Rural V. Urban A National Survey on Determinants of Business Innovation Activities

Conference Paper · March 2017

John Mann
Michigan State University

Rural V. Urban: A National Survey on Determinants of Business Innovation Activities

Jason Parker, Michigan State University

John Mann, Michigan State University

Scott Loveridge, Michigan State University

Presented at the 2017 Midwest Economics Association Meeting
March 31-April 2, Cincinnati, Ohio

Abstract

The data for this paper comes from the 2014 National Survey of Business Competitiveness – Rural Establishment Innovation Survey (REIS), a survey of 10,913 US businesses (53,234 including null responses) collected by the USDA Economic Research Service. The REIS data includes 257 variables for each firm including 40 measures of innovation (e.g., patent activity, improved market share, reduced labor costs, etc.). Many papers have suggested that patents are a poor measure of innovation because not all innovation is patented (or even patentable) and not all patents are indicative of real innovation. In our data, we find that 6% of the firms produce 100% of the patents. Further, we find that patent activity is only weakly correlated with our other measures of innovation. While this might indicate that innovation should not be defined as patent activity, these factors alone do not preclude patent activity from being used a proxy variable for the innovation process. To test this hypothesis, we construct joint models for patent activity and another innovation measure to test for significant differences between the models. We model these innovation measures using a bivariate probit specification with fixed-effects for the census region and the 3-digit NAICS industry code. Within this framework, we find very few statistically significant differences between patent models and other more general measures of innovation. We isolate three variables which have a disproportionately large impact on the patent model: difficulty hiring skilled workers, the age of the firm, and having an employee ownership plan. Our findings could be interpreted to support firm-level research papers which use patents as proxies for innovation, with the caveat that any coefficients on difficulty hiring, firm age, and employee ownership are likely to be overstated in the patent models. Our findings could also be interpreted to support macroeconomic research papers which use patents as proxies for innovation, realizing that regional variation in difficulty hiring may have a slight downward bias on the innovation proxy.

Introduction

In the post-World War II era, the United States dominated the world's high technology economy in nearly all arenas. Rebuilding and social transformation in other parts of the world reduced that dominance. To remain competitive, it is necessary to re-examine how and why US firms innovate. Policies that are appropriate for some sectors or regions may be entirely inappropriate for others. In addition to their intended role in protecting intellectual property (IP) thereby rewarding innovation, patents have come to serve a secondary function that is important in policy development—serving as a proxy for innovation activity in the nation.

Patent activity evolved rapidly in recent years. The number of US utility patents quadrupled between 1983 and 2003, with no corresponding increase in research and development expenditure or total factor productivity (Boldrin and Levine, 2013). In the twelve years following the period covered by Boldrin and Levine's study, patenting increased by over 92% (USTPO, 2017). While many of these new patents are undoubtedly valuable, there are unresolved concerns related to the use of patenting data (grants, applications, citations) as innovation proxies. Also, not all innovations run through the patent system, possibly reducing the accuracy of patents as a measure of technical change (Griliches 1990; Pakes and Griliches 1980). The economic impact of a particular patent may vary considerably compared to others and this variability may be influenced by characteristics of the firm, industry, or region. Further compounding concerns is the changing motivation behind a firm's choice to patent. For example, critics note the presence of other actors (aka "trolls"), at least some of whom appear to impose costs without benefits in the affected industries (Pohlmann, and Opitz, 2013). Another example is seen in the university system where certain disciplines are shifting to patents (downsizing the role of refereed journal articles—an alternative innovation proxy (NSB 2016) as a measure of faculty productivity. Additionally, the print and electronic media often include advertisements from businesses offering patenting services that may bilk gullible would-be inventors.

While the trends and problems of the US patenting system are generating debate related to how to fix the system (Dolin, 2015; Aydin, 2016), the question remains: Are patents still a good measure of innovation? Thus, this article addresses the issue of patent reliability for economic modeling nationally, by sector, and by community type. The article takes advantage of a large national sample survey of business innovation practices. By comparing patenting activity to a range of self-reported innovation practices we are able to show how patenting (and the other innovation practices) vary by type of community and sector. The results, developed using a bivariate probit model with fixed-effects for NAICS sector, show that despite count inflation concerns, patents continue to be a reasonable proxy for innovation across sectors and community types. Furthermore, we show that by controlling for sector and community factors, rural-urban differences in patenting and other innovation activity seem to disappear. We thus contribute to understanding of low rates of innovation in certain places and sectors.

Literature Review

Schumpeter describes "creative destruction" as the process by which new innovations are created, making the technology currently in use obsolete (Aghion and Howitt 1990; Schumpeter 1942). Since this groundbreaking work, much research has been dedicated to measuring and testing hypotheses related to innovation (there is extensive literature on this topic, a few example include: Acs and Audretsch 1988; Aghion and Howitt 1990; Griliches 1990; Pakes and Griliches 1980). The innovation process (or technical change) can be categorized in one of three general ways: initial inputs (e.g., R&D expenditures); intermediate outputs (e.g., patents); or final output (e.g., new good or service) (Acs, Anselin, and Varga 2002). Each form appears in the literature modeled as proxies for innovation, and each has its strengths and weaknesses. However, researchers continue to face the challenge of selecting appropriate proxies for innovation due to a lack of consensus about the best measure (Acs and Audretsch 1988; Acs, Anselin, and Varga 2002; Kleinknecht, Van Montfort, and Brouwer 2002). One issue is that innovation measures can be viewed through multiple lenses, making a single proxy potentially incomplete in the context of information conveyed (Kleinknecht, Van Montfort, and Brouwer 2002; Mann and Shideler 2015). Another concern is that innovation proxies can only be compared to other innovation proxies, which adds to the concern about knowing whether a measure is capturing what it purports (Acs, Anselin, and Varga 2002).

