Exploring innovation creation across rural and urban firms

Analysis of the National Survey of Business Competitiveness

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Abstract

Purpose – The innovation creation literature primarily focuses on urban firms/regions or relies heavily on these data; less studied are rural firms and areas in this regard. The purpose of this paper is to employ a new firm-level data set, national in scale, and analyze characteristics that potentially influence innovation creation across rural and urban firms.

Design/methodology/approach – The authors use the 2014 National Survey of Business Competitiveness (NSBC) covering multiple firm-level variables related to innovation creation combined with secondary data reflecting the regional business and innovative environments where these firms operate. The number of patent applications filed by these firms measures their innovation creation, and the paper employs a negative binomial regression estimation for analysis.

Findings – After controlling for industry, county and state factors, rural and urban firms differ in their innovation creation characteristics and behaviors, suggesting that urban firms capitalize on their resources better than rural firms. Other major findings of the paper provide evidence that: first, for rural firms, the influence of university R&D is relevant to innovation creation, but their perception of university-provided information is not significant; and second, rural firms that are willing to try, but fail, in terms of innovation creation have a slight advantage over other rural firms less willing to take on the risk.

Originality/value – This paper is one of the first to analyze the 2014 NSBC, a firm-level national survey covering a wide range of innovation-related variables. The authors combine it with other regional secondary data, and use appropriate analytical modeling to provide empirical evidence of influencing factors on innovation creation across rural and urban firms.

Keywords Innovation, National Survey of Business Competitiveness, Negative binomial, Patent counts, Rural enterprise innovation survey, Rural firms, Rural-urban innovation gap

Paper type Research paper

1. Introduction

Innovative firms are essential to sustain economic growth. Established firms must continuously innovate to survive the forces of creative destruction in the face of new and disruptive technologies. Innovation also serves as a mechanism for new firm entry into emerging markets and enables these new entrants to compete with existing firms as well as other new entrants (Christensen, 2013; Schumpeter, 1942). The literature on regional innovation is primarily focused on urban innovation and based on firm data from urban areas that foster innovation creation and adoption; less studied is rural innovation and potential differences in innovation drivers between rural and urban areas (Dabson, 2011). Of the studies comparing rural and urban innovation, many conclude that rural America

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lags in its innovation performance (Orlando and Verba, 2005; Porter *et al.*, 2004; Wojan *et al.*, 2015).

Economies need innovation-based entrepreneurship to achieve and sustain growth (Mann and Shideler, 2015), and competitiveness of the overall US economy builds on the rural–urban interdependency (Dabson, 2007, 2011). The rural–urban innovation gap has long-term consequences. For example, lower education rates and fewer economic opportunities for youth lead to sluggish wealth creation which, in turn, contributes to the persistence of rural poverty (Lyons *et al.,* 2018; Orlando and Verba, 2005; Porter *et al.*, 2004; Ratner and Markley, 2014).

Innovation in urban areas is generally explained in terms of the agglomeration effect supported by the higher population density as well as higher concentrations and diversity of firms and industries in these areas (Carlino *et al.*, 2001; Glaeser *et al.*, 1992; Orlando and Verba, 2005). Urban agglomeration facilitates the urban firms' opportunities to capitalize on their scale economies through enhanced communication and knowledge spillovers among innovative firms and industries, better supply of critical innovation resources such as human capital, extended buyer and supplier networks, and financial and professional support services (Aryal *et al.*, 2018; Orlando and Verba, 2005). On the other hand, scattered populations and less developed markets in rural areas restrict the opportunities for innovation by rural firms.

Related to the locational obstacles to innovation, rural firms have lower levels of skilled managers, professionals, and technicians and rural entrepreneurs are more likely to start new businesses based on necessity rather than opportunity, which frequently leads to a non-innovative enterprise that may be abandoned when better paying jobs arise (Acs, 2006; Henderson, 2002). Rural firms are also less likely to be growth-oriented, which may be attributed to owner characteristics such as embracing multi-generational business ownership models or the tendency to avoid risk associated with adopting and/or creating innovation (Knickel *et al.*, 2009; Renski and Wallace, 2012). Such business models are less likely to attract equity and venture capital due to reduced interest or flexibility in potential exit strategies, a necessity for innovative startups (Markley, 2001).

In terms of policy obstacles, rural economies are often framed as primarily agriculture-dependent, with substantial public resources focused on cost-saving technologies for agriculture production (Mowery *et al.*, 2010; Stauber, 2001). While these kinds of innovations are important for the growth and development of the US agricultural sector, dependence of rural economies on agriculture significantly declined after the industrial revolution, and this gave rise to a new diversity of rural industries. Thus, when policy makers overlook rural industrial diversity, this omission likely negatively impacts non-agriculture related innovation in rural areas through missed opportunities for new firms and reduced competition for existing firms (Stauber, 2001).

To provide guidance for policy makers that helps mitigate the negative effects of the challenges highlighted above, it remains necessary to continue expanding our understanding of the obstacles faced by rural firms in terms of innovation creation and adoption (Chatterji *et al.*, 2014; Fortunato, 2014). This is the underlying motivation for this study. We develop our analytical models from firm-level data provided by the 2014 National Survey of Business Competitiveness (NSBC). The NSBC data were made available by United States Department of Agriculture (USDA) for confidential access. The NSBC is a unique survey of the US firms, containing 257 variables from questions covering topics such as Research and Development (R&D) activities, innovation outputs, failed innovations, patents, other intellectual property protection, employee education levels, affiliated industry, location factors including local amenities, market share, location-based barriers and local government impact, among others. We combine selected innovation-related firm variables from the NSBC data with county-level secondary data from the Bureau of Economic

Analysis (BEA), National Science Foundation (NSF) and US Census Bureau, to capture the external business and innovation environment in which these firms operate.

We use the number of patent applications as our measure for innovation creation and employ negative binomial regression models to empirically test firm-level characteristics that influence innovation creation. Three models are estimated, one for the combined sample of rural and urban firms ($n = 4{,}351$), one for urban firms only ($n = 1{,}117$) and one for rural firms only ($n = 3{,}234$). In our empirical analysis, we first test whether there is a difference between the innovation-related characteristics of rural and urban firms once external regional factors are controlled. Further, we examine potential firm-level characteristics and behaviors that drive innovation across urban and rural firms. We find that there are differences between rural and urban firms in terms of influencers of their patenting activities, with urban firms exhibiting better capability to capitalize on their resources compared to rural firms. Additionally, we find evidence that the influence of university R&D is relevant to innovation creation in rural firms, but their perception of university-provided information may not be significant.

