Firm Behavior Across Increasing Levels of Innovation Activity

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Abstract

The paper examines competitive behaviors of rural and urban firms across increasing levels of innovation activity intensity. Data are from the 2014 National Survey of Business Competitiveness which includes 10,952 firm-level observations and 257 variables, 41 of which are measures of innovation. Four innovation activity intensity categories are constructed, ranging from “non-innovative” to “highly innovative.” Average partial effects (APE’s) from a multinomial logit regression reveal differences in behaviors of highly innovative rural and urban firms are likely from reduced competitive pressures and limited spillovers access. However, moderately innovative rural and urban firms appear more similar in behaviors.

Key words:
National Survey of Business Competitiveness, Rural Establishment Innovation Survey, rural and urban firm, innovation activity, competitive firm behaviors, revealed choice

JEL codes:
O14, O18, O31, O32, R11

1. Introduction

"High-tech," "R&D intensive," and "cutting edge" are not terms typically associated with firms operating in rural America. In fact, rural establishments are often viewed as technology laggards, slow to adopt innovative practices, processes and methods to conduct business (Lyons, Miller, and Mann 2018). As much of the federal resources directed to rural areas are primarily related to farm policy, the perception that rural is synonymous with agriculture is reinforced (Goetz, Partridge, and Stephens, 2018). Thus, the activities associated with innovative industries may not match with the stereotypes of rural business activities and this discounts a significant portion of rural America's industry (Lichter and Brown 2011).

On the other hand, private sector nonfarm employers such as manufacturing, transportation and warehousing, finance and insurance, and information (and not including forestry, fishing, and related activities), account for roughly 73% of the total compensation received by rural workers[1] and rural firms operating in these industries do innovate. However, the majority of empirical studies focused on the activities of innovative firms and related policies depend on data collected in urban centers (for some examples see Acs, Anselin, and Varga 2002; Hall, Helmers, Rogers, and Sena 2014; Robb and Robinson 2012). At the same time, firms operating in these urbans centers account for a substantial portion of new innovations (Marco, et al. 2015). Given the perception of rural firms, however, one might ask if it makes sense to generalize the behaviors and activities of urban firms across all firms including those operating rural areas. This question motivates the study at hand.

In the next section, a brief discussion is provided on selected literature that examined the competitive behaviors of innovative firm. This section also includes identifying some of the main

[1] Based on Bureau of Economic Activity regional economic accounts data for nonmetropolitan areas for 2016.

challenges faced by rural firms in this regard. This is followed by a description or the study data and the construction of the independent variable, the modeling framework and empirical methods used, and discussion of the results. The paper concludes with a brief presentation of study highlights and related policies prescriptions.

2. Background

The competitive strategies of innovative firms' to protect R&D investments, and their innovative outputs, rely on multiple tools including formal intellectual property (IP) protections (Brouwer and Kleinknecht 1999; Cohen, Nelson, and Walsh 2000; Hall, Helmers, Rogers, and Sena 2014). For example, the competitive behavior of firms that conduct in-house R&D may entail applying for patents, using secrecy, capitalizing on the first mover advantage, adding complementary sales and service to product offerings, and using different marketing method all as part of a coherent strategy (Cohen, Nelson, and Walsh 2000; Hall, Helmers, Rogers, and Sena 201; Moser 2013). A considerable amount of literature is focused on formal and informal IP use, especially patents, in terms of protecting R&D, and empirical studies reveal firms that seek formal IP protection is less emphasized strategy across innovative firms compared to other behaviors (Aghion et al. 2005; Cohen, Nelson, and Walsh 2000; Hall, Helmers, Rogers, and Sena 2014). In fact, data from the Kauffman Firm Survey which included an oversampling of new high-tech firms, shows that only about 25% of firms reported using any kind of formal IP protection (Robb and Robinson 2014).