One of the most common sources of innovation proxies, and the primary focus of this study, is the publicly available United States Patents and Trademark Office (USPTO) data (Kleinknecht, Van Montfort, and Brouwer 2002). However, this innovation proxy has two possible flaws in the context of how innovations occur (Pakes and Griliches 1980 and Griliches 1990). First, not all innovations are patented. Thus, patents data potentially reveals an incomplete picture of the innovative process. Second, the impact on the economy of patented innovations will vary greatly by the invention itself and industry through which it is applied. This fact may be further compounded depending on the motivation for seeking a patent. Thus it is important to assess how patents measure up in terms of their ability to proxy innovation nationally as well as across sectors and places.

Nagaoka, Motohashi, and Goto (2010) review the literature review on patents, including exploration of concerns about their use as proxies for innovation. One explanation regarding the reason not all innovations are patented is that alternative and potentially cost saving paths such as complex product design and rapid product development can be used by firms in place of patenting. Additionally, patents are expensive and many firms may not wish to direct resources toward this effort. For firms that do obtain patents, roughly 50% are never put into direct use by a firm or licensed to another firm (*op. cit.*). Instead, they are used strategically, for example, to restrict competitors from working around an existing or future innovation. A patent in this context may be used to support or prolong the life of another innovation, or, conversely, restrict the life of a yet-to-be-created innovation. Thus, for patent data use to be a more effective innovation proxy, considerations may need to be made that account for patent alternatives and motivation.

The limits of patenting data as innovation proxies produced alternative measures based on the three general ways the innovation process can be categorized as described above.[1] For example, Kleinknecht, Van Montfort, and Brouwer (2002) used the Netherlands' 1992 Community Innovation

[1] One of the most comprehensive list of innovation metrics is provided by the National Science Foundation's (NSF's) Science and Engineering (S&E) Indicators which are often used in the economics literature to proxy for different facets of the innovation process (NSB 2016; some examples include Adams 2002; Branstetter and Ogura (2005); Lichtenberg 1992; Mann and Shideler 2015).

Survey to compare five proxies for innovation (patent applications, R&D expenditure, total expenditure on innovation, and proportion of sales from new products). One concern motivating the study was that each innovation proxy may reveal different results depending on industry. For example, certain industry patents may be more impactful on the economy relative to others, and this may be true of other innovation proxies. Their results supported earlier concerns highlighted by Pakes and Griliches (1980) and Griliches (1990): patents provide an incomplete picture of innovation and many factors may exacerbate the issue. Some examples of these factors include firm characteristics, industry that generated the patents, linkages to product lines, or the economic value resulting from the extent to which a new patent changes an existing technology.

Acs, Anselin, and Varga (2002) provide an additional consideration--the effect of geography on patent performance as an innovation proxy, arguing that innovation metrics may also be impacted by unique characteristics of a regional innovation system. They compared USPTO patent data to the US Small Business Administration's (SBA) literature-based innovation outputs (data and information taken from trade and technical journals), which they considered a more direct measure of innovation and allowed for greater regional variation given the applied nature of the data. The SBA data also addressed, to an extent, the industry-specific uses issue explored by Kleinknecht, Van Montfort, and Brouwer (2002). Despite the short comings of patenting data, however, Acs, Anselin, and Varga (2002) reported that the patents represent a reliable measure of innovative activity.

Another important characteristic explored in studies using firm-level survey data, is how firms' assets may influence decisions to patent. For example, using the 2008 Berkeley Patent Survey, Graham, Merges, Samuelson, and Sichelman (2009) reported firms obtaining venture capital were more likely to patent as it may act as means of protection or leverage regarding the investment. Additionally, they identified firms' desires to secure financial capital and improving their reputations as other characteristics impacting patenting decisions. Contrary to previous literature (e.g., Hugo and Jaumandreu 2004), they also reported that firm age is not a factor on patenting activity. Instead, more relevant characteristics increasing the chance a firms seeks to obtain patents are its business model and strategy.

Studies using the Kauffman Firm Survey[2] also showed that firms with IP protection (e.g., patents, trademarks, copyrights) were more likely to obtain new sources of financing, and that firms with greater financial capital were more likely to obtain IP protection (Coleman and Robb 2009; Cotei and Farhat 201; Pergelova & Angulo-Ruiz 2014; Zaleski 2011;). Thus, a firm's assets impact IP decisions and vice versa. Within the Kauffman Firm Survey, only about 25% of firms surveyed reported having any type of IP protection (Robb and Robinson 2012). Hart and Acs (2011) combined the Kauffman Firm Survey with the Panel Study of Entrepreneurial Dynamics and discovered that firms that hold patents tended to be younger and larger—this was contrary to Graham, Merges, Samuelson, and Sichelman (2009) but supported earlier works.

One study using the Kauffman data also provided additional geographic insight on differences between rural and urban areas. More specifically, Renski and Wallace (2012), identified five characteristics that distinguished rural from urban firms:

1. Ownership structure: new rural firms were more frequently sole proprietors, and less likely to establish a formal legal structure;
2. Growth: new rural firms created fewer jobs during the observation period;
3. Industry mix: new rural firm entry was more likely in low-tech industries;
4. R&D and innovation adoption/creation: rural firms were less likely to invest in R&D and less likely to seek IP protection; and
5. Sales and revenue: rural firms were more likely to sell a product or service, and generate revenues in the first year.

Their findings supported earlier rural firm innovation research of Barkley, Henry, and Lee (2006) and Henderson and Abraham (2004) who, for example, also identified restricted industry mix as a limiting factor to innovative activity. These two studies also recognized proximity to metro areas and access to labor pools with scientific researchers were factors impacting rural firms' ability to produce

2 This was a longitudinal survey from 2004-2009 of new start-ups that began operation in 2004 (Coleman and Robb 2009).

R&D leading to new innovations. These results are also similar to studies that did not uniquely focus on rural areas, but considered non-regional characteristics of innovative (e.g., patent holding) and non-innovative (non-patent-holding) firms. For example, the decision to seek profits by selling goods or services is a business strategy that could eliminate a firm's ability to obtain future venture capital and potentially become less innovative (Freedman, 2013; Graham, Merges, Samuelson, and Sichelman 2009; Nagaoka, Motohashi, and Goto 2010). Additionally, ownership structure may impact decision-making regarding a firm's business model. Thus, the combination of many of these factors may contribute to observations of lower rural firm innovation rates and slower growth relative to urban firms.