The remainder of this paper is organized as follows. Section 2 provides a review of literature on firm innovation and its measure. Section 3 provides a description of the data and selection of variables, and Section 4 describes our research methodology including the empirical model. Results are presented and discussed in Section 5, and Section 6 concludes with a brief summary and policy recommendations.

2. Literature review of innovation and its measurement

During the 1950s through 1970s, innovation studies as well as policies directed toward improving innovation mainly focused on the role large firms play in driving the innovation process (Chandler, 1977; Schumpeter, 1942). The belief was that large firms, through scale economies, were best suited to bear the risk of R&D investment necessary to create new innovations. The role of small businesses in this process was viewed as minimal as they were argued to be handicapped by a lack of financial, physical, and human capital needed to innovate and commercialize new technologies (Galbraith, 1956). With the emergence of new technologies and new evidence showing that small firms played a major role in job creation, this belief evolved. Scholars recognized that scale economies also occurred through geographic proximity to a large number of small firms and this is as important to the innovation process as the scale economies of large enterprises. This new understanding recognized the importance of the links between entrepreneurship, small and large firms, and innovation creation in terms of driving technological progress (Audretsch, 2005). From this view and based on the knowledge production function framework formalized by Griliches (1979), business formation is a key starting point in the innovation process. While new firms are created exogenously, innovation and technological change occurs through the performance of these firms endogenously as they pursue knowledge creation for the purpose of improving the firm's standing (Arrow, 1962; Cohen and Levin, 1989; Scherer, 1984). Therefore, R&D efforts are considered as the most important inputs to innovation creation, but these efforts remain relevant to both new and established firms regarding innovation creation (Cohen and Klepper, 1991, 1992).

The focus on the firm as a central unit of the innovation process shifted to a broader geographical level of analysis, following Jaffe's (1989) modification of Griliches' (1979) knowledge production function to study the spillover of knowledge between universities and private industries (Audretsch and Feldman, 2004). Over the years, a wide theoretical consensus has emerged showing that knowledge spillover is an important source of innovation in urban areas (Audretsch and Feldman, 1996; Rosenthal and Strange, 2004). This led to wider scholarly interest in urban innovation studies as densely co-located firms tend to facilitate face-to-face interaction among knowledge workers and give rise to a greater extent of tacit knowledge spillover in urban areas (Glaeser *et al.*, 1992; Henderson, 2003).

On the empirical side, difficulty in measuring innovation and technological progress, generally arising from data availability, made estimation of the knowledge production function challenging (Cohen and Levin, 1989; Kuznets, 1962). The available measures act as proxies reflecting one or more aspect of the innovation process. Typically, innovation metrics are categorized in one of three ways, as: the initial innovative input, such as R&D expenditures and human capital; intermediate outputs, such as the number of patents; or final innovative outputs, such as new product announcements (Acs *et al.*, 2002; Aghion and Howitt, 1990; Acs and Audretsch, 2005).

Each category and respective measure has limitations, and this fact is reflected in the literature. For example, tangible innovation creation appears lumpy relative to the levels of inputs such as R&D expenditures (Kleinknecht, 1987; Kleinknecht and Verspagen, 1989). Additionally, formal R&D budgets are not necessarily solely directed toward innovation creation; instead, they may include activities such as imitation and technology transfer (Mansfield, 1984). Similarly, patent applications and awards data, often used as a measure of innovation, are frequently criticized in the literature. For example, using the number of patents as a measure of innovation suffers from the implicit assumption of homogeneity regarding the innovation's economic value both in terms of market value and total R&D investment (Cohen and Levin, 1989; Pakes and Griliches, 1980). Further, not all innovations are likely to result in patents nor are all patents likely to be used for a final innovative output, for example, they may be used as leverage for financing or held as defense against competing products (Nagaoka *et al.*, 2010). Challenges also arise in the use of direct measures of innovative outputs such as new product or service launches in a market. Most notably, new product or service launches and similar output measures are expensive and labor intensive to measure (Acs *et al.*, 2002; Huang *et al.*, 2010)

While patents as innovation measures have limitations, the literature maintains that patents remain a reliable metric for innovation creation (Acs *et al.*, 2002; Czarnitzki *et al.*, 2009; Pakes and Griliches, 1980). For example, Acs *et al.* (2002) compared patent applications to an SBA data set constructed from information in trade and technical journals on new products and reported that patents performed as well as this alternative innovation creation measure. Similarly, comparing 40 different potential innovation measures constructed from the 2014 NSBC data (the same data set as used in the current study), Parker *et al.* (2017) showed that patent applications were significantly correlated with the other 39 innovation measures. Additionally, current availability and the historical use of patent data makes it a popular measure in terms of examining changes over time and for comparing different levels of aggregation (e.g. influencers at the firm-level vs the regional-level).

3. Data

Two types of variables are included in our model – firm and county level. Firm-level data are from the 2014 NSBC conducted by the USDA. Respondents ($n = 10{,}929$) are comprised of US establishments with more than five employees in the tradable sectors that include mining, manufacturing, wholesale trade, transportation and warehousing, information, finance and insurance, professional/scientific/technical services, arts and management of business. In total, there are 257 potential variables from survey questions covering topics such as R&D activities, innovation output (sales from new or improved products or services), failed innovations, patents, other intellectual property protection, employee education levels, affiliated industry, business founder's conceptualization, location factors including local amenities, effects of the 2008–2009 recession, market share, location-based barriers and local government impact[1]. However, only a portion of the total 2014 NSBC observations were included in this study due to incomplete responses (1,927), observations with missing firm location information in terms of county FIPS (350), observations for which the respondents reported either they were "not familiar" or "slightly familiar" with how innovation was carried out in their businesses (704), and observations with missing responses to relevant variables in our analysis (3,404)[2].