Brouwer and Kleinknecht (1999) provides a ratings by innovators on the effectiveness of different IP tools. For those IP tools rated as moderate or higher in terms of their effectiveness, industrial design was rated highest, followed by patent protection, trademarks, and copyrights. In terms of competitive behaviors, it is important to point out that the motivation for firms seeking

IP protection varies, for example, the use of patens extends beyond protecting profits, and may be used to mitigate competitors from copying innovations or patenting related innovations, and used as leverage in negotiations or to prevent lawsuits (Brouwer and Kleinknecht 1999).

Another body of literature focused on competitive and innovative behaviors of firms is through the lens of firms' R&D capabilities (Aghion and Howitt 1990; Huang, Arundel and Hollanders 2010; Lin, Hsiao, and Lin 2013). Many firms produce "non-R&D" innovation (innovations developed without formal internal or external R&D investment), and these firms are associated with weak in-house R&D capabilities and sourcing information from suppliers and competitors (Huang, Arundel and Hollanders 2010). Some literature has referred to this group as gap-filling in terms of the type of innovations developed (or entrepreneurship practiced) (Goetz, Partridge, Deller, and Fleming 2010). Non-R&D innovative firms are smaller in size relative to firms that conduct and use R&D, are less likely to export their final outputs, and have fewer employees with the appropriate education and skills for conducting R&D. On the other hand, R&D-intensive innovative firms are associated with product innovations (compared to process innovations) and rely on universities for important and relevant information in terms of product development and innovative opportunities (Huang, Arundel and Hollanders 2010). R&D-intensive firms are also much more likely to apply for patents or use other IP protections (such as trademarks, copyright, or industrial designs). Interestingly, Lin, Hsiao, and Lin (2013) found that robust complementary relationships exist across different R&D strategies. In particular, the R&D outcomes of innovative firms depends on mix of R&D related activities such as in-house R&D, contracted or purchased R&D, and cooperative R&D. The implication is that innovative firms, including R&D-intensive firms, include multiple forms of new knowledge creation and protection in their competitive strategies. Thus, there are many dimensions of competitive behaviors and innovative activities, and the use of different innovative strategies depends on the competitive pressure on firms (Tang 2006).

The understanding of some of these competitive pressure has evolved over time, and, at the same time, firms' behavior may also have evolved in response to competition. For example, Geroski, Reenen and Walters (1997) examined innovative firm's behavior with respect to the replacement effect, in which firms do not innovate in the future in fear of cannibalizing their monopoly rents from existing innovations, versus the pre-emption effect, in which firms do innovate in the future to capitalized on monopoly rents from both existing and future innovations. The two alternative or competing views are framed as either economic substitutes or compliments, where successive innovations act as substitutes (replacement effect), or as compliments (pre-emption effect). Using data are from two groups of firms, one over the period 1969-1988 and the other over the period 1945-1982, Geroski, Reenen and Walters found that firms have a low persistently to innovate. In other words, future innovation were viewed by firms as substitutes and firms with existing innovations were reluctant to develop new ones. Roughly a decade later, Raymond, et al. (2010) used innovative firm data from the period 1994-2002, and showed that high-tech firms are persistent innovators (firms viewed innovations as compliments), and that low-tech firms also develop innovations but new innovations from these firms are more spurious over time. Further studies that followed Geroski, Reenen and Walters (1997) reported similar findings to Raymond et al. (2010), that there is persistence in innovating among firms (Duguet and Monjon 2002), and that firms in more competitive industries and those near the technological frontier also innovate persistently (Aghion et al. 2005). These latter results demonstrated that the development of new innovations is strongly linked to competitive pressures, and is also likely related to the increasing rate of technological growth in industry.