One gap in literature that remains is a broader comparison of patents to the range of ways in which innovation may occur—but is not able to be easily observed or measured. For example, a firm may create an innovative product or service, but choose not to pursue a patent or communicate through other measurable outlets (e.g., trade or technical journals) related to the innovation. Additionally, other strategies, such as, alternative protections (registered industrial designs) or expedited product development and launch as well as means of developing or obtaining, such as in house or purchased R&D, product licenses, or hired consulting and expertise also be relevant innovation metrics that vary by firm, industry, or regional factors. Thus, expanding the work of Kleinknecht, Van Montfort, and Brouwer (2002), by increasing the range of innovation proxies to which patents are compared and incorporating a broader range of controls for firm, industry, and regional characteristics (Acs, Anselin, and Varga 2002; Graham, Merges, Samuelson, and Sichelman 2009; Renski and Wallace 2012) is necessary to provide a better understanding for patent use as innovation proxies.

Data

Our data come from the 2014 National Survey of Business Competitiveness—also referred to as the Rural Establishment Innovation Survey (REIS)—(Wojan, 2015). The survey, administered by mixed mode, contacted 53,234 US businesses requesting completion of questions by mail, internet, or telephone. The response rate was 22.4%. The target respondent was a firm with more than five employees, operating in the one of the following sectors: mining, manufacturing, manufacturing, wholesale trade, transportation and warehousing, information, finance and insurance, professional/scientific/technical services, arts, or management of business. In its paper form, the survey was sixteen pages long; the questions covered a wide array of location and business operation items. The sample was stratified by firm size categories, NAICS codes, and whether the location of the firm was metropolitan or non-metropolitan. More detail on the survey questions and implementation is available in Wojan (2015).

The REIS data itself consists of 53 questions resulting in 257 variables. The questions concern: location factors, labor structure, education distribution, information and technology usage, sales, improvements and innovations, failed innovations, research and development, green innovations, patent and intellectual property activity, effects of the 2008-2009 recession, market share, location-based barriers, local government impact, and capital structure. About 48.2% of the questions were binary response, 37.4% of the questions were multiple response beyond two, and 14.4% were open response.

Ignoring null responses, the data consists of 10,913 observations. Of those, 1,943 responses were dropped because the respondent failed to complete the survey to the end or did not report the location of their firm. Additionally, 834 responses were dropped from our analysis because the respondent answered that they were not familiar or only slightly familiar with innovation at the firm. There were n=8,136 responses remaining. The data was designed so that one fourth of the responses would be from urban firms and three fourths of the responses would be from rural firms (i.e., firms located in rural counties according to metropolitan status in the census code). Accordingly, 25.2% of the firms are in metropolitan counties and 74.8% of firms are in nonmetropolitan counties.

Table 1 contains information about the distribution of patents in the REIS sample. Firms were asked to report whether their firm participated in patent activity from 2012-2014 and how many patents were awarded to the firm over that period. The distribution of patents is clearly heavily right-skewed. The average firm earned 0.554 patents over 2012-2014 (standard deviation: 14.08). Only 6.0% of firms were involved in patent activity.

Within our data, we have 40 indicators for innovation including patents. To save space, we are going to focus on 20 of these variables. The variables we have eliminated were selected either because they were more tangentially related to the innovation process (e.g., “In the past 3 years, did this business introduce new or significantly improved support activities for your process?”). For a detailed analysis of all the innovation variables, please see the supplementary materials. Observations counts and means of the 20 primary variables are reported in Table 2.

Table 3 reports the correlation coefficients for different measures of innovation. Patent activity is moderately correlated with in-house R&D (0.34), improved varieties of goods (0.36), and improved goods (0.54). There are a few other moderate correlations between indicators for related questions, but otherwise the variables are only weakly correlated.

Because of the low participation rate in patent activity and because patent activity is only weakly correlated with other innovation indicators, it might seem reasonable to conclude that patent activity is a poor measure of overall innovation. While defining innovation purely in terms of patent activity might be a mistake, that does not preclude patent activity from being used as a proxy for the innovation process. In the sections that follow, we will provide evidence that patent activity is reasonably similar to using other measures to model the innovation process.

Modeling Approach

The innovation variables were modeled using a bivariate probit (Greene, 2000) model:

$$y_i = \mathbf{1}(y_i^* \geq 0)$$

$$z_i = \mathbf{1}(z_i^* \geq 0)$$

for $i = 1, \ldots, n$ where y_i is an indicator of patent activity and z_i is some other measure of innovation. y_i^* and z_i^* are the unobserved latent variables associated with y_i and z_i respectively. The linear specification selected[3] for the latent variables was

$$y_i^* = \alpha_{NAICS(i)} + \theta_{region(i)} + \boldsymbol{X}_i'\boldsymbol{\beta} + \epsilon_i$$

$$z_i^* = a_{NAICS(i)} + h_{region(i)} + \boldsymbol{X}_i'\boldsymbol{b} + e_i$$

[3] Various models were considered including different fixed effects profiles including state-level fixed effects and coarser NAICS code specifications. Detailed statistics on these specifications can be found in the Appendix.

for $i = 1, \ldots, n$ where $\alpha_{NAICS(i)}$ and $a_{NAICS(i)}$ are fixed effects for the 3-digit NAICS industry code for firm i, $\theta_{region(i)}$ and $h_{region(i)}$ are fixed effects for the census region (1 to 4) for firm i, $\boldsymbol{X}_i$ is an r×1 vector of firm-level characteristics/question responses, $\boldsymbol{\beta}$ and $\boldsymbol{b}$ are r×1 vectors of estimated coefficients, and ϵ_i and e_i are stochastic errors. In this framework ϵ_i and e_i are allowed to be correlated.