County-level data are intended to represent the regional business climate and include variables for university R&D, human capital, industrial structure, and selected demographic, and fiscal characteristics. The county-level data cover the 48 contiguous states not including the District of Columbia[3]. These data come from the US Census Community Business Patterns (CBP) and American Community Survey (ACS), the BEA and NSF. When matching firm- and county-level data by the county FIPS codes, 193 additional observations were dropped due to missing values within the county-level data set. Thus, our effective sample for this study includes 4,351 establishments. Table I includes variable names, a brief description and source, and the next few subsections provide details about variables selection and construction.

3.1 Dependent variable: firm innovation creation

The 2014 NSBC included three questions about patenting that occurred between 2011 and 2013, including whether or not the firm applied for one or more patents (binary), the number of patent applications filed (count) and the number of patents awarded (count). Part of our motivation for use of the self-reported patent counts is to make these study results comparable to prior work, and patent counts allow for more modeling flexibility relative to a binary response as it includes magnitude (Acs *et al.*, 2002; Czarnitzki *et al.*, 2009; Grilliches, 1998; Trajtenberg, 1987). Of the two patent count options from the survey (applications and awards), patent applications are frequently used in the literature as they reflect the most recent level of firm inputs[4]. Further, the patent award date relative to when the application is filed can occur in the same year or even decades from the application date (Hall *et al.,* 2005). This makes patent applications more consistent with other variables generated from the 2014 NSBC as they reflect input levels in the nearby period as when new applications were filed but not necessarily for those applications leading to awards if the application-award lags were many years later. Further, while patent applications reflect the firm's effectiveness in endogenous innovation efforts, patent awards depend on whether other firms/individuals were first movers with a similar patent application. Therefore, we selected patent applications as the most appropriate indicator of innovation output and dependent variable for our estimations.

3.2 Independent variables

We include a range of firm specific characteristics in our model including: location (rural/urban county), innovation creation actions and behaviors, and perceptions and characteristics related to human capital. First, we distinguish between firms located in rural and urban counties[5]. In the combined model (discussed more in the methods section), an indicator for rural is included. The other two models include urban-only or rural-only firms[6]. Similar to prior literature, we anticipate that the rural parameter in the combined model will be negative, and/or that differences in urban and rural firm models necessitate separate models, one for rural and one for urban firms.

Second, we consider specific firm behaviors and activities in the innovation creation process. Aghion and Howitt (1990) identified three categories or stages of innovation development, R&D inputs (R&D expenditures), intermediate R&D output (patent) and final innovative output (new product or process), and the most innovative firms were active in each. We broaden their description of each category to include other ways in which these activities may occur and based on 2014 NSBC responses. Within our modeling framework, each category is represented with an indicator variable. The first category (R&D input) includes in-house R&D, purchased external R&D, design activities and

Variables	Definition	Source (year)
Firm-level		
Patent applications	Total number of patent applications during 2011–2013	2014 NSBC
Rural	Located in a non-metro county (1 = yes; 0 = no)	
Academic information	Academia as valuable source of new ideas (not at all valuable = 0, somewhat valuable = 1, very valuable = 2)	
Bachelor's degree	Employs individuals with at least bachelor education (1 = yes; 0 = no)	
Difficulty hiring	Difficulty finding qualified applicants (0 = very difficult; 1 = somewhat or not difficult)	
High-tech (NSF def.)	Firm belonging to high-tech industry (1 = yes; 0 = no)	
Firm size	Establishment size (total number of employees)	
Firm age	Establishment age (years in operation until 2013)	
Percent man. and prof.	Management and professional employees as percent of full and part time employees on payroll (percentage points)	
Final innovative output	Introduced innovation in product, service, production or distribution method in past 3 years (1 = yes; 0 = no)	
Other IP activity	Involved in other forms of IP protection than patents in past 3 years (1 = yes; 0 = no)	
Abandoned innovation	Any improvement or innovation activities abandoned in past 3 years (1 = yes; 0 = no)	
R&D activity	Conducted internally or hired, R&D and design services in past 3 years (1 = yes; 0 = no)	
Angel/venture funding	Received some venture or angel capital financing in past 3 years (1 = yes; 0 = no)	
Rejected for loan	Tried to borrow but received none from financial institutions in past 3 years (1 = yes; 0 = no)	
Green tech	Production or service provision to any green energy sector (1 = yes; 0 = no)	
Internet sales	Sold products or services over the internet (1 = yes; 0 = no)	
Export products	Exported products/services internationally (1 = yes; 0 = no)	
Industry-level Fixed Effects	Industry indicators at two-digit level NAICS (NAICS 21, 31, 32, 33, 42, 48, 51, 52, 54, 55 and 71)	
County-level		
Univ. R&D per cap.	University R&D per capita	NSF (2016)
SPLAG univ. R&D per cap.	University R&D per capita in neighboring counties	NSF (2016)
Percent pop. bach. degree	Bachelor or higher degree holders as percent of population 25 years and over	US Census Bureau (2013)
High-tech variety	High-tech variety	US Census Bureau (2015)
Percent foreign born	Foreign-born population as percent of total county population	US Census Bureau (2013)
Percent prof., sc., and tech. employment	Employment in professional, scientific, and technological industries as percent of civilian employed population 16 years and over	US Census Bureau (2013)
Unemp. rate	Unemployment rate	BEA (2013)
Total tax per capita	Total taxes per capita	US Census Bureau (2014)

Table I. Variables description and data source

design services. The second (intermediate R&D output) is made up of forms of IP protection other than patents (the dependent variable) and includes industrial design, trademark, copyrights, trade secrets and first mover's advantage. The third (final innovative output) was expanded to include producing any new or significantly improved goods or services, introduction of new or significantly improved methods of manufacturing, and use of new logistics, delivery and distribution methods for inputs, goods or services. Additionally, firms may choose to abandon an innovation at some stage of development, and we include an indicator for this decision. Lin *et al.* (2013) showed that innovative firms with mixed and complementary IP strategy (e.g. using multiple forms of IP protection) tend to be more successful. Additionally and keeping within the tradition of the framework described by Aghion and Howitt (1990), we identified firms as "high-tech" if it operated in an NSF-designated high-tech industry based on the four- and six-digit NAICS codes of firms provided by the 2014 NSBC (National Science Foundation, 2016). We expect all these parameters to be positively associated with patenting activity.