One gap in literature on competitive behaviors of innovative firms is an examination that includes geographical considerations, specifically comparing the behaviors of urban and rural firms. The majority of literature focused on firm innovation relied heavily on data of urban firms, and any generalizations implies that urban and rural firms are the same in terms of innovative activities, competitive behaviors, and the broader business environment. However, rural firms frequently face a number disadvantages compared to urban firms in terms of their geography. For example, rural firms' remoteness restricts their abilities to: (1) achieve economies of scale due to limited access to supplies/suppliers, transportation, and markets, (2) tap into new knowledge and spillovers; and (3) access financial and human capital (Acs and Varga 2005; Henderson, 2002; Lyons, Miller, and Mann 2018; Sass Rubin 2010). Consider figure 1 which shows the stark contrast in the average number of patent applications (per 100 firms) between firms in rural and urban areas. While there are a larger number of rural counties relative to urban counties with firms that apply for patents, a widely used metric to measure innovation (Acs, Anselin, and Varga 2002), there are far fewer patents applications per 100 firms in rural areas.[2]

Rural firms' limited access to new knowledge, in whatever form acquired, may be especially debilitating in terms of firms' capacities to innovate. Lopez-Garcia and Montero (2012) demonstrated that there is a positive link between firms' innovative behaviors and spillovers, and this link appears stronger where firms are able to capitalize on these spillovers (e.g., in agglomeration economies). Spillovers and firms abilities to absorb them is also related to the labor pool quality and firms' investments in training employees. Thus, for rural firms, the disadvantages they faced contributed to an observed urban-rural innovation adoptions and creation gap (Artz,

[2] Based on the data used to construct figure 1, the mean and median number of patent applications (per 100 firms) where counties had at least one firm that applied for a patent was 9.1 and 3.0 for rural counties respectively compared to 90.7 and 19.0 respectively for urban counties. The total number of patents applications (averaged over the 5 year period) for rural and urban counties was 11,550.8 and 336,867.2 respectively.

Kim, and Orazem 2016; Aryal et al., 2018; Barkley, Henry, and Lee 2006; Henderson and Abraham 2004; Renski and Wallace 2012). More specifically, rural firms, compared to urban firms are more likely to be in low-technology industries, less likely to conduct or invest in any form of R&D, and less likely to pursue IP petitions (Renski and Wallace 2012). Further, these factors contribute to a cycle of lower-innovative capacity relative to urban firms as the restricted industry mix and availability of scientific professionals in the labor force negatively impacts firms' innovation activities, which, in turn limits firm growth and a regions future ability to attract new innovative firms and high-skilled human capital (Artz, Kim, and Orazem 2016; Barkley, Henry, and Lee 2006; Henderson and Abraham 2004).

The goal of this study is to construct a model of innovative activities linked to competitive behaviors and that is able to distinguish between rural and urban firms. This study uses a new and unique data set, the 2014 National Survey of Business Competitiveness (NSBC) developed by the USDA ERS, which includes a large sample of rural and urban firms, and their innovative activities and competitive behaviors. One purpose of the NSBC is to provide better data that allows for comparisons of US firms across a wider range of behaviors, innovation practices, industries, and geographies (specifically in rural versus urban settings). This study attempt to capitalize on particular features of the NSBC by taking advantage of the comprehensive list of innovation-related questions that includes a range of competitive behaviors including various forms of formal and informal IP protection.

3. Data

The NSBC[3] a large national-level survey of U.S. firms with more than 5 employees and representing industries (NAICS 2-digit in parenthesis) in mining (21), manufacturing (31-33), wholesale trade (42), transportation and warehousing (48; 49 not included), information (51), finance and insurance (52), professional, scientific, and technical services (54), management of businesses (55), and arts, entertainment, and recreation (71) (for a more detailed discussion of the data and survey see Wojan and Parker 2017). Data include both young and established firms; average firm age is about 32 years. About 25% of the firms in the sample are from urban areas and roughly 75% are from rural areas. The survey includes responses from 10,952 firms, consists of 257 variables, and primarily covers the period 2011-2013.[4] About half of the variables are binary responses, about one-third are multiple response variables, and roughly one-sixth are opened ended questions. The NSBC is cross-sectional and includes at least 41 potential measures of innovation-type behavior or activities. After accounting for null and incomplete responses, there were 8862 firm-level observations used this study.

