Skills and knowledge-based entrepreneurship: evidence from US cities

Haifeng Qian

ABSTRACT
Skills and knowledge-based entrepreneurship: evidence from US cities. Regional Studies. This paper explores the association between human capital and knowledge-based entrepreneurship. While the existing literature mostly focuses on education-based human capital, this paper adopts a skills-based human capital approach and examines the associations between various types of labour market skills and high-technology entrepreneurship in US metropolitan regions. Spatial regression results show that cognitive, technical, problem-solving, social and managerial skills are positively associated with high-technology start-up activity. Additionally, these skills also play moderating roles in turning university research into entrepreneurial activity in knowledge-based regional economies. This research contributes to the search for regional entrepreneurship policy from a skills-enhancing perspective.

KEYWORDS
entrepreneurship; high-technology; human capital; skills; regional development

CONTACT
haifeng-qian@uiowa.edu
School of Urban and Regional Planning, The University of Iowa, Iowa City, IA, USA.
ZUSAMMENFASSUNG
Unternehmertum auf der Grundlage von Fähigkeiten und Wissen: Belege aus Städten der USA. Regional Studies. In diesem Beitrag wird der Zusammenhang zwischen Humankapital und wissensbasiertem Unternehmertum untersucht. Während der Schwerpunkt der vorhandenen Literatur größtenteils auf bildungsbasiertem Humankapital liegt, verfolge ich in diesem Beitrag einen Ansatz des Humankapitals auf der Grundlage von Fähigkeiten und untersuche die Zusammenhänge zwischen verschiedenen Arten von Fähigkeiten des Arbeitsmarkts und Unternehmertum im Hochtechnologiebereich in Metropolitano- regionen der USA. Die Ergebnisse einer räumlichen Regression zeigen, dass kognitive, technische, Problemlösungs-, soziale und Führungsfähigkeiten in einem positiven Zusammenhang mit den Gründungsaktivitäten von Hochtechnologiefirmen stehen. Darüber hinaus spielen diese Fähigkeiten in wissensbasierten regionalen Ökonomien eine vermittelnde Rolle bei der Umwandlung von Hochschulforschung in unternehmerische Aktivität. Diese Studie ist ein Beitrag zur Suche nach einer Politik für regionales Unternehmertum aus einer Perspektive der Verbesserung von Fähigkeiten.

SCHLÜSSELRÜTERN
Unternehmertum; Hochtechnologie; Humankapital; Fähigkeiten; Regionalentwicklung

RESUMEN
Iniciativa empresarial basada en el conocimiento y las habilidades: ejemplos de ciudades estadounidenses. Regional Studies. En este artículo se analiza la relación entre el capital humano y la iniciativa empresarial basada en el conocimiento. Mientras que en la bibliografía actual se presta atención sobre todo al capital humano basado en la educación, en este artículo se adopta un planteamiento de capital humano basado en las habilidades y se analiza el vínculo entre los diferentes tipos de habilidades en el mercado laboral y la iniciativa empresarial de alta tecnología en las regiones metropolitanas de los Estados Unidos. Los resultados de una regresión espacial muestran que las habilidades cognitivas, técnicas, de solución de problemas, sociales y directivas tienen una relación positiva con la creación de empresas de alta tecnología. Asimismo estas habilidades también desempeñan un papel de moderación a la hora de convertir la investigación universitaria en actividades empresariales en las economías regionales basadas en el conocimiento. Este estudio contribuye a buscar una política para el empresariado regional desde una perspectiva de mejorar las habilidades.

PALABRAS CLAVES
iniciativa empresarial; alta tecnología; capital humano; habilidades; desarrollo regional

INTRODUCTION
In a notable essay, Lazear (2004) argues that a successful entrepreneur should be a generalist who has multiple skills. What are the relationships between skills and entrepreneurship in regional economic development? What types of labour market skills are conducive to regional entrepreneurial activity? Answers to these questions shed a light on regional policies to build a vibrant entrepreneurial economy. Examining the impact of skills on knowledge-based entrepreneurial activity is of particular importance, as technology- or knowledge-intensive jobs and businesses underpin regional competitive advantage (Moretti, 2013). But so far, these questions have rarely been studied.

In a broader context, skills are usually considered as part of human capital (Becker, 1964), and the role of human capital in knowledge-based entrepreneurial activity has recently gained some scholarly attention. Human capital is an indicator of a region’s new knowledge that gives rise to entrepreneurial opportunities (Acs, Audretsch, Braunherjelm, & Carlsson, 2009; Audretsch, 1995). Human capital is also an indicator of the ability of entrepreneurs to discover and exploit market opportunities (Qian & Acs, 2013). In addition, human capital is associated with a skilled labour force desired by entrepreneurs when they start new businesses, especially in knowledge-intensive industries (Berry & Glaeser, 2005; Millan, Congregado, Roman, van Praag, & van Stel, 2014). These recognized contributions of human capital imply that skills may also have impacts on knowledge-based regional entrepreneurial activity.

The goal of this study, therefore, is to examine systematically the effects of various types of regional skills on knowledge-based entrepreneurship. With a focus on the knowledge economy, this research examines entrepreneurial activity only in high-technology industries. Therefore, knowledge-based entrepreneurship and high-technology entrepreneurship are interchangeably used in this paper. Multivariate regressions are used to explain regional variations in high-technology entrepreneurship in the United States and spatial econometric methods are employed to address the presence of spatial dependency. Along with new knowledge, regional skills are included as primary explanatory variables for high-technology entrepreneurship, and other variables suggested in the literature are controlled for. This research explores both direct and
moderating effects of skills in knowledge-driven entrepreneurial activity. It provides new insights into regional entrepreneurship policy from the perspective of workforce development.

The paper is organized as follows. The next section lays the theoretical foundation and discusses the importance of human capital and skills to knowledge-based regional entrepreneurial activity and proposes the hypotheses. The third section introduces the variables, data and regression methods; the fourth section presents the regression results. The last section summarizes the research and discusses policy implications.

THEORIES AND HYPOTHESES

Literature review: human capital and knowledge-based entrepreneurship

Knowledge has been widely considered as one of the core driving forces of long-term economic growth (Romer, 1990). However, successful commercialization of knowledge with market potential is not warranted (Michelacci, 2003). Audretsch and others (Acs et al., 2009; Audretsch, 1995) introduce the knowledge spillover theory of entrepreneurship (KSTE) to explore one of the mechanisms that facilitate knowledge commercialization. They argue that entrepreneurs can commercialize new knowledge developed in incumbent firms, universities or other research institutions in newly created firms. In this process, entrepreneurship serves as a mechanism of facilitating knowledge spillover and a mechanism of bringing commercially useful knowledge into the market. KSTE implies that new knowledge represents one source of entrepreneurial activities. Qian and Acs (2013) advance KSTE by integrating absorptive capacity into knowledge spillover entrepreneurship. Their absorptive capacity theory of knowledge spillover entrepreneurship demonstrates that successful commercialization of new knowledge in an entrepreneurial process of creating a new firm depends not only on new knowledge but also on absorptive capacity of entrepreneurs. They further address the importance of human capital as the major determinant of both new knowledge and entrepreneurial absorptive capacity.