Third, we include a number of indicator variables based on activities that may influence innovation creation. Many businesses collaborate with academic institutions in conducting research activities. However, Howells *et al.* (2012) showed that while these collaborations benefited the firms, the firms did not necessarily acknowledge this benefit. It may be that the firm-level variables for obtaining academic information are negative and the county-level controls for university R&D (discussed below) are positive, supporting Howells *et al.* (2012) finding. Similarly, the research findings and the extension outreach programs of universities can benefit firms by introducing them to new knowledge (Lyons *et al.*, 2018). These results may be similar or different from what Howells *et al.* (2012) found.

Firms may also get access to angel or venture funding to help further develop and scale up an innovation, or they may be limited to pursuing more traditional forms of financing such as loans from financial institutions (Renski and Wallace, 2012). We expect the former to be positively associated with patenting, and the latter, which is framed as rejection for private financing (rejected for loan), to be negatively associated with patenting. We also include indicators for firms that said they sold their products or services via the internet, exported their products or services, and produced products or provided services in any of the five "green" sectors (production of renewable energy, increasing energy efficiency, conservation of natural resources, prevention, reduction, and cleaning up of pollution, and production of clean transportation fuels). We anticipate these indicators for broader market access and new markets (green tech) are positively associated with patenting.

Fourth, the NSBC survey provides information about different aspects of human capital choices and perceptions. We include an indicator for firms that required individuals with at least a bachelor's degree for any of their occupational categories, and an indicator for firms that reported having difficulty in finding qualified applicants for their positions in the labor market. Following Aghion and Howitt (1990), we anticipate the first (bachelor's degree) to be positively correlated with patenting, while the second (difficulty hiring) to be negatively associated with patenting. We include the share of management and professionals to total employees at the firms, a measure of establishment size (total number of employees), and the age of the firm. Based on the prior literature (Aghion and Howitt, 1990; Henderson, 2003) we expect that these final variables are positively associated with patenting[7].

3.3 Industry controls

Firms in different industries likely vary in terms of their patenting propensity and intensity (Wojan *et al.*, 2015). We control for this heterogeneity across firms by including two-digit NAICS industries associated with the respondent firms in our sample. The industries included in the 2014 NSBC are: mining, quarrying, and oil and gas extraction (NAICS 21); food, beverage, textile and animal products manufacturing (31); wood products, paper, chemical, petroleum, plastics and rubber, and nonmetallic mineral products manufacturing (32); metal, machinery, computer and electronic products, transportation equipment, furniture and related products, and miscellaneous manufacturing (33); wholesale trade (42); transportation (48), information (51), finance and insurance (52); professional, scientific and technical services (54), management of companies and enterprises (55); and arts, entertainment and recreation (71).

3.4 County-level controls

To control for regional heterogeneity and the business environment in which the firms operate, we include university R&D per capita in own-county of the firm location, university R&D in neighboring counties located within 100-mile radius[8] (variable constructed as a spatial lag of university R&D), percentage of population with bachelor or higher degree of education, number of high-tech establishments as a percentage of total establishments, variety of high-technology industries, foreign-born population as a percentage of total population, share of employment in professional, scientific and technical services sector to total civilian employment, unemployment rate and total taxes per capita. With the exception of the last two variables (unemployment and taxes which we anticipate to be negatively correlated with patenting), we expect these parameters to be positively associated with patenting.

Finally, we include state-level fixed effects to control for the heterogeneity among states. We use California as the reference state as it is well known for innovation centers such as Silicon Valley (Mann and Shideler, 2015). Since we construct separate models for rural and urban firms, we examine the state fixed effects in terms of which states may provide a relative advantage or disadvantage to firms compared to California. The state fixed effects are discussed further at the end of the results Section 5.3.

4. Methods

We operationalize firm innovation by using the number of patent applications that firms reported filing between 2011 and 2013 as the dependent variable and are guided by the traditional literature on modeling patents counts (e.g. see Allison and Waterman, 2002; Hall *et al.*, 1986). As the number of patent applications is a count variable taking on only non-negative integer values, analyses using linear regression models are not appropriate. The violation of the assumptions of linear regression regarding homoscedasticity and normal distribution of residuals, which is atypical to a count dependent variable like ours, is likely to lead to biased and inconsistent coefficient estimates (Greene, 2003). The count models such as Poisson and negative binomial are more appropriate for analyzing count data such as the number of patent applications filed in a given year (Allison and Waterman, 2002; Greene, 2003; Hall *et al.*, 1986).

Figure 1 shows that the distribution of patent applications data in our combined sample[9] of rural and urban firms is clearly right-skewed. Thus, we turn to Poisson and negative binomial distributions in terms of constructing our regression models. However, based on our preliminary modeling evidence, specifically the likelihood ratio tests between the initial Poisson and negative binomial models (discussed more in the results section), our output indicates that patent applications data in our sample are over-dispersed. In the presence of such over-dispersion of the dependent variable, the Poisson regression model is inappropriate as the over-dispersion likely causes spurious significance of the coefficient estimates due to underestimated standard errors (Cameron and Trivedi, 1986). On the other hand, the negative binomial models allow over-dispersion (variance > mean) through separate parameterization. Therefore, we settle on the negative binomial model which has the following form expressed in terms of its log-likelihood function (Hilbe, 2011):

$$\mathcal{L} = \sum_{i=1}^{n} \left\{ y_i ln\left(\frac{\alpha \exp(x_i'\beta)}{1+\alpha \exp(x_i'\beta)}\right) - \frac{1}{\alpha}\ln\left(1+\alpha \exp(x_i'\beta)\right) + ln\Gamma\left(y_i+\frac{1}{\alpha}\right) - ln\Gamma(y_i+1) - ln\Gamma\left(\frac{1}{\alpha}\right) \right\}$$

where y_i represents the outcome variable for firm i, measured with reported patent applications it filed during 2011–2013; x_i represents the vector of explanatory variables,

