and subsequently impact the level of employment. The failure to consider this interaction effect may hinder effectively leveraging each funding source.

To address these issues, we elaborate on the perspective of explorative and exploitative learning (March 1991; Levinthal and March 1993). This framework can be readily integrated with the distinguishable characteristics of venture capital and research grants. Exploitative learning is associated with short-term return and involved with the refinement, efficiency, and execution of existing capabilities. These characteristics are consistent with the investment patterns of venture capital funding that often focus on the investee’s commercialization in order to harvest capital gains in the short term. In contrast, explorative learning is related to uncertain and long-term returns and focuses on research for experimenting with and developing new competencies. These features resemble research grants that aim to search fundamental scientific discoveries in uncertain research settings. We hypothesize that these dual strategic initiatives may impact the level of employment in a different manner.

The synthesis of literature allows us to predict the effects of venture capital and research grants on the level of employment. Exploring more distant and fundamental scientific discoveries, research grants (e.g., National Institutes of Health (NIH) research grants) are more likely to facilitate hiring scientists into existing research-based organizations. Venture
capital funding is likely to facilitate the level of employment by establishing start-ups. This
direct effect of venture capital may be less than that of research grants because it has an
offset effect in which venture capital funding may expel incumbent businesses as well as
form new businesses. Furthermore, these positive effects can be differentiated by how
intellectual capital is abundant in the region. The interaction effect of venture capital
funding and intellectual capital may be greater than that of NIH funding and intellectual
capital in the short term because venture capital is often invested in more applied technol-
gies that can be commercialized immediately. In contrast, the interaction effect of research
grants and intellectual capital may gradually increase and surpass that of research grants
and venture capital funding in a long term because research grants tend to create basic
knowledge that takes a considerable time to be commercialized.

To empirically examine these predictions, this study uses 2,573 annual employment
records of 247 distinct metropolitan statistical areas (MSAs) in the medical device
sector between 1990 and 2001. Using the information of NIH research grants and
venture capital funding endowed in these regions, we find systematic evidence that
governmental research grants creates a greater level of employment compared to
venture capital funding. This finding justifies the societal support of research projects
proceeded in universities and leading laboratories. Furthermore, using the production
function approach, we find that the interaction effect of research grants and intellectual
capital is of an initially lower magnitude that that of venture capital and intellectual
capital for the first three years after endowments, but then increases at a greater rate,
eventually surpassing that of venture capital and intellectual capital. These findings
highlight the heterogeneous motivations and consequences of research grants and
venture capital funding. While research grants often aim to support basic research to
create and enhance inventions (e.g., ‘Research’ in R&D), venture capital invests in the
applied research that may commercialize these inventions (e.g., ‘Development’ in R&D)
quickly. Given these distinguishable motivations, research grants take a significantly
longer time to realize the interaction effect with intellectual capital in order to create
local jobs than venture capital does. Using two-stage least squares regression, we
present that these findings are robust to possible endogeneity issues.

This paper is organized as follows. The next section presents our theoretical frame-
work and hypotheses. The following section describes our data, empirical strategy, and
variables. We then report empirical results and conclude.

2. Theoretical framework of research grants and venture capital funding

2.1. Related literature

Ever since Solow (1956) provided his model of economic growth, which is based on the
neoclassical production function in which financial and labor capital serve as key
factors of production, many researchers have relied on this model as a basis for
explaining the determinants of the regional economy measured by regional employ-
ment levels. With the endogenous growth theory, Romer (1986) and Lucas (1988)
suggested that intellectual capital (e.g., technology, knowledge, and innovation) should
also be an important factor that determines employment levels, along with traditional
financial and labor capital. Following this line of studies, Audretsch (1995) further
suggested that entrepreneurial capital would play a critical role in determining the employment level. Specifically, the knowledge spillover theory of entrepreneurship and new venture creation explicitly consider the importance of new ventures on employment effects. Hence, a simple production function has developed thus far in this strand of literature as:

\[ Y_i = \alpha K_i^{\beta_1} L_i^{\beta_2} R_i^{\beta_3} E_i^{\beta_4} e^{\varepsilon_i} \] (1)

where \( Y_i \) is the level of employment, \( K_i \) is financial capital, \( L_i \) is labor capital, \( R_i \) is intellectual capital, \( E_i \) is entrepreneurial capital, and \( i \) refers to the respective regions.

This argument, however, is not complete because financial capital is not homogeneous (Audretsch 1995; Samila and Sorenson 2010). Each financial capital source has its own motive and investment pattern. By the source of capital, financial capital can be divided into public and private funding. NIH research grants and venture capital funding represent such public and private funding, respectively, in this study. However, other funding sources are available in public and private funding. The justification for allocating research grants stems largely from a belief that the ideas and inventions emerging from the research, which has been funded by government, lead to new inventions and improved products, and to more efficient and higher quality manufacturing, and thus to an acceleration in economic growth (Malakoff 2000). In contrast, venture capital funding leads to the formation of new start-ups that, in turn, may create new employment opportunities. In this context, Samila and Sorenson (2010) suggest that the public funding of academic research and venture capital have a complementary relationship in fostering innovation and the creation of new firms.

Along with distinguished sources of financial capital in the literature, we suggest not only the direct effect of venture capital and NIH funding on regional employment, but also the interaction effect of intellectual capital and these two funding sources. An interaction effect is defined as the effect of financial capital on regional employment is differentiated by the level of intellectual capital that also eventually enhances regional economy. As a result, we suggest an advanced model from Equation (1):

\[ Y_i = \alpha K_{1i}^{\beta_1} K_{2i}^{\beta_2} L_i^{\beta_2} R_i^{\beta_3} K R_i^{\beta_4} E_i^{\beta_5} e^{\varepsilon_i} \] (2)

where \( K_{1i} \) is venture capital funding, \( K_{2i} \) is NIH funding, and \( KR_i \) is viewed as the interaction function of \( K_{1i} \) and \( K_{2i} \) and \( R_i \), respectively.

Furthermore, as entrepreneurial firms and research institutions serve as intermediaries between funding sources and subsequent economic outcomes, the nature of their activities can be either exploitative or explorative. There are considerable differences between the two types of learning activities. Exploitative learning is associated with certain and short-term return that involves the refinement, efficiency, and execution of current abilities. In contrast, explorative learning is related to uncertain and long term return that focuses on searching for, experimenting with, and developing new competencies (March 1991). Many organizations pursue complementary returns from both types of activities, yet they face trade-offs associated with the execution of both, a situation referred to as the exploration-exploitation paradox (Tushman and O’Reilly 1996).

We argue that the economic outcomes of financial capital are, at least in part, contingent on the motivation of funding sources and the strategic goals of organizations
that have received the funding. In particular, NIH research grants often support existing research institutions, are driven by social objectives, and focus on fundamental scientific discoveries. This motivation of governmental funding is consistent with the characteristics of exploration activities. In contrast, venture capital funding enhances the formation of new entities, primarily pursues capital gains in a short term (less than 10 years in the limited partnership agreement), and thus focuses on more applied technology that can be commercialized quickly. To fulfill these distinguishable motivations and secure future funding, each organization operates differently.

2.2. Hypotheses development

The relationship between venture capital funding and local employment is quite complex because analyzing this relationship requires comprehensive entrant and incumbent effects (Fritsch and Mueller 2004; Fritsch 2008). Considering the entrant effect, there are three primary reasons that venture capital funding can increase regional employment levels. First, venture capital funding leads to the formation of new start-ups that create new employment opportunities and thus augments the stock of regional jobs (Kenney 1986; Lerner 1994, 1995; Wennekers and Thurik 1999; Von Burg and Kenney 2000; Furman, Porter, and Stern 2002; Puri and Zarutskie 2012; Samila and Sorensen 2011). For example, venture capital-backed companies created 12 million jobs and generated nearly 3 trillion U.S. dollars in revenue in 2008 (NVCA 2009). These figures accounted for 11% of private-sector employment and represented the equivalent of 21% of U.S. GDP during the same year.