The $\boldsymbol{X}_i$ variables selected for the model include the firm's age, labor structure (i.e., size, part-time to total employment ratio, employee benefits, and occupational distribution), capital structure (i.e., borrowing from debt, equity, and personal sources and re-investing of past profits) and metropolitan or nonmetropolitan status. For more information on the selection of the fixed effects and any interaction terms, see the supplementary materials. In total, we included r=26, $\boldsymbol{X}_i$ variables. While this number may seem large, the data has n=8,136 responses.

The coefficients were estimated using the 'biprobit' command in Stata. This specification was selected to test for differences between patent activity and other measures of innovation. The null hypothesis is $\mathcal{H}_0\colon \beta_j = b_j$ for $j = 1, \ldots, r$, and the alternative is $\mathcal{H}_1\colon \beta_j \neq b_j$.

Results

The estimated coefficients from the bivariate probit specifications are listed in Table 4. In each case, dependent variable 1 is reported patents; these are compared with the other innovation variables we selected from the survey (dependent variable 2). While there were 26 variables included in the models, coefficients for only 10 of the variables are reported to save space. The other variables were found to be insignificant in at least 31 of the 40 specifications at the 5% level, and at least 36 specifications at the 1% level. These other coefficients can be found in supplementary materials.

In this paragraph, we define the selected independent variables in Tables 4 & 5 and discuss the frequency of their significance in the models (Table 4). "Firm age" is an integer-valued variable denoting how many years the firm has been in operation and is significant in 30 specifications at the 5% level. "Total employment" is an integer-valued variable denoting how many employees the firm has and is significant in 24 specifications. "PT/total ratio" is a continuous variable denoting the ratio of part-time employees to all employees and is significant in 29 specifications. “Paid training” is an indicator of whether or not the firm offers paid employee training and is significant in 38 specifications. “Paid maternity” is an indicator of whether or not the firm offers paid maternity and/or paternity leave and is significant in 39 specifications. “Employee ownership” is an indicator of whether or not the firm offers an employee ownership plan and is significant in 20 specifications. “Paid volunteer” is an indicator of whether or not the firm offers paid time off for volunteering and is significant in 28 specifications. “Difficulty hiring” is an indicator of whether or not the firm reports having difficulty hiring and is significant in 15 specifications. “Profits refinanced” is an indicator of whether or not the firm is at least partly financed by past profits and is significant in 25 specifications. “Metro” is an indicator of whether or not the firm is located in a metropolitan census county and is significant in 30 specifications. “Rho” is the estimated correlation between the residuals of the patent model latent variable and that of the other innovation model.

Table 5 reports the results from the tests for significant differences between estimates for variable 1 (patents) and the other indicators used for dependent variable 2. The results from Table 5 indicate that patent activity is a reasonable proxy for innovation by most measures. The notable exceptions to this are: difficulty hiring, firm age, and employee ownership. Difficulty hiring is found to be significantly different in 33/39 models at the 5% level (1%: 30/39). From Table 4, difficulty hiring was found to be statistically significant for the patent model but was not found to be statistically significant in 25 of the 39 other specifications. This indicates that patent activity may be influenced by hiring difficulty in ways that other measures of innovation are not. Specifically, if we are modeling firm-level data on patent output as a proxy for innovation, we should keep in mind that hiring difficulty is perhaps not as important to overall innovation as the model might suggest. Alternatively, if we are using patent activity as a proxy for innovation in a macroeconomic modeling context, greater hiring difficulty in a region may bias our estimates downward where a more suitable innovation measure (e.g., Improved: Market share) would not. This bias could be corrected by including a measure of unemployment in the model.

Firm age is found to be significantly different in 22/39 models at the 5% level (1%: 17/39). Firm age has a larger (in magnitude) negative impact on patent activity than on other measures of innovation. Specifically, these other measures are related to improved services, manufacturing, performance, and features as well as reduced labor costs and material inputs. Employee ownership is found to be significantly different in 13/39 models at the 5% level (1%: 6/39). Like difficulty hiring, statistically significant differences in the employee ownership coefficients usually occur because the innovation variable is less affected by employee ownership than the patent variable. Total employment is found to be significantly different in 8/39 models at the 5% level (1%: 6/39). As total employment is only significant in fewer than 25% of our models, we forgo interpreting these results. Paid maternity, profits refinanced, and metro are all found to be significant in at most 5/39 models, and PT/total ratio, paid training, and paid volunteer are all found to be significant in only 1/39 specification.

Summary and Conclusions

The primary motivation of this paper is to consider whether or not patent data, e.g., counts of applications or grants, provide a creditable proxy for innovation. A number of authors have also considered this question and provide alternative measures; however, the general consensus has been that patent data remains a creditable innovation measure. On the other hand, prior research was restricted by limited alternatives to which patent data was compared. Thus, part of the concern remains that much of what is considered as innovation is not captured by patent data. Another issue, potentially skewing patent counts to the other extreme, is that some amount of the patenting activity cannot necessarily be framed as innovation, for example, in the case of patent trolls or where patents may be used as a means to leverage financial capital. While we are unable to control for the latter concerns, the main contribution this study provides is greatly expanding the list of alternative innovation proxies to which patents are compared. Our results indicate that despite their shortfalls patents remain a credible innovation proxy when compared to a wide range of alternative proxies. Models that include hiring difficulty, firm age, or an employee ownership structure might exhibit some bias if patents are used as the innovation measure, as it appears that these controls perform differently than patents depending on the innovation measure at hand.

Our study does have some limitations. First, the data are cross-sectional and were collected post-recession. Therefore, we only see a single year snapshot and are unable to see how firm behavior with respect to patenting (or other innovative activity) may be different with respect to the 2008 recession. Next, data are from firms operating in a selected number of industries and may limit our generalization of results across all industries. Finally, data is comprised of established firms—not new startups—which may further limited the generalization of results.