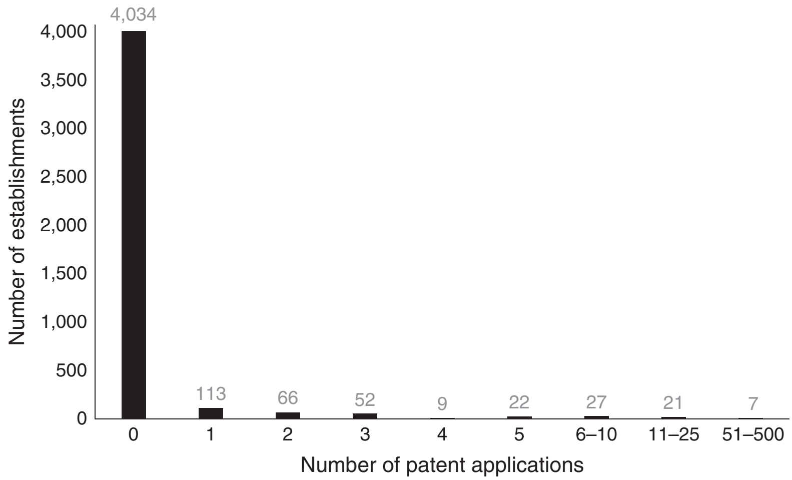

Figure 1. Frequency distribution of firm-level total patent applications during 2011–2013 (pooled sample)

including firm-level variables, industry controls, county-level controls and state indicators; and α and β represent over-dispersion parameter and the vector of other model parameters to be estimated, respectively.

5. Results

Results and discussion are presented as follows. First, we include a brief discussion of the summary statistics of the model data. Second, we discuss the regression diagnostics and model selection. Third, we present the significant findings and their potential implications.

5.1 Summary statistics

We report the descriptive statistics in Table II separately for the sample of firms located in urban and rural counties and those for the combined sample. The Spearman's rank correlation coefficients for the combined sample are presented in Table III. The combined sample of 4,351 firms are across 1,562 US counties, and about 25 percent (1,117 firms) are located in 422 urban counties and remaining roughly 75 percent in 1,140 rural counties.

Firms located in urban areas had higher values for the average number of patent applications (1.24) compared to those in rural area (0.27). Overall, however, 93 percent (4,034 out of 4,351 firms, see Figure 1) of the firms reported zero patent applications during the period 2011–2013, and the average number of patent applications for our combined sample is 0.52. Firm age is negatively correlated with patenting, and urban areas, on average, host younger firms compared to rural areas. All other variables that are positively correlated with patenting, except final innovative output and green tech, have higher average values or frequencies for urban regions compared to rural regions. The observations from the descriptive statistics indicate that rural firms innovate less frequently than urban firms. We also discuss selected variables' summary statistics in the context of the parameter results in Section 5.3.

5.2 Regression model diagnostics and interpretation of results

As discussed in the methods section, we first estimated Poisson models separately for rural and urban firms and the combined sample. Most coefficient estimates were statistically significant at the 5 and 1 percent levels (Poisson results not shown). We then estimated negative binomial models, which allowed incorporation of the over-dispersion of the patents data. The results reported in Table IV for α (the over-dispersion parameters) provide a test

Variables[a]	Combined Mean (SD)	Urban Mean (SD)	Rural Mean (SD)	Variables	Combined Mean (SD)	Urban Mean (SD)	Rural Mean (SD)
Firm-level variables				*Industrial (2-digit NAICS)*			
Patent apps. (counts)	0.52	1.24	0.27	21	2%	1%	2%
	(8.41)	(16.12)	(2.28)	31	5%	3%	6%
Firm size (No. of employees)	55.04	63.57	52.09	32	9%	6%	9%
	(275.55)	(398.94)	(217.23)	33	18%	17%	19%
Firm age (No. of years)	32.86	26.46	35.07	42	17%	21%	16%
	(28.09)	(23.92)	(29.07)	48	6%	3%	7%
Percent man. and prof. (% points)	23.57	28.55	21.85	51	8%	5%	9%
	(21.00)	(25.22)	(19.03)	52	4%	2%	4%
Academic information				54	25%	34%	22%
Not valuable	13%	16%	12%	55	3%	5%	3%
somewhat valuable	52%	48%	53%	71	3%	3%	3%
very valuable	35%	36%	35%	*County-level variables*			
Bachelor's degree (1 = yes; 0 = no)	56%	67%	52%	Univ. R&D peer cap. ($)	94.05	187.07	59.62
Difficulty hiring (1 = yes; 0 = no)	26%	22%	27%		(776.48)	(512.11)	(851.46)
High-tech (NSF def.)	20%	31%	17%	SPLAG univ. R&D peer cap. ($)	336.3	283.64	355.8
Final innovative output (1 = yes; 0 = no)	71%	70%	72%		(994.36)	(740.47)	(1,072.85)
Other IP activities (1 = yes; 0 = no)	33%	46%	29%	Percent bach. degree pop. (% points)	9.15	11.89	8.13
Abandoned innovation (1 = yes; 0 = no)	26%	30%	25%		(3.63)	(3.72)	(3.02)
R&D activity (1 = yes; 0 = no)	60%	66%	58%	High-tech variety	15.99	28.57	11.33
Angel/venture funding (1 = yes; 0 = no)	2%	2%	1%		(9.94)	(8.58)	(5.28)
Rejected loan (1 = yes; 0 = no)	5%	5%	5%	Percent foreign born pop (% points)	4.71	8.57	3.28
Green tech (1 = yes; 0 = no)	33%	31%	34%		(5.45)	(7.32)	(3.66)
Internet sales (1 = yes; 0 = no)	48%	50%	48%	Unemployment rate (% points)	7.28	7.15	7.32
Export products (1 = yes; 0 = no)	27%	35%	25%		(2.46)	(2.04)	(2.59)
				Tax per capita ($)	1,441.25	1,686.57	1,350.44
Number of Observations (N)[b]	4,351	1,117	3,234		(955.72)	(91,354)	(737.17)

Notes: [a]Variables defined in Table I; [b]Number of counties in combined, metro and non-metro samples are 1,562, 422, and 1,140 respectively

Table II. Summary statistics

of appropriateness of the Poisson models. The statistically significant alpha coefficients in all three columns of the coefficient estimates demonstrated that the null hypothesis of zero dispersion is rejected at 1 percent significance level, thus suggesting the statistically significant coefficients in the Poisson regression models were likely due to underestimated standard errors arising from the over-dispersed patent data.