The absorptive capacity theory of knowledge spillover entrepreneurship explains knowledge-based entrepreneurial activity from a human capital perspective. Indeed, the relationship between human capital and entrepreneurship has gained attention from both management scholars who are interested in traits, behaviour and performance of individual entrepreneurs, and urban economists and economic geographers who are interested in regional environmental factors associated with new firm formation. This is not surprising, since entrepreneurial skills can actually be considered as part of human capital, i.e., knowledge and skills embodied in people (Schulz, 1961). At the individual level, the effects of different types of human capital on entrepreneurship have been explored by management scholars, including education, experience and more specific human capital such as market knowledge, industry knowledge, managerial knowledge and technological knowledge (Bosma, van Praag, Thurik, & De Wit, 2004; Cassar, 2006; Colombo & Grilli, 2005; Cooper, Gimeno-Gascon, & Woo, 1994; Davidson & Honig, 2003; Dimov, 2010;Marvel & Lumpkin, 2007; Ucbasaran, Westhead, & Wright, 2008). It is not surprising for one to think that human capital plays a particularly important role in knowledge-intensive entrepreneurial activity. Therefore, some of these empirical studies (Colombo & Grilli, 2005; Marvel & Lumpkin, 2007) focus exclusively on high-technology ventures, a perspective also adopted in this research. Human capital in general contributes to entrepreneurship in both low- and high-technology sectors (Bosma, Praag, Thurik, & Wit, 2004; Unger, Rauch, Frese, & Rosenbusch, 2011), but some specific types of human capital, especially in terms of technology and absorptive capacity, are more desired in the high-technology sector. Unger et al. (2011) provide a comprehensive review of the management literature on this topic and find a small relationship between human capital and entrepreneurial success in a meta-analysis. Following the tradition of Becker (1964), Unger et al. distinguish human capital investments (i.e., education and experience) and outcomes of human capital investments (i.e., knowledge and skills). They further report that the relationship between human capital and entrepreneurship is larger when using knowledge/skills to measure human capital instead of using education/experience.

At the regional level, human capital is generally measured by human capital investments instead of their outcomes due to data availability. For instance, some studies (Acs & Armington, 2006; Qian, 2013; Qian & Haynes, 2014) find that higher education measured by the share of population with a bachelor’s degree or above is a strong predictor of regional start-up activity. Such an effect is even stronger for high-technology entrepreneurship (Qian, Acs, & Stough, 2013). Acs and Armington (2006) also report that the share of the population with a high-school diploma is positively associated with new firm formation in the service sector.

Despite being a widely used indicator of human capital, education does not directly measure or reflect knowledge, abilities and skills of human beings, i.e., the outcomes of human capital investments. Recently, regional scientists (Feser, 2003; Florida, Mellander, Stolarick, & Ross, 2012) have started to adopt direct measures of regional skills thanks to a new dataset on occupational skills in the US context: the Occupational Information Network (O*NET). So far, these skills have not been used to explain regional variations in entrepreneurial activity. In a simple test of the absorptive capacity theory of knowledge spillover entrepreneurship, Qian and Acs (2013) follow the tradition of the literature and measure absorptive capacity effects via education-based human capital. This calls for efforts to examine the relationship between regional skills and knowledge-based entrepreneurship, since such skills are not only outcomes of human capital investments but also can be good indicators of absorptive capacity. Identifying regional skills associated with entrepreneurial activity also
contributes to the debate on entrepreneurship policy at the sub-national level.

It should be noted that regional skills include skills of both (realized or potential) entrepreneurs and non-entrepreneurs in the labour market. The former are associated with the theoretical framework of the absorptive capacity theory of knowledge spillover entrepreneurship. The latter reflect human resources that are available to local technology entrepreneurs, which may also contribute to knowledge-intensive entrepreneurial activity. As Berry and Glaeser (2005) note, skilled entrepreneurs tend to employ skilled workers. The innovative capacity of firms depends on the elite management team as well as on employees’ problem-solving ability (Holm & Lorenz, 2015). Further, Millan et al. (2014) find that the education level of the local population has a positive impact on entrepreneurial performance after controlling for the human capital level of entrepreneurs. In reality, however, it is difficult to separate entrepreneurs from employees in the labour market. Employees are potential entrepreneurs. If an employee sees a higher return from starting a new business than staying in an incumbent firm, she or he is likely to quite the job and become an entrepreneur (Acs & Armington, 2006).

**Effects of regional skills and knowledge-based entrepreneurship: two hypotheses**

Based on the literature discussed above, this paper proposes a two-hypothesis theoretical framework on the relationship between skills and knowledge-based entrepreneurship, as shown in Figure E1 in Appendix E in the supplemental data online. First, skills may have direct impacts on start-up activity in the regional technology sector independent of commercializing new knowledge. Indeed, most new businesses are created not as a result of bringing a new technology into the market even in technology-intensive industries. For instance, businesses in information service industries, such as Internet publishing and data processing, mostly use existing technology to provide services that fit certain market niches, but do not introduce innovative new products or services as a way to commercialize new knowledge created in universities or research laboratories. Nevertheless, skills of (potential) entrepreneurs and/or their (potential) employees can still be very important, as they are facing knowledge-intensive and perhaps very complex tasks.

Entrepreneurial activity is multidimensional, which requires entrepreneurs to be multi-skilled (Lazear, 2004; Ucbasaran et al., 2008). It is reasonable to believe that some specific skills are more relevant to high- than low-technology entrepreneurs. To begin with, the cognitive skills of entrepreneurs contribute to the identification of market opportunities embedded in differentiated consumer demand or market inefficiency. As Shane and Venkataraman (2000) note in their classic piece defining the field of entrepreneurship, along with prior knowledge, cognitive ability is critical to the process of discovering entrepreneurial opportunities. It is difficult for one to undervalue the importance of technical skills of both entrepreneurs and the workforce to entrepreneurial activity in the high-technology sector. Even if the goal of a new venture is not to commercialize a new technology, the firm usually adopts some technologies as a means of production, requiring technical skills of its founder or co-founders. Moreover, and consistent with the argument of Berry and Glaeser (2005), technology entrepreneurs will be deferred from starting businesses if the regional labour market does not supply a technically competent labour force. Identifying a solution to a problem is one of motivations of entrepreneurs to create a new firm (Corman, Perles, & Vancini, 1988). Therefore, problem-solving skills are associated with the exploitation of entrepreneurial opportunities. Such skills of entrepreneurs continue to be important after new venture creation, as problem solutions can always be improved, a process that also benefits from employees’ problem-solving ability (Holm & Lorenz, 2015). In addition to cognitive skills, Baron and Markman (2000) argue that the social skills of entrepreneurs help build their personal networks that lead to the resources needed for the creation and success of new ventures. Last but not least, managerial skills are needed in a usually volatile business environment of knowledge-intensive industries. The recently popular lean start-up model (Ries, 2011) accredits entrepreneurial success primarily to management. To sum up, the first hypothesis is:

**Hypothesis 1:** Regional skills, such as cognitive, technical, problem-solving, social and managerial skills, have direct effects on knowledge-intensive start-up activity independent of commercializing new knowledge or technologies.