Finally, there are a few considerations for additional study that could apply the REIS data to existing data sets and expand the depth of analysis used to address our primary research motivation. Since patent data were self-reported, it may be useful (though labor intensive) to match firms responses to historical USPTO patent applications. Similarly, these data could be matched to other innovation-related data such as Small Business Innovation Research (SBIR) grants. Finally, incorporating secondary data with relevant regional metrics with the REIS data would expand the potential controls included in this study.

References

[1] Acs, Z. J., & Malecki, E. J. (2003). Entrepreneurship in rural America: The big picture. *Federal Reserve Bank of Kansas City*.

[2] Acs, Z. J., Anselin, L., & Varga, A. (2002). Patents and innovation counts as measures of regional production of new knowledge. *Research policy*, *31*(7), 1069-1085.

[3] Adams, J. D. (2002). Comparative localization of academic and industrial spillovers. *Journal of Economic Geography*, *2*(3), 253-278.

[4] Aghion, P., & Howitt, P. (1990). *A model of growth through creative destruction* (No. w3223). National Bureau of Economic Research.

[5] Albena P., & Angulo-Ruiz, F. (2014). The impact of government financial support on the performance of new firms: the role of competitive advantage as an intermediate outcome. *Entrepreneurship & Regional Development, 26*(9-10), 663-705.

[6] Aydin, Senem. "Shooting Ourselves in the Foot to Kill a Fly? Patent Enforcement and Market for Technology." *Academy of Management Proceedings*. Vol. 2016. No. 1. Academy of Management, 2016.

[7] Barkley, D. L., Henry, M. S., & Lee, D. (2006). Innovative activity in rural areas: the importance of local and regional characteristics. *Community Development Investment Review*, *2*(3), 1-14.

[8] Boldrin, Michele, and David K. Levine (2013). The Case Against Patents. Journal of Economic Perspectives. 27(1): 3-22.

[9] Branstetter, L., & Ogura, Y. (2005). *Is academic science driving a surge in industrial innovation? Evidence from patent citations* (No. w11561). National Bureau of Economic Research.

[10] Coleman, S., & Robb, A. (2009). A comparison of new firm financing by gender: evidence from the Kauffman Firm Survey data. *Small Business Economics*, *33*(4), 397.

[11] Cotei, C., & Farhat, J. (2017). The Evolution of Financing Structure in US Startups. *The Journal of Entrepreneurial Finance*, *19*(1), 4.

[12] Dolin, Gregory. "Dubious Patent Reform." *BCL Rev*. 56 (2015): 881.

[13] Freedman, D. H. (October 2013). Why Series A Crunch Might Be A Good Thing. Money: Inc. Magazine.

[14] Graham, S. J., Merges, R. P., Samuelson, P., & Sichelman, T. (2009). High technology entrepreneurs and the patent system: Results of the 2008 Berkeley patent survey. *Berkeley Technology Law Journal*, 1255-1327.

[15] Greene, W. H. (2000). *Econometric analysis* (International edition). p.817-826

[16] Griliches, Z. (1990). *Patent statistics as economic indicators: a survey* (No. w3301). National Bureau of Economic Research.

[17] Henderson, J., & Abraham, B. (2004). Can rural America support a knowledge economy?. *Economic Review-Federal Reserve Bank of Kansas City*, *89*(3), 71.

[18] Huergo, E., & Jaumandreu, J. (2004). How does probability of innovation change with firm age?. *Small Business Economics*, *22*(3-4), 193-207.

[19] Kleinknecht, A., Van Montfort, K., & Brouwer, E. (2002). The non-trivial choice between innovation indicators. *Economics of Innovation and new technology*, *11*(2), 109-121.

[20] Lemley, Mark A., and Bhaven Sampat. "Is the patent office a rubber stamp." *Emory LJ* 58 (2008): 181.

[21] Lichtenberg, F. R. (1992). *R&D investment and international productivity differences* (No. w4161). National Bureau of Economic Research.

[22] Litwin, A. S., & Phan, P. H. (2013). Quality over quantity: Reexamining the link between entrepreneurship and job creation. *Industrial & Labor Relations Review*, *66*(4), 833-873.

[23] Mann, J., & Shideler, D. (2015). Measuring Schumpeterian activity using a composite indicator. *Journal of Entrepreneurship and Public Policy*, *4*(1), 57-84.

[24] National Science Board. 2016. *Science and Engineering Indicators 2016*. Arlington, VA: National Science Foundation (NSB-2016-1).

[25] Pakes, A., & Griliches, Z. (1980). Patents and R&D at the firm level: A first report. *Economics letters*, *5*(4), 377-381.

[26] Pohlmann, Tim, and Marieke Opitz (2013). Typology of the Patent Troll Business. R&D Management 43(2): 103-120.

[27] Renski, H., & Wallace, R. (2012). Entrepreneurship in Rural America. *Financing Economic Development in the 21st Century, 245*.

[28] Robb, A. M., & Robinson, D. T. (2012). The capital structure decisions of new firms. *Review of Financial Studies*, hhs072.

[29] Schumpeter, J. A. (1942, 2013). *Capitalism, socialism and democracy*. Routledge.

[30] USTPO. U.S. Patent Activity Calendar Years 1790 to the Present. Accessed on February 11, 2017 at https://www.uspto.gov/web/offices/ac/ido/oeip/taf/h_counts.htm

[31] Wojan, Timothy. 2015. National Survey of Business Competitiveness. Data Report 15-56. Social and Economic Sciences Research Center. Washington State University.

[32] Zaleski, P. A. (2011). Start-ups and external equity: The role of entrepreneurial experience. *Business economics*, *46*(1), 43-50.