The primary independent variables of interest include competitive behaviors that may be associated with the firm's innovative activity intensity. The NSBC also allows for the variable list used in prior studies to be expanded (e.g., see Brouwer and Kleinknecht 1999; Cohen, Nelson, and Walsh 2000; Hall, Helmers, Rogers, and Sena 2014; Huang, Arundel and Hollanders 2010). It is important to highlight that the inclusion of particular variables are considered in the context of associations or correlations with the independent variable as the outcomes do not necessarily imply causality. Instead, this study examines behaviors of firms associated or correlated with particular levels of innovation activity intensity. Other independent variables include firm characteristics,

[3] Data are also referred to as the Rural Establishment Innovation Survey (REIS). We use the name "National Survey of Business Competitiveness" (NSBC) so as not to confuse the data with that provided by the Bureau of Economic Activity by the same REIS acronym.

[4] A few questions are asked about activities in 2008, when the recession first occurred.

county-level variables from secondary sources intended to control for the innovative capacity of the region in which the firms are located, controls for 2-digit NAICS industry of the firms, and state-level fixed effects. Table 1 provides a description of the independent variables included in the model. The summary statistics (mean and standard deviations)[5] and correlations matrix are shown in tables 2 and 3 respectively.

[Insert table 1 approximately here]

[Insert table 2 approximately here]

[Insert table 3 approximately here]

The dependent variable, the choice by a firm of its respective intensity level of innovation activity, is established by grouping related innovation activities into a discrete number of categories (discussed in more detail in the next subsection). The model is framed as a "revealed choice" by firms when they participate in one or more categories of innovative activities. Although the choice variable is based on survey responses, the survey was not set up as a choice experiment. Instead, the revealed choices by firms is constructed by aggregating groups of related variables. The selected sets of variables used to develop the independent variable choices are grouped into categories that establish the discrete choice model of innovation activity intensity levels used in tis study. A firm's level of innovation activity intensity is based on the number of categories in which they participate, and this is used to develop a hierarchical range of innovation activity intensity (i.e., an increasing level of innovation activity from non-innovative firms to the most innovative firms given the data used).

3.1 Establishing multiple categories of firm-level innovative activity

[5] As part of the USDA agreement to access the use NCSB data, information such as minimums and maximums that may disclose details on specific observations was omitted from tables.

The first step was to describe and define what is meant by innovation activity intensity. To do this, Schumpeter's framing of innovation and the concept of creative destruction is used as a starting point (Aghion and Howitt 1990). Firm competition drives innovation, and one results is that innovation leads to technological progress. Technological progress—also framed as the process of creative destruction—occurs when current practices change (become obsolete) to accommodate new innovations. Conceptually, Aghion and Howitt (1990) show that firms combine human and R&D capital to generate an intermediate output, such as a patent, and this is used as an input into a final output. In terms of levels of innovation activity intensity, consider a "hypothetical continuum" along which the gauge moves from least to most innovative. At one extreme—the most innovative—firm-level behavior includes activities driving the creative destruction process: (1) investment in R&D inputs; (2) generating intermediate outputs; and (3) producing final outputs based on these prior activities (Aghion and Howitt 1990; Hall, Jaffe, and Trajtenberg 2005; Mann and Shideler 2015). On the other extreme of this hypothetical innovation continuum (and ignoring non-innovative firms at the moment), Drucker (2005) suggests that innovation—at a minimum—occurs when firms "exploit change as an opportunity for a different business or a different service" (p. 19). This implies that an innovative final output, for example, when a firm introduces a new product, process, or service in the market, is the baseline or minimal requirement for a firm to be considered innovative (Garcia and Calantone 2002; Tether 2002). However, not all innovations are of equal value and firms choose to invest different levels of resources to develop and/or launch an innovative final output (Garcia and Calantone 2002). At the same time, this framework provides guidance for identifying the level of innovative activity intensity of firms by establishing the two references points, i.e., the minimally and most innovative firms.

