Do diversity, creativity and localized competition promote endogenous firm formation? Evidence from a high-tech US industry

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Abstract

This paper tests the effect of diversity, creativity and localized competition on firm formation in US computer and electronic product manufacturing within the knowledge spillover theory of entrepreneurship (KSTE) framework. Fixed effects instrumental variable estimation results support the KSTE contention of a positive relationship between knowledge and entrepreneurship. Industrial diversity and diversity of knowledge tend to promote endogenous firm entry, whereas evidence on other factors is mixed. This points to sensitivity of conclusions in the KSTE literature to regional and industrial environments and calls for caution in interpreting and generalizing findings obtained in various settings.

Key words: innovation, entrepreneurship, firm formation, knowledge spillover theory of entrepreneurship, computer and electronic product manufacturing

JEL codes: L26, O18, O39

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1. Introduction

New firm formation, especially in high-technology industries, is an important source of economic growth and innovation (Fritsch, 2013). Newly established companies actively introduce new products and markets (Knight, 2001), disproportionally contribute to job creation (Acs & Armington, 2004; OECD, 1997) and technological evolution (Fritsch & Mueller, 2004). For these reasons economists and policy-makers are interested in firm formation determinants. Many studies observe uneven firm birth rates across regions (Bosma, van Stel, & Suddle, 2008; Reynolds, Storey, & Westhead, 2007), which suggests the importance of regional factors in addition to the personal determinants of entrepreneurship. Local knowledge spillovers (LKS), believed to be strong in dense urban areas in general and in knowledge-intensive urban regions in particular, make increasing returns to scale possible (Griliches, 1992; López-Bazo, Vayá, & Artís, 2004) boosting economic performance.

The role of knowledge spillovers in firm formation is an emerging area of research that offers scholars and practitioners interested in the determinants of firm entry an important vantage point to reconcile and systematize the insights from the perspectives centered on agglomeration, entrepreneurship, and technology. The knowledge spillover theory of entrepreneurship (KSTE) proposed recently by Acs and co-authors (Acs, Audretsch, & Lehmann, 2013; Acs, Braunerhjelm, Audretsch, & Carlsson, 2009) is a promising lens to look at the relationship between knowledge and firm creation. The theory contends that knowledge accumulated in a region is at the heart of high-tech business entry. The knowledge-rich environments stimulate emergence of new firms via plentiful opportunities to commercialize existing ideas generated by knowledge incubators such as incumbent companies (Acs et al., 2013) or universities (Plummer & Acs, 2014). Since urban areas are naturally more knowledge-intensive than rural communities, the theory is better positioned to explain firm formation in the metropolitan areas in general, and in knowledge-intensive industries in particular.

The theory has gained considerable attention in the last few years. Ghio and co-authors (Ghio, Guerini, Lehmann, & Rossi-Lamastra, 2015) document its growing influence among scholars together with the spread of KSTE applications in various fields of economics and management. In addition to empirical tests (Lee, Hong, & Sun, 2013; Tsvetkova, 2015), several extensions were proposed (Audretsch & Belitski, 2013; Audretsch, Dohse, & Niebuhr, 2010; Bishop, 2012; Plummer & Acs, 2014; Qian & Acs, 2013). In most general terms, these extensions are of three major types. The first one offers further formalization of the theory such as in Acs and Sanders (2013). The second deals with special cases of the KSTE or with its mechanisms in special circumstances. Examples of the second type include individual perspective (Guerrero & Urbano, 2014), the KSTE in alliances (Shu, Liu, Gao, & Shanley, 2014) and the possibility of inventors to be employed in both innovative firms/research organizations and as entrepreneurs (Stam, 2013). Finally, the third type of KSTE extensions includes contributions that modify the general mechanism of the relationship between knowledge and entrepreneurship postulated by the KSTE. For example, Bishop (2012) and Audretsch and Belitski (2013) argue that diversity and creativity, respectively, play an additional role in the knowledge-entrepreneurship nexus. Plummer and Acs (2014) introduce localized competition as potentially promoting and hampering factor in endogenous firm formation. These latter extensions are the focus of this paper. If true, they should be applicable in all circumstances where the knowledge spillover theory of entrepreneurship is applicable.

The purpose of this paper is to test what mechanisms of the relationship between knowledge and high-tech entrepreneurship within the KSTE framework are at work in the US urban regions. The paper empirically assesses the validity of three KSTE extensions that directly extend the process delineated by the theory, those focusing on diversity, creativity and localized competition. The need for such a test follows from the fact that diverse settings and perspectives adopted in the studies, which extend the knowledge spillover theory of entrepreneurship, limit usefulness of the KSTE for policy-makers as applicability and validity of the theory in specific circumstances is somewhat unclear.

The U.S. computer and electronic product manufacturing industry (NAICS334) is selected as the industry well positioned to be the focus of the empirical testing. Lee and co-authors show that the link between locally created knowledge and firm formation is particularly strong in high-technology industries (Lee et al., 2013). According to the US Bureau of Labor Statistics, innovations are behind many NAICS334 start-ups with knowledge entrepreneurs setting up new companies in order to commercialize original ideas (BLS, 2011), which is the exact mechanism the KSTE proposes. The study focuses on US Metropolitan

Statistical Areas (MSA) and covers 16-year time period from 1993 to 2008, which is long enough for the relationship between knowledge creation and business formation to be observable and measurable in the data.

The rest of the paper is organized as follows. The next section briefly reviews the KSTE followed by the discussion of the role of diversity, creativity and localized competition in endogenous firm formation. Section four describes the sample, variables and data sources, while section five presents estimation strategy. Section six contains results and discussion. Section seven covers several sensitivity tests. Section eight concludes.

2. Endogenous firm formation within the KSTE perspective

The knowledge spillover theory of entrepreneurship formalizes the Audretsch's insight (1995) that companies may be endogenously created to capitalize on exogenously existing knowledge. Like the neoclassical (Lucas, 1988) and endogenous (Romer, 1990) growth theories, the KSTE emphasizes the role played by technological knowledge in economic growth. Unlike these theories, though, the knowledge spillover theory of entrepreneurship assumes neither exogenous technological progress, nor automatic knowledge spillovers and focuses on business formation based on new ideas.

According to the theory, knowledge entrepreneurs are the central agents who turn exogenously existing knowledge into endogenously created firms. Knowledge entrepreneurs are the ones willing to set up a firm to commercialize a new promising idea (e.g. technology or innovation) that is abandoned by its creators (incumbent firms) and is not utilized in the market. The inclination of potential entrepreneurs to start a new knowledge-based company is not the focus of the KSTE in contrast to vast entrepreneurship literature. Instead, the KSTE postulates that inclination or ability of a person to start a firm may be relatively unchanging over time unlike changing environment, where new business opportunities based on unutilized ideas present themselves at an uneven rate. Because knowledge tends to be spatially bound (Howells, 2002), regional innovative environment with more knowledge-based business opportunities, i.e. new ideas discarded by incumbents, should lead to greater firm formation (Acs et al., 2013) if knowledge entrepreneurs take the risks of setting up new firms, thus, penetrating the so-called 'knowledge filter' (Acs & Plummer, 2005; Acs, Plummer, & Sutter, 2009).

3. Diversity, creativity and localized competition for ideas

The KSTE is one of many perspectives that elucidate the importance of knowledge environment for economic performance in general, and for business formation in particular. Long-standing debates between proponents of Marshall, Arrow, Romer (MAR) and Jacobian externalities attempt to determine what industrial structure of a region (diversified or dominated by few – or even one - industries) is more conducive to knowledge generation and exchange. The MAR supporters contend that local monopoly and concentration of one industry would facilitate knowledge flows ensuring greater positive effect on economic outcomes (Audretsch, 2003; van der Panne, 2004; van Stel & Nieuwenhuijsen, 2004). Other researchers present evidence that industrial diversity is related to increased innovation, greater economic output and employment (Feldman & Audretsch, 1999; Frenken, van Oort, & Verburg, 2007; van Stel & Nieuwenhuijsen, 2004).

Various forms of diversity and creativity have received increased attention in regional economic research, especially in urban settings, as factors affecting knowledge environment and knowledge spillovers. With respect to business formation in the spirit of the knowledge spillover theory of entrepreneurship, diversity other than industrial plays perhaps a more substantial role. Numerous studies incorporate diversity and creativity into the KSTE framework. Bishop (2012) shows that the diversity of regional knowledge stock and a balance between knowledge-based manufacturing and knowledge-based services are related to firm birth rates in Britain. Audretsch, Dohse and Niebuhr (2010) focus on the role of regional environment, knowledge and cultural diversity. They conclude that diversity of people is more important for firm formation than business diversity. Likewise, Audretsch and Belitski (2013) believe that creativity of well-educated people and diverse environments provide a fertile ground for entrepreneurs to start new firms. Marino and co-authors (Marino, Parrotta, & Pozzoli, 2012) find different effects of ethnic diversity on business formation depending on the sector, while the diversity of workforce education promotes firm start-up rates in general.

The regional knowledge milieu and the density of companies that can both result from this milieu and shape it are inherently related to competition for ideas that follows from the endogenous firm formation perspective. Plummer and Acs (2014) call such competition for ideas localized competition and study its effects on start-up decisions of knowledge entrepreneurs as a part of the KSTE perspective. They argue that, on the one hand, increased localized competition for ideas is tantamount to rivalry, which forces incumbents to become more innovative (Feldman & Audretsch, 1999). This, in turn, increases the stock of exploitable ideas promoting knowledge entrepreneurship. On the other hand, increased rivalry is a deterrent in the decision of potential knowledge entrepreneurs to start a new business, as greater competition decreases the likelihood of success. Empirical results of the analysis based on counties in the states of Colorado and California show that increased knowledge stock promotes knowledge entrepreneurship but this effect is smaller in the areas with greater localized competition. In the densely populated counties, however, the negative moderating effect of localized competition is less pronounced.