Table 1: Patents awarded

Patents awarded	Firms	%
0	7,428	0.940
1	167	0.021
2	104	0.013
3	72	0.009
4	17	0.002
5	34	0.004
6-10	40	0.005
11-20	21	0.003
21-50	9	0.001
>50	10	0.001

Table 2: Means for selected innovation variables

ID	Variable	Obs	Mean
q36	IP: Patents	7,842	0.066
q37a	IP: Industrial designs	8,054	0.030
q37b	IP: Trademarks	8,048	0.106
q37c	IP: Copyright	8,028	0.133
q37d	IP: Trade secrets	8,031	0.208
q33a	In-house R&D	7,098	0.444
q33b	Purchase R&D	7,093	0.124
q33f	Purchase patents	7,090	0.085
q40a	Improved: Variety	8,055	0.659
q40b	Improved: Market share	8,037	0.558
q27a	Improved: Goods	5,713	0.588
q27b	Improved: Services	7,097	0.682
q27c	Improved: Manufacturing	5,758	0.546
q30a	Improved: Performance	6,948	0.575
q30d	Improved: Features	6,949	0.551
q40g	Reduced: Labor costs	7,984	0.322
q40h	Reduced: Material inputs	7,958	0.240
q28a	Abandoned: Innovations	7,955	0.223
q38	Inn. Resources: '08-'09	7,217	0.145
q39	Inn. Resources: '13-'14	8,041	0.276

Table 3: Correlations for selected innovation variables

ID	Variable	Correlations by ID																			
		q36	q37a	q37b	q37c	q37d	q33a	q33b	q33f	q40a	q40b	q27a	q27b	q27c	q30a	q30d	q40g	q40h	q28a	q38	q39
q36	IP: Patents	1.00																			
q37a	IP: Industrial designs	0.18	1.00																		
q37b	IP: Trademarks	0.26	0.31	1.00																	
q37c	IP: Copyright	0.20	0.27	0.39	1.00																
q37d	IP: Trade secrets	0.25	0.22	0.31	0.29	1.00															
q33a	In-house R&D	0.34	0.16	0.20	0.16	0.31	1.00														
q33b	Purchase R&D	0.05	0.14	0.15	0.14	0.16	0.12	1.00													
q33f	Purchase patents	0.19	0.22	0.09	0.01	-0.16	0.00	0.23	1.00												
q40a	Improved: Variety	0.36	-0.03	0.04	0.11	0.09	0.31	0.07	0.12	1.00											
q40b	Improved: Market share	0.05	-0.05	0.07	0.06	0.15	0.10	-0.02	0.00	0.22	1.00										
q27a	Improved: Goods	0.54	0.18	0.17	0.21	0.27	0.32	0.06	0.15	0.34	0.01	1.00									
q27b	Improved: Services	0.05	0.08	0.01	0.16	0.04	0.11	0.06	0.10	0.20	0.11	0.18	1.00								
q27c	Improved: Manufacturing	0.10	0.13	0.16	0.09	0.15	0.14	0.09	0.01	0.15	0.16	0.21	0.24	1.00							
q30a	Improved: Performance	0.12	0.17	0.19	0.09	0.18	0.32	0.01	-0.03	0.22	0.18	0.29	0.11	0.23	1.00						
q30d	Improved: Features	0.18	0.12	0.17	0.13	0.17	0.20	-0.01	0.08	0.22	0.08	0.34	0.13	0.15	0.39	1.00					
q40g	Reduced: Labor costs	0.01	0.15	0.12	0.08	0.15	0.07	0.05	-0.08	-0.02	0.16	0.11	0.00	0.12	0.16	0.11	1.00				
q40h	Reduced: Material inputs	0.03	0.14	0.10	0.08	0.20	0.04	0.13	0.06	0.17	0.20	0.23	0.18	0.17	0.14	0.07	0.51	1.00			
q28a	Abandoned: Innovations	0.11	-0.01	0.10	0.09	0.13	0.23	0.06	-0.12	0.04	0.09	0.10	0.09	-0.06	0.21	0.01	-0.03	0.01	1.00		
q38	Inn. Resources: '08-'09	-0.07	0.07	0.07	0.17	0.13	0.11	0.05	-0.04	0.02	0.12	0.13	0.08	0.11	0.18	0.09	0.04	0.02	0.03	1.00	
q39	Inn. Resources: '13-'14	0.05	-0.08	0.08	0.02	0.05	-0.01	0.10	0.01	0.15	0.20	0.06	-0.01	0.11	0.08	0.03	0.06	0.08	-0.07	0.06	1.00

Table 4a: Model coefficients for biprobit models (Standard error)