The NSBC data include responses about a wide range of activities and behaviors which may be broadly considered as innovative; 41 specific activities and behaviors were identified in the survey. More recent literature broadened the framework of activities that might be included in the 3-stage process of an R&D input leading to an intermediate output, which in turn is used to generate a final output (Cohen, Nelson, and Walsh 2002; Hall, Helmers, Rogers, and Sena 2014; Hall, Jaffe, and Trajtenberg 2005). In this spirit of broadeneding innovative activities, this study uses 5 firm-level activities at each stage (referred to also as the innovation activity intensity category).[6] The broadened descriptiosn are:

- R&D input (also referred to as the initial input) – activities used for the initial development of an innovation such creating or obtaining new knowledge by conducting in-house R&D or design;
- R&D intermediate output (or intermediate output) – activities related to obtaining formal intellectual property IP protections or rights such as applying for or licensing a patent, or registering industrial design;
- Final innovative output (or final output) – generating a new or improved output (good or service), or using a new or improved process to develop or deliver an output.

Table 4 provides brief description of the variables used to populate the three categories, initial input, intermediate output, and final output. The summary statistics and correlation matrix for these variables is shown in tables 5 and 6.

[6] Given the category descriptions above, factor analysis (FA) was used to help guide the selection the five variables that comprised each category. The 41 potential innovation metrics were reduced to a set of 15 based on the category definitions as well as variable clustering in the (FA) analysis. For example, In-house R&D, applying for a patent application, and producing a new or improved good were known to be in each of the three categories of R&D input, intermediate output, and final innovative output respectively. Although other variables were assumed to be associated with known variables in a category, for example, other forms of IP protection with patent applications, only the top four variables that cluster closest with the initially assigned (known) variable in each category were kept. Interestingly, most of the variables initially assumed to fit in each category were retained.

[Insert table 4 approximately here]

[Insert table 5 approximately here]

[Insert table 6 approximately here]

The second step was to determine the number of discrete categories by which firms can be effectively segmented given the NSBC data. To be counted as “participating in a category,” a firm must have indicated that it completed, used, or otherwise participated in one or more of the 5 activities within a specific category. Examination of completed survey responses revealed that about 28% of firms in the data could be classified as non-innovative (we will refer to these as “type-0” firms) based on the above framework as they did not participate in any of the activities associated with any of the three categories (i.e., initial input, intermediate output, or final output). About 22% of firms participated in the final innovative output category, but did not participate in either of the other two categories (this group is referred to as “type-1” firms). This group represents the minimal required activities to be considered an innovative firm in this study. Approximately 17% of firms participated in all three categories (referred to as “type 3” firms), which represents the firms with the highest level of innovative activity intensity used in this study. This left about 34.0% of firms that produced a final innovative output and participated in one of the other two categories, but not both, or that participated in both the initial input and intermediate output categories but did not participate in the final innovative output category. The latter group that did not produce a final innovative output included about 200 firms. Given the minimum requirement established above, this group of firms was dropped from our model data. Additionally, only a small number of firms (< 50) participated in both the final innovative output and intermediate output categories (but not in the initial input categories). This group was also dropped from the data leaving type-2 firms made up of firms that participated in both the final innovative output and initial input categories (but not the middle, intermediate output category). The idea of the type-2 firms assumes that firms may participate in creating or otherwise obtaining new knowledge, but do not seek formal IP protections or exclusive rights regarding this new knowledge. The firm categorization is classified as non-innovative or type-0 firms, minimally innovative or type-1 firms, moderately innovative or type-2 firms, and highly innovative or type-3 firms. Table 7 distinguishes between the four different firm types modeled in this study. This includes the frequency of participation in each of the activities included under each category, and the number of firms comprising each firm type, and firms are further separated as rural or urban firms based on the firms location. Additionally, the percentage of firms in each firm type that operate in an NSF designated high-tech industry (at the 4- or 6-digit NAICS level) are included (NSF 2017). The NSF measure is used to demonstrate how the categorization thematic established in this study compares with another established measure of high-tech firms.