3. Sample, data and variables

The brief review of the literature presented above implies that scholars and policy-makers interested in understanding the determinants of firm formation in high-technology sectors (where endogenous nature of start-ups is more likely) need to look at many factors such as knowledge environment, diversity, creativity and localized competition to name just a few. This study assesses the generalizability of the findings in the KSTE literature to other settings by testing the extensions of the theory that suggest a special role of diversity, creativity, and localized competition in creating new knowledge-intensive firms in a high-technology industry in the US. The analysis uses the data on the computer and electronic product manufacturing (NAICS334) industry that includes NAICS 3341 (Computer and Peripheral Equipment Manufacturing), NAICS 3342 (Communications Equipment Manufacturing), NAICS 3343 (Audio and Video Equipment Manufacturing), NAICS 3344 (Semiconductor and Other Electronic Component Manufacturing), NAICS 3345 (Navigational, Measuring, Electromedical, and Control Instruments Manufacturing), and NAICS 3346 (Manufacturing and Reproducing Magnetic and Optical Media). The importance of this industry for the U.S. economy is discussed elsewhere (see, for example, Tsvetkova, Thill, and Strumsky (2014)). In brief, NAICS334 is one of the most innovative industries in the country; Business success of the computer and electronic product manufacturing companies largely depends on their ability to introduce new products and technologies and to benefit from access to knowledge spillovers. Aware of this, NAICS334 firms tend to co-locate to reap the benefits of knowledge flows

(BLS, 2011). The unit of observation is US MSA. The estimation dataset contains 362 MSAs followed for 15 years between 1994 and 2008 with explanatory variables lagged by one year.

Following other KSTE studies (Plummer & Acs, 2014; Qian & Acs, 2013), the dependent variable is the number of new start-ups in the NAICS334 industry standardized by population in a metropolitan area[1] (*Entrepreneurship*). In the sensitivity analysis section, a negative binomial model uses the total (unadjusted) number of NAICS334 start-ups as a dependent variable. The National Establishment Time Series (NETS) Database[2] is used to count new businesses[3], while population estimates come from the U.S. Census Bureau. The data from these sources were aggregated to the MSA level to create the variable of interest.

The key factor that, according to the KSTE, determines new firm formation in a region is a pool of ideas available for market exploitation, which is a very elusive concept to measure. Several previous studies used patenting activity as a metrics of knowledge production and innovation in an area (Camp, 2005; Plummer & Acs, 2014; Qian & Acs, 2013). Using patent counts to approximate the level of regional knowledge creation has its limitations. Patent data capture only those innovations, that were brought to the attention of the US Patent and Trademark Office (US PTO) and were granted a patent, which is only a part of overall innovative activity in a region. Additionally, economic value of patents, and, thus, their contribution to the knowledge base of a region, differ considerably (Griliches, 1979; Pakes & Griliches, 1980). Nevertheless, if a relatively constant share of newly created knowledge in a region gets patented, modeling knowledge entrepreneurship as a function of patent counts should produce valid results. Several prominent scholars note that patents are perhaps the best available measure of regional innovation (Feser, 2002; Griliches, 1990). Patenting activity was shown to adequately characterize new knowledge generation in urban areas (Acs, Anselin, & Varga, 2002), which are the unit of observation in this study.

The pool of ideas available for market exploitation is approximated in this study by population-adjusted number of patents granted to inventors residing in a MSA (*Patents*). If a patent lists multiple inventors, each inventor receives a corresponding fraction of a patent

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[1] These studies focus on firm formation in high-tech industries; they standardize entrepreneurship variable by the

[2] The NETS Database is created by Walls & Associates from the Dun and Bradstreet's (D&B) DUNS Marketing Information archive. The database consists of yearly snapshots of the U.S. economy (all firms recoded by D&B to be active). The database has been increasingly used to study US economic activity at regional level.

[3] The author thanks Professor Deborah A. Strumsky for sharing the data used to calculate this variable.

count and this fraction is assigned to the MSA of residence. Each patent enters the estimation dataset on the year it was applied for, not the year the patent was actually granted[4]. It is hoped that such operationalization is able to better capture knowledge production in a region because patents are often granted years after the research leading to these grans has concluded. The US PTO is the data source[5] for the variable.

The KSTE postulates that new firms are set up in order to commercialize new ideas not utilized in the market. This implies that innovation and knowledge production begets entrepreneurship (new firm formation), which in turn begets new knowledge, as knowledge-based companies are likely to create knowledge themselves. Such a recursive relationship may lead to the endogeneity problem. If endogeneity is present, an instrumental approach is justified. Indeed, previous research relied on instrumental variables (IV) approach to model firm formation within knowledge spillover theory of entrepreneurship (Plummer & Acs, 2014)

To instrument for *Patents,* this study develops a novel measure of patenting activity (*PatMix*)[6] that follows the logic of the industry mix term in shift-share analysis (and corresponding so-called Bartik's instrument used in the analysis of economic and social outcomes across regions (Bartik, 1991; Betz, Farren, Lobao, & Partridge, 2015; Partridge, Rickman, Rose Olfert, & Tan, 2016)). The instrument is based on the national patenting activity across groups of manufacturing industries and each MSA's manufacturing industrial composition[7]. Since there are at least 10 MSAs that produce remarkably more patents than other metropolitan areas (Figure 1), no singe MSA is likely to shape national patenting, making *PatMix* an exogenous variable by construction.

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[4] Patent application count that includes both successful and unsuccessful patent applications is perhaps a better measure of knowledge production in a region. Unfortunately, the US PTO provides data on patent applications starting in 2001, which makes this measure inappropriate for present study.

[5] The author thanks Professor Deborah A. Strumsky for providing total patent application counts at MSA-level for the variable.

[6] Other potential instruments, such as total R&D university expenditures, employment in high-tech industries excluding NAICS334 and the number of technology transfer offices in an MSA were tested as well. All of them are likely to be related to high-tech entrepreneurship both directly and indirectly (via creation of knowledge). The direct link makes them invalid instruments. Adding any of them to the *IndMix* term weakens the overall predictive power of the combined instrument. For these reasons only *IndMix* is used in estimation.

[7] The measure is based on manufacturing because US PTO classifies utility patents into manufacturing industries only.

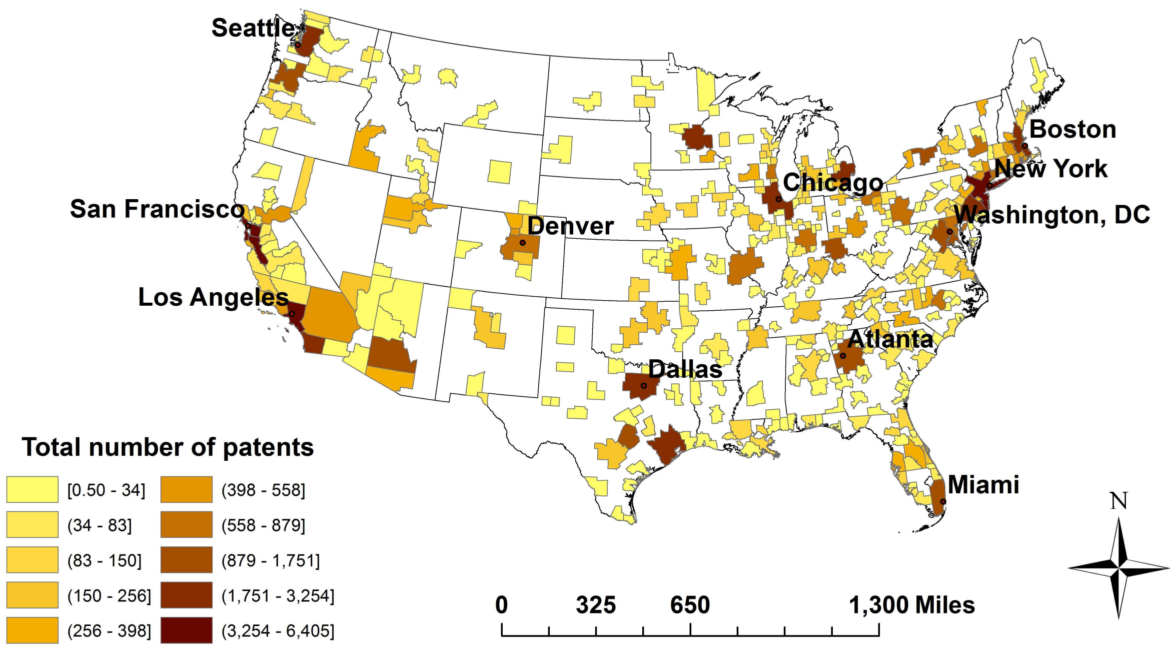

Figure 1. Total number of patents by MSA, averaged over the 1993-2008 period

PatMix is calculated as in (1) below

$$PatMix = \sum_i^n S_i \log(NP_i) \qquad (1)$$

where S_i is the share of manufacturing industry i employment in total manufacturing MSA employment; NP_i stands for the national count of patents in industry i as reported by US PTO and there are n manufacturing industries. *PatMix* is calculated using employment data (aggregated to metropolitan level) from the Economic Modeling Specialists International (EMSI), a proprietary dataset that contains employment, earnings and establishment counts by 4-digit NAICS industry codes for all US counties. National patenting by industry and year comes from US PTO, report *U.S. Patenting Trends by NAICS Industry Category Utility Patent Grants, Calendar Years 1963-2012*[8].

This study empirically assesses the effects of diversity, creativity and localized competition on NAICS334 firm formation in the US MSAs within the KSTE perspective. To do so, the basic model of the relationship between firm creation and knowledge stock is supplemented by a set of additional explanatory variables for each extension of the theory. The

[8] http://www.uspto.gov/web/offices/ac/ido/oeip/taf/naics/stc_naics_faall/usa_stc_naics_fa.htm

model of competition for ideas (Plummer & Acs, 2014) includes the localized competition variable (*LocalComp*), which is calculated from the EMSI database as the ratio of NAICS334 establishments to NAICS334 employees in an MSA divided by the same ratio for the whole economy. A set of interaction effects of *LocalComp* with other variables, used in the original contribution by Plummer and Acs, had to be excluded from estimation due to multicollinearity.