Independent variables	Dependent variable 1	Dependent variable 2									
	q36	q37a	q37b	q37c	q37d	q33a	q33b	q33f	q40a	q40b	q27a
Firm age	-0.0093**	-0.0062*	-0.0054**	-0.0033*	-0.0104**	-0.0061**	-0.0064**	-0.0001	-0.0063**	-0.0083**	-0.0054**
	(0.0020)	(0.0024)	(0.0016)	(0.0015)	(0.0014)	(0.0014)	(0.0012)	(0.0013)	(0.0012)	(0.0012)	(0.0014)
Total employment	0.0002**	0.0003**	0.0004**	0.0003**	0.0003**	0.0011**	0.0003**	0.0008**	0.0003	0.0017**	0.0002*
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0003)	(0.0001)	(0.0003)	(0.0002)	(0.0003)	(0.0001)
PT/Total ratio	-0.46**	-0.66**	-0.51**	-0.73**	-0.36**	-0.19	-0.26*	-0.14	-0.18	-0.23*	-0.21
	(0.18)	(0.20)	(0.14)	(0.12)	(0.12)	(0.13)	(0.11)	(0.12)	(0.11)	(0.11)	(0.13)
Paid training	0.23**	0.10	0.15**	0.14**	0.34**	0.34**	0.25**	0.34**	0.24**	0.35**	0.22**
	(0.07)	(0.08)	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)
Paid maternity	0.24**	0.29**	0.26**	0.24**	0.17**	0.17**	0.22**	0.06	0.09*	0.14**	0.18**
	(0.06)	(0.07)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)
Emp. ownership	0.35**	0.10	0.23**	0.11	0.16*	0.18	0.31**	0.08	0.16	0.19*	0.25**
	(0.10)	(0.13)	(0.09)	(0.09)	(0.08)	(0.09)	(0.08)	(0.09)	(0.08)	(0.08)	(0.09)
Paid volunteer	0.12	0.16	-0.04	0.10*	-0.02	0.14**	0.16**	0.14**	0.07	0.22**	0.04
	(0.07)	(0.08)	(0.06)	(0.05)	(0.05)	(0.05)	(0.04)	(0.05)	(0.04)	(0.04)	(0.05)
Difficulty hiring	-0.19**	-0.10	-0.02	-0.06	0.06	0.08	0.06	0.09*	0.03	0.10*	0.12**
	(0.07)	(0.08)	(0.05)	(0.05)	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)
Profits refinanced	0.24*	0.15	0.20**	0.15*	0.20**	0.24**	0.18**	0.10	0.11*	0.19**	0.12
	(0.09)	(0.11)	(0.07)	(0.07)	(0.06)	(0.06)	(0.06)	(0.06)	(0.05)	(0.05)	(0.06)
Metro	0.07	0.20**	0.31**	0.28**	0.36**	0.01	0.17**	0.02	0.08*	0.16**	0.18**
	(0.07)	(0.08)	(0.05)	(0.05)	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)
rho		0.86**	0.64**	0.52**	0.57**	0.42**	0.53**	0.13**	0.27**	0.19**	0.49**
		(0.02)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)
log like		-1745.594	-3036.053	-3319.796	-3937.673	-3783.582	-4617.342	-4327.043	-5156.494	-5209.741	-3802.921
Pseudo R-Squared		0.294	0.270	0.297	0.276	0.247	0.259	0.244	0.245	0.270	0.269
n		6,597	6,592	6,567	6,577	4,523	5,803	5,805	6,586	6,578	4,672

q36 denotes IP:Patents; q37a-IP:Industrial designs; q37b-IP:Trademarks; q37c-IP:Copyright; q37d-IP:Trade secrets; q33a-In-house R&D; q33b-Purchase R&D; q33f-Purchase patents; q40a-Improved:Variety; q40b-Improved:Market share; q27a-Improved:Goods; *-significant at the 5% level; **-significant at the 1% level

Table 4b: Continued model coefficients for biprobit models (Standard error)

Independent variables	Dependent variable 1	Dependent variable 2								
	q36	q27b	q27c	q30a	q30d	q40g	q40h	q28a	q38	q39
Firm age	-0.0093**	-0.0030*	-0.0022	-0.0024*	-0.0010	-0.0019	-0.0023	-0.0036**	-0.0069**	-0.0075**
	(0.0020)	(0.0013)	(0.0013)	(0.0012)	(0.0012)	(0.0012)	(0.0013)	(0.0013)	(0.0015)	(0.0012)
Total employment	0.0002**	0.0004	0.0009**	0.0005*	0.0002*	0.0002*	0.0002**	0.0002**	0.0002*	0.0001
	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
PT/Total ratio	-0.46**	-0.26*	-0.30*	-0.13	-0.22	-0.33**	-0.40**	-0.42**	-0.39**	-0.44**
	(0.18)	(0.12)	(0.13)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.13)	(0.11)
Paid training	0.23**	0.29**	0.22**	0.26**	0.22**	0.16**	0.11**	0.21**	0.33**	0.27**
	(0.07)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)
Paid maternity	0.24**	0.19**	0.17**	0.16**	0.10**	0.14**	0.19**	0.20**	0.12**	0.11**
	(0.06)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)
Emp. ownership	0.35**	0.06	0.17	0.23**	0.13	0.07	0.23**	0.01	0.30**	0.07
	(0.10)	(0.09)	(0.09)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Paid volunteer	0.12	0.06	0.07	0.12**	0.09*	0.11*	0.17**	0.00	0.15**	0.10*
	(0.07)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	(0.04)
Difficulty hiring	-0.19**	0.10*	0.09*	0.08*	0.07	-0.05	0.04	0.23**	0.05	0.03
	(0.07)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)
Profits refinanced	0.24*	0.00	0.14*	0.28**	0.34**	0.12*	0.19**	0.19**	0.13	-0.01
	(0.09)	(0.06)	(0.06)	(0.06)	(0.06)	(0.05)	(0.06)	(0.06)	(0.07)	(0.06)
Metro	0.07	0.06	0.13**	0.04	0.01	0.08*	0.09*	0.11*	0.16**	0.16**
	(0.07)	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)
rho		0.10**	0.24**	0.35**	0.37**	0.15**	0.19**	0.21**	0.26**	0.21**
		(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)
log like		-4473.497	-4057.134	-4766.654	-4758.005	-5044.361	-4456.706	-4500.542	-3427.931	-4929.258
Pseudo R-Squared		0.256	0.242	0.238	0.245	0.240	0.255	0.237	0.252	0.226
n		5,834	4,724	5,677	5,677	6,547	6,526	6,509	5,926	6,571

q36 denotes IP:Patents; q27b-Improved:Services; q27c-Improved:Manufacturing; q30a-Improved:Performance; q30d-Improved:Features; q40g-Reduced:Labor costs; q40h-Reduced:Material inputs; q28a-Abandoned:Innovations; q38-Inn. Resources:'08-'09; q39-Inn. Resources:'13-'14; *-significant at the 5% level; **-significant at the 1% level

Table 5a: Test for significant differences between the patent model coefficients and those of the other innovation indicators (Standard errors)