[Insert table 7 approximately here]

About 17% of the 2538 type-0 firms operate in an industry classified by the NSF as high-tech (26% of the 690 urban firms, and 14% of the 1848 rural firms); however, none of these firms participated in any of the innovative activity categories. Most (72% urban and 75% rural) type-1 firms reported producing a new or improved service, while only about 1 out of 3 indicated participation in any of the other final output-related activities. Interestingly, 12% of type-1 firms operated in NSF designated high-tech industries (20% of 431 urban and 10% of 1563 rural), which is less than the percentage of type-0 firms. Type-2 firms include firms that participated in at least one initial input activity and at least one final output activity. Similar to type-1 (and type-3), about 75% of type-2 firm reported producing a new or improved service, but participation in the other final output activities increased to around half. For the initial input category, close to 60% of type-

2 firms conducted in-house R&D. Additionally, 20% of these firms operate in the NSF designated high-tech industries (27% of 675 urban and 18% of 2160 rural), which is an increase over both the type-0 and type-1 firms. Finally, firms considered type-3 participated in at least one activity in each of the three categories, with copyrighting as the highest and registering for an industrial design as the lowest. The general trend shown in table 7 is that the proportion of firms participating in a particular activity within a given category increases with firm type, for example, the activity "produced new or improved good" is 0%, 31.6%, 53.3%, 74.4% for firms type-0 to type-3 respectively. It is also noteworthy that the intermediate output category, in general, has the lowest level of participation across activities (for example, 29% of type-3 firms, about 5% of total firms in the study, reported applying for a patent). Additionally, the table also shows that the share of NSF high-tech industry designation increases from type-1 (minimally innovative) to type-3 (most innovative).[7] It is also noteworthy, that the differences between rural and urban firms regarding individual activities are very small compared to the differences in rural and urban firms in NSF high-tech industries.

4. Method of Empirical Analysis

The goal of this study is to compare the competitive behaviors of firms across varying levels of innovation activity intensity, and determine how rural with urban firms may be different or the same in this regard. To accomplish this goal, this paper builds on the methods used by two prior studies, both of which constructed discrete revealed choices of firms from innovation surveys in

[7] The rates of firm participation in the different innovation activities used to create the three categories for firms that are operating in NSF designated high-tech industries (table not shown) are about 5% to 50% higher (depending on the activity, firm type, and industry) compared to the rates of firms participating in the different activities that are not in NSF designated high-tech industries. In other words, firms operating in the NSF designated high-tech industries are more likely to participate in one or more innovative activities compared to firms not in NSF designated high-tech industries. However, the latter group of firms are still participating in the innovative activities but at lower rates.

Canada and Europe. In the first, Tang (2006) developed a discrete revealed choice model based on firms choosing the kinds of innovative outputs they develop. Dependent variable construction incorporated product and process innovations into four categories of innovation outputs. In the second study, Huang, Arundel and Hollanders (2010) applied a discrete revealed choice model to firms engaged in innovation activity related to R&D, separating firms into those that perform in-house R&D, contract R&D, non-R&D innovators, or technology adopters. The approach in this paper uses a similar strategy but constructs discrete categories of innovation activity intensity described in the previous section. Firms are segmenting from non-innovative to most innovative for comparison of rural and urban firms' competitive behaviors across the choices. A discrete choice modeling approach is used for the analysis and assumes that firms make decisions about their respective level of innovation activity, which in turn impact the utility of the decision makers. In this case, the firm is the entity framed as the decision maker. The decisions or revealed choices used in the analysis are based on survey responses about past innovation activity-related actions taken by firms. While this approach is typically used to identify factors that determine or influence choices, the application here is somewhat different. Instead, the idea is to be able to compare firm-level competitive behaviorism and other characteristics across innovation activity intensity categories to understand how rural and urban firms may differ or are same at a particular level of innovation intensity. While some model variables may influence choices, others may simply be correlated or related to the underlying factors that drive innovation activity choices. Therefore, the approach does not necessarily imply the selected independent variables are determinants of innovation activity choices, but that they are related in some ways to these choices.