Additionally, we estimated four specifications of the negative binomial regression model: (i) no county-level controls or state-level fixed effects, (ii) county-level controls only, (iii)

Variables	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1. Patent applications																	
2. Academic information	0.00																
3. Bachelor's degree	0.08	−0.08															
4. Difficulty hiring	−0.02	0.04	−0.09														
5. High tech (NSF designated industry)	0.10	−0.07	0.11	−0.03													
6. Firm size	0.20	0.03	−0.03	−0.01	0.06												
7. Firm age	−0.05	0.02	−0.02	−0.01	−0.12	0.15											
8. Percent management and professionals	0.10	−0.11	0.18	−0.09	0.18	−0.27	−0.04										
9. Final innovative output	0.14	0.90	−0.08	0.04	0.00	0.18	−0.03	−0.11									
10. Other IP activity	0.33	−0.02	0.09	−0.02	0.00	0.21	−0.11	0.04	0.20								
11. Abandon innovation	0.13	0.00	0.03	0.06	0.06	0.11	−0.05	−0.02	0.12	0.20							
12. R&D activity	0.21	0.01	0.07	0.01	0.13	0.21	−0.06	0.01	0.30	0.35	0.17						
13. Angel/venture funding	0.12	−0.01	0.02	−0.01	0.03	0.09	−0.06	0.01	0.02	0.08	0.06	0.09					
14. Rejected for loan	0.02	0.01	−0.03	0.05	−0.01	−0.04	−0.10	−0.02	0.00	0.04	0.05	0.02	0.08				
15. Green tech	0.11	0.08	0.01	0.04	0.11	0.13	0.02	−0.07	0.13	0.09	0.06	0.17	0.02	0.00			
16. Internet sales	0.06	0.01	−0.03	0.01	−0.04	0.07	0.01	−0.03	0.11	0.10	0.08	0.11	0.02	0.02	0.02		
17. Export products	0.30	0.01	0.01	−0.01	0.06	0.24	−0.05	−0.04	0.22	0.28	0.09	0.28	0.05	−0.02	0.10	0.14	
18. Rural	−0.06	0.01	−0.13	0.06	−0.15	−0.02	0.14	−0.10	0.01	−0.16	−0.05	−0.07	−0.02	−0.01	0.03	−0.01	−0.10

Table III.
Spearman's rank correlation coefficients

Variables (DV: Number pat. apps.)	Combined β	Combined IRR-1	Urban β	Urban IRR-1	Rural β	Rural IRR-1
Firm-level						
Rural	0.0770	0.08				
Academic information						
Somewhat valuable	−0.6120**	−0.46	−0.1670	−0.15	−0.2510	−0.22
Very valuable	−0.6990**	−0.50	−0.5880	−0.44	−0.2010	−0.18
Bachelors degree	0.4650**	0.59	0.2190	0.24	0.5500***	0.73
Difficulty hiring	−0.2330	−0.21	−0.2850	−0.25	−0.1400	−0.13
High-tech (NSF def.)	0.3140	0.37	0.8300**	1.29	0.0420	0.04
Firm size	0.6550***	0.93	0.8230***	1.28	0.5760***	0.78
Firm age	−0.0250	−0.02	−0.2000	−0.18	−0.0360	−0.04
Percent man. and prof.	0.0130***	0.01	0.0140*	0.01	0.0110*	0.01
Final innovative output	0.2550	0.29	0.4620	0.59	0.4650	0.59
Other IP activity	2.2000***	8.03	3.1090***	21.40	2.0920***	7.10
Abandon innovation	0.4520***	0.57	0.0660	0.07	0.4730***	0.60
R&D activity	1.2990***	2.67	1.5930**	3.92	1.4600***	3.31
Angel/venture funding	0.9830**	1.67	1.7360*	4.67	0.3190	0.38
Rejected for loan	−0.1170	−0.11	−0.7580	−0.53	0.0420	0.04
Green tech	0.1950	0.22	0.6960*	1.01	0.3080*	0.36
Internet sales	0.3930**	0.48	0.9650***	1.62	0.3020	0.35
Export products	1.1520***	2.16	1.3540***	2.87	1.0560***	1.87
County-level						
Univ. R&D per cap.	0.0830**	0.09	0.0490	0.05	0.1210**	0.13
SPLAG univ. R&D per cap.	0.0460	0.05	0.1260	0.13	0.0000	0.00
Per. pop. bach. degree	−0.0050	0.00	0.0390	0.04	−0.0480	−0.05
High-tech variety	0.0160	0.02	0.0090	0.01	0.0250	0.03
Per. foreign born	0.0210	0.02	−0.0180	−0.02	0.0180	0.02
Unemp. Rate	0.0350	0.04	−0.1420	−0.13	0.0820	0.09
Tax per cap.	0.8100**	1.25	0.8950	1.45	0.5960	0.81
Constant	−18.1120***		−17.3090**		−17.8600***	
ln(α)	1.6890***		1.7450***		1.2210***	
Number of obs.	4,351		1,117		3,234	
Log-likelihood	−1,410		−487.1		−858.1	
Model DF	81		79		76	
AIC	2,985.78		1,136.17		1,872.22	
BIC	3,515.17		1,542.66		2,346.58	

Notes: Statistical significance denoted as $*p < 0.1$; $**p < 0.05$; $***p < 0.01$

Table IV. Negative binomial regression results

state-level fixed effects only, and (iv) both county-level controls and state-level fixed effects. While we do not report the results from the first three specifications, (i)–(iii), the model chosen is based on the AIC and BIC selection criteria which identified the one with county-level controls and state-level fixed effects as the better specification of the four.

Regression results are presented in Table IV for the combined, urban and rural models. The β coefficients and their statistical significance are shown in the first column under each group category and the incidence rate ratio minus 1 (IRR-1) are shown in the second[10]. We report the IRR-1 as this is a straightforward method to interpret results (for recent examples in the literature using this method see Howell, 2017; Murray and Stern, 2007; Rothaermel and Hess, 2007). For example, under the combined model, the percentage of management and professional employees (percent man. and prof.) parameter is interpreted as a one-unit increase (in this case a 1 percent increase) in the share of management and professional employees is expected to increase patenting activity by 1 percent.