Furthermore, new start-ups further constitute a competitive threat to incumbents and encourage the incumbents to perform better (Disney, Haskel, and Heden 2003). Specifically, start-ups can induce the re-allocation of inputs and outputs, trigger knowledge spillovers, and affect the productivity of incumbents, eventually creating employment opportunities in the incumbents. Finally, start-ups provide multiple channels for the transfer of new ideas and innovation to an economy, which has been shown to be a key source of long-term economic growth (Romer 1986; Audretsch and Stephan 1996).

On the other hand, there are also three reasons that venture capital funding may not increase the level of employment. First, start-ups newly formed and funded by venture capital may have a competitive advantage over incumbents, and these inferior incumbents can be forced out of business (Van Stel and Storey 2004). As a result, new employment opportunities created in the start-ups may come at the expense of a decrease in the stock of jobs in the incumbents (i.e., incumbent effect). If this decrease is greater than the number of jobs created by new start-ups funded by venture capital, we will observe a negative effect of venture capital on the level of employment. Secondly, there is a possibility that these start-ups will contribute only a negligible portion of jobs in the local economy because of their high mortality rate. In some cases, upward of 40% of start-ups funded by venture capital end up with three years in assisted suicide, known as the 'venture capital Dr. Kevorkian effect’ (Puri and Zarutskie 2012). Finally, the formation of start-ups may facilitate labor mobility from incumbents without creating new jobs in industries that require a highly educated and skilled labor force.
These contrasting predictions may be resolved by the possible reactions of incumbents against the formation of start-ups funded by venture capital. Empirical studies provide mixed findings on how incumbents react against the start-ups (Aitken and Harrison 1999; Pavcnik 2002; Javorcik 2004). Aghion et al. (2006) suggest that new entries affect the innovative effort by incumbents in a systematically different way according to the initial state of the productivity of incumbents. Incumbents that are further behind the productivity frontier have no hope of winning against a potential entrant. Therefore, the effect of an increased entry threat is to reduce the incumbents’ competition against the entrant. In contrast, incumbents that are close to the frontier are willing to compete against the potential entrant because they may want to maintain their positions of productivity. This ‘escape-competition’ theory implies that the new formation of start-ups funded by venture capital may selectively force out less-competitive incumbents from the business and enhance the productivities of more-competitive incumbents simultaneously. Furthermore, the crowding-out of existing entities requires a substantial amount of time to occur, and the addition of new capacities by new entities funded by venture capital quickly create the stock of regional jobs. To summarize, we hypothesize:

**Hypothesis 1. Venture capital (VC) funding increases regional employment levels.**

NIH grants are important funding sources not only for hiring scientists who pursue scientific discoveries but also in supporting entrepreneurs who establish new start-ups. For example, the NIH training program supports universities in hiring post-docs and principal investigators at laboratories. NIH stipend levels set post-doc pay, which are combined with research grants, and determine the number of employed post-docs (Freeman 2010). For those seeking to work as principal investigators, winning a research project grant (R01) is critical for their career trajectory. R01 is the original and historically oldest grant mechanism used by the NIH. The R01 provides support for health-related R&D (Research & Development) based on the mission of the NIH. Consistent with this role of the NIH, Hausman (2012) finds that NIH funding and regional employment levels have statistically significant and positive correlations with each other. In addition, Stephan (2006) suggests that a highly trained workforce will be maintained only if the federal government increasingly steps in to provide financial support for higher education. Since there is not incumbent effect involved with NIH grants, the potential effect of NIH funding on the regional employment is much simpler and greater than that of venture capital is. To summarize, we hypothesize:

**Hypothesis 2. National Institutes of Health (NIH) funding increases regional employment levels.**

Both venture capital and research grants could be understood, at least in part, as a critical resource to create intellectual capital, and vice versa. Indeed, the financial and intellectual capital may interact with each other in enhancing the level of regional employment. Specifically, while venture capital helps start-ups transform intellectual capital into economic outputs, abundant intellectual capital often attracts venture capital funding in the region. For example, Kortum and Lerner (2000) find that venture capital funding may have
accounted for 8% of industrial intellectual capital between 1983 and 2002. Hellmann and Puri (2002) find that venture capital funding is related to a start-up’s professionalization that facilitates the creation of intellectual capital. In addition, venture capital firms often seek compelling evidence as to whether and where a start-up’s intellectual capital fits in the marketplace. A start-up’s patenting performance is often used to evaluate this capability and thus often attracts venture capital funding. Moreover, the existing literature suggests that intellectual capital positively impacts regional economic performance in several ways, including the formation of start-ups, knowledge spillovers, and product development (Audretsch 1995; Sutton 1997; Caves 1998; Audretsch and Fritsch 2002; Acs and Armington 2002; Barkley, Henry, and Nair 2006).

Venture capital funding is typically involved with the commercialization of intellectual capital that would require more applied research rather than basic research. Start-ups often seek technology spillovers to leverage specialized and fundamental scientific discoveries without capturing the R&D costs (Jaffe 1986, 1989; Jensen and Thursby 2001; Thursby and Thursby 2002; Rothaermel and Thursby 2005). This feature is suitable to pursue exploitative learning activities that are associated with the refinement, efficiency, and execution of existing capabilities. As noted, these activities allow venture capital firms to pursue capital gains in a short time. If abundant intellectual capital is available in the region, venture capital funding may be more attracted and facilitate the formation and growth of start-ups more efficiently by pursuing cost and time efficient product development processes. Consequently, this interaction between venture capital and intellectual capital can help start-ups grow and achieve a greater level of employment. In contrast, if there is a lack of intellectual capital in the region, start-ups would be less efficient to advance the commercialization processes because it imposes additional costs to develop necessary intellectual capital, thereby slowing the formation and growth of start-ups and creating a lower level of employment. As such, we hypothesize that venture capital funding is particularly more effective to enhance regional employment when there is plenty of intellectual capital available in the region. With the motivation of venture capital funding, it is predicted that this interaction effect between venture capital funding and intellectual capital is likely to occur in a shorter term.

This prediction is coupled with a discussion that intellectual capital may be ‘sticky’ at certain times (Szulanski 1996), which indicates that it may not be completely transferred to the market place. Stickiness occurs particularly if a significant amount of knowledge is tacit in nature (Rothaermel and Ku 2008). Hence, intellectual capital tends to be heterogeneously distributed across geographical regions (Glaeser et al. 1992; Jaffe, Trajtenberg, and Henderson 1993; Agrawal, Kapur, and McHale 2008). To summarize, we hypothesize:

**Hypothesis 3.** (A) The positive relationship between venture capital (VC) funding and regional employment levels is stronger when a greater amount of intellectual capital is available in the region; and (B) this interaction effect occurs in a shorter term.