The diversity hypothesis is tested by incorporating three diversity measures intended to reflect the multifaceted nature of this urban characteristic. Following previous studies (Attaran, 1986; Bishop & Gripaios, 2007), industrial diversity (*DivIndustry*), is calculated as entropy index for the whole economy as in (2) below.

$$ID = \sum_{1}^{n} S_i \ln\left(\frac{1}{S_i}\right) \tag{2}$$

where S_i stands for the share of a 4-digit NAICS industry *i* employment in total metropolitan employment and there are *n* industries. The entropy index is zero if all employment is concentrated in one industry and it is maximized if employment is distributed evenly among industries. The second diversity measure, total knowledge diversity (*DivKnowledge*) as defined by Bishop (2012), is approximated by entropy index calculated using (2) for high-tech industries only. In this case, S_i is the share of a high-tech 4-digit NAICS industry and there are *n* high-tech industries. High-technology industries are identified by using standard 1997 to 2002 crosswalk between SIC and NAICS codes from the U.S. Census Bureau website[9] to determine industries corresponding to those reported as high-tech by Plummer and Acs (2014). The final measure of metropolitan diversity, racial diversity (*DivRace*), accounts for the diversity of people. It is calculated as in (2) with S_i being the share of race *i* in an MSA and there are *n* races represented in that metropolitan region. The former two indicators are derived from the EMSI employment data, while the latter uses the data from the U.S. Census Bureau's *Annual Population Estimates by Sex, Race and Hispanic Origin, Selected Years* files.

To test the effects of creativity within knowledge spillover theory of entrepreneurship, the following variables are used in estimation in addition to the measures of knowledge stock and control variables. The degree to which an MSA is 'Bohemian' in the spirit of Audretsch

[9] http://www.census.gov/eos/www/naics/concordances/concordances.html

and Belitski (2013) is characterized by the variable *Arts* calculated as a number of employees in NAICS71 (Arts, Entertainment and Recreation) per 1,000 employed. Variable *Professionals* is the number of employed in NAICS52 (Finance and Insurance), NAICS54 (Professional, Scientific, and Technical Services), and NAICS55 (Management of Companies and Enterprises) per 1,000 working people in an MSA. EMSI is the data source for the variables. The share of foreign-born population in an MSA – *Foreign* – as reported by the US decennial census, is an approximation for what Audretsch and Belitski (2013) call the Melting Pot Index.

Besides variables described above, all models include a set controls that account for industrial structure, economic conditions and human capital in metropolitan areas[10]. The number of employed in knowledge-intensive manufacturing per each 1,000 of total employment (*HTmanuf*) captures concentration of high-tech manufacturing in metropolitan regions and the resulting opportunities for knowledge spillovers and other benefits associated with agglomerations. Identically calculated variable for high-tech services (*HTservemp*) captures the maturity of a local market in its ability to cater to the needs of computer and electronic manufacturing companies. Both these urban characteristics should reflect the thickness of local input market that has been recently shown to be important for entrepreneurship in general and high-tech entrepreneurship in particular (Bublitz, Fritsch, & Wyrwich, 2015; Dohse & Vaona, 2014; Helsley & Strange, 2011). The EMSI data were used to compute these variables. Density is an important characteristic of an agglomerated economy that is instrumental to knowledge spillovers (Griliches, 1992; Koo, 2005; López-Bazo et al., 2004). This study uses population density (*PopDensity*), calculated from the US Census Bureau data, to capture this urban characteristic.

Personal income growth (*IncomeGrowth*) and unemployment rate (*Unemployment*) are used as proxies for economic conditions in MSAs. Income growth reflects economic trends in regional economy. Growing income may indicate widening opportunities and deepening of local market, which stimulate firm formation (Armington & Acs, 2002). The rate of unemployment, on the other hand, is a parsimonious measure of economic hardships. Although in some contexts high level of unemployment in an area might be attractive to firms in certain

[10] The estimated models do not include more traditional demographic characteristics, except for racial diversity in the diversity extension, as previous research seems to suggest that demography has little explanatory power in start-up decisions when analysis is performed by industry (Glaeser & Kerr, 2009).

industries due to the availability of cheap labor, this is not likely to be true for the NAICS334, which relies on highly trained workforce and pays higher than average wage (Helper, Krueger, & Wial, 2012). The US Bureau of Economic Analysis (BEA) is the data source for the former variable, while the latter variable comes from the US Bureau of Labor Statistics (BLS).

Two education variables control for the nature of human capital in general and the quality of the labor pool available to potential NAICS334 entrepreneurs in particular. The ratio of adult population with at least four years of college to the total number of employed (*Education*) captures the general level of educational attainment in a region. The data from the US Census Bureau and EMSI are aggregated to calculate this variable at metropolitan level. *Education*, however, is a fairly broad measure; younger and more active population might be a better approximation for the group of potential knowledge entrepreneurs, as well as for the pool of highly qualified individuals entering labor force and being available to be employed by both incumbents and start-ups. To refine the measure of education, which is likely to be crucial in the context of a knowledge-intensive industry, this paper uses the total number of graduates with a bachelor's degree or higher in computer sciences and engineering[11] standardized by population (*Engineers*). Data on the completion rates come from the Integrated Postsecondary Education Data System (IPEDS) and are aggregated from university-level information into MSA-level variable. Table 1 summarizes all variables used in this research and lists their data sources.

Table 1. Summary of the variables and their data sources

Variable	Measurement	Source
Variables used in the main analysis		
Entrepreneurship	Number of NAICS334 (Computer and Electronic Product Manufacturing) start-ups per 1 million residents	NETS
Patents (ln)	Number of utility patents granted to investors residing in MSA per 1,000 residents (log)[12]	US PTO
PatMix	A measure of expected patent count in MSA if metropolitan distribution of patents across industries follows the national distribution	US PTO, EMSI
LocalComp	A standardized measure of the number of NAICS334 establishments per NAICS334 employee	EMSI
DivIndustry	Entropy index calculated for all 4-digit NAICS industries	EMSI

[11] Computer sciences and engineering are defined by the Classification of Instructional Programs (CIP) codes: code *11.extension#* for Computer and Information Sciences, and code *14.extension#* for Engineering.
[12] Several explanatory variables were used in natural logarithm form in order to improve model fit. Since log does not exist for zero and explanatory variables often contain zero values, the following formula was used *LnVariable*=ln(*UntransformedVariable*+1).

	in MSA	
DivKnowledge	Entropy index calculated for high-tech 4-digit NAICS industries in MSA	EMSI
DivRace	Entropy index calculated for races present in MSA	US Census
Foreign	Percent of foreign-born population	US Census
Professionals	Number of employees in NAICS52 (Finance and Insurance), NAICS54 (Professional Services), NAICS55 (Management of Companies and Enterprises) per 1,000 employed	EMSI
Arts	Number of employees in NAICS71 (Arts, Entertainment and Recreation) per 1,000 employed	EMSI
HTmanufemp (ln)	Number of employees in high-technology manufacturing per 1,000 employed	EMSI
HTservemp (ln)	Number of employees in high-technology services per 1,000 employed	EMSI
PopDensity	Population in 1,000/land area	US Census
Education	Number of adults with Bachelor's degree or higher/number of employees	US Census, EMSI
Engineers (ln)	Number of graduates in Computer Sciences and Engineering per 1,000 residents	IPEDS
IncomeGrowth	Percent change in inflation-adjusted income	BEA
Unemployment	Unemployment rate	BLS
Entrepreneurship (in negative binomial model)	Total number of NAICS334 (Computer and Electronic Product Manufacturing) start-ups	NETS

The empirical evidence on the relationship between explanatory variables used in this research and firm formation and growth in general is rather heterogeneous. Most likely, heterogeneity of the findings stems from the complexity of the social and economic phenomena studied, varying research designs that cover different regions and time spans; use various measures to approximate the outcomes of interest and explanatory variables. Table 2 brings together (by no means complete) outline of the existing evidence on the effects of explanatory variables on entrepreneurship measured by start-up activity and, in some cases, on other metrics of growth. Although this latter evidence may seem somewhat irrelevant in the context of this study, it is hoped that this evidence nevertheless helps painting a broader picture that would allow placing current research within the literature. The table also shows expected signs for the main factors that should, according to the KSTE and its extensions tested here, determine high-tech entrepreneurship together with the expected signs for the control variables.

Table 2. A brief outline of the existing evidence and expected signs

Factor	Variables	Sign	Extant evidence
Knowledge	*Patents*	+/-	Innovation and knowledge production stimulate firm formation (Acs, 2002; Acs et al., 2013; Audretsch & Keilbach, 2007; Plummer & Acs, 2014); the opposite evidence comes from (Qian, Acs, & Stough,

			2012)
Localized Competition	*LocalComp*	+/-	Localized competition may promote knowledge creation and, thus, offer more opportunities for knowledge entrepreneurs; on the other hand, it may hamper firm entry (Plummer & Acs, 2014)
Diversity	*DivIndustry*	+/-	Promotes recombination of ideas that may be a fertile ground for knowledge entrepreneurs (Feldman & Audretsch, 1999; Jacobs, 1969). Audretsch et al. (2010), in contrast, find that sectoral diversity hampers firm entry in Germany
	DivKnowledge	+	Diversity of knowledge is conducive to firm formation (Audretsch et al., 2010; Bishop, 2012)
	DivRace	+/-	Literature finds that in the US context racial fragmentation may have positive (Alesina & La Ferrara, 2005), negative (Alesina & La Ferrara, 2005; Ratna, Grafton, & Kompas, 2009), or no effect (Glaeser, Scheinkman, & Shleifer, 1995b) on growth
Creativity	*Foreign*	+	Culturally diverse urban environments tend to promote firm formation (Audretsch & Belitski, 2013), have positive "amenity effects" (Ottaviano & Peri, 2012) and may attract human capital (Florida, 2002a, 2002b); another study, however, finds no evidence of the positive relationship between the share of foreign-born population and entrepreneurship (Lee et al., 2013)
	Professionals *Arts*	+ +	Creativity measured by the large share of professionals and people of creative occupations promotes firm entry (Audretsch & Belitski, 2013)
Industrial structure and density	*HTmanufemp* *HTservemp*	+ +	Specialization in high-tech industries promotes entrepreneurship (Qian et al., 2012)
	PopDensity	+/-	Population density is associated with higher firm entry
Human capital	*Education*	+	Number of adults with higher education is an important regional determinant of economic growth and entrepreneurship (Armington & Acs, 2002; Glaeser, Scheinkman, & Shleifer, 1995a)
	Engineers	+/-	Total number of graduates and graduates in engineering, as well as proximity to universities, promote firm formation in Portugal (Baptista, Lima, & Mendonça, 2011); in US MSAs, direct effect of universities measured by faculty to population ratio was found to be negative after controlling for positive effects of universities on firm start-ups via human capital (Qian et al., 2012)
Economic conditions	*IncomeGrowth*	+	Income growth explains firm formation across US regions (Armington & Acs, 2002)
	Unemployment	+/-	Unemployment may have both positive and negative effects on entrepreneurship depending on industry and region (Acs & Armington, 2006; Audretsch & Fritsch, 1999; Storey, 1991)

Table 3 presents summary statistics of the variables used in estimation of the main models, as well as in sensitivity analysis. Since many variables are used in natural logarithm form in order to improve their fit, Table 3 shows descriptives for both transformed and untransformed variables.