4.1 The Multinomial logit model and empirical estimation

Four categories of firms are used to establish the choice model methodology, ranging from non-innovative (type-0; used as the reference group) to the most innovative (type-3).[8] The model assumes that firms make decisions to innovate and to what degree. The model begins with a random utility function which defines a firm's utility as:

(1) $$U_{i,j} = \boldsymbol{x}'_{i,j}\boldsymbol{\beta}_j + e_{i,j}$$

where firm *i*'s utility, $U_{i,j}$, is based on choosing innovation activity intensity level *j*, for *i* = 1, …, *N* and *j = 0, …, 3*; $\boldsymbol{x}_{i,j}$ is a vector of firms' competitive behaviors, other characteristics and the business environment ($\boldsymbol{x}_{i,j}$ = 0 when type-0 is selected[9]); $\boldsymbol{\beta}_j$ are the parameters estimated and $e_{i,j}$ is the error term. Assuming the error term is independently and identically distributed for all firms with Gumbel distribution (McFadden 1973), the probability, *P*, that firm *i* selects innovation activity level *j* is given by:

(2) $$P(T_i = j|\boldsymbol{x}_i) = \frac{\exp(\boldsymbol{x}'_i\boldsymbol{\beta}_j)}{1+\sum_{k=1}^{j}\exp(\boldsymbol{x}'_i\boldsymbol{\beta}_j)}.$$

where T_i is the firm type selected (corresponding to the level of innovation activity intensity of firm *i*). Equation (2) is the multinomial logit (MNL) model (Nerlove and Press 1973) where the resulting parameter estimates predict the change in the log-odds for given values of $\boldsymbol{x}_{i,j}$. To provide a more familiar parameter to interpret, the average partial effects (APE), $\boldsymbol{\alpha}_j$, and there standard errors are calculated following Greene (2012):

(3) $$\boldsymbol{\alpha}_j = \bar{P}_j(\boldsymbol{\beta}_j - \sum_k^J \bar{P}_k\boldsymbol{\beta}_k)$$

(4) $$\mathrm{Var}[\boldsymbol{\alpha}_j] = \{[\mathbf{1}(j=l) - \bar{P}_l](\bar{P}_j\boldsymbol{I} + \boldsymbol{\alpha}_j\boldsymbol{x}') - \bar{P}_l(\boldsymbol{\alpha}_l\boldsymbol{x}')\}\boldsymbol{V}\{[\mathbf{1}(j=l) - \bar{P}_l](\bar{P}_j\boldsymbol{I} + \boldsymbol{\alpha}_j\boldsymbol{x}') - \bar{P}_l(\boldsymbol{\alpha}_l\boldsymbol{x}')\}'$$

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[8] While the proposed choice set implies a hierarchy or order, for example, a level of progression from type-0 to type-3, the proposed empirical estimate does not impose this restriction.

[9] Type-0 firms are considered as the "chose none" in terms of innovation activity intensity levels. This step is included so that parameter results can be discussed in absolute terms in place of relative terms.

where $\overline{P_j}$ is the average probability of choice j estimated across all observations of the data, $\mathbf{1}(j = l)$ is equal to 1 when $j = l$ and 0 otherwise, and $\boldsymbol{V}$ is the estimated covariance matrix of the parameters in equation (2). Note that while $\boldsymbol{\beta}_0 = 0$, $\boldsymbol{\alpha}_0 \neq 0$.[10] Therefore, the APE results include all j categories and can be interpreted as the marginal effects of the parameters.