5.3 Rural and urban firm innovation

To address our broader research question, we used a likelihood ratio test to empirically check for a difference in the innovation creation (patenting) behavior of rural and urban firms that were otherwise identical in their characteristics. For this test, the null hypothesis is framed as rural and urban firms represented by common innovation behavior parameters. Thus, we consider if the use of the combined model for analysis is appropriate, or are two models more appropriate, one for rural and another for urban. The test statistics for the first test is derived as two times the difference between the log-likelihood of model 1 and the sum of the log-likelihoods of model 2 and 3 ($-1410.0-(-487.1+-858.1)=-64.8$; $2\times|-64.8|=129.6$)[11]. The critical chi-square value with 76 degrees of freedom and at the 99 percent confidence level (107.58) is less than the test statistic. Thus, we reject the null hypotheses in favor of using individual urban and rural models in place of the combined model. In other words, our test reveals that there are some differences between rural and urban firms in terms of potential influencers of patenting activities.

Of the statistically significant firm-level parameters, participation in other forms of IP protection has the largest magnitude in difference between rural and urban firms; however, both are positive and support the findings from Lin *et al.* (2013). The IRR-1 reveals that for urban firms, use of other forms of IP protection is correlated with a three-fold increase in patent activity compared to rural firms. In other words, other forms of IP protection appear much more important for urban firms in terms of their innovation creation. It may be that closer proximity to or higher density of other innovative firms contributes to this result. It could also be that since innovative urban firms compete in broader markets more frequently compared to innovative rural firms (revealed by the internet sales and export products summary statistics and parameters), increased participation in other forms IP protection is necessary. These results may also be influenced by some of the other differences in characteristics in which urban firms have an advantage, for example, access to angel and venture capital funding, participation in green tech (urban firms show a greater magnitude impact on patenting activity although a higher portion of rural firms participate in this), and R&D activity. It may be that private equity investors insist on more protections for the innovations developed and greater R&D investments motivate broader IP protection.

Another interpretation of these results is that there is a connectedness between different innovation-related activities, and that urban firms are able to better capitalize from the synergies among these activities relative to rural firms. Thus, our results support prior studies that demonstrate that urban firms have higher levels of innovative activity compared to rural firms. The results in this study also provide additional insight on this phenomenon, showing more detail on some of the nuances of how and/or why this may be occurring. One surprising result is that the urban-rural innovation gap is not seen in some of the county-level business environment control variables, such as high-tech variety or educated labor force in the urban areas. For example, using a county-level regional model, Aryal *et al.* (2018) show these factors are positive and statistically significant for urban and rural firms but to different degrees.

There are two firm-level results that also provide additional insight. First, the bachelor's degree parameter (one or more jobs at the firms requiring a bachelor's or higher degree) is relevant (and statistically significant) to rural firms in the context of our modeling of patenting activity, but not to urban firms. In terms of innovative activity, the difference in the human capital needs between rural and urban firms may show that there is greater variability among rural firms. In short, innovative rural firms need educated employees but other rural firms rely less on an educated workforce; whereas, for urban firms both patenting and non-patenting firms depend on an educated labor force. The summary statistics showed that 67 percent of urban firms had at least one (or more) positions that required at least a bachelor's degree (it was 52 percent for rural firms). Thus, for urban firms, the employee standard appears higher which may imply that the distinction between different urban firms is more about bachelor's degree field and less about whether or not the employee has the degree (the opposite appears relevant for rural firms).

Second, the "abandoned innovation" parameter is also positive and statistically significant for rural firms but not for urban firms. This implies that rural firms that expend effort, even if not successful, are more likely to create new innovations. From the summary statistics, only 25 percent of rural firms reported that they had innovation activities that were abandoned (compared to 30 percent of urban firms). This result may also reveal something about the level of risk rural firms are willing or able to manage. Rural firms that are more willing to take on risk – as evident from starting and abandoning innovations – innovate more frequently.

For the county-level controls, only university R&D per capita is statistically significant for rural firms. This result is interesting considering that the coefficient estimate of the variable "academic information" is not statistically significant (and negative). Howells *et al.* (2012) reported that firms place a low value on the impacts of university technology transfer and partnerships, yet firms were shown to greatly benefit from these relationships. Given the results in our study, this may be especially true for rural firms.

Finally, Table V shows the statistically significant (10 percent or lower level) state-level fixed-effect parameter estimates from the rural firms model. While not the main focus this research, the results provide an interesting contrast to firms operating in urban areas. In both the urban and rural models, California is the reference state. Only Kentucky in the urban model was statistically different than California (and negative). However, 16 states in the rural model were different than California and all were positive. California and Massachusetts historically are the leaders in innovation creation (Mann and Shideler, 2015), but much of the literature focusing on firm- or regional-level innovation creation is relative to urban firms. The results of Table V suggest that when it comes to rural firm innovation creation, many other states may be ahead of the traditional leaders. Interestingly, several of the tops states in this table are small in terms of population (Wyoming, Montana and Vermont). But larger states, such as New York and Texas also appear in this list. It may be that the location of some of these firms in rural areas benefit more substantially from urban spillovers (in the case of rural areas adjacent to urban centers). On the other hand, some state's policies may also be better geared to serve innovative rural firms relative to California.

State	Coefficient estimate	IRR-1
Wyoming	4.21	66.3
Nevada	3.64	36.9
Vermont	3.39	28.5
Montana	3.29	25.8
Alabama	3.18	23.1
Kansas	2.98	18.7
Missouri	2.82	15.8
New York	2.75	14.7
Texas	2.74	14.5
Iowa	2.73	14.3
Ohio	2.68	13.5
Colorado	2.67	13.4
Kentucky	2.57	12.0
Mississippi	2.52	11.4
Tennessee	2.45	10.6
Minnesota	2.41	10.2

Table V. Rural innovative firms – statistically significant state fixed effects (Ref. State = CA)

The above interpretation of the results is subject to some caveats arising from both sampling and data limitations. First, the final estimation sample may not be a random representative sample of the universe of urban and rural firms due to: oversampling of rural firms by design in NSBC survey to ensure an adequate sample of rural firms; and dropping of a number of observations due to missing data. A simple dichotomous definition of rural and urban may not adequately capture the nuances of a more refined rural-urban continuum. Next and similarly, the analyses using a single "university" variable (university R&D per capita, which only accounts for four-year research intensive universities and their R&D expenditures) overlooks the potential influence of two-year and other university types, and may average the potential differentiated impacts of the variety of universities in a given region. Finally, previous research considers greater diversity in degree attainment (e.g. see Conroy and Weiler, 2015) which we do not model in this study due, in part, to data constraints. The results of the bachelor's degree parameter in the urban model may reflect this limitation.