The second hypothesis is derived from the absorptive capacity theory of knowledge spillover entrepreneurship (Qian & Acs, 2013). Different from Qian and Acs’s approach, this paper focuses on the outcomes of human capital investments, i.e., skills, instead of education-based human capital investments. Technology entrepreneurs constantly search for new knowledge with market potential and try to bring it into the market. To understand and discover technology-based entrepreneurial opportunities, it is necessary for entrepreneurs to have certain technical skills (Qian & Acs, 2013). In this process, cognitive skills are also needed to recognize these potential market opportunities embedded in new knowledge or technology. Cognitive capacity represents an indispensable part of absorptive capacity (Zahra & George, 2002) that leads to success in commercializing external knowledge. Dosi and Grazzi (2006) consider technological innovation as problem-solving activity. Along with this line of thinking, problem-solving skills of entrepreneurs underpin the commercialization of technologies through their new ventures. Other skills, such as social and managerial skills, help streamline the technology transfer/spillover process, mobilize resources and build new firms. Social skills shape the networks among researchers, entrepreneurs, investors and other support organizations that characterize a vibrant technological entrepreneurial ecosystem (Feld, 2012).

To sum up, high levels of cognitive, technical, problem-solving, social and managerial skills facilitate the commercialization of new knowledge by entrepreneurs in newly
created firms. In other words, these skills moderate the relationship between knowledge and new firm formation in knowledge-driven regional economies. The second hypothesis can be summarized as follows:

_Hypothesis 2:_ Regional skills, such as cognitive, technical, problem-solving, social and managerial skills, play moderating roles in the effect of new knowledge on knowledge-intensive start-up activity.

**METHODS**

**Geographical units and time periods for analysis**

The empirical part of this study tests the two hypotheses on the associations between various skills and knowledge-based entrepreneurial activity in US metropolitan statistical areas (MSAs). A US metropolitan area is an internally integrated market in terms of both products/services and labour. Most residents in one metropolitan area shop and work in the same area. Geographical proximity also allows people within the same metropolitan area to have regular face-to-face communication, which is important to information or knowledge spillovers. All MSAs in the lower 48 states are taken into account, leading to 358 observations based on the 2005 MSA definition. This is a cross-sectional study examining entrepreneurial activity in 2006, right before the 2007–09 Great Recession. The explanatory variables use the average value of 2005 and 2006 unless otherwise stated.

**Variables and data**

Table A1 in Appendix A in the supplemental data online describes all variables and their measures. The dependent variable is high-technology entrepreneurship, measured by the number of new single-unit establishments in high-technology industries standardized by metropolitan employment. New establishments data are available from the US Census Bureau’s Business Information Tracking Series (BITS). Based on four-digit North American Industry Classification System (NAICS) industries, US Bureau of Labor Statistics (BLS) economist Daniel Hecker (Hecker, 2005) defines a set of level-1 high-technology industries, which are used to identify high-technology start-ups in this study. Figure 1 presents spatial variations in high-technology entrepreneurship.

The primary explanatory variables are new knowledge and various types of skills. New knowledge according to KSTE represents entrepreneurial opportunities. New knowledge is first measured by the number of patents standardized by population. Patents are used because they can better reflect commercially viable new knowledge than other indicators, such as publications. Technology transfer via patents has become ‘a large scale activity’ (Baumol,
Litan, & Schramm, 2007, p. 243). Measuring new knowledge via patents is also consistent with other recent regional studies of knowledge spillover entrepreneurship (Plummer & Acs, 2014; Qian et al., 2013). The data cover all new patents between 2000 and 2006.

However, the number of patents as a measure of new knowledge has its own limitations, as many patents have little economic value and not all commercially useful knowledge is patented (Parker & Griliches, 1980). Patents also capture disproportionately more new knowledge created in industries than in universities. According to the US Patent and Trademark Office (USPTO) (2014), fewer than 2% of patents are granted to universities. Therefore, university research is adopted as an alternative, examining the 2005 total university research and development (R&D) spending in science and engineering fields standardized by metropolitan gross domestic product (GDP). The inter-metropolitan distribution of university R&D spending based on this standardized measure is highly skewed: 137 out of 358 MSAs had zero university R&D spending, while small college-town MSAs with one or more major research universities exhibited much higher R&D activity than most other metropolitan regions. Facing this situation, all MSAs are split into three categories based on the ranking of standardized university R&D spending — the zero R&D group (137 MSAs), the low R&D group (111 MSAs) and the high R&D group (110 MSAs) — and three dummy variables are accordingly created. Zero R&D activity is used as the baseline scenario and its dummy variable is not included in the regression model to avoid perfect multicollinearity.

Skills are used as a better measurement of human capital than formal education, which may have both direct and moderating effects on knowledge-based entrepreneurship as discussed above. To measure regional skills, this research relies on two datasets. The first, called O*NET and supported by BLS, was created based on survey data and includes results on 52 abilities and 35 skills by occupations (see Table B1 in Appendix B in the supplemental data online). The rationale behind the survey is that each occupation has its unique combination of abilities and skills, among other indicators. Using the ability named ‘Oral Comprehension’ as an example, two questions were asked in the questionnaire: ‘How important is ORAL COMPREHENSION to the performance of your current job?’ (with a scale of 1–5) and ‘What level of ORAL COMPREHENSION is needed to perform your current job?’ (with a scale of 0–7). From these questions, one can tell that O*NET asks about perceptions of occupational skills but not about the skills that occupational workers really have. In this study, the final ability/skill value for each occupation is calculated by averaging the importance value of one ability/skill and its level value. The second dataset, named Occupational Employment Statistics (OES) and available from the BLS, provides employment data by occupation and by MSA. Ability or skill values for each MSA are accordingly derived by combining O*NET and OES and calculating the ability or skill value per worker. The result is a weighted average of one ability or skill, using occupational employment as the weight. O*NET 15.0 version is used, which provides the latest ability/skill values based on the same definition of occupations with the 2005 and 2006 OES data.