Governmental research grants often support existing research institutions and aim to generate scientific knowledge through basic research. For example, Freeman (2010) finds that *Science* listed 276 papers as contributing to its top ten breakthroughs from 2003 through
2008, when 110 (40%) of the papers were funded by NIH. Beyond this effect on publication, NIH funding allows the employment of highly educated scientists that provide a means by which knowledge is transferred from the university to industry (Agrawal and Henderson 2002; Stephan 2006; Sumell, Stephan, and Adams 2009). These knowledge creation and transfer activities are, by nature, involved with developing new competencies in the uncertain environment with a long-term setting. These activities fall into exploratory learning activities, which are not suitable for venture capitalists that pursue capital gains in a short time. It is hypothesized that these activities are facilitated within an environment where abundant intellectual capital is available in the region because it reduces uncertainty in the research processes and facilitates scientific discoveries by combined with the efforts of scientists.

As such, the effects of venture capital and NIH funding are different in terms of what kind of knowledge is created and when the knowledge is created. Given the framework of exploratory and exploitative learning, we argue that venture capital funding is likely to facilitate exploitative learning in which learning occurs relatively in a short term. On the other hand, NIH funding is likely to be suitable to pursue exploratory learning and takes a longer time to realize its learning effect. To summarize, we hypothesize:

*Hypothesis 4. (A) The positive relationship between National Institutes of Health (NIH) funding and regional employment levels is stronger when a greater amount of intellectual capital is available in the region; (B) this interaction effect occurs in a longer term.*

*Figure 1* summarizes our discussion thus far and illustrates the direct and interaction effects of venture capital (*Figure 1(a)*) and research grants (*Figure 1(b)*) and intellectual capital, respectively, on the level of employment. $\beta_1$ is the direct effect of venture capital funding; $\beta_2$ is the interaction effect of venture capital funding and intellectual capital; $\beta_3$ is the direct effect of NIH funding; and $\beta_4$ is the interaction effect of NIH funding and intellectual capital on the level of employment. (+) and (−) indicate positive and negative effects, respectively. In *Figure 1(a)*, we predict that $\beta_1$ is positive, although there is a trade-off between the effect of venture capital funding on new and existing entities. We also predict that $\beta_2$ is positive because venture capital funding interacts with intellectual capital that secures industry efficiency, resulting in job creation. In *Figure 1(b)*, we predict that $\beta_3$ is positive because NIH funding increases the level of employment in existing entities and new entities. We also predict that $\beta_3$ is significantly greater than $\beta_1$ because there is no trade-off between the effects of NIH funding on new and existing entities. Because NIH funding focuses on basic research (e.g., academic publication) rather than applied research, we predict that $\beta_4$ is smaller than $\beta_2$ for a substantial period and then increases at a greater rate, eventually dominating $\beta_2$.

### 3. Data, empirical strategy, and measures

#### 3.1. Data

Our sample is based on medical device cluster performance data between 1990 and 2001. We obtained this data from the *Cluster Mapping Project* at the Institute for Strategy and Competitiveness (ISC) at the Harvard Business School. The medical device sector is
characterized as a vibrant high-technology sector, which invents, develops, manufactures, and sells medical device implants and other external products, allowing us to observe closely how venture capital, research grants, and intellectual capital plays to shape the regional employment. We select the Cluster Mapping Project rather than census data, such as the Country Business Patterns from the Census Bureau, because we want to consider the agglomeration forces arising among closely related industries and complementarities in the medical device sector. Industries within a cluster benefit from complementarities by sharing common technologies, knowledge, inputs, and cluster-specific institutions (Delgado, Porter, and Stern 2012). Regional clusters are primarily constructed by a prominent core industry in the medical device sector. Other industries that have statistically significant and substantial intercorrelations among each other define the cluster (http://www.isc.hbs.edu). By focusing solely on the medical device sector, we naturally control for factors that prior studies have argued were important: tax burdens (Easterly and Sergio 1993; Mofidi and Stone 1990), public infrastructure (Aschauer 1989; Evans and Karras 1994), and industry structure (Higgins, Levy, and Young 2006).

Coupling with the concept of cluster, we included all metropolitan statistical areas (MSAs) with nonzero medical device employment. Zero medical device employment areas are excluded to avoid sampling on the dependent variable, a frequently observed problem of cluster studies relying on small samples. We identified medical device firms located in 247 MSAs. These observations are matched with several data sources,
including the SDC Platinum VentureXpert database, the Office of Extramural Research at the NIH, the USA Patent and Trademark Office, and the National Science Foundation (NSF), to construct variables. We finally obtained 2,537 MSA-year observations after counting missing values.

### 3.2. Empirical strategy

We use the specification of the neoclassical model presented in Equation (2) as a base model that is predominant in the literature: an additively separable linear specification using the production function. While the base model is simple to estimate, there are some concerns. The first concern is related to the time lag between the endowments of venture capital and NIH funding and the realization of their effects on the level of employment. This potential time lag should be considered in a model specification because venture capital and NIH funding may not always immediately impact the level of employment. Since the existing literature is sparse on the topic of specifying the time lag, we investigate the period of seven years after venture capital and NIH funding are endowed in order to secure the model identification.

The second concern is related to the choice of control variables. It is possible that the level of employment can be impacted by some other factors that are not included in Equation (2). To address this concern, we control for the level of employment in the previous year \((t − 1)\) of the endowments of venture capital and NIH funding \((t)\) (i.e., \(E_{it−1}\)) and MSA- and year-fixed effect, resulting in our empirical specification being a first-order autoregressive model (i.e., AR(1)) with fixed effects. This inclusion also controls for the size of the medical device industry in the region. Specifically, we estimate the following fixed-effects AR(1) models that predict the level of employment \((E_{it})\) in the medical device industry at \(t\), \(t + 1\), \(t + 2\), \(t + 3\), \(t + 4\), \(t + 5\), \(t + 6\), and \(t + 7\), respectively:

\[
E_{it} = \alpha_0 + \beta_1 E_{it−1} + \beta_2 X_{it} + \beta_3 Z_{it} + \mu_{it} \tag{3}
\]

where \(X_{it}\) are independent variables of interest; \(Z_{it}\) are control variables; and \(t\) denotes the year in which venture capital and NIH funding is endowed in region \(i\).

To estimate the interaction effects of venture capital and NIH funding and intellectual capital, we use a production function approach that performs a simple one-tailed \(t\)-test on the interaction term of the two funding sources and intellectual capital, respectively. This approach examines the cross-derivative of interaction variables. If hypotheses 3 and 4 are supported, we should see that the regression coefficients of two interaction variables are significant and positive on the level of employment.

As a sensitivity analysis, we elaborate endogeneity issues potentially pertained in the empirical model. Specifically, we use two stage least squares (2SLS) or instrumental variable estimation, which allows for consistent estimation of simultaneous equation with endogenous explanatory variables. This approach is used when an explanatory variable of interest is correlated with the error term, in which case ordinary least squares (OLS) provides biased results. To implement this approach, we need to find a valid instrument variable that induces changes in the explanatory variable but has no independent effect on the dependent variable. Our potential endogenous explanatory variables include VC funding, NIH funding, and intellectual capital.
Since our model is focused on the estimation in the level of local employment, it is very hard to find appropriate instrumental variables, which are not correlated with the level of employment and correlated with the variables of interest, to perform 2SLS regressions. To remedy this issue, we use Lewbel’s (2012) approach. This approach allows us to generate instrumental variables with existing variables in the model and does not require use of external instruments or repeated measurement. This technique allows the identification of structural parameters in regression models with endogenous or mismeasured regressors in the absence of traditional identifying information. As such, instruments are constructed as simple functions of the model’s data. This approach may thus be applied when no external instruments are available, or, alternatively, used to supplement external instruments to improve the efficiency of the instrumental variable estimator. We believe this approach helps clarify the causality between venture capital and NIH funding and the level of employment and alleviates the concern of an omitted variable, which may produce inconsistent estimates.