Table 3. Summary statistics

Variable	Mean	Std. Dev.	Min	Max
Variables used in estimation				
Entrepreneurship	12.10	12.49	0.00	168.69

Patents (ln)	0.21	0.21	0.00	1.84
PatMix	7.15	0.59	2.95	8.89
LocalComp	0.83	1.34	0.00	16.47
DivIndustry	0.19	0.21	0.05	1.74
DivKnowledge	4.52	0.27	2.46	4.94
DivRace	0.42	0.20	0.08	0.90
Foreign	5.55	5.90	0.39	35.05
Professionals	9.33	3.19	2.33	25.22
Arts	10.01	5.59	1.25	80.49
HTmanufemp (ln)	3.24	0.70	0.83	5.22
HTservemp (ln)	3.01	0.46	1.38	4.78
PopDensity	0.36	1.90	0.01	37.24
Education	0.23	0.07	0.07	0.68
Engineers	0.39	0.50	0.00	2.78
IncomeGrowth	4.27	2.33	-10.12	33.11
Unemployment	5.40	2.41	1.20	31.10
Untransformed variables that are used in natural logarithm form				
Patents	0.26	0.37	0.00	5.30
HTmanufemp	30.83	21.79	1.29	183.17
HTservemp	21.65	12.06	2.98	117.51
Engineers	0.77	1.77	0.00	15.06

4. Estimation approach

The regression-based test of endogeneity (its statistics and significance levels are reported in the last two rows of Table 5 respectively) indicates that knowledge production is endogenous in the model of NAICS334 entrepreneurship. Thus, the relationship of interest is estimated using simple IV model, which is supplemented with MSA fixed effects in the next step (Schaffer, 2012). Factoring out location-specific unchanging traits is important given that the relationship between regional characteristics and firm formation may differ by location (Cheng & Li, 2011).

Variable *Patents* is instrumented with *PatMix* (Equation (4)). *Entrepreneurship* is modeled as a function of fitted value of patenting activity in a MSA; a vector of explanatory variables that corresponds to one of the three KSTE extensions tested in this paper ***Z*** and a vector of control variables ***X*** (Equation (3)). Equation (4) fits an instrument for the stock of knowledge that can partially be exploited by potential knowledge entrepreneurs, while equation (3) presents the core model, which is supplemented by ***Z*** elements. All explanatory variables in Equations (3) and both dependent and independent variables in Equation (4) are lagged by one year to help mitigate endogeneity.

$$Entrepreneurship_{it} = \alpha + \beta_1 \widehat{Patents}_{it} + \boldsymbol{Z}_{it}\boldsymbol{\beta}_z + \boldsymbol{X}_{it}\boldsymbol{\beta}_x + \delta_i + \varepsilon_{it} \quad (3)$$

$$\widehat{Patents}_{it} = \alpha + \beta_1 PatMix_{it} + \delta_m + \varepsilon_{it} \quad (4)$$

where subscript *i* refers to a MSA, subscript *t* to a year, δ_i is MSA fixed effect and ε_{it} is an error term clustered at MSA level to account for explicitly spatial nature of the KSTE.

Five models are fitted in this paper using various approaches with results reported in this and the next section. The first model, M1, is the basic model that includes only the knowledge variable and all controls. Model 2, M2, adds localized competition variable to M1 and is a test of this KSTE extension. Model 3, M3, includes diversity characteristics in addition to the variables used in the base model. Model 4, M4, tests the creativity extension of the KSTE and includes creativity and Melting Pot measures. Finally, model 5, M5, combines variables of the base model and of the three extensions.

Although the KSTE literature proposes quite a few extensions to the basic model of Acs and co-authors (Acs et al., 2013; Acs, Braunerhjelm, et al., 2009), many of these extensions use closely related, if not identical, constructs to approximate various facets of the relationship between knowledge and firm creation. The empirical analysis presented in this paper attempts to follow closely, within reason, the operationalization used in previous research, specifically in the studies by Plummer and Acs (2014), Bishop (2012) and Audretsch and Belitski (2013). Many variables, however, had to be omitted due to multicollinearity problem.

5. Results and discussion

This section presents IV estimation results in Table 5. Basic model, the three extensions and unified model are presented together. Appendix Table 1A shows correlations of the variables and their variance inflation factor (VIF). Correlations with an asterisk are significant at 0.05 level. Overall, although some correlations are rather high, relatively low VIF suggests that multicollinearity is not likely to be a problem. Mean VIF for all variables is 1.85.

Before turning to the main results, Table 4 demonstrates first stage IV estimates. The first stage F-statistics in the last row suggests that the instrument is strong if a conventional cut-off value of 14 is used as a benchmark. Stock-Yogo weak instrument test critical value

(Stock & Yogo, 2005) for fixed effects IV model is 16.38, implying that *PatMix* passes the test for being a strong instrument.

Table 4. First stage estimation results (*PatMix* as instrument for *Patents*)

Variables	No fixed effects					Fixed effects				
	M1	**M2**	**M3**	**M4**	**M5**	**M1**	**M2**	**M3**	**M4**	**M5**
PatMix	0.07***	0.07***	0.07***	0.07***	0.06***	0.09***	0.09***	0.09***	0.09***	0.09***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
HTmanufemp	0.09***	0.09***	0.10***	0.11***	0.12***	0.02	0.02	0.02	0.02*	0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
HTservemp	0.01***	0.01***	0.01***	0.01***	0.01***	0.00***	0.00***	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
IncomeGrowth	-0.00	-0.00	-0.00	-0.00**	-0.00*	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Unemployment	0.01***	0.01***	0.01***	0.00	0.00	-0.00	-0.00	-0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Popdensity	0.00	0.00	0.00	0.00	0.00	-0.03	-0.03	-0.04**	-0.07***	-0.07***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)
Education	0.72***	0.72***	0.80***	0.61***	0.63***	-0.08*	-0.08**	-0.09**	-0.17***	-0.18***
	(0.12)	(0.12)	(0.14)	(0.12)	(0.13)	(0.04)	(0.04)	(0.04)	(0.06)	(0.06)
Engineers	0.04**	0.04**	0.02	0.04**	0.03**	0.00	0.01	0.01	0.01	0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
LocalComp		0.00			-0.00		-0.00			-0.00
		(0.00)			(0.00)		(0.00)			(0.00)
DivIndustry			-0.06**		-0.07**			0.02		-0.01
			(0.03)		(0.03)			(0.11)		(0.11)
DivKnowledge			-0.07**		-0.09**			0.04		0.05
			(0.04)		(0.03)			(0.04)		(0.04)
DivRace			-0.10***		-0.11***			0.08		0.05
			(0.03)		(0.03)			(0.10)		(0.09)
Foreign				0.01***	0.01***				0.01***	0.01***
				(0.00)	(0.00)				(0.00)	(0.00)
Professionals				-0.00	0.00				-0.01**	-0.01***
				(0.00)	(0.00)				(0.00)	(0.00)
Arts				0.00	0.00				0.00	0.00
				(0.00)	(0.00)				(0.00)	(0.00)
Constant	-0.95***	-0.96***	-0.59***	-0.91***	-0.52***	--	--	--	--	--
	(0.13)	(0.14)	(0.18)	(0.12)	(0.18)					
First stage F-stat	17.31	16.47	17.22	16.35	39.96	42.8	43.12	46.05	42.3	45.88

*** - significant at the 0.01 level; ** - significant at the 0.05 level; * - significant at the 0.1 level; standard errors in parentheses; the number of observations in all models is 5,430; robust standard errors are clustered at MSA level (362 clusters)

Table 5 shows results of the second stage IV estimation for the base model, three extensions of the knowledge spillover theory of entrepreneurship tested in this paper, and a unified model that brings together all the extensions. Following the format of Table 4, the left panel displays estimation results for models that do not control for MSA-level constant characteristics, whereas the right panel is for the models with MSA fixed effects. Variables in logarithmic form are indicated by postscript *(ln)*.

Table 5. Estimation results for NAICS334 entrepreneurship, fixed effects IV approach

Variables	**No fixed effects**					**Fixed effects**				
	M1	**M2**	**M3**	**M4**	**M5**	**M1**	**M2**	**M3**	**M4**	**M5**
Patents	44***	42***	45***	42***	42***	28***	28***	34***	28***	35***
	(4.05)	(3.91)	(3.96)	(3.77)	(3.50)	(3.47)	(3.50)	(4.30)	(3.55)	(4.36)
HTmanufemp	-3.8***	-3.7***	-4.7***	-3.4**	-4.2**	.63	.61	-6.8e-03	.14	-.49
	(-2.90)	(-2.89)	(-3.24)	(-2.29)	(-2.56)	(0.59)	(0.57)	(-0.01)	(0.14)	(-0.45)
HTservemp	.2**	.21**	.18	.15	.19*	-.24***	-.24***	-.26***	-.19*	-.21**
	(2.06)	(2.17)	(1.64)	(1.44)	(1.87)	(-2.88)	(-2.89)	(-2.66)	(-1.88)	(-2.02)
IncomeGrowth	.33***	.33***	.33***	.31***	.3***	.1*	.1*	.11**	.086	.099*
	(3.86)	(3.82)	(3.91)	(3.64)	(3.57)	(1.89)	(1.90)	(2.06)	(1.61)	(1.80)
Unemployment	.088	.091	.11	.017	-8.8e-03	-.25**	-.25**	-.23**	-.31***	-.29**
	(0.48)	(0.50)	(0.64)	(0.12)	(-0.06)	(-2.33)	(-2.32)	(-2.03)	(-2.89)	(-2.55)
Popdensity	-.025	-.026	-.093	-.055	-.1*	-2.4	-2.4	.42	-.65	1.9
	(-0.44)	(-0.47)	(-1.59)	(-1.11)	(-1.80)	(-0.78)	(-0.78)	(0.15)	(-0.35)	(0.91)
Education	-36***	-36***	-42***	-41***	-44***	-34***	-34***	-32***	-26***	-25***
	(-4.03)	(-4.05)	(-4.37)	(-4.91)	(-5.05)	(-5.37)	(-5.37)	(-5.97)	(-4.30)	(-4.14)
Engineers	-1	-.95	-.059	-.52	.14	-1.7*	-1.7*	-1.6	-1.5	-1.5
	(-1.07)	(-1.03)	(-0.06)	(-0.52)	(0.14)	(-1.68)	(-1.68)	(-1.63)	(-1.57)	(-1.54)
LocalComp		-.37*			-.29		-.049			-.049
		(-1.94)			(-1.54)		(-0.32)			(-0.31)
DivIndustry			-2.1		-1.9			29**		30**
			(-1.06)		(-0.93)			(2.28)		(2.38)
DivKnowledge			6.2***		6.3***			6.4*		7.2**
			(3.30)		(2.98)			(1.82)		(2.04)
DivRace			4.1**		3.8*			-22		-19
			(2.07)		(1.91)			(-1.49)		(-1.37)
Foreign				.12	.13				-.35**	-.34**
				(1.22)	(1.41)				(-1.98)	(-2.08)
Professionals				.25	-.092				-.39	-.36
				(1.30)	(-0.43)				(-1.26)	(-1.14)
Arts				.062	.047				-4.7e-03	-.015
				(0.83)	(0.64)				(-0.11)	(-0.34)
Constant	17***	17***	-8.5	15**	-8.7					
	(2.77)	(2.84)	(-1.09)	(2.44)	(-1.14)					
R^2	0.251	0.264	0.259	0.266	0.278	0.037	0.036	0.028	0.038	0.028
Endogeneity stat	9.86	8.57	8.47	10.01	23.56	10.47	10.73	16.26	10.40	16.68