As shown in Table B1 in Appendix B in the supplemental data online, 52 abilities and 35 skills are assigned to four categories of abilities and six categories of skills in the O*NET database. This study excludes three categories of abilities — namely, physical abilities, psychomotor abilities and sensory abilities — that in theory can hardly be associated with entrepreneurship. The seven categories of abilities/skills used are cognitive abilities, basic skills, social skills, complex problem-solving skills, technical skills, systems skills and resource management skills. These categories are consistent with the five types of skills discussed in the theoretical section — cognitive, technical, problem-solving, social and managerial — that may play direct and/or moderating roles in high-technology entrepreneurial activity. Based on the descriptions in Table B1, O*NET categories may correspond to the five types of skills in the way shown in Table B2 in Appendix B in the supplemental data online. Both cognitive abilities and basic skills in O*NET are defined in terms of the acquisition of knowledge, and can be considered as cognitive skills. Technical skills and systems skills in O*NET are both related to capacities needed to tackle complex social–technical systems, and can be considered as broadly defined technical skills discussed in the theoretical section. The rest of the O*NET categories — complex problem-solving skills, social skills and resource management skills — are respectively connected with problem-solving skills, social skills and managerial skills in hypotheses.

The following regression analysis uses each of these seven categories of O*NET skills as an independent variable. The MSA values of each category of skills are obtained by averaging the values of all the ability or skill components under each category (as shown in Table B1). Table C1 in Appendix C in the supplemental data online present the top-ranked MSAs by each category of skills.

Other variables that are commonly used in regional studies of entrepreneurship are controlled for, including both demographic indicators (population size, population growth and foreign born) and economic indicators (establishment size, regional productivity, unemployment, manufacturing share and industry diversity). It is well documented and theorized that innovative activity is more likely to occur in large cities (Duranton & Puga, 2001; Jacobs, 1969). Knowledge spillover entrepreneurship, defined as the commercialization of new knowledge by entrepreneurs in new firms (Acs et al., 2009; Audretsch, 1995), is essentially one type of innovative activity and, thus, expected to be more prevailing in large cities. Population growth is perhaps the best indicator of the dynamics and growth of a region, which signals new entrepreneurial opportunities (Reynolds, Storey, & Westhead, 1994). The population growth rate during
2000–06 is used. Recently, the entrepreneurship literature has documented disproportionately high entrepreneurial activity among immigrants, especially in the field of science and technology (Saxenian, 2002). Accordingly, the share of the foreign-born population is introduced as the third demography-based control variable, using the 2005–07 three-year average from the American Community Survey.4

For economic factors, new firms are generally small and can hardly compete with large incumbent firms when they enter the market. Therefore, a market characterized by the dominance of numerous small businesses is friendlier to new entries than a market dominated by one or a few giant firms. This is supported by the empirical research of Acs and Armington (2006) who find a negative association between establishment size and entrepreneurial activity. Better regional economic conditions, measured by higher GDP per worker, may lead to more vibrant entrepreneurial activity. Regional productivity is therefore hypothesized to be positively associated with entrepreneurship. The impact of unemployment on entrepreneurship is ambiguous in the literature. On the one hand, those who are unemployed are forced to start their own businesses, thus increasing new business formation. This is known as necessary entrepreneurship (Acs, 2006). On the other hand, a high unemployment rate is an indicator of economic stagnation, a business environment that discourages entrepreneurs to start new businesses. In the context of the knowledge economy, necessity entrepreneurship is less relevant, and it is reasonable to hypothesize a negative relationship between unemployment and high-technology entrepreneurship.

Lastly, two industry-related control variables are also included: manufacturing share and a diversity index, both calculated based on employment by two-digit NAICS industries. As exhibited in Figure 1, the manufacturing-based Midwest MSAs tend to have lower start-up rates. The diversity index is calculated by the reversed Herfindahl–Hirschman Index (HHI), following Qian (2013). Innovative and entrepreneurial opportunities may lie at the boundaries of different industries; therefore, a more diverse economy may lead to a higher level of entrepreneurship and economic performance (Glaeser, Kallal, Scheinkman, & Shleifer, 1992; Jacobs, 1969). For all economic indicators, this analysis only uses the 2005 data to reduce possible reverse causalities.

Table D1 in Appendix D in the supplemental data online presents descriptive statistics of all variables. Table D2 shows the correlation matrix. It can be seen that, except for technical skills, the skills variables are highly correlated with each other. Moreover, most knowledge and skills variables are significantly and positively correlated with high-technology entrepreneurship.

A surprising correlation is shown between technical skills and high-technology entrepreneurship, with an insignificant coefficient of ~0.05. A closer look at the 11 components under this skill category (see Table A1 in Appendix A in the supplemental data online) provides some insights into this unexpected relationship. Some components, including programming, technology design and operations analysis, fall into technological skills that are important to high-technology industries; the other ones, including troubleshooting, operation monitoring, repairing, equipment selection, equipment maintenance, quality control analysis, operation and control, and installation, can be better described as mechanical skills, important to the Fordist standard production that usually discourages entrepreneurship. A factor analysis among these 11 skills was conducted in which these two subcategories based on their shared variances were confirmed.5 After separating technical skills into these two subcategories, the correlation between technological skills (measured by the average value of its three skills components) and high-technology entrepreneurship has a coefficient of 0.47; when using mechanical skills (measured by the average value of its eight skills components), the coefficient is ~0.25. These two subcategories of technical skills are added to Tables D1 and D2 and are also considered in following regression models.

Regression methods

The empirical part of this research tests the two hypotheses proposed in the theoretical section using multivariate regressions. Giving the geographical dimension of the data, there are likely spatial dependence effects. In other words, entrepreneurial activity in one MSA might be influenced by entrepreneurial activity in surrounding MSAs. Figure 1 clearly shows some clusters of regions with high levels of technology entrepreneurship, e.g., in California, Colorado and Florida. Indeed, Moran’s I-tests confirm the existence of spatial dependence of high-technology entrepreneurship. The presence of spatial dependence makes ordinary least squares (OLS) results biased. Following Anselin (1988), this study uses the following spatial lag model:

\[ y = \lambda Wy + X_1 \beta_1 + X_2 \beta_2 + \varepsilon \]  

(1)

where \( y \) is a vector of observations of high-technology entrepreneurship; \( X_1 \) is a matrix of observations of primary explanatory variables (i.e., knowledge and skills variables, as well as their interaction terms used to measure the moderating effects of skills); \( X_2 \) is a matrix of observations of all control variables; \( W \) is a closeness-based, row-standardizing spatial weight matrix and \( Wy \) represents spatially lagged entrepreneurial activity, i.e., a spatially weighted average of neighbours’ high-technology new firm formation rates; \( \lambda \) measures the spillover effect of neighbours’ entrepreneurial activity; and \( \varepsilon \) is an error term. While the apparent correlation between \( Wy \) and \( \varepsilon \) leads to endogeneity, this model is estimated in a two-stage least squares (2SLS) process, employing spatially lagged independent variables as instrumental variables for \( Wy \) (Anselin, 1988). Fifty MSAs have no continuity-based neighbours. Therefore, three-nearest neighbours are used to construct the spatial weight matrix. Due to the presence of heteroskedasticity, significance levels of parameter estimations are reported based on White’s heteroskedastic-consistent standard errors.
RESULTS

Results from commercially exploiting patents-based new knowledge
Table 1 presents the regression results when new knowledge measured by patents per capita is used as an explanatory variable. The spatially lagged dependent variable is highly significant in all models, further supporting the presence of spatial lag dependence. The Anselin–Kelejian test shows that there is no significant remaining spatial autocorrelation in spatial lag models. Model 1 in Table 1 excludes the skills variables as the base model. In models 2–10, each includes one skills variable alone (to test its direct effect) as well as its interaction with new knowledge (to test its moderating effect). Each skills variable is separately put into the regression models because of the high correlations among these skills variables, as shown in Table D2 in the supplemental data online. By doing this, however, the model becomes incomplete and possibly misspecified when dropped skills variables are factors significantly associated with high-technology entrepreneurship.