3.3. Dependent variable

In this study we attempt to explain inter-cluster performance differentials in terms of employment; thus, our dependent variable is the level of employment in the region. To assess the level of employment, we use the log of the number of employees in the medical device sector at year t and in region i. This information was collected from the Cluster Mapping Project.

3.4. Independent variables

3.4.1. Financial capital

We examine the effects of two types of financial capital: venture capital and NIH funding. Venture capital funding is the log of the amount of venture capital invested in the medical device firms at t and in i. This variable was collected from the SDC Platinum VentureXpert database published by Thomson Financial. Since there is a possibility that a single venture capital transaction is recorded repeatedly across sectors, we limited venture capital transactions invested in medical device firms to the medical and health sector, eliminating the possibility of double counting. To alleviate any estimation biases caused by inflation, we converted all financial data into 2001 constant U.S. dollars using the Current Consumer Price Index (CPI-U) published by the Bureau of Labor Statistics.

NIH funding is measured by the log of the amount of NIH research grants annually awarded with research projects related to the development of medical devices within i at t. We obtained the data from the Office of Extramural Research at the NIH. This variable is also deflated using the CPI-U index. Please note that all the following explanatory variables are estimated at t. For simplicity, t is omitted in the notation.

3.4.2. Intellectual capital

We proxy an MSA’s intellectual capital using the number of medical device patents assigned to each cluster by the U.S. Patent and Trademark Office. Patenting is an important competitive element in this sector because firm growth is greatly determined by continued innovation, and protecting intellectual property through patents appears to be quite effective (Cohen, Nelson, and Walsh 2000).
3.5. Control variables

3.5.1. Human capital
Prior studies suggest that inter-cluster innovation and economic growth differentials are a function of the clusters’ endowments in human capital. Specifically, research universities provide critical elements for innovation within technology clusters because they are a primary source of knowledge spillovers (Zucker, Darby, and Brewer 1998; Thursby and Thursby 2002; Rothaermel and Thursby 2005; Audretsch, Lehmann, and Warning 2005; Mueller 2006). We use the log of the number of science Ph.D. graduates who achieve the degree from universities located within i at t to assess an MSA’s human capital endowment (e.g., MacGarvie and Furman 2005; Stephan 2006). It is expected that a wide variety of engineering disciplines from the chemical, electrical, mechanical, and biomedical areas contribute to but do not dominate the medical device sector. For example, medical sciences are more fundamental in nature than the engineering sciences and tend to span these specific disciplines. However, engineering sciences are critical for converting inventions into commercially viable products. Annual data on individuals with Ph.D.s were obtained from the National Science Foundation (NSF) and then mapped onto each medical device cluster.

3.5.2. Entrepreneurial capital
Many of the elements that determine entrepreneurial capital exist in the present definition of entrepreneurship. In any case, entrepreneurial capital, like all other types of capital, is multifaceted and heterogeneous (Audretsch and Keilbach 2004). However, it manifests itself singularly in new enterprises. Thus, entrepreneurial capital is primarily estimated using the size of medical device firms and the vigor of medical device industry simultaneously within i at t. In particular, we use a discrete variable that includes three sub-groups of MSAs using the number and average size of the medical device firms as two demarcation lines. Group I represents the MSAs that record below the median of the number of firms and above the median of the average size of firm, and it is coded as 0. Group III represents the MSAs that record above the median of the number of firms and below the median of the average size of firms, and it is coded as 2. Group II represents the MSAs that do not fall into these two groups and is coded as 1. A greater value indicates a higher level of entrepreneurial capital endowed in i at t.

4. Empirical results

4.1. Descriptive statistics
Table 1 reports descriptive statistics for our sample. As noted, the statistics are for 2,573 annual records of 247 distinct MSAs in the U.S. medical device sector between 1990 and 2001. Variable names are in italic. Since the level of employment, VC funding, and NIH funding are log numbers, the real numbers are provided in parentheses for better understanding. The real amounts of VC funding and NIH funding are in thousand U. S. dollars. The number of employees in the medical device sector is, on average, 1414 and the standard deviation is 3018. These statistics suggest that medical device firms are typically large and the size of firms are widely distributed. Interestingly, while the standard deviation (S.D.) of real numbers is considerably greater than the mean of
Table 1. Descriptive statistics.

|                          | All sample | High VC funding | Low VC funding | High NIH funding | Low NIH funding |
|--------------------------|------------|-----------------|----------------|------------------|-----------------|
|                          | Mean       | S.D.            | Min            | Max              | Mean            | S.D.            | Min            | Max              | Mean            | S.D.            | Min            | Max              |
| 1. Level of employment   | 5.81       | 1.84            | 0.69           | 10.28            | 7.64            | 1.38            | 5.33           | 1.63            | 7.27            | 1.60            | 5.31           | 1.64            |
|                          | (1414)     | (3018)         | (2)            | (29278)          | (4310)          | (5278)          | (646)          | (1156)          | (3537)          | (4747)          | (693)          | (1584)          |
| 2. VC funding            | 3.55       | 6.95            | 0.00           | 21.11            | 16.97           | 1.69            | 0.00           | 0.00            | 8.67            | 8.69            | 1.82           | 5.21            |
|                          | (16589)    | (78693)        | (0)            | 1.48e+06         | (79194)         | (156965)        | (0)            | (0)             | (44449)         | (108877)        | (7134)         | (62635)         |
| 3. NIH funding           | 3.77       | 6.56            | 0.00           | 19.35            | 9.43            | 7.75            | 2.27           | 5.27            | 14.87           | 2.13            | 0.00           | 0.00            |
|                          | (4517)     | (20402)        | (0)            | (253449)         | (17808)         | (40044)         | (996)          | (6559)          | (17829)         | (37508)         | (0)            | (0)             |
| 4. Intellectual capital  | 10.35      | 22.17           | 0.00           | 243.00           | 32.59           | 37.62           | 4.46           | 9.03            | 26.31           | 32.16           | 4.93           | 13.85           |
|                          | (4517)     | (20402)        | (0)            | (253449)         | (17808)         | (40044)         | (996)          | (6559)          | (17829)         | (37508)         | (0)            | (0)             |
| 5. Human capital         | 21.47      | 44.57           | 0.00           | 362.00           | 57.36           | 68.94           | 11.96          | 28.71           | 53.07           | 64.52           | 10.74          | 28.21           |
|                          | (4517)     | (20402)        | (0)            | (253449)         | (17808)         | (40044)         | (996)          | (6559)          | (17829)         | (37508)         | (0)            | (0)             |
| 6. Entrepreneurial capital| 1.02       | 0.59            | 0.00           | 2.00             | 1.23            | 0.50            | 0.97           | 0.60            | 1.23            | 0.50            | 0.95           | 0.60            |
| Number of observations   | 2573       | 539             | 2034           | 652              | 1921            | 1921            | 1921           | 1921            | 1921            | 1921            | 1921           | 1921            |

Notes. Since three variables, including level of employment, VC funding, and NIH funding, are log numbers, the real numbers of these variables are provided in parentheses for better understandable information. The amount of funding, including VC and NIH funding, is in thousand U.S. dollars.
those, the S.D. of the level of employment is notably smaller than the mean of it. This small standard deviation in log numbers attenuates, at least in part, our concern of heteroskedasticity, in which the number of analysis is geographical areas of varying sizes and the variability of the variable is unequal across the range of values.