6. Summary and conclusion

Much of the innovation creation literature is focused on urban firms or areas, or relies heavily on data based on these (National Science Foundation, 2016). Less studied are rural firms and areas in this context. The goal of this paper is to empirically test if and how much rural and urban firms differ in terms of behaviors and characteristics that may influence innovation creation. To accomplish this goal, we use the 2014 NSBC and combine it with regional secondary data that reflects the business and innovative environments in which these firms operate. Our overarching finding is that firms in urban areas are able to better capitalize on firm characteristics and behaviors that may influence innovation creation relative to rural firms. This finding is revealed as most of the parameters that are statistically significant for urban firms are also statistically significant for rural firms, but the magnitudes are higher for urban firms. While our main finding supports prior studies that show rural firms lag behind urban firms, our study also provides a few other insights as to how and why this is occurring.

First, our results provide some evidence that innovation creation within rural firms is influenced more by university R&D than for urban firms. At the same time, information from universities (e.g. from extension services) may not necessarily be perceived by these firms as impactful with respect to innovation creation. This finding supports Howells *et al.*'s (2012) counterintuitive results – with specific applications to rural firms – that while firms may not perceive value from universities, they do benefit in economic terms from their interactions with universities. Second, rural firms that are willing to try, but fail, in terms of innovation creation have a slight advantage over other rural firms less willing to take on the risk. This result is shown by the "abandoned innovation" parameter (from the 2014 NSBC question asking firms if any innovation project had been abandoned during 2011–2013 period). The implication is that rural firms that are more risk averse may also be less likely to innovate. Third, workers with at least a bachelor's degree appear to be more important for rural firms regarding innovation creation than for urban firms. However, we do not suggest here that an educated labor force is not important for urban firms in this regard. Our summary statistics show that two out of three urban firms require a four-year degree for at least some positions compared to about half of rural firms. Instead, it is likely that for rural firms, having qualified workers capable of innovation creation is a higher barrier relative to urban firms. Fourth, there are several factors that suggest urban firms are more competitive than rural firms, for example, due to their proximity to other innovative firms or based on the degree/intensity of accessing broader markets (such as via exports and ecommerce). Thus, for urban firms mixed IP protection strategies appear much more important compared to rural firms. Combined, these findings suggest potential opportunities for policies directed toward rural firms that can: help mitigate the risk in innovation creation; provide university support in terms of R&D, for example, access to intermediate R&D outputs such as licensing technologies; provide qualified labor/assistance in terms of innovation creation or development; and help rural firms access broader markets. One example may be improving access to public and/or private equity for R&D, such as through the Small Business Innovation Research program, or access to other kinds of programs designed to fund early stage R&D. Such improved access could occur with the aid of university-based training or research partnerships, and may include improved access to university developed technologies.

Fifth, the states that typically lead innovation creation among urban firms and areas are not necessarily the same for rural areas. Although the evidence presented to support this notion is only suggestive (state-level fixed effects parameters), it provides a topic for further research. For example, Wyoming, Vermont and Montana appear in the top four of these rural leader states and all three are ranked near the bottom with respect to population, and Wyoming and Montana are lowest in population density among the 48 contiguous states. Thus, it is likely that state-level policies that impact innovation creation in these states cater to rural firms. An analysis of these policies relative to those for the leading states for urban firm innovation creation could provide important insights for other states wishing to improve rural firm innovation creation.

Notes

1. For additional details on the survey, please refer to Wojan *et al.* (2015) available at www.oecd.org/sti/193%20-%20SelfReportedInnovationSurveys_IncreasingReliability_ClearedManuscript.pdf
2. Based on lost observations due to matching the NSBC to other secondary sources, and the oversampling of rural firms by design in the NSBC survey, we recognize that the final data set used in this analysis may not be a statistically representative sample of the universe of rural and urban firms. However, we control for a range of regional and industrial factors to account for this possibility.
3. Alaska and Hawaii were excluded because of missing observations for several counties; District of Columbia was also excluded as it has a single county and we control for the state-level fixed effects using state dummies in our analysis. From the 48 included states, we also eliminated the counties with missing values for county-level variables.
4. We considered scaling patents by the number of persons in the inventive class (engineers and other scientists), but the "number of professionals" may include some creative professionals as well as a wide range of other non-inventor/creative professional fields such as book-keeping. Thus, self-reported firm-level patent application counts were used.
5. In an early version of our model, we used the 2013 Rural Urban Continuum Codes (RUCC) as a basis to distinguish between three county types (from the 9 RUCC types): metro, non-metro-adjacent and non-metro remote. However, matching the NSBC with other secondary data sources resulted in a reduced number of observations as discussed above further impacting degrees of freedom. For the sake of parsimony, we decided to only distinguish between firms in non-metro (rural) and metro (urban) areas. Future analysis using alternative secondary data may want to consider a more detailed regional landscape in terms of different types of rural geography.
6. A primary goal of the 2014 NSBC was to collect data allowing for detailed analysis of industries and other characteristics in rural areas, and also enable comparisons with urban firms. The survey over-sampled rural firms relative to urban firms to achieve this. Thus, the rural-only model includes about three times the number of firms as the urban-only model does, and the combined model is heavily weighted toward rural firms. For our analysis, we include a range of other controls and independent variables as our motivation is to consider similarities/differences between rural and urban firms.

7. Data for the human capital variables are from the 2013 five-year American Community Survey (ACS) which includes the NSBC survey range, 2011–2013 (see Table I). While the five-year ACS provides an average that includes data for all areas, data in sparsely populated areas may not be comparable to those in densely populated areas.
8. The 100 mile distance is based on the county centroid. Our model attempts to capture both the presence and magnitude of the average impact by using a single variable, university R&D expenditure, and the spatial lag of this. Future specifications may want to experiment with alternative university measures by including indicators for the presence of different types of universities (e.g. community colleges, four-year degree granting and research intensive) as well and R&D expenditures. Additional analyses employing more granular zip code level data and more disaggregate educational levels may potentially generate more insights. We acknowledge these limitations and potential extensions.
9. The frequency distribution of total number of patent applications is similar for urban and rural sub-samples (not reported).
10. These are constructed as IRR-1 = $\exp(\beta)-1$ (Hilbe, 2011).
11. See Brooks and Lusk (2010) or Mann and Henneberry (2012) for the inferential approach using likelihood ratio test.

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