Independent	Coefficient differences from the patent model									
variable	q36-q37a	-q37b	-q37c	-q37d	-q33a	-q33b	-q33f	-q40a	-q40b	-q27a
Firm age	-0.0021	-0.0032	-0.0059**	0.0006	-0.0031	-0.0026	-0.0092**	-0.0031	-0.0014	-0.0044
	(0.0023)	(0.0021)	(0.0022)	(0.0021)	(0.0025)	(0.0022)	(0.0024)	(0.0022)	(0.0023)	(0.0024)
Total employment	-0.0001	-0.0001	0.0000	-0.0001	-0.0008**	0.0000	-0.0006*	-0.0001	-0.0015**	0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0003)	(0.0001)	(0.0003)	(0.0002)	(0.0003)	(0.0001)
PT/Total ratio	0.17	0.04	0.19	-0.14	-0.22	-0.24	-0.29	-0.31	-0.24	-0.18
	(0.19)	(0.18)	(0.19)	(0.18)	(0.23)	(0.19)	(0.21)	(0.20)	(0.20)	(0.22)
Paid training	0.13	0.08	0.09	-0.10	-0.13	-0.05	-0.13	-0.01	-0.12	0.03
	(0.08)	(0.07)	(0.07)	(0.07)	(0.08)	(0.07)	(0.08)	(0.07)	(0.08)	(0.08)
Paid maternity	-0.06	-0.04	-0.03	0.07	0.06	0.02	0.17*	0.16*	0.12	0.05
	(0.07)	(0.06)	(0.07)	(0.06)	(0.07)	(0.06)	(0.07)	(0.07)	(0.07)	(0.07)
Emp. ownership	0.23	0.12	0.24*	0.19	0.25	0.04	0.27*	0.19	0.15	0.13
	(0.12)	(0.11)	(0.11)	(0.11)	(0.13)	(0.11)	(0.13)	(0.12)	(0.12)	(0.13)
Paid volunteer	-0.05	0.16*	0.01	0.15*	0.01	-0.02	-0.01	0.05	-0.10	0.09
	(0.08)	(0.07)	(0.07)	(0.07)	(0.08)	(0.07)	(0.08)	(0.08)	(0.08)	(0.08)
Difficulty hiring	-0.10	-0.17*	-0.13	-0.24**	-0.23**	-0.24**	-0.29**	-0.23**	-0.30**	-0.33**
	(0.08)	(0.07)	(0.08)	(0.07)	(0.08)	(0.07)	(0.08)	(0.08)	(0.08)	(0.08)
Profits refinanced	0.07	0.07	0.10	0.06	-0.02	0.05	0.12	0.11	0.03	0.13
	(0.11)	(0.10)	(0.10)	(0.10)	(0.11)	(0.10)	(0.11)	(0.10)	(0.10)	(0.11)
Metro	-0.14	-0.22**	-0.21**	-0.28**	0.03	-0.08	0.07	0.00	-0.09	-0.13
	(0.07)	(0.07)	(0.07)	(0.07)	(0.08)	(0.07)	(0.08)	(0.07)	(0.07)	(0.08)

q36 denotes IP:Patents; q37a-IP:Industrial designs; q37b-IP:Trademarks; q37c-IP:Copyright; q37d-IP:Trade secrets; q33a-In-house R&D; q33b-Purchase R&D; q33f-Purchase patents; q40a-Improved:Variety; q40b-Improved:Market share; q27a-Improved:Goods; *-significant at the 5% level; **-significant at the 1% level

Table 5b: Continued test for significant differences between the patent model coefficients and those of the other innovation indicators (Standard errors)

Independent variable	Coefficient differences from patent model								
	q36-q27b	-q27c	-q30a	-q30d	-q40g	-q40h	-q28a	-q38	-q39
Firm age	-0.0070**	-0.0070**	-0.0072**	-0.0088**	-0.0075**	-0.0073**	-0.0054*	-0.0025	-0.0016
	(0.0024)	(0.0024)	(0.0023)	(0.0022)	(0.0023)	(0.0023)	(0.0023)	(0.0025)	(0.0022)
Total employment	-0.0002	-0.0007**	-0.0002	0.0000	0.0001	0.0000	0.0000	0.0000	0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
PT/Total ratio	-0.24	-0.02	-0.32	-0.24	-0.12	-0.08	-0.09	0.00	0.00
	(0.22)	(0.23)	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)	(0.22)	(0.20)
Paid training	-0.08	0.05	-0.04	0.00	0.10	0.14	0.04	-0.06	-0.03
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Paid maternity	0.08	0.08	0.07	0.11	0.12	0.06	0.04	0.14	0.13*
	(0.07)	(0.08)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Emp. ownership	0.24	0.18	0.11	0.21	0.27*	0.12	0.35**	0.01	0.28*
	(0.13)	(0.13)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)
Paid volunteer	0.06	0.04	0.00	0.05	0.02	-0.05	0.11	-0.06	0.02
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Difficulty hiring	-0.27**	-0.30**	-0.27**	-0.25**	-0.13	-0.23**	-0.40**	-0.26**	-0.21**
	(0.08)	(0.08)	(0.08)	(0.07)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Profits refinanced	0.24*	0.14	-0.06	-0.11	0.12	0.06	0.03	0.14	0.23*
	(0.11)	(0.11)	(0.11)	(0.10)	(0.11)	(0.11)	(0.11)	(0.11)	(0.10)
Metro	0.04	-0.14	0.03	0.08	-0.01	-0.01	-0.04	-0.11	-0.09
	(0.08)	(0.08)	(0.07)	(0.07)	(0.07)	(0.08)	(0.07)	(0.08)	(0.07)

q36 denotes IP:Patents; q27b-Improved:Services; q27c-Improved:Manufacturing; q30a-Improved:Performance; q30d-Improved:Features; q40g-Reduced:Labor costs; q40h-Reduced:Material inputs; q28a-Abandoned:Innovations; q38-Inn. Resources:'08-'09; q39-Inn. Resources:'13-'14; *-significant at the 5% level; **-significant at the 1% level