$\chi^2(1)$	0.001	0.004	0.004	0.002	0.000	0.001	10.001	0.000	0.001	0.000

*** - significant at the 0.01 level; ** - significant at the 0.05 level; * - significant at the 0.1 level; *t*-statistic in parentheses; the number of observations in all models is 5,430; robust standard errors are clustered at MSA level (362 clusters)

The results presented in Table 5 indicate that when other relevant factors and time-invariant metropolitan characteristics are accounted for, the intensity of computer and electronic product manufacturing business formation is positively affected by the knowledge stock in a MSA. It implies that the KSTE is supported, as fitted variable *Patents* has consistent positive effect on NAICS334 entrepreneurship across the models both with and without MSA fixed effects. In the baseline specification, which excludes MSA dummies, employment in high-technology manufacturing, which has been found to be important determinant of business formation in Great Britain (Bishop, 2012), has positive effect in models 1 and 3 with only marginally significant effect in the combined model 5. The effect of high-tech manufacturing employment concentration, on the other hand, is consistently negative across models 1-5 in the left panel of Table 5. Once metropolitan fixed effects are accounted for, however, the positive effect of high-tech services concentration reverses, whereas concentration of high-tech manufacturing becomes insignificant. The negative relationship between NAICS334 firm formation and overall education level, as well as the lack of significance of the other education variable, *Engineers,* is an unexpected finding. New graduates are likely to be well prepared to recognize new business ideas and to establish companies based on those ideas, which should promote knowledge entrepreneurship. If not setting firms themselves, fresh graduates may bolster incumbent companies' absorptive capacity by bringing cutting-edge university training and the ability to recognize new ideas and implement them in the market. As a possible explanation, the model may capture availability of opportunities other than setting up a firm (e.g. employment) or indicate a time gap between graduation and when an average graduate is ready to set up a firm. A 1-year lag used in the models might be too short for the positive effect to be detectable. These negative and unexpected effects of high-technology concentration and education variables should be kept in mind when the conclusions about the overall evidence on the KSTE in the context of the NAICS334 industry in the US MSAs are drawn. If one believes that graduates and high-tech employment are a definite source of knowledge that is available for market exploitation, the estimation coefficients on *HTservemp*, *HTmanufemp*, and

Engineers imply that the KSTE is only partially supported. Recent evidence, however, shows that there is a possibility of universities having suppressing effect on entrepreneurship (Qian et al., 2012), which may suggest that equating universities and knowledge is a valid estimation strategy only in certain circumstances.

The effect of localized competition is statistically insignificant, although the coefficient is negative. Most likely, the opposing impacts of this variable described by Plummer and Acs (2014) on firm entry cancel each other. This result does not change in the analysis by subsamples of MSAs grouped by the metropolitan size and population density reported in the table below.

Model 3 focuses on the diversity hypothesis. Several measures of diversity were excluded from estimation due to high correlation among various approximations of this urban characteristic. In general, diversity does play a role in NAICS334 entrepreneurship but its effects are not uniform. The estimation results in the right panel imply that NAICS334 start-ups are attracted to the urban areas with diversified industrial structure, lending support to the Jacobian (Jacobs, 1969) view of knowledge externalities. The argument by Bishop (2012) that the diversity of knowledge base promotes firm entry is also supported. Racial diversity, on the other hand, is not statistically related to NAICS334 firm formation. This may seem counter-intuitive if one takes into account the debate about the benefits of diversity within urban environments. The special nature of racial diversity in the context of the US could be a potential explanation. A detailed theoretical analysis and thorough literature review on the issue is presented in Alesina and Ferrara (2005). Existing research suggests that racial diversity fundamentally differs from other types of social diversity in its economic causes and consequences and finds positive (Alesina & La Ferrara, 2005), negative (Alesina & La Ferrara, 2005; Ratna et al., 2009), or no effect (Glaeser et al., 1995b) of racial diversity on growth.

The creativity perspective, tested previously in the context of European cities (Audretsch & Belitski, 2013) is presented in columns M4. All measures of creativity are statistically insignificant except for the percent of foreign-born population. MSAs with smaller share of residents born outside of US appear to enjoy higher birth rates of firms in computer and electronic product manufacturing after controlling for a set of characteristics and factoring out time-invariant metropolitan traits. This is again a surprising finding but one needs to keep in mind that the foreign-born population includes both naturalized citizens and not citizens, who are likely to be in the country on a student or working visa and, thus, may be less likely to start a company because of difficulties associated with the change of immigration status. Overall, the striking difference between the findings presented here and those reported for European countries suggests that business dynamics in Europe and the US is likely to differ considerably along many dimensions.

Model 5 brings together all the KSTE extensions for a unified test. The estimation results are practically identical to the individual models reported in other columns. Overall, while the positive effect of local knowledge measured by metropolitan patenting activity on NAICS334 firm formation is a robust finding across all specifications, the three extensions of the KSTE enjoy only partial support at best. As will be shown in the sensitivity analysis section below, some of those results fade when other modeling approaches are taken. This points to the subtle nature of the relationships being tested and their sensitivity to the measurement and estimation issues. As a take away, neither of the KSTE extensions tested here can be taken for granted in the US context. It is important to keep this in mind if (or when) policy-makers start drafting economic development policies based on the insights from the KSTE in all its forms. Another important conclusion coming from Table 5 is the difference in estimation results for several variables when MSA unchanging traits are factored out. This may potentially corroborate the finding that mechanisms of business formation are place dependent (Cheng & Li, 2011) and somewhat unexpectedly contribute to the recent debates on the place-based versus place-neutral policy (Barca, McCann, & Rodríguez‐Pose, 2012; Betz & Partridge, 2013).

In the case of dissimilar mechanisms of the relationship between knowledge and entrepreneurship across localities, the instability of the results for KSTE extensions are not surprising because such extensions offer a potential explanation of how exactly knowledge translates into firm formation. If varying mechanisms of the knowledge-entrepreneurship nexus depend on characteristics of a MSA, dividing the sample into groups based on such characteristics may give further insights. Below, all metropolitan areas used in the original analysis are grouped into three categories using the 33rd and 67th percentiles of the average population density and average population size of each MSA over years 1993 to 2008. Table 6 shows fixed effects IV estimation results for each of the six groups.

Table 6. Estimation results for NAICS334 entrepreneurship; fixed effects IV approach, alternative samples

Variable	**Grouped by MSA size**			**Grouped by MSA density**		
	Small	Medium	Large	Least dense	Average	Most dense
Patents	34	36***	30***	34**	51***	20**
	(1.61)	(2.68)	(3.71)	(2.03)	(3.37)	(1.98)
HTmanufemp	-2.9*	.093	4.6*	-1.3	-.95	.29
	(-1.65)	(0.05)	(1.92)	(-0.72)	(-0.40)	(0.18)
HTservemp	-.16	-.49***	.024	-.18	-.26***	-.072
	(-1.13)	(-3.21)	(0.14)	(-1.38)	(-2.69)	(-0.24)
IncomeGrowth	.11	-.013	.14**	.038	.11	.11
	(1.16)	(-0.12)	(2.18)	(0.40)	(1.51)	(1.13)
Unemployment	-.24	-.24	-.41**	-.68***	-.21	-.027
	(-1.01)	(-1.59)	(-2.26)	(-3.36)	(-0.97)	(-0.11)
Popdensity	31	3.5	2.3	-14	-5.2	2.3
	(0.55)	(0.15)	(1.24)	(-0.28)	(-0.18)	(1.04)
Education	-26*	-20**	-25***	-37***	-1.1	-37***
	(-1.92)	(-2.11)	(-2.88)	(-3.56)	(-0.10)	(-3.53)
Engineers	-.19	-1.8	-3.4***	.13	-1.4	-4.2**
	(-0.09)	(-1.23)	(-2.60)	(0.08)	(-0.82)	(-2.54)
LocalComp	8.3e-03	-.27	.62	-.2	.21	-.16
	(0.04)	(-1.03)	(0.67)	(-0.91)	(0.68)	(-0.59)
DivIndustry	14	35*	41**	41*	-16	50**
	(0.47)	(1.77)	(2.47)	(1.81)	(-0.87)	(2.01)
DivKnowledge	14**	3.5	-2.2	.88	11**	14
	(2.46)	(0.58)	(-0.24)	(0.14)	(2.23)	(1.60)
DivRace	-.93	4.2	-36	-3.4	5.9	-36

	(-0.09)	(0.39)	(-1.63)	(-0.43)	(0.43)	(-1.61)
Foreign	-.66*	-.15	-.19	-.72**	-.38	.012
	(-1.67)	(-0.57)	(-1.06)	(-2.54)	(-1.54)	(0.07)
Professionals	-1.1*	.083	-.38	-.21	-.46	-.57
	(-1.66)	(0.22)	(-0.76)	(-0.45)	(-1.30)	(-0.71)
Art	.029	-.023	-.1	-3.0e-03	-.043	-2.4e-03
	(0.14)	(-0.59)	(-0.35)	(-0.01)	(-0.64)	(-0.07)
# of observations	1,800	1,845	1,785	1,785	1,860	1,785
# of MSAs	120	123	119	119	124	119
First stage f-stat	7.19	16.15	30.52	9.03	46.52	40.21
Endogeneity test	3.74 (0.05)	8.68 (0.00)	6.85 (0.01)	3.02 (0.08)	12.18 (0.00)	2.56 (0.11)