As a remedy, a composite index of skills is constructed, averaging all skills that are highly correlated with each other including cognitive abilities, basic skills, social skills, complex problem-solving skills, technological skills (one subcategory of technical skills), systems skills and resource management skills. These seven skills variables exhibit high internal consistency with a Cronbach’s alpha of 0.976. Model 11 uses this composite skills variable, in addition to the mechanical skills variable (the other subcategory of technical skills) that is not highly correlated with other skills. Model 11 represents a complete model; however, the individual effect of each type of skills cannot be identified through composite skills.

For primary explanatory variables, patented knowledge shows a positive, highly significant association with high-technology entrepreneurship in the base model (model 1). However, this positive effect is outweighed by skills variables. Once the regression model includes cognitive abilities (model 2), basic skills (model 3), social skills (model 4), complex problem-solving skills (model 5), systems skills (model 9) or resource management skills (model 10), the skills variable presents a positive and significant coefficient and meanwhile the effect of the patented knowledge variable becomes insignificant. Among skills variables, technical skills do not significantly contribute to technology start-ups (model 6). As discussed following the correlation table, technical skills under the O*NET classification include both mechanical skills and technological skills. When replaced by its technological subcategory (model 8), the positive effect of technological skills becomes significant. Lastly, in the complete model (model 11), the effect of composite skills is positive and significant, and that of mechanical skills is expectedly insignificant. These results support the first hypothesis of this paper: to start businesses in knowledge-intensive industries, cognitive, technical (or, more specifically, technological), problem-solving, social and managerial skills are needed, even if the goal of new firms is not to commercialize new technologies.

The results from the interaction terms show no significant moderating effects of any skills variables and therefore provide no evidence of knowledge spillover entrepreneurship when focusing on patented knowledge. This is surprising at first glance, but may be explained by the competition between entrepreneurs and incumbent firms in commercializing local knowledge (Plummer & Acs, 2014). Most patents are created and owned by (generally large) incumbent firms. If incumbent firms decide to commercialize their patents themselves, there will be no room for entrepreneurs to do the same. The incumbent firms therefore have an edge over entrepreneurs in exploiting patented knowledge.

For control variables, population growth is positively and significantly associated with high-technology new firm formation in all models, consistent with the existing literature (Qian & Haynes, 2014; Reynolds et al., 1994). Also highly significant is the negative relationship between establishment size and high-technology entrepreneurship, consistent with the finding of Acs and Armington (2006). Unemployment rate, an indicator of economic stagnation, shows a negative association with high-technology new firm formation. The coefficient of population size is positive and significant in five of out the 11 models. Foreign born, although positive in all models, is significant only in model 8 which includes technological skills as an explanatory variable. Perhaps unexpectedly, regional productivity is not significantly associated with high-technology entrepreneurship. It may be a result of its correlation with the knowledge variable (when the latter is excluded from the base model, productivity turns into a positive and significant predictor). Lastly, no significant association between industrial diversity or manufacturing share and high-technology start-up activity is found.

Results from commercially exploiting university research
Now replace patent-based new knowledge with university research. It is not only an alternative measure of new knowledge, but also a better measure in the context of testing knowledge spillover entrepreneurship. Most research universities are not businesses and cannot commercialize their R&D outcomes themselves. New knowledge created in the university can be transferred or spilled over to the private sector, either incumbents or entrepreneurial start-ups. Compared with patented knowledge mostly owned by the incumbents, entrepreneurs are not necessarily in a disadvantageous position in competing for university knowledge. Without ownership, incumbents can no longer prevent entrepreneurs with high absorptive capacity from taking advantage of market opportunities embedded in university research output.

Models in Table 2 replace patented knowledge in Table 1 with two university research variables: the low R&D dummy and the high R&D dummy. Regression results are reported in a similar way to those in Table 1. As noted above, the zero R&D group is used as the baseline scenario and its dummy variable is not included in regression models. The significant impact of the spatially
| Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 | Model 7 | Model 8 | Model 9 | Model 10 | Model 11 |
|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|
| Dependents: High-technology entrepreneurship* |
| Spatially lagged dependent variable | 0.212** | 0.200** | 0.193** | 0.201** | 0.180** | 0.216** | 0.211** | 0.176*** | 0.188** | 0.186** | 0.182** |
| Population size | 0.025*** | 0.013 | 0.011 | 0.019** | 0.005 | 0.024*** | 0.024*** | -0.001 | 0.007 | 0.020** | 0.009 |
| Population growth | 0.004*** | 0.005*** | 0.005*** | 0.004*** | 0.005*** | 0.004*** | 0.005*** | 0.005*** | 0.005*** | 0.005*** | 0.005*** |
| Foreign born | 0.001 | 0.002 | 0.002 | 0.002 | 0.002 | 0.001 | 0.001 | 0.003** | 0.002 | 0.002 | 0.002 |
| Establishment size | -0.019*** | -0.021*** | -0.021*** | -0.019*** | -0.023*** | -0.020*** | -0.018*** | -0.024*** | -0.022*** | -0.021*** | -0.022*** |
| Regional productivity | 0.042 | 0.025 | 0.029 | 0.044 | 0.007 | 0.031 | 0.050 | -0.021 | 0.006 | -0.006 | 0.008 |
| Unemployment | -0.014*** | -0.012*** | -0.012*** | -0.013*** | -0.010*** | -0.014*** | -0.014*** | -0.005 | -0.010** | -0.010** | -0.010** |
| Manufacturing share | 0.000 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.000 | 0.001 | 0.001 | 0.001 | 0.001 |
| Industrial diversity | 0.303 | 0.178 | 0.173 | 0.329 | 0.060 | 0.255 | 0.346 | -0.088 | 0.115 | 0.155 | 0.111 |
| New knowledge | 0.152*** | -0.179 | -0.327 | -0.611 | 0.135 | 0.194 | 0.316 | 0.096 | -0.081 | 0.144 | 0.042 |
| Cognitive | 0.674*** |
| New knowledge*Cognitive | 0.110 |
| Basic | 0.514*** |
| New knowledge*Basic | 0.158 |
| Social | 0.389** |
| New knowledge*Social | -0.162 |
| Complex problem-solving | 0.743*** |
| New knowledge*Complex | -0.006 |
| problem-solving |
| Technical | 0.156 |
| New knowledge*Technical | -0.030 |
| Mechanical | -0.115 | 0.034 |
| New knowledge*Mechanical | -0.117 | -0.317 |
| Technological | 0.935*** |
| New knowledge*Technological | -0.006 |
| Systems | 0.619*** |
| New knowledge*Systems | 0.076 |
| Resource management | 0.871*** |
| New knowledge*Resource | -0.009 |

(Continued)
lagged dependent variable again supports the existence of spatial dependency.