It is noteworthy that the mean of the level of employment is considerably greater in the sub-sample of high venture capital (noted as VC in the following tables) funding than that of low venture capital funding. High and low venture capital funding are observations above and below the mean of venture capital funding, respectively. Specifically, the means of the real number of the level of employment is 4310 in the sample of high venture capital funding and 646 in that of low venture capital funding. These univariate results provide supportive evidence that venture capital funding may be important factor that creates regional jobs. Similarly, the mean of the level of employment is greater in the sub-sample of high NIH funding (i.e., 3537) than in that of low NIH funding (i.e., 693). These simple statistics suggest that the level of employment and NIH funding can be significantly related with each other.

Furthermore, consider that the number of observations in the sub-sample of high venture capital and NIH funding are notably smaller than those in the sub-samples of low venture capital and NIH funding. These statistics suggest that the distribution of venture capital and NIH funding are heterogeneously distributed and skewed left, indicating that a small number of MSAs have a great portion of venture capital and NIH funding.

The distribution of intellectual capital indicates the mean of 10.35 and the S.D. of 22.17. Since intellectual capital is estimated by the number of medical device patents in the region, these statistics suggest that patenting is vigorous and serves as a way to create and claim a value from inventions in the medical device sector. Consistent with the means of level of employment, the means of intellectual capital in high venture capital funding and high NIH funding are considerably greater than those in low venture capital funding and low NIH funding. These statistics imply that our focal variables, including level of employment, VC funding, NIH funding, and intellectual capital, are closely related with each other, supporting our theoretical and empirical discussions that focus on these variables.

Table 2 reports the top 10 MSAs in terms of the number of employees, venture capital and NIH funding, and intellectual capital in 2000 to investigate the spatial distribution of these variables. The most notable pattern is that these variables are heavily concentrated in several MSAs within California. Inconsistent with the spatial homogeneity hypothesis that globalization and drastic advancement in technology reduce the importance of firm location, this concentration within California is supportive of the notion that, ‘paradoxically, the enduring competitive advantages in a global economy lie increasingly in local things – knowledge, relationships, and motivation that distant rivals cannot match (Porter 1998, 78).’ Interestingly, while the Chicago area has the greatest level of employment, its venture capital and NIH funding are not ranked in the top 10 (e.g., ranked 20 and 20, respectively). This type of region can be understood as one that has a high level of incumbents that experience stable operational performance with a great level of employment and, thus, do not necessarily seek venture capital and NIH funding.

Table 3 reports the number of employees, the amount of financial capital, including venture capital and NIH funding, and the levels of intellectual, human, and
entrepreneurial capital over time. It is important to investigate the descriptive statistics over time whether these variables co-move across time. Specifically, if there are positive relationships among VC funding, NIH funding, and intellectual capital and the level of employment, we will find notable co-movement patterns among these variables over time. Consistent with this prediction, the level of employment and other variables gradually increased in the early and mid-1990s and all peaked together in the late 1990s. This finding supports the notion that VC funding, NIH funding, and intellectual capital are important to explain the variance in the level of employment.

4.2. Effects of venture capital, NIH funding, and intellectual capital

As noted in the empirical strategy section, we estimate the direct effects of venture capital and NIH funding on the level of employment by inserting both VC funding and NIH funding along with control variables in AR(1) models. To examine the interaction effects of VC funding and NIH funding and intellectual capital, respectively, we also insert the interaction variables, including VC funding \( \times \) Intellectual capital and NIH funding \( \times \) Intellectual capital in the models. Table 4 reports several AR(1) models that predict the level of employment at \( t, t + 1, t + 2, t + 3, t + 4, t + 5, t + 6, \) and \( t + 7 \). Control variables include the level of employment \( (t - 1) \), human capital, entrepreneurial capital, and MSA and year fixed effects.

VC funding and NIH funding both indicate positive and significant regression coefficients across models with the conventional level of significance. These results support hypotheses 1 and 2. Note that these focal variables, including VC funding, NIH funding, and the level of employment, are estimated by log numbers. Since both

### Table 2. Top 10 Metropolitan statistical areas (MSAs) by the variables of interest.

| Rank | MSA                  | Number of employees | MSA                  | VC funding |
|------|----------------------|---------------------|----------------------|------------|
| 1    | Chicago, IL          | 27,418              | San Jose, CA         | 1,479      |
| 2    | BWLLB, MA-NH         | 23,634              | San Diego, CA        | 863        |
| 3    | Minneapolis-St. Paul, MN-WI | 18,329              | BWLLB, MA-NH         | 775        |
| 4    | Los Angeles-Long Beach, CA| 12,015              | Orange County, CA    | 666        |
| 5    | Orange County, CA    | 11,288              | San Francisco, CA    | 474        |
| 6    | San Jose, CA         | 11,069              | Minneapolis-St. Paul, MN-WI | 307        |
| 7    | San Diego, CA        | 10,402              | Oakland, CA          | 244        |
| 8    | Salt Lake City-Ogden, UT | 9,963               | Middlesex-Somerset-Hunterdon, NJ | 161        |
| 9    | Tampa-St. Petersburg-Clearwater, FL | 7,787               | Riverside-San Bernardino, CA | 161        |
| 10   | Oakland, CA          | 7,690               | Philadelphia, PA-NJ  | 139        |

| Rank | MSA                  | NIH funding | MSA                  | Intellectual capital |
|------|----------------------|-------------|----------------------|----------------------|
| 1    | San Diego, CA        | 253         | BWLLB, MA-NH         | 220                  |
| 2    | BWLLB, MA-NH         | 208         | San Jose, CA         | 169                  |
| 3    | Seattle-Bellevue-Everett, WA | 183       | Minneapolis-St. Paul, MN-WI | 133                  |
| 4    | New York, NY         | 145         | Philadelphia, PA-NJ  | 132                  |
| 5    | Washington, DC-MD-VA-WV | 125       | San Diego, CA        | 121                  |
| 6    | Los Angeles-Long Beach, CA | 89       | San Francisco, CA    | 121                  |
| 7    | Philadelphia, PA-NJ  | 76          | Chicago, IL          | 113                  |
| 8    | San Francisco, CA    | 52          | Los Angeles-Long Beach, CA | 106                  |
| 9    | Raleigh-Durham-Chapel Hill, NC | 50       | New York, NY         | 98                   |
| 10   | Cleveland-Lorain-Elyria, OH | 41       | Oakland, CA          | 89                   |

Note. These rankings were estimated in 2000.
dependent variable and independent variables are estimated by log numbers, the resulting regression coefficients should be understood as elasticity in which the dependent variable responds proportionally to changes in the independent variable. Specifically, when 1% of VC funding increases, 2.22% of level of employment increases at t, 1.65% at t + 1, 1.77% at t + 2, and so on. It is notable that the effects of VC funding decreases as time goes. By the same logic, when 1% of NIH funding increases, 2.07% of level of employment increases at t, 1.66% at t + 1, 2.02% at t + 2, and so on. It is notable that while the effects of NIH funding are smaller than that of VC funding at t, they gradually increase as time goes, and eventually surpass in the long term. These contrasting results are consistent with our discussions regarding heterogeneous motivations of venture capital and NIH funding. Hence, we provide empirical evidence that suggests that venture capital and NIH funding positively impact regional employment levels predicted in hypotheses 1 and 2.

Furthermore, the level of employment (t − 1), human capital, and entrepreneurial capital indicate positive and significant regression coefficients at different levels of significance. Interestingly, human capital does not indicate strongly significant regressions coefficients across models. These insignificant effects of human capital could be understood by a fact that medical device sector employers, including research universities, labs, and firms, hire employees by their own strategic projects and current budgets rather than the munificence of human capital. The effects of entrepreneurial capital are positive and significant at t though t + 2 but become insignificant afterwards. These results indicate that entrepreneurial capital may share the characteristics of venture capital funding that may generate the crowding-out of existing entities. Since the crowding-out effect takes a substantial amount of time to occur, the effects of entrepreneurial capital occurs quickly, but gradually disappear as existing entities are out of business.