*** - significant at the 0.01 level; ** - significant at the 0.05 level; * - significant at the 0.1 level; *t*-statistic in parentheses; robust standard errors are clustered at MSA level

Table 6 documents heterogeneity of results depending on the MSA population density and size. The positive effect of knowledge on NAICS334 firm formation as suggested by the KSTE is perhaps the only result that practically does not change. The coefficient on *Patents* is positive and statistically significant in all subsamples except for the small MSAs. In this group the relationship disappears. Industrial diversity promotes NAICS334 entrepreneurship in large and most dense MSAs. This is in line with the literature that establishes the importance of knowledge spillovers, which are more likely to happen in dense and urbanized regions characterized by rich industrial structure. Diversity of knowledge base, on the other hand, favors business entry in a group of small urban areas and those with average level of population density. Racial diversity does not play any role, which is a consistent result across all models with fixed effects in this and the next section. Creativity measures in Table 6 are still insignificant. The evidence of the negative relationship between share of foreign-born population and NAICS334 entrepreneurship is found only in the group of least dense MSAs and, to a lesser extent, in the group of small metropolitan areas. Localized competition is not important for computer and electronic product manufacturing business entry in all subsamples.

The influence of control variables also depends on the type of regions that the analysis focuses on. Concentration of high-technology services seems to hamper business entry in the industry of interest in the subsamples of MSAs with medium population size and population density. Income growth promotes business entry in the largest metropolitan areas, whereas unemployment in this subsample is negatively related to NAICS334 entrepreneurship, as well as in the group of least dense urban areas. The surprising negative effect of the general education level and the number of computer science and engineering graduates tends to be stronger in larger and denser MSAs, potentially confirming the intervening role of employment opportunities in the relationship between education and NAICS334 entrepreneurship. It may also suggest that larger metros are more demanding in terms of new ideas and the sets of skill that are able to be the foundation of a viable business introducing a lag between graduation and setting up a business.

The last row of Table 6 suggests that in the groups of small, least dense and most dense MSAs there is no evidence of endogeneity. Moreover, *PatMix* is a weak instrument in two of these subsamples. Panel data fixed effects estimation results are generally in line with the ones displayed above except for the insignificant coefficient on *Patents* when the model is estimated using the most dense metropolitan areas. Thus, there is some evidence that the positive effect of knowledge on NAICS334 firm entry disappears in small and most dense MSAs, although the small number of observations in the subsample analysis calls for caution when interpreting those results.

6. Sensitivity analysis

This section presents several tests intended to probe sensitivity of the findings reported in the previous section to various estimation approaches. Table 7 shows simple OLS estimation and panel data fixed effects model results.

Table 7. Estimation results for NAICS334 entrepreneurship; OLS and panel data fixed effects

Variables	No fixed effects					Fixed effects				
	M1	M2	M3	M4	M5	M1	M2	M3	M4	M5
Patents	20***	20***	21***	18***	18***	6.7***	6.7***	7.3***	6.7***	7.2***
	(3.75)	(3.71)	(3.91)	(3.54)	(3.51)	(2.73)	(2.73)	(3.10)	(2.71)	(2.94)
HTmanufemp	-.92**	-1**	-1.5***	-.15	-.83	1.8*	1.7*	1.4	1.3	.92
	(-2.04)	(-2.30)	(-3.01)	(-0.31)	(-1.43)	(1.76)	(1.76)	(1.34)	(1.29)	(0.88)
HTservemp	.37***	.37***	.37***	.31***	.34***	-.15*	-.15*	-.14	-.077	-.075
	(5.85)	(5.74)	(5.65)	(3.87)	(4.37)	(-1.83)	(-1.83)	(-1.52)	(-0.80)	(-0.72)
IncomeGrowth	.3***	.3***	.3***	.25***	.25***	.05	.05	.048	.038	.038
	(3.15)	(3.17)	(3.22)	(2.79)	(2.84)	(0.92)	(0.92)	(0.91)	(0.72)	(0.72)
Unemployment	.26	.25	.26	.025	9.4e-03	-.27***	-.27***	-.25**	-.29***	-.26**
	(1.39)	(1.30)	(1.52)	(0.18)	(0.07)	(-2.64)	(-2.63)	(-2.43)	(-2.79)	(-2.46)
Popdensity	.019	.014	-.023	-.027	-.061	-2.9	-2.9	-.55	-1.9	6.8e-03
	(0.39)	(0.30)	(-0.47)	(-0.57)	(-1.24)	(-1.08)	(-1.08)	(-0.24)	(-1.06)	(0.00)

Education	-18** (-2.43)	-20*** (-2.69)	-22*** (-3.15)	-25*** (-3.65)	-28*** (-4.17)	-39*** (-6.75)	-39*** (-6.72)	-38*** (-7.52)	-33*** (-6.19)	-33*** (-6.23)
Engineers	.055 (0.09)	.05 (0.08)	.68 (1.02)	.66 (1.01)	1.1 (1.62)	-1.6 (-1.57)	-1.6 (-1.57)	-1.5 (-1.50)	-1.4 (-1.50)	-1.4 (-1.44)
LocalComp		-.44*** (-2.73)			-.36** (-2.21)		-.029 (-0.20)			-.015 (-0.11)
DivIndustry			-4.2** (-2.44)		-4.1** (-2.38)			24** (2.02)		25** (2.08)
DivKnowledge			4.4*** (2.80)		4.1** (2.35)			5.5 (1.57)		6.8* (1.91)
DivRace			1.5 (0.99)		1.1 (0.73)			-18 (-1.46)		-16 (-1.36)
Foreign				.28*** (4.30)	.28*** (4.41)				-.21 (-1.32)	-.17 (-1.26)
Professionals				.14 (0.82)	.023 (0.13)				-.6** (-2.03)	-.63** (-2.06)
Arts				.12 (1.62)	.094 (1.33)				.015 (0.32)	.011 (0.25)
Constant	3.9 (1.48)	5.2* (1.83)	-14* (-1.92)	2.1 (0.81)	-12 (-1.63)	19*** (4.58)	20*** (4.60)	-2.7 (-0.16)	25*** (5.35)	-3.7 (-0.22)
R^2	0.326	0.328	0.333	0.340	0.348	0.060	0.060	0.065	0.063	0.067

*** - significant at the 0.01 level; ** - significant at the 0.05 level; * - significant at the 0.1 level; *t*-statistic in parentheses; the number of observations in all models is 5,430; robust standard errors are clustered at MSA level (362 clusters)

Table 8 shows estimation results of the negative binomial Poisson regression. Unadjusted number of NAICS334 start-ups is used as a dependent variable in fitting the model[13]. As in the previous models, the left panel shows results for a model without MSA fixed effects, whereas the right one displays negative binomial estimation coefficients for a model that includes MSA indicator variables.

Table 8. Estimation results for NAICS334 entrepreneurship; negative binomial regression

Variables	No fixed effects					Fixed effects				
	M1	M2	M3	M4	M5	M1	M2	M3	M4	M5
Patents	1.4*** (2.61)	1.2** (2.41)	2.1*** (4.97)	.62** (2.07)	1.2*** (4.54)	.55*** (4.22)	.55*** (4.22)	.55*** (4.46)	.45*** (3.27)	.45*** (3.70)
HTmanufemp	-0.01** (-2.41)	-.01*** (-2.82)	-.02*** (-3.77)	0.002 (0.85)	-0.004* (-1.81)	0.01*** (5.78)	0.01*** (5.84)	0.01*** (5.02)	0.01*** (5.20)	0.01*** (4.34)

[13] The author thanks one of the anonymous reviewers for suggesting to use negative binomial estimation.

HTservemp	.079***	.074***	.041***	-0.006	0.006	0.000	0.000	0.000	0.001	0.001
	(5.25)	(5.22)	(5.49)	(-0.62)	(1.14)	(0.15)	(0.16)	(0.08)	(0.39)	(0.43)
IncomeGrowth	.012	.014*	.023***	0.006	0.008	-0.004	-0.006	-0.007	-0.003	-0.003
	(1.43)	(1.69)	(3.13)	(0.85)	(1.40)	(-1.21)	(-1.22)	(-1.27)	(-0.88)	(-0.96)
Unemployment	.028	.022	.07***	-.038**	-.029**	-.03***	-.03***	-.029***	-.025***	-.023***
	(1.01)	(0.83)	(3.60)	(-2.20)	(-2.15)	(-3.85)	(-3.85)	(-3.59)	(-3.19)	(-2.96)
Popdensity	.83	.76	.096	.026	.011	.072	.071	.13	-.055	.011
	(1.03)	(0.99)	(0.23)	(0.99)	(1.35)	(0.91)	(0.90)	(1.23)	(-0.86)	(0.20)
Education	-.31	-.59	-.9	-3.3***	-3.3***	-1.6***	-1.5***	-1.5***	-2.1***	-2.1***
	(-0.16)	(-0.32)	(-0.85)	(-4.01)	(-4.48)	(-6.66)	(-6.63)	(-6.04)	(-7.79)	(-7.41)
Engineers	-.39**	-.4**	.069	.048	.25***	-.22***	-.21***	-.2***	-.24***	-.21***
	(-2.22)	(-2.36)	(0.72)	(0.56)	(2.93)	(-3.55)	(-3.55)	(-3.17)	(-3.90)	(-3.48)
LocalComp		-.32***			-.19***		.021			.024
		(-6.49)			(-7.63)		(0.99)			(1.10)
DivIndustry			.97***		1.1***			.12		.28
			(3.16)		(5.46)			(0.29)		(0.72)
DivKnowledge			2.9***		2.1***			.71***		.9***
			(6.72)		(7.77)			(2.88)		(3.54)
DivRace			1.9***		1.4***			-.054		-.31
			(3.96)		(7.12)			(-0.23)		(-1.09)
Foreign				.081***	.088***				.02***	.023***
				(7.85)	(12.42)				(3.58)	(3.57)
Professionals				.36***	.13***				-.022	-.024
				(12.01)	(4.39)				(-1.20)	(-1.32)
Arts				.013	.014*				1.5e-03	2.2e-03
				(1.25)	(1.95)				(0.33)	(0.50)
Constant	-.33	.17	-14***	-1.7***	-10***	.43***	.42***	-2.8**	.6***	-3.4***
	(-0.62)	(0.35)	(-6.44)	(-5.65)	(-8.53)	(5.07)	(4.94)	(-2.46)	(4.09)	(-2.94)
R^2										