The key focus in the results similarly is on the effect of university research and the direct and moderating effects of regional skills. In the base model where skills variables are excluded (model 12), the impact of the high R&D dummy variable is positive and significant at the 0.01 level, showing that metropolitan regions with high R&D activity have significantly higher levels of high-technology start-up rates than those without university R&D. However, there is no statistical difference in high-technology start-up rates between low R&D metros and zero R&D metros. Similar to patented knowledge, the entrepreneurship effect of high university R&D is outweighed by skills variables. It no longer has a positive and significant impact when any of the skills variables are included in the regression models (models 13–22). Consistent with Table 1, each skills variable, except for technical skills in model 17 and the mechanical subcategory of technical skills in model 18, presents a positive and significant direct impact on high-technology start-up rates, including the composite skills variable in the complete model (model 22). It should be noted that the resource management skills variable is now only marginally significant at the 0.10 level.

Most interestingly, the results now support the moderating effects of skills in the relationship between university research and high-technology entrepreneurship. The interaction terms involving cognitive skills (i.e., cognitive abilities in model 13 or basic skills in model 14), social skills (model 15), problem-solving skills (model 16), technical skills (i.e., systems skills in model 20) or managerial skills (i.e., resource management skills in model 21) all present a positive association with the dependent variable at least at the 0.05 significance level. The moderating effect of the composite skills variable, as shown in model 22, is also positive and significant at the 0.05 level. The moderating role of technological skills is only marginally significant at the 0.10 level and, therefore, should be interpreted with caution. These results provide evidence for the second hypothesis of this paper in the context of university research and also confirm the absorptive capacity theory of knowledge spillover entrepreneurship (Qian & Acs, 2013).

For control variables, compared with Table 1, foreign born now shows a positive and significant association with high-technology new firm formation in most models after university research is controlled for. This provides some evidence supporting the argument of Saxenian (2002). Manufacturing, *ceteris paribus*, is positively associated with high-technology entrepreneurship at the 0.05 level in seven of the 11 models.

### Summary and Policy Discussion

This research focuses on the association between human capital and knowledge-intensive entrepreneurship in regional economies. While the existing literature mostly examines education-based human capital, this study adopts a skills-based human capital approach and explores both the direct and moderating effects of regional skills on
Table 2. Regression results: university research and development (R&D) models.

| Dependent variable: High-technology entrepreneurship<sup>a</sup> |
|---------------------------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| Model 12                          | Model 13         | Model 14         | Model 15         | Model 16         | Model 17         | Model 18         | Model 19         | Model 20         | Model 21         | Model 22         |
|---------------------------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| Spatially lagged dependent variable | 0.325***         | 0.232***         | 0.214***         | 0.231***         | 0.204**          | 0.286***         | 0.330***         | 0.200***         | 0.209***         | 0.164**          | 0.205***         |                  |
| Population size                  | 0.015            | -0.005           | -0.004           | 0.006            | -0.011           | 0.010            | 0.016*           | -0.012           | -0.009           | 0.012            | -0.006           |                  |
| Population growth                | 0.003***          | 0.005***          | 0.005***          | 0.005***         | 0.003**          | 0.004***         | 0.005***         | 0.005***         | 0.005***         | 0.005***         | 0.005***         | 0.005***         | 0.005***         |
| Foreign born                     | 0.003*            | 0.004***          | 0.003**           | 0.003**          | 0.004***         | 0.003**          | 0.003**          | 0.004***         | 0.003**          | 0.004***         | 0.004***         | 0.004***         | 0.004***         |
| Establishment size               | -0.017***         | -0.022***         | -0.022***         | -0.020***        | -0.024***        | -0.019***        | -0.015***        | -0.024***        | -0.023***        | -0.024***        | -0.023***        |                  |
| Regional productivity            | 0.079*            | 0.036             | 0.042             | 0.074*           | 0.015            | 0.059            | 0.095**          | -0.022           | 0.010            | 0.009            | 0.022            |                  |
| Unemployment                     | -0.019***         | -0.014***         | -0.014***         | -0.016***        | -0.012**         | -0.019***        | -0.018**         | -0.006           | -0.011**         | -0.012***        | -0.011**         |                  |
| Manufacturing share              | 0.002             | 0.003**           | 0.003**           | 0.004***         | 0.002*           | 0.001            | 0.003**          | 0.001            | 0.003**          | 0.003**          | 0.003**          | 0.003**          |
| Industrial diversity             | 0.515*            | 0.249             | 0.264             | 0.477            | 0.083            | 0.367            | 0.580*           | -0.101           | 0.154            | 0.155            | 0.166            |                  |
| Low R&D                          | 0.003             | -0.443            | -0.225            | -0.001           | -0.519           | -0.270           | -0.204           | -0.314           | -0.606           | 0.156            | -0.793           |                  |
| High R&D                         | 0.074***          | -2.944**           | -1.897**           | -2.839**         | -1.865*          | -0.978           | 0.192            | -0.580*          | -1.512**         | -3.080***        | -2.155**         |                  |
| Cognitive                        | 0.713**           |                  |                  |                  |                  |                  |                  |                  |                  |                  |                  |                  |                  |
| Low R&D*Cognitive                | 0.166             |                  |                  |                  |                  |                  |                  |                  |                  |                  |                  |                  |
| High R&D*Cognitive               | 1.087**           |                  |                  |                  |                  |                  |                  |                  |                  |                  |                  |                  |
| Basic                            | 0.567**           |                  |                  |                  |                  |                  |                  |                  |                  |                  |                  |                  |
| Low R&D*Basic                    | 0.084             |                  |                  |                  |                  |                  |                  |                  |                  |                  |                  |                  |
| High R&D*Basic                   | 0.696**           |                  |                  |                  |                  |                  |                  |                  |                  |                  |                  |                  |
| Social                           | 0.448**           |                  |                  |                  |                  |                  |                  |                  |                  |                  |                  |                  |
| Low R&D*Social                   | 0.003             |                  |                  |                  |                  |                  |                  |                  |                  |                  |                  |                  |
| High R&D*Social                  | 1.014**           |                  |                  |                  |                  |                  |                  |                  |                  |                  |                  |                  |
| Complex problem-solving          |                  |                  |                  |                  |                  |                  |                  |                  |                  |                  |                  | 0.727***       |
| Low R&D*Complex problem-solving  |                  |                  |                  |                  |                  |                  |                  |                  |                  |                  |                  | 0.190           |
| High R&D*Complex problem-solving |                  |                  |                  |                  |                  |                  |                  |                  |                  |                  |                  | 0.681**         |
| Technical                        |                  |                  |                  |                  |                  |                  |                  |                  |                  |                  |                  |                  |
| Low R&D*Technical                 |                  |                  |                  |                  |                  |                  |                  |                  |                  |                  |                  |                  |
| High R&D*Technical                |                  |                  |                  |                  |                  |                  |                  |                  |                  |                  |                  |                  |
| Mechanical                       |                  |                  |                  |                  |                  |                  |                  |                  |                  |                  |                  |                  |
| Low R&D*Mechanical                |                  |                  |                  |                  |                  |                  |                  |                  |                  |                  |                  |                  |