Given the positive effects of VC funding and NIH funding on the level of employment, we explore the complementarities between intellectual capital and two funding sources on the level of employment. As noted earlier, a production function approach is utilized. Specifically, we created the interaction variables, including VC funding × Intellectual

| Year | Number of employees | VC funding | NIH funding | Intellectual capital | Human capital | Entrepreneurial capital |
|------|---------------------|------------|-------------|---------------------|---------------|------------------------|
| 1990 | 256,185             | 2,027.25   | 869.17      | 1,462               | 4,102         | 1.03                   |
| 1991 | 275,369             | 2,048.45   | 985.91      | 1,674               | 4,638         | 1.02                   |
| 1992 | 278,914             | 2,692.50   | 1,073.45    | 1,670               | 4,899         | 1.07                   |
| 1993 | 335,319             | 2,060.64   | 973.03      | 1,789               | 4,837         | 1.04                   |
| 1994 | 331,019             | 2,366.56   | 1,014.09    | 1,897               | 4,954         | 0.96                   |
| 1995 | 288,543             | 2,469.23   | 749.38      | 1,725               | 4,245         | 0.99                   |
| 1996 | 329,747             | 3,426.58   | 1,083.13    | 2,269               | 5,235         | 0.99                   |
| 1997 | 306,712             | 3,880.34   | 780.17      | 2,129               | 4,451         | 1.07                   |
| 1998 | 305,533             | 4,286.49   | 1,193.41    | 2,930               | 4,599         | 1.02                   |
| 1999 | 268,836             | 4,236.94   | 1,411.59    | 2,877               | 3,943         | 1.04                   |
| 2000 | 335,338             | 7,002.77   | 1,491.42    | 3,128               | 4,631         | 1.01                   |
| 2001 | 326,296             | 6,188.07   | 3,082       | 4,725               | 1.03         |
| Total| 3,637,811           | 42,685.85  | 11,624.8    | 26,632              | 55,237        | 1.02                   |

Note. Number of employees indicates the real number of individual employees in the U.S. medical device sector. Financial capital, including venture capital and NIH funding, is estimated in constant 2001 U.S. million dollars. Intellectual and human capital indicate the actual numbers of patents and science Ph.D.s. Entrepreneurial capital reports the mean of estimates rather than their sum to provide better information.
Table 4. Effects of VC and NIH funding on the level of employment.

| Model          | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|----------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| Dependent variable | Level of employment $(t) - 1$ | Level of employment $(t)$ | Level of employment $(t + 1)$ | Level of employment $(t + 2)$ | Level of employment $(t + 3)$ | Level of employment $(t + 4)$ | Level of employment $(t + 5)$ | Level of employment $(t + 6)$ | Level of employment $(t + 7)$ |
| Level of employment $(t - 1)$ | 0.8356*** (0.0196) | 0.7836*** (0.0247) | 0.8090*** (0.0227) | 0.7105*** (0.0321) | 0.7702*** (0.0288) | 0.7487*** (0.0297) | 0.5327*** (0.0417) | 0.4969*** (0.0399) | 0.3861*** (0.0437) |
| VC funding $(t)$ | 0.0211*** (0.0036) | 0.0165*** (0.0033) | 0.0177*** (0.0037) | 0.0153*** (0.0036) | 0.0141*** (0.0044) | 0.0122*** (0.0042) | 0.0122*** (0.0042) | 0.0090*** (0.0044) | 0.0081** (0.0042) |
| NIH funding $(t)$ | 0.0207*** (0.0045) | 0.0166*** (0.0057) | 0.0202*** (0.0050) | 0.0171*** (0.0054) | 0.0198*** (0.0066) | 0.0287*** (0.0086) | 0.0287*** (0.0086) | 0.0350*** (0.0086) | 0.0190*** (0.0086) |
| Intellectual capital $(t)$ | 0.0075*** (0.0020) | 0.0170*** (0.0036) | 0.0162*** (0.0037) | 0.0219*** (0.0045) | 0.0209*** (0.0051) | 0.0288*** (0.0074) | 0.0288*** (0.0074) | 0.0055*** (0.0127) | 0.0055*** (0.0127) |
| VC funding $(t) \times$ Intellectual capital $(t)$ | 0.0006*** (0.0002) | 0.0005*** (0.0001) | 0.0007*** (0.0002) | 0.0006*** (0.0002) | 0.0005*** (0.0002) | 0.0005*** (0.0002) | 0.0005*** (0.0002) | 0.0005*** (0.0002) | 0.0005*** (0.0002) |
| NIH funding $(t) \times$ Intellectual capital $(t)$ | 0.0002*** (0.0001) | 0.0003*** (0.0001) | 0.0004*** (0.0002) | 0.0005*** (0.0002) | 0.0005*** (0.0002) | 0.0005*** (0.0002) | 0.0005*** (0.0002) | 0.0005*** (0.0002) | 0.0005*** (0.0002) |
| Human capital $(t)$ | 0.0016*** (0.0006) | 0.0001 (0.0005) | 0.0003 (0.0005) | 0.0008 (0.0006) | 0.0004 (0.0005) | 0.0000 (0.0007) | 0.0015 (0.0007) | 0.0006 (0.0007) | 0.0014 (0.0007) |
| Entrepreneurial capital $(t)$ | 0.1707*** (0.0357) | 0.2004*** (0.0392) | 0.1844*** (0.0344) | 0.0665* (0.0378) | 0.0068 (0.0349) | 0.0036 (0.0415) | 0.0649 (0.0468) | 0.0097 (0.0473) | 0.0030 (0.0496) |
| Constant | 0.7146*** (0.0853) | 0.9602*** (0.1079) | 0.7080*** (0.0854) | 0.8343*** (0.0991) | 0.4858*** (0.0862) | 0.5238*** (0.0907) | 0.9691*** (0.1221) | 1.0949*** (0.1135) | 1.3614*** (0.1124) |
| MSA and year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Number of observations | 2573 | 2573 | 2349 | 2128 | 1913 | 1697 | 1489 | 1275 | 1068 |
| Number of groups | 247 | 247 | 247 | 243 | 242 | 241 | 239 | 240 | 241 |
| Overall $R^2$ | 0.8639 | 0.8690 | 0.8830 | 0.8791 | 0.8891 | 0.8868 | 0.8648 | 0.8576 | 0.8401 |

Note. *, **, and *** denote significance at 1%, 5%, and 10%, respectively.
capital and NIH funding × Intellectual capital, and carry out a simple one-tailed t-test in the models. These two interaction variables indicate positive and significant regression coefficients at the conventional level of significance throughout the models. More specifically, VC funding × Intellectual capital indicates 0.006 of regression coefficient at t, 0.0005 at t + 1, 0.0007 at t + 2, and so on. These effects maintain constantly throughout the models. In contrast, NIH funding × Intellectual capital indicates 0.0002 of regression coefficient at t, 0.0003 at t + 1, 0.0004 at t + 2, and so on. These effects drastically increase as time goes and become much greater than those of VC funding × Intellectual capital as time flows. These findings indicate that both funding sources, create a greater level of employment when intellectual capital is abundant in the region. While venture capital funding creates this interaction effect in a short term, NIH does in a long term, supporting hypotheses 3 and 4.