*** - significant at the 0.01 level; ** - significant at the 0.05 level; * - significant at the 0.1 level; *t*-statistic in parentheses; the number of observations in all models is 5,430; robust standard errors are clustered at MSA level (362 clusters)

Two main conclusions follow from the estimation results reported in this section. First, the positive relationship between knowledge approximated by the patenting activity and NAICS334 entrepreneurship is remarkably robust. The coefficients tend to become smaller once MSA constant characteristics are factored out but the central result of this paper persists. Second, evidence in favor or against the hypotheses proposed in the diversity, creativity and localized competition extensions of the KSTE depends on the estimation approach. In all models with MSA fixed effects included, *LocalComp* is insignificant. This runs counter to the findings reported by Plummer and Acs (2014) for Colorado and California but is perhaps not surprising if the KSTE mechanisms differ by location. The results for diversity reported in Table 7 and Table 8 coincide only for the *DivRace,* which is not significant. The remaining two measures, *DivIndustry* and *DivKnowledge,* are either positively related to NAICS334 firm formation or insignificant depending on estimation approach. The results of the creativity extension tests are the most inconsistent. Whereas concentration of creative professions is usually insignificant, employment in professional services is negatively related to computer and electronic product manufacturing firm formation in panel data fixed effects model and is unrelated in other specifications, although coefficients are negative in all cases. Share of foreign-born population, which approximates the Melting Pot index, is negative in main specification, and positive or insignificant in sensitivity analysis. Taken together, these results may be regarded as lending strong support to the relationship between knowledge and entrepreneurship in the context of NAICS334 in US MSAs as suggested by the knowledge spillover theory of entrepreneurship. The evidence on the three extensions is mixed at best and may point to the need of better definitions and operationalization of the broad concepts described in KSTE extensions.

Conclusion

Both scholars and policy-makers have long been interested in the determinants of business formation as a major contributor to employment growth, productivity and regional economic wellbeing. A long-standing understanding that innovation leads to growth (Romer, 1990; Solow, 1956) was incomplete, as the exact mechanisms of this relationship are still somewhat unclear (Audretsch & Keilbach, 2008). The recently proposed knowledge spillover theory of entrepreneurship has received close attention in the literature empirically confirming the importance of knowledge for firm formation and suggesting that other regional characteristics may play important role as well (Acs et al., 2013; Lee et al., 2013; Plummer & Acs, 2014; Shu et al., 2014; Stam, 2013; Tsvetkova, 2015).

This paper presents an attempt to bring together a number of recent extensions of the knowledge spillover theory of entrepreneurship. The KSTE implies that firm formation is endogenous to the regional knowledge creation, which is particularly likely to hold in knowledge-intensive industries and in metropolitan areas. The theory emphasizes the effects of regional environment and the ability of agents to turn knowledge into economically useful knowledge that finds profitable market applications. Three extensions were empirically tested using the 1993 – 2008 data for NAICS334, computer and electronic product manufacturing, in the US MSAs. The results of a fixed effects instrumental variable procedure support the KSTE contention of the positive effect of knowledge on business formation in the industry of interest. This result is robust in all specifications except for two cases when the analysis is performed using MSA subsamples and can potentially be unreliable due to the small number of observations. Somewhat weakening this result, however, concentration in high technology and the number of graduates in computer sciences and engineering appear to hamper NAICS334 firm formation.

The empirical support for the tested extensions is mixed. Industrial diversity, in line with the argument of Jacobian externalities, promotes entrepreneurship in US computer and electronic product manufacturing industry, whereas measures of localized competition for ideas and racial diversity are insignificant. The effect of the share of foreign-born population appears to be positive negative or insignificant depending on estimation approach. This points to sensitivity of the conclusions in the KSTE literature to regional and industrial environments and calls for caution – especially in the context of regional economic policy-making – in interpreting and generalizing the results obtained in various settings.

One needs to keep in mind potential limitations of this study and its conclusions. The data source used to calculate the dependent variable, NETS, tends to underrepresent small companies and self-employed that do not enter the D&B DUNS marketing archive or enter it with a lag. For this reason the findings are likely to apply to larger NAICS334 companies. Caution should be exercised when interpreting the results for specific explanatory variables too because they often represent rather broad and generally difficult to capture concepts that are naturally prone to measurement error. In practice, simplified perspectives offered by the KSTE itself and its extensions tested in this paper could conceal a potentially richer data structure and the patterns of relationships.

This brings the question of further KSTE development and its limitations as a theory. The KSTE focuses on the entrepreneurship opportunities offered by the environment and their role in firm formation. An alternative theoretical perspective that relates innovative and diverse environment to business creation was recently proposed by Helsley and Strange (2011) followed by a number of empirical tests (Bublitz et al., 2015; Dohse & Vaona, 2014). It shows that one of the roles agglomeration plays in enhancing entrepreneurship is supplementing the skills entrepreneurs need to successfully start and run a business in the case they miss such skills. According to the theory, agglomerated urban areas with thick input markets should be conducive to complex task firm formation. This perspective seems particularly relevant for the knowledge entrepreneurship because for an average researcher switching to entrepreneurship would require completely different set of skills that are not routinely obtained in academia or a research organization. A theoretical framework that merges these two perspectives would be a promising avenue of research shedding additional light on the complex interrelationships among knowledge, agglomeration, entrepreneurship and potentially other metropolitan features and phenomena that exist in urban context, such as the role of amenities, entrepreneurial self-selection into tasks and localities, and others.

References

Acs, Z. J. (2002). *Innovation and the growth of cities*. Cheltenham: Edward Elgar Publishing Limited.

Acs, Z. J., Anselin, L., & Varga, A. (2002). Patents and innovation counts as measures of regional production of new knowledge. *Research Policy, 31*, 1069–1085.

Acs, Z. J., & Armington, C. (2004). Employment growth and entrepreneurial activity in cities. *Regional Studies, 38*(8), 911–927.

Acs, Z. J., & Armington, C. (2006). *Entrepreneurship, geography, and American economic growth*: Cambridge University Press.

Acs, Z. J., Audretsch, D., & Lehmann, E. E. (2013). The knowledge spillover theory of entrepreneurship. *Small Business Economics, 41*, 757-774.

Acs, Z. J., Braunerhjelm, P., Audretsch, D., & Carlsson, B. (2009). The knowledge spillover theory of entrepreneurship. *Small Business Economics, 32*(1), 15-30.

Acs, Z. J., & Plummer, L. (2005). Penetrating the "knowledge filter'' in regional economies. *The Annals of Regional Science, 39*(3), 439-456.

Acs, Z. J., Plummer, L., & Sutter, R. (2009). Penetrating the knowledge filter in "rust belt" economies. *The Annals of Regional Science, 43*(3), 989-1012.

Acs, Z. J., & Sanders, M. (2013). Knowledge spillover entrepreneurship in an endogenous growth model. *Small Business Economics, 41*, 775-795.

Alesina, A., & Ferrara, E. L. (2005). Ethnic Diversity and Economic Performance. *Journal of Economic Literature, XLIII*, 762-800.

Alesina, A., & La Ferrara, E. (2005). Ethnic diversity and economic performance. *Journal of Economic Literature, 43*(3), 762-800.
Armington, K., & Acs, Z. J. (2002). The determinants of regional variation in new firm formation. *Regional Studies, 36*(1), 33-45.
Attaran, M. (1986). Industrial diversity and economic performance in U.S. areas. *The Annals of Regional Science, 22*(2), 44-54.
Audretsch, D. (1995). *Innovation and industry evolution*. Cambridge, MA: MIT Press.
Audretsch, D. (2003). Innovation and spatial externalities. *International Regional Science Review, 26*(2), 167-174.
Audretsch, D., & Belitski, M. (2013). The missing pillar: The creativity theory of knowledge spillover entrepreneurship. *Small Business Economics, 41*, 819-836.
Audretsch, D., Dohse, D., & Niebuhr, A. (2010). Cultural diversity and entrepreneurship: a regional analysis for Germany. *Annals of Regional Science, 45*, 55-85.
Audretsch, D., & Fritsch, M. (1999). The industry component of regional new firm formation processes. *Review of Industrial Organization, 15*(3), 239-252.
Audretsch, D., & Keilbach, M. (2007). The theory of knowledge spillover entrepreneurship. *Journal of Management Studies, 44*(7), 1242-1254.
Audretsch, D., & Keilbach, M. (2008). Resolving the knowledge paradox: Knowledge-spilover entrepreneurship and economic growth. *Research Policy, 37*, 1697-1705.
Baptista, R., Lima, F., & Mendonça, J. (2011). Establishment of higher education institutions and new firm entry. *Research Policy, 40*(5), 751-760.
Barca, F., McCann, P., & Rodríguez ‐ Pose, A. (2012). The case for regional development intervention: Place-based versus place-neutral approaches. *Journal of Regional Science, 52*(1), 134-152.
Bartik, T. J. (1991). Who benefits from state and local economic development policies? *Books from Upjohn Press*.
Betz, M. R., Farren, M., Lobao, L., & Partridge, M. (2015). Coal mining, economic development, and the natural resource curse. *Energy Economics, 50*, 105-116.
Betz, M. R., & Partridge, M. D. (2013). Country road take me home: Migration patterns in Appalachian America and place-based policy. *International Regional Science Review, 36*(3), 267-295.
Bishop, P. (2012). Knowledge, diversity and entrepreneurship: a spatial analysis of new firm formation in Great Britain. *Entrepreneurship & Regional Development, 24*(7-8), 641-660.
Bishop, P., & Gripaios, P. (2007). Explaining spatial patterns of industrial diversity: An analysis of sub-regions in Great Britain. *Urban Studies, 44*(9), 1739–1757.
BLS. (2011). Career guide to industries, 2010-2011 edition. Washington, DC: U.S. Department of Labor.
Bosma, N., van Stel, A. J., & Suddle, K. (2008). The geography of new firm formation: Evidence from independent start-ups and new subsidiaries in the Netherlands. *The International Entrepreneurship and Management Journal, 4*(2), 129-146.
Bublitz, E., Fritsch, M., & Wyrwich, M. (2015). Balanced skills and the city: An analysis of the relationship between entrepreneurial skill balance, thickness, and innovation. *Economic Geography, 91*(4), 475-508.