(Continued)
Table 2. Continued.

| Model | High R&D*Mechanical | High R&D*Technological | High R&D*Systems | High R&D*Resource management | High R&D*Composite |
|-------|----------------------|-------------------------|------------------|-----------------------------|-------------------|
| 12    | -0.089               | 0.871***                |                  |                            |                   |
| 13    |                      |                         |                  |                            | 0.584***          |
| 14    |                      | 0.271                   |                  | -0.068                      |                   |
| 15    |                      |                         |                  |                            | 0.720*            |
| 16    |                      |                         |                  |                            | 0.636**           |
| 17    |                      |                         |                  |                            |                   |
| 18    |                      |                         |                  |                            | 1.485***          |
| 19    |                      |                         |                  |                            |                   |
| 20    |                      |                         |                  |                            |                   |
| 21    |                      |                         |                  |                            |                   |
| 22    |                      |                         |                  |                            |                   |

| Observations | 358 | 358 | 358 | 358 | 358 | 358 | 358 | 358 | 358 | 358 | 358 |
|--------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| Spatial pseudo-$R^2$ | 0.489 | 0.551 | 0.556 | 0.520 | 0.578 | 0.501 | 0.494 | 0.646 | 0.590 | 0.582 | 0.584 |
| Anselin–Kelejian test | 0.666 | 1.055 | 1.735 | 1.302 | 1.771 | 0.033 | 0.603 | 0.560 | 1.772 | 4.883** | 2.261 |

Note: ****Significant at 0.01 level; **significant at 0.05 level; *significant at 0.10 level; significance levels are based on robust standard errors.
high-technology entrepreneurship in US metropolitan regions. Multivariate regression analysis reports direct contributions of cognitive, technical, problem-solving, social and managerial skills to high-technology entrepreneurship. The empirical results also provide evidence on the moderating effects of these skills in converting university research (but not patented knowledge) into high-technology start-ups.

This study provides evidence for the absorptive capacity theory of knowledge spillover entrepreneurship and the importance of human capital to high-technology entrepreneurship. It also sheds a light on regional entrepreneurship policy. Despite the established consensus over the importance of entrepreneurship to regional economic development, there has been no consensus over what are appropriate entrepreneurship policies. A popular approach in industrialized countries is to encourage new firm formation via public incentive programmes, e.g., grants, subsidies, tax breaks and loans (Shane, 2009). Different from that, the policy implication of this study is to strengthen labour market skills through workforce development programmes. This capacity-building approach is drastically different from the incentives approach and, when compared with the latter, can benefit long-term regional economic development. The job-creation effect of an incentives-based entrepreneurship policy may be gone once the recipient businesses exit the market. By contrast, the increased skills in the labour market as a result of workforce development policy will last even after some entrepreneurial efforts fail. In particular, for regions that adopt a technology-led economic development strategy, this research suggests that strengthening cognitive, technical, problem-solving, social and managerial skills in the labour market contributes to knowledge-intensive entrepreneurial activity, which will further lead to productivity growth.

ACKNOWLEDGEMENTS

The author thanks Edward ‘Ned’ Hill, then Dean of the Levin College, for his support via teaching release; and Hyejin Jung for her research assistance.

DISCLOSURE STATEMENT

No potential conflict of interest was reported by the author.

FUNDING

This work was supported by the Regional Studies Association under its Early Career Grant Scheme, November 2012. It started in 2013 when the author was a faculty member at Levin College of Urban Affairs, Cleveland State University.

SUPPLEMENTAL DATA

Supplemental data for this article can be accessed at https://doi.org/10.8080/00343404.2016.1213383

NOTES

1. For details about these high-technology industries, see Appendix F in the supplemental data online.
2. Science and engineering fields under the National Science Foundation (2014) definition include engineering, physical sciences, environmental sciences, mathematical sciences, computer sciences, life sciences, psychology, social sciences and other sciences.
3. For more details on matching O*NET and OES data, see Appendix F in the supplemental data online.
4. The one-year foreign-born data for 2005 and 2006 from the American Community Survey miss a few MSAs. As a result, this research uses the 2005–07 three-year average data, which include all MSAs.
5. Factor loading results are available from the author upon request.

REFERENCES

Acs, Z. J. (2006). How is entrepreneurship good for economic growth? Innovations: Technology, Governance, Globalization, 1(1), 97–107. doi:10.1162/nigg.2006.1.1.197
Acs, Z. J., & Armington, C. (2006). Entrepreneurship, geography, and American economic growth. New York: Cambridge University Press.
Acs, Z. J., Audretsch, D. B., Braunerhjelm, P., & Carlsson, B. (2009). The knowledge spillover theory of entrepreneurship. Small Business Economics, 32, 15–30. doi:10.1007/s11187-008-9157-3
Anselin, L. (1988). Spatial econometrics: Methods and models. Dordrecht: Kluwer.
Audretsch, D. B. (1995). Innovation and industry evolution. Cambridge, MA: MIT Press.
Baron, R. A., & Markman, G. D. (2000). Beyond social capital: How social skills can enhance entrepreneurs' success. Academy of Management Executive, 14(1), 106–116.
Baumol, W. J., Litan, R. E., & Schramm, C. J. (2007). Good capitalism, bad capitalism, and the economics of growth and prosperity. New Haven and London: Yale University Press.
Becker, G. S. (1964). Human capital. New York: Columbia University Press.
Berry, C. R., & Glaeser, E. L. (2005). The divergence of human capital levels across cities. Papers in Regional Science, 84(3), 407–444. doi:10.1111/j.1435-5957.2005.00047.x
Bosma, N., van Praag, M., Thurik, R., & De Wit, G. (2004). The value of human and social capital investments for the business performance of startups. Small Business Economics, 23(3), 227–236. doi:10.1023/B:SBEJ.0000032032.21192.72
Cassar, G. (2006). Entrepreneur opportunity costs and intended venture growth. Journal of Business Venturing, 21(5), 610–632. doi:10.1016/j.jbusvent.2005.02.011
Colombo, M. G., & Grilli, L. (2005). Founders' human capital and the growth of new technology-based firms: A competence-based view. Research Policy, 34(6), 795–816. doi:10.1016/j. respol.2005.03.010
Cooper, A. C., Gimeno-Gascon, F. J., & Woo, C. Y. (1994). Initial human and financial capital as predictors of new venture performance. Journal of Business Venturing, 9(5), 371–395. doi:10.1016/0883-9026(94)90013-2
Corman, J., Perles, B., & Vancini, P. (1988). Motivational factors influencing high-technology entrepreneurship. Journal of Small Business Management, 26, 36–42.
Davidsson, P., & Honig, B. (2003). The role of social and human capital among nascent entrepreneurs. *Journal of Business Venturing, 18*(3), 301–331. doi:10.1016/S0883-9026(02)00097-6