4.3. Causality between venture capital and NIH funding and employment

We now investigate the endogeneity issues of our model. This analysis is important because our estimates may be inconsistent if endogeneity issues are not alleviated. As noted, we use Lewbel’s (2012) approach that estimates a hypothetical instrumental variable within the model. Table 5 reports our models that examine endogeneity issues related to VC funding in Panel A, NIH funding in Panel B, and intellectual capital in Panel C. These models alleviate concerns regarding causality between variables, the existence of confounding and omitted variable, and correlation between explanatory variables. The resulting models are similar with the models presented in Table 4. In Panel A, the level of employment (t − 1), VC funding, NIH funding, and intellectual capital indicate positive and significant regression coefficients. Entrepreneurial capital also indicates similar results presented in Table 4. The level of employment (t − 1), VC funding, NIH funding, and intellectual capital indicate positive and significant regression coefficients throughout the models. Interestingly, entrepreneurial capital indicates positive and significant regression coefficients at the 1% level throughout the models. It suggests that, when NIH funding is instrumented and consistent results are estimated, the positive effect of entrepreneurial capital is more salient. These results support our hypothesis 2 and this support is robust against endogeneity issues.

Panel B also indicate similar results presented in Table 4. The level of employment (t − 1), VC funding, NIH funding, and intellectual capital indicate positive and significant regression coefficients throughout the models. Interestingly, entrepreneurial capital indicates positive and significant regression coefficients at the 1% level throughout the models. It suggests that, when NIH funding is instrumented and consistent results are estimated, the positive effect of entrepreneurial capital is more salient. These results support our hypothesis 2 and this support is robust against endogeneity issues.

Similarly, Panel C tests the endogeneity issues by instrumenting intellectual capital with a hypothesized instrumental variable generated by Lewbel’s (2012) approach. Consistent with our findings in Table 4, intellectual capital indicates overall positive and significant regression coefficients. We also find VC funding and NIH funding maintain positive and significant regression coefficients. This set of endogeneity tests suggest that our focal variables, including VC funding, NIH funding, and intellectual capital, do not suffer from endogeneity issues. It is noteworthy that these tests also alleviate our concerns about the potential endogeneity of associated interaction variables, such as VC funding (t) × Intellectual capital (t) and NIH funding (t) × Intellectual capital (t), if each main variable (i.e., non-interaction variable) is not endogenous.
### Table 5. Causality between VC and NIH funding and employment.

#### Panel A. Instrumental variables estimation of VC funding

Two stage least squares regression with an instrumental variable

| Model | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|-------|-----|-----|-----|-----|-----|-----|-----|-----|
| Dependent variable | Level of employment \((t-1)\) | Level of employment \((t+1)\) | Level of employment \((t+2)\) | Level of employment \((t+3)\) | Level of employment \((t+4)\) | Level of employment \((t+5)\) | Level of employment \((t+6)\) | Level of employment \((t+7)\) |
| Level of employment \((t-1)\) | 0.8052*** | 0.8291*** | 0.8201*** | 0.8196*** | 0.8287*** | 0.8129*** | 0.7987*** | 0.7987*** |
| VC funding \((t)\) | (0.0145) | (0.0143) | (0.0164) | (0.0170) | (0.0189) | (0.0191) | (0.0208) | (0.0242) |
| NIH funding \((t)\) | 0.0127*** | 0.0101*** | 0.0096*** | 0.0083*** | 0.0068*** | 0.0069*** | 0.0046 | 0.0075** |
| Intellectual capital \((t)\) | 0.0189*** | 0.0139*** | 0.0115*** | 0.0114*** | 0.0092*** | 0.0039 | 0.0064 | 0.0097** |
| Human capital \((t)\) | 0.0055*** | 0.0043*** | 0.0049*** | 0.0049*** | 0.0086*** | 0.0116*** | 0.0140*** | 0.0142*** |
| Entrepreneurial capital \((t)\) | 0.0002 | 0.0004 | 0.0004 | 0.0003 | −0.0001 | 0.0004 | 0.0001 | −0.0002 |
| Constant | 0.2083*** | 0.1001*** | 0.0404 | 0.0178 | 0.0442 | 0.0619* | 0.0432 | 0.0391 |
| MSA and year fixed effects | 0.9106*** | 0.6428*** | 0.5499*** | 0.3426 | 0.3368 | 0.2617 | 0.3191** | 0.3012** |
| Number of observations | 0.2094 | 0.2004 | 0.2004 | 0.2004 | 0.2004 | 0.2004 | 0.2041 | 0.1364 |
| Log likelihood | (0.0274) | (0.0278) | (0.0279) | (0.0296) | (0.0334) | (0.0373) | (0.0403) | (0.0448) |
| Overall R² | −2.6e+03 | −2.2e+03 | −2.1e+03 | −1.7e+03 | −1.6e+03 | −1.4e+03 | −1.2e+03 | −9.9e+02 |

#### Panel B. Instrumental variables estimation of NIH funding

Two stage least squares regression with an instrumental variable

| Model | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|-------|-----|-----|-----|-----|-----|-----|-----|-----|
| Dependent variable | Level of employment \((t-1)\) | Level of employment \((t+1)\) | Level of employment \((t+2)\) | Level of employment \((t+3)\) | Level of employment \((t+4)\) | Level of employment \((t+5)\) | Level of employment \((t+6)\) | Level of employment \((t+7)\) |
| Level of employment \((t-1)\) | 0.8222*** | 0.8121*** | 0.8311*** | 0.8221*** | 0.8221*** | 0.8254*** | 0.8232*** | 0.7867*** |
| VC funding \((t)\) | (0.0145) | (0.0143) | (0.0164) | (0.0170) | (0.0189) | (0.0191) | (0.0208) | (0.0242) |
| NIH funding \((t)\) | 0.0508*** | 0.0490*** | 0.0469*** | 0.0432*** | 0.0362*** | 0.0356*** | 0.0317*** | 0.0358*** |
| Intellectual capital \((t)\) | 0.0775*** | 0.0799*** | 0.0783*** | 0.0767*** | 0.0708*** | 0.0671*** | 0.0675*** | 0.0674*** |
| Human capital \((t)\) | 0.0304*** | 0.0276*** | 0.0297*** | 0.0347*** | 0.0496*** | 0.0559*** | 0.0604*** | 0.0605*** |
| Entrepreneurial capital \((t)\) | 0.0010 | 0.0009 | 0.0007 | 0.0005 | 0.0000 | 0.0003 | 0.0003 | 0.0002 |

(Continued)
Panel A. Instrumental variables estimation of VC funding

Two stage least squares regression with an instrumental variable

| Model | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|-------|-----|-----|-----|-----|-----|-----|-----|-----|
| Dependent variable | Level of employment (t) | Level of employment (t + 1) | Level of employment (t + 2) | Level of employment (t + 3) | Level of employment (t + 4) | Level of employment (t + 5) | Level of employment (t + 6) | Level of employment (t + 7) |
| Entrepreneurial capital | 0.3501*** (0.0375) | 0.2737*** (0.0407) | 0.2315*** (0.0432) | 0.1879*** (0.0481) | 0.1747*** (0.0515) | 0.1729*** (0.0558) | 0.1975*** (0.0602) | 0.2066*** (0.0648) |
| Constant | 3.2240*** (0.1493) | 2.8427*** (0.1376) | 2.6541*** (0.1408) | 2.5443*** (0.1419) | 2.5825*** (0.1413) | 2.4513*** (0.1287) | 2.4303*** (0.1049) | 2.3883*** (0.0974) |
| MSA and year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Number of observations | 2573 | 2349 | 2128 | 1913 | 1697 | 1489 | 1275 | 1068 |
| Log likelihood | −4.0e+03 | −3.7e+03 | −3.3e+03 | −2.9e+03 | −2.6e+03 | −2.3e+03 | −1.9e+03 | −1.6e+03 |
| Overall R² | 0.5992 | 0.5989 | 0.6043 | 0.6105 | 0.6183 | 0.6246 | 0.6280 | 0.6394 |