Camp, S. M. (2005). The Innovation-Entrepreneurship NEXUS: A National Assessment of Entrepreneurship and Regional Economic Growth and Development: Small Business Administration Office of Advocacy.
Cheng, S., & Li, H. (2011). Spatially varying relationships of new firm formation in the United States. *Regional Studies, 45*(6), 773-789.
Dohse, D., & Vaona, A. (2014). Start-up complexity and the thickness of regional input markets. *Economics Letters, 124*(3), 424-427.
Feldman, M. P., & Audretsch, D. (1999). Innovation in cities: Science-based diversity, specialization and localized competition. *European Economic Review, 43*(2), 409-429.
Feser, E. J. (2002). Tracing the sources of local external economies. *Urban Studies, 39*(13), 2485-2506.
Florida, R. (2002a). Bohemia and economic geography. *Journal of Economic Geography, 2*(1), 55-71.
Florida, R. (2002b). The economic geography of talent. *Annals of the Association of American Geographers, 92*(4), 743-755.
Frenken, K., van Oort, F., & Verburg, T. (2007). Related variety, unrelated variety and regional economic growth. *Regional Studies, 41*(5), 685-697.
Fritsch, M. (2013). New business formation and regional development—a survey and assessment of the evidence. *Foundations and Trends in Entrepreneurship, 9*, 249–364.
Fritsch, M., & Mueller, P. (2004). Effects of new business formation on regional development over time. *Regional Studies, 38*(8), 961-975.
Ghio, N., Guerini, M., Lehmann, E. E., & Rossi-Lamastra, C. (2015). The emergence of the knowledge spillover theory of entrepreneurship. *Small Business Economics, 44*(1), 1-18.
Glaeser, E. L., & Kerr, W. R. (2009). Local industrial conditions and entrepreneurship: how much of the spatial distribution can we explain? *Journal of Economics & Management Strategy, 18*(3), 623-663.
Glaeser, E. L., Scheinkman, J. A., & Shleifer, A. (1995a). Economic growth in a cross section of cities. *Journal of Monetary Economics, 36*(1), 117-143.
Glaeser, E. L., Scheinkman, J. A., & Shleifer, A. (1995b). Economic growth in a cross-section of cities. *Journal of Monetary Economics, 36*(1), 117-143.
Griliches, Z. (1979). Issues in assessing the contribution of R&D to productivity growth. *Bell Journal of Economics, 10*, 92-116.
Griliches, Z. (1990). Patent statistics as economic indicators: A survey. *Journal of Economic Literature, 28*(4), 1661-1707.
Griliches, Z. (1992). The search for R&D spillovers. *Scandinavian Journal of Economics, 94*(0), S29-S47.
Guerrero, M., & Urbano, D. (2014). Academics' start-up intentions and knowledge filters: An individual perspective of the knowledge spillover theory of entrepreneurship. *Small Business Economics, 43*(57-74).
Helper, S., Krueger, T., & Wial, H. (2012). Why does manufacturing matter? Which manufacturing matters? A policy framework. Washington, DC: Brookings Institutions.

Helsley, R. W., & Strange, W. C. (2011). Entrepreneurs and cities: Complexity, thickness and balance. *Regional Science and Urban Economics, 41*(6), 550-559.
Howells, J. (2002). Tacit knowledge, innovation and economic geography. *Urban Studies, 39*(5-6), 871-884.
Jacobs, J. (1969). *The economy of cities*. New York: Random House.
Knight. (2001). Entrepreneurship and strategy in the international SME. *Journal of International Management, 7*(3), 155-171.
Koo, J. (2005). Agglomeration and spillovers in a simultaneous framework. *Annals of Regional Science, 39*(1), 35-47.
Lee, I. H., Hong, E., & Sun, L. (2013). Regional knowledge production and entrepreneurial firm creation: Spatial dynamic analyses. *Journal of Business Research, 66*(10), 2106-2115.
López-Bazo, E., Vayá, E., & Artís, M. (2004). Regional externalities and growth: Evidence from European regions. *Journal of Regional Science, 44*(1), 43-73.
Lucas, R. (1988). On the mechanics of economic development. *Journal of Monetary Economics, 22*(1), 3-42.
Marino, M., Parrotta, P., & Pozzoli, D. (2012). Does labor diversity promote entrepreneurship? *Economics Letters, 116*(1), 15-19.
OECD. (1997). Globalization and small & medium enterprises (SMEs). Paris: Organisation for Economic Co-operation and Development.
Ottaviano, G. I., & Peri, G. (2012). Rethinking the effect of immigration on wages. *Journal of the European Economic Association, 10*(1), 152-197.
Pakes, A., & Griliches, Z. (1980). Patents and R&D at the firm level: A first report. *Economics Letters, 5*(4), 377-381.
Partridge, M. D., Rickman, D. S., Rose Olfert, M., & Tan, Y. (2016). International trade and local labor markets: Do foreign and domestic shocks affect regions differently? *Journal of Economic Geography*. doi: 10.1093/jeg/lbw006
Plummer, L., & Acs, Z. J. (2014). Localized competition in the knowledge spillover theory of entrepreneurship. *Journal of Business Venturing, 29*, 121-136.
Qian, H., & Acs, Z. J. (2013). An absorptive capacity theory of knowledge spillover entrepreneurship. *Small Business Economics, 40*(2), 185-197.
Qian, H., Acs, Z. J., & Stough, R. (2012). Regional systems of entrepreneurship: The nexus of human capital, knowledge and new firm formation. *Journal of Economic Geography*. doi: 10.1093/jeg/lbs009
Ratna, N. N., Grafton, R. Q., & Kompas, T. (2009). Is diversity bad for economic growth?: Evidence from state-level data in the US. *The Journal of Socio-Economics, 38*(6), 859-870.
Reynolds, P., Storey, D. J., & Westhead, P. (2007). Cross-national comparisons of the variation in new firm formation rates. *Regional Studies, 28*(4), 443-456.
Romer, P. M. (1990). Endogenous technological change. *The Journal of Political Economy, 98*(5, Part 2: The Problem of Development: A Conference of the Institute for the Study of Free Enterprise Systems), S71-S102.
Schaffer, M. E. (2012). xtivreg2: Stata module to perform extended IV/2SLS, GMM and AC/HAC, LIML and k-class regression for panel data models. *Statistical Software Components*.

Shu, C., Liu, C., Gao, S., & Shanley, M. (2014). The knowledge spillover theory of entrepreneurship in alliances. *Entrepreneurship Theory and Practice, 38*(4), 913-940.
Solow, R. M. (1956). A contribution to the theory of economic growth. *The Quarterly Journal of Economics, 70*(1), 65-94.
Stam, E. (2013). Knowledge and entrepreneurial employees: a country-level analysis. *Small Business Economics, 41*, 887-898.
Stock, J. H., & Yogo, M. (2005). Testing for weak instruments in linear IV regression. *Identification and inference for econometric models: Essays in honor of Thomas Rothenberg*.
Storey, D. J. (1991). The birth of new firms - does unemployment matter? A review of the evidence. *Small Business Economics, 3*, 167-178.
Tsvetkova, A. (2015). Innovation, entrepreneurship, and metropolitan economic performance: Empirical test of recent theoretical propositions. *Economic Development Quarterly, 29*(4), 299-316.
Tsvetkova, A., Thill, J.-C., & Strumsky, D. (2014). Metropolitan innovation, firm size, and business survival in a high-tech industry. *Small Business Economics, 43*(3), 661-676.
van der Panne, G. (2004). Agglomeration externalities: Marshall versus Jacobs. *Journal of Evolutionary Economics, 14*, 593-604.
van Stel, A. J., & Nieuwenhuijsen, H. R. (2004). Knowledge spillovers and economic growth: An analysis using data of Dutch regions in the period 1987-1995. *Regional Studies, 38*(4), 393-407.

Appendix

Table 1A. Correlation matrix for the variables and their VIF statistics

	VIF	*Patents*	*LocalComp*	*DivIndustry*	*DivKnowledge*	*DivRace*	*Foreign*	*Professionals*	*Arts*	*HTmanufemp*	*HTservemp*	*PopDensity*	*Education*	*Engineers*	*IncomeGrowth*	*Unemployment*
Patents	2.51	1														
LocalComp	1.1	-0.21*	1													
DivIndustry	1.48	0.04*	-0.13*	1												
DivKnowledge	2.04	0.16*	-0.15*	0.32*	1											
DivRace	1.24	-0.08*	-0.02	0.30*	-0.13*	1										
Foreign	1.66	0.20*	-0.10*	-0.00	-0.10*	0.13*	1									
Professionals	3.87	0.42*	-0.21*	0.44*	0.47*	0.13*	0.24*	1								
Arts	1.25	0.22*	-0.08*	0.07*	0.18*	-0.03*	0.07*	0.33*	1							
HTmanufemp	2.07	0.41*	-0.15*	0.06*	0.39*	-0.14*	-0.30*	0.05*	-0.04*	1						
HTservemp	3.36	0.54*	-0.22*	0.32*	0.29*	0.08*	0.19*	0.79*	0.40*	0.10*	1					
PopDensity	1.04	0.09*	-0.05*	0.02	0.10*	0.07*	0.09*	0.12*	0.02	0.04*	0.09*	1				
Education	2.06	0.42*	-0.20*	0.16*	0.13*	0.12*	0.28*	0.54*	0.32*	-0.10*	0.58*	0.13*	1			
Engineers	1.46	0.35*	-0.11*	0.04*	-0.15*	0.04*	0.03*	0.17*	0.04*	0.07*	0.35*	0.00	0.41*	1		
IncomeGrowth	1.05	-0.01	0.01	0.01	-0.00	0.02	-0.00	0.04*	0.04*	-0.01	0.07*	-0.00	0.01	0.01	1	
Unemployment	1.59	-0.22*	0.06*	-0.14*	-0.20*	0.04*	0.36*	-0.27*	-0.21*	-0.27*	-0.37*	-0.02	-0.21*	-0.21*	-0.19*	1

Note: * - significant at 0.05 level