Dimov, D. (2010). Nascent entrepreneurs and venture emergence: Opportunity confidence, human capital, and early planning. *Journal of Management Studies, 47*(6), 1123–1153. doi:10.1111/j.1467-6486.2009.00874.x

Dosi, G., & Grazzi, M. (2006). Technologies as problem-solving procedures and technologies as input–output relations: Some perspectives on the theory of production. *Industrial and Corporate Change, 15*(1), 173–202. doi:10.1093/icc/dj010

Duranton, G., & Puga, D. (2001). Nursery cities: Urban diversity, process innovation, and the life cycle of products. *American Economic Review, 91*(5), 1454–1477. doi:10.1257/aer.91.5.1454

Feld, B. (2012). *Start-up communities: Building an entrepreneurial ecosystem in your city*. Hoboken: Wiley.

Feser, E. J. (2003). What regions do rather than make: A proposed set of knowledge-based occupation clusters. *Urban Studies, 40*(10), 1937–1958. doi:10.1080/0042098032000116059

Florida, R., Mellander, C., Stolarick, K., & Ross, A. (2012). Cities, skills and wages. *Journal of Economic Geography, 12*(2), 355–377. doi:10.1093/jeg/bbr017

Glaeser, E. L., Kallal, H. D., Scheinkman, J. A., & Shleifer, A. (1992). Growth in cities. *Journal of Political Economy, 100*, 1126–1152. doi:10.1086/261856

Hecker, D. E. (2005). High-technology employment: A NAICS-based update. *Monthly Labor Review, 128*, 57–72.

Holm, J. R., & Lorenz, E. (2015). Has ‘discreetional learning’ declined during the Lisbon Agenda? A cross-sectional and longitudinal study of work organization in European nations. *Industrial and Corporate Change, 24*, 1179–1214. doi:10.1093/icc/dtv005

Jacobs, J. (1969). *The economy of cities*. New York: Random House.

Lazear, E. P. (2004). Balanced skills and entrepreneurship. *American Economic Review, 94*(2), 208–211. doi:10.1257/0002828041301425

Marvel, M. R., & Lumpkin, G. T. (2007). Technology entrepreneurs’ human capital and its effects on innovation radicalness. *Entrepreneurship Theory and Practice, 31*(6), 807–828. doi:10.1111/j.1540-6520.2007.00209.x

Michelacci, C. (2003). Low returns in R&D due to the lack of entrepreneurial skills. *Economic Journal, 113*, 207–225. doi:10.1111/1468-0297.00095

Millan, J. M., Congregado, E., Roman, C., van Praag, M., & van Stel, A. (2014). The value of an educated population for an individual’s entrepreneurship success. *Journal of Business Venturing, 29*, 612–632. doi:10.1016/j.jbusvent.2013.09.003

Moretti, E. (2013). The new geography of jobs. New York: Mariner.

National Science Foundation. (2014). *Guide for public use data files – National Science Foundation’s higher education research and development surveys: Fiscal year 2013*. Retrieved from http://www.nsf.gov/statistics/herd/data/fy-2013-herd-dug-text-file-format.pdf

Parkers, A., Griliches, Z. (1980). Patents and R&D at the firm level: A first report. *Economic Letters, 5*, 377–381. doi:10.1016/0165-1768(80)90136-6

Plummer, L. A., & Acs, Z. J. (2014). Localized competition in the knowledge spillover theory of entrepreneurship. *Journal of Business Venturing, 29*(1), 121–136. doi:10.1016/j.jbusvent.2012.10.003

Qian, H. (2013). Diversity versus tolerance: The social drivers of innovation and entrepreneurship in US cities. *Urban Studies, 50*(13), 2718–2735. doi:10.1177/0042098013477703

Qian, H., & Acs, Z. J. (2013). An absorptive capacity theory of knowledge spillover entrepreneurship. *Small Business Economics, 40*(2), 185–197. doi:10.1007/s11187-011-9368-x

Qian, H., Acs, Z. J., & Stough, R. R. (2013). Regional systems of entrepreneurship: The nexus of human capital, knowledge and new firm formation. *Journal of Economic Geography, 13*(4), 559–587. doi:10.1093/jeg/lbs009

Qian, H., & Haynes, K. E. (2014). Beyond innovation: The small business innovation research program as entrepreneurship policy. *Journal of Technology Transfer, 39*(4), 524–543. doi:10.1007/s10961-013-9323-x

Reynolds, P. D., Storey, D. J., & Westhead, P. (1994). Cross national comparisons of the variation in new firm formation rates. *Regional Studies, 28*, 443–456. doi:10.1080/0033433942313148386

Ries, E. (2011). *The lean startup: How today’s entrepreneurs use continuous innovation to create radically successful businesses*. New York: Crown.

Romer, P. M. (1990). Endogenous technological change. *Journal of Political Economy, 98*(5), S71–S102. doi:10.1086/261725

Saxenian, A. (2002). Silicon Valley’s new immigrant high-growth entrepreneurs. *Economic Development Quarterly, 16*(1), 20–31. doi:10.1177/0891240202016001003

Schultz, T. W. (1961). Investment in human capital. *American Economic Review, 51*(1), 1–17.

Shane, S. (2009). Why encouraging more people to become entrepreneurs is bad public policy. *Small Business Economics, 33*, 141–149. doi:10.1007/s11187-009-9215-5

Shane, S., & Venkataraman, S. (2000). The promise of entrepreneurship as a field of research. *Academy of Management Review, 25*(1), 217–226.

Ucbasaran, D., Westhead, P., & Wright, M. (2008). Opportunity identification and pursuit: Does an entrepreneur’s human capital matter? *Small Business Economics, 30*(2), 153–173. doi:10.1007/s11187-006-9200-3

Unger, J. M., Rauch, A., Frese, M., & Rosenbusch, N. (2011). Human capital and entrepreneurial success: A meta-analytical review. *Journal of Business Venturing, 26*(3), 341–358. doi:10.1016/j.jbusvent.2009.09.004

US Patent and Trademark Office (USPTO) (2014). *U.S. colleges and universities – Utility patent grants 1969–2012*. Retrieved from http://www.uspto.gov/web/offices/ac/ido/oep/taf/univ/doc/doc_info_2012.htm

Zahra, S. A., & George, G. (2002). Absorptive capacity: A review, reconceptualization, and extension. *Academy of Management Review, 27*(2), 185–203.