Panel C. Instrumental variables estimation of intellectual capital

| Level of employment (t – 1) | 0.8136*** (0.0144) | 0.8291*** (0.0143) | 0.8270*** (0.0162) | 0.8300*** (0.0169) | 0.8196*** (0.0189) | 0.8394*** (0.0188) | 0.8208*** (0.0206) | 0.7987*** (0.0242) |
| VC funding | 0.0142*** (0.0024) | 0.0101*** (0.0022) | 0.0109*** (0.0023) | 0.0095*** (0.0023) | 0.0068*** (0.0025) | 0.0087*** (0.0029) | 0.0061** (0.0030) | 0.0075** (0.0032) |
| NIH funding | 0.0196*** (0.0028) | 0.0139*** (0.0028) | 0.0128*** (0.0029) | 0.0128*** (0.0030) | 0.0092*** (0.0035) | 0.0060* (0.0035) | 0.0084** (0.0041) | 0.0097** (0.0048) |
| Intellectual capital | 0.0019** (0.0009) | 0.0045*** (0.0010) | 0.0014 (0.0010) | 0.0015 (0.0011) | 0.0086*** (0.0021) | 0.0055** (0.0022) | 0.0092*** (0.0028) | 0.0142*** (0.0036) |
| Human capital | 0.0005 (0.0004) | 0.0004 (0.0004) | 0.0006 (0.0004) | 0.0005 (0.0005) | −0.0001 (0.0005) | 0.0006 (0.0006) | 0.0002 (0.0006) | −0.0002 (0.0007) |
| Entrepreneurial capital | −0.2010*** (0.0278) | −0.1001*** (0.0279) | −0.0345 (0.0297) | 0.0239 (0.0334) | 0.0442 (0.0378) | 0.0738* (0.0407) | 0.0526 (0.0448) | 0.0391 (0.0449) |
| Constant | 0.8989*** (0.2121) | 0.6428*** (0.2004) | 0.5404*** (0.2074) | 0.3376 (0.2347) | 0.3368 (0.2264) | 0.2346 (0.2072) | 0.2962** (0.1378) | 0.3012** (0.1371) |
| MSA and year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Number of observations | 2573 | 2349 | 2128 | 1913 | 1697 | 1489 | 1275 | 1068 |
| Log likelihood | −2.6e+03 | −2.2e+03 | −2.0e+03 | −1.7e+03 | −1.6e+03 | −1.4e+03 | −1.2e+03 | −9.9e+02 |
| Overall R² | 0.8668 | 0.8816 | 0.8795 | 0.8876 | 0.8856 | 0.8861 | 0.8805 | 0.8852 |
As a final diagnostic test, we use the Hansen J statistic to examine the possibility of over-identification in our model. This statistic, an extension of the Sargan statistic, is consistent in the presence of heteroskedasticity and autocorrelation. The null hypothesis is a joint hypothesis that the error term is uncorrelated with the instruments, and that the instruments are correctly excluded from the regression. Specifically, in our first specification of Panel A, Chi-square distributed test statistics takes on a value of 16.741, with an associated p-value of 0.34. A statistically significant test statistic always indicates that the instruments may not be valid. Thus, we fail to reject the null of valid over-identifying restrictions and our instrument approach is valid. Similar and consistent results are obtained for the specifications of Panel B and C.

5. Discussions and conclusion

In this study, we present a new perspective coupled with the taxonomy of explorative and exploitative learning activities on how venture capital and NIH funding are related to the level of regional jobs in the medical device sector. We find systematic evidence that NIH funding tends to create more jobs directly compared to venture capital funding. Moreover, these positive effects are more salient when intellectual capital is abundant in the region. While venture capital tends to interact with intellectual capital in the short term, NIH funding does so in the long term.

5.1. Contributions and managerial implications

This study contributes to several strands of literature. More specifically, this study contributes to the innovation, entrepreneurial finance, and economics literature by providing a novel perspective to avoid a potential misestimation of the relationship between financial capital and economic outcomes. This study explicitly suggests that the economic impact of distinct forms of financial capital should be estimated in an appropriate manner. As noted, the first possible source of misestimating is the lack of appropriate typology for financial capital. While some policy makers have often treated financial capital as a homogeneous factor that determines employment levels, financial capital should be grouped according to its own motivation and investment pattern. The second source of misestimating is the lack of proper dissection of the direct and interaction effects of financial capital. Anecdotal evidence suggests that, while financial capital directly impacts employment levels (i.e., direct effect), it can also interact with intellectual capital, which may subsequently impact the level of employment (i.e., interaction effect). The failure to properly decompose financial capital into its respective direct and interact components may lead to partial prognostication of how to effectively leverage different financial resources for investment strategies. Therefore, equal focus should be allocated towards the interaction effects of financing sources and intellectual capital as well as the direct effects of public and private capital.

Furthermore, our findings contribute to the existing literature, which has documented the presence of a lag between the appearance of research in the academic community and its effect on productivity in the form of knowledge absorbed by an industry (Adams 1990). In essence, given the interplay between the public funding of academic research and venture capital funding in innovation and entrepreneurship (Samila and Sorenson 2010), our findings have an important implication about the timing issues of
public and private funding. Due to the nature of public capital that supports basic research, which may be consequently commercialized by industries and venture capital funding, public funding requires much less amount of funding, takes a longer time to be commercialized, and thus should precede venture capital funding in a region. When this condition is met, venture capital funding may more effectively perform its role as a catalyst to commercialization.

5.2. Limitations and conclusions

This study has several limitations that provides avenues for future research. Firstly and obviously, this study is focused on a single sector and thus our findings need to be interpreted with caution in the context of other industries. For example, while venture capital funding is widely distributed across high-tech industries, NIH funding is strictly limited within research projects that pursue health care issues. This narrow scope of funding creates a distinguishable way to make decisions that are consistent with the specific motivations of scientists in the field. As a result, it is hard to generalize our findings to other high-tech sectors, such as information technology, that is less involved with ethical issues and has a considerably shorter technology life expectancy. This notion highlights that each industry may have specific managerial and technological environments and uses financial capital according to its own context.

Furthermore, our data shows that both venture capital and NIH funding are increasingly endowed between 1990 and 2001. This trend may have continued beyond the time period of our investigation due to the accelerating managerial and technological races in the medical device sector. Future studies need to extend the window for this trend. Our data is also limited to evaluate the level of employment in new and existing firms, respectively, and the changes in the ownerships of medical device firms (e.g., the ownership of venture capital firms). Due to these limitations, we do not directly observe where both forms of financial capital create or remove local jobs and how the change of ownership affects the local employment. Moreover, this study aims to examine the roles of venture capital and NIH funding that impact entrepreneurs and scientists who utilize these funding sources for their own purposes. It would be ideal if we were able to directly observe the behaviors of entrepreneurs and scientists. Unfortunately, this observation is not allowed in this study mainly due to the limitation of data.

It is a fundamental pursuit of managers and policy makers to optimize the endowments of financial resources. We hope that our perspective that distinguish the endowments of private and public capital and the associated consequences of these endowments will enlighten our understanding regarding the effects of other types of resources on the level of employment in an appropriate manner.

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No potential conflict of interest was reported by the authors.

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