5. Discussion of Results

Two modeling strategies are presented, one assumes rural and urban firms are the same in terms of estimated parameters by combining rural and urban firms into the same data set (table 8), and the other relaxes this assumption using only the rural firm data in one estimation and only urban firms data in the other estimation (tables 9 and 10). For convenience, only the APE results are presented as these are the basis for the discussion of the results but the fit statistics from the MNL estimations are included. Comparing the combined estimation with those of rural and urban the estimations, the results of a log likelihood test[11] point two the individual estimates of the rural and urban models as more appropriate. Therefore, the discussion is center around the results of tables 9 and 10. The APE coefficients are interpreted as a one unit change in the variable (or the addition of an indicator variables) is expected to be associated with a percentage change (coefficient) in the probability of a particular choice of innovation activity intensity level. Recall that the innovation intensity levels are based on firms' participation in one or more of the three categories of innovation activity (producing a final innovative output, use initial knowledge-based inputs, and seeking formal IP protection) and used to establish firms as non-innovative (type-0 firms), minimally innovative (type-1), moderately innovative (type-2), and highly innovative

[10] The variance-covariance matrix for the APEs were estimated using an algorithm in SAS which was pre-tested on published data and results in Greene (2012).

[11] The test used is -2 times the log likelihood of the combined model minus the sum from the urban and rural models, which is 262. This value is much larger than the chi-squared critical value.

(type-3). Additionally, the main considerations discussed are: (1) differences (or similarities) between urban and rural firms for a given firm type; and (2) comparisons of APE's across four firm types.

[Insert table 8 approximately here]

[Insert table 9 approximately here]

[Insert table 10 approximately here]

Starting with *first mover on new innovations*, it appears that for urban firms the strongest association is with highly innovative firms, followed closely by moderately innovative, and then minimally innovative firms. The APE for non-innovative firms is negative and larger in magnitude compared to the other firm types. For rural firms, the strongest association appears to be with moderately innovative firms, followed by highly innovative. The APE is not statistically significant for minimally innovative firms, but is negative, statistically significant, and large for non-innovative firms which is similar to urban non-innovative firms. One explanation for these results is that the competitive pressures on highly innovative firms (and to nearly the same extent for moderately innovative firms in both rural and urban areas) necessitate taking advantage of the first mover's advantage. However, the same level of competitive pressures may not be experienced by highly innovative rural firms.

A similar result is also seen for the *offer green technologies/innovations* APE's, but the explanation could be more complex. For highly innovative urban firms, offering green tech appears slightly more important than for moderately innovative urban firms. In rural areas, the case reverses as offering green tech appears a little more important for moderately innovative rural firms compared to highly innovative rural firms. Relative to the *first mover on new innovations* APE's, the *offer green technologies/innovations* APE's in urban areas appears to be just under half as important while in rural areas it is closer to a third as important. Since offering green tech is a recent trend in industry, this may reflect that rural firms lag urban firms in terms of adopting new ideas and ways of conducting business, an effect from limited access to knowledge spillovers. At the same time, there may be reduced competitive pressures to offer green tech by innovative rural firms compared to their urban counterparts. The results may also be picking up the effects of rural and urban firms in different industries. Recall that the share of NSF designated high-tech firms was higher for firms in urban areas than in those rural areas.

Looking at the APE's for *increased variety of goods/services* and *increased production capacity/service provisions*, these appear to be more important for moderately innovative firms in both urban and rural areas (the second APE for highly innovative rural firms is not statistically significant). Additionally, the APE's for *more responsive to customers* and *improved worker satisfaction* are positive and statistically significant for urban and rural moderately innovative firms, but not statistically significant for highly innovative or moderately innovative firms. Taken as a whole, these results may identify specific competitive behaviors used by moderately innovative firms in both rural and urban areas as alternatives to seeking any form of IP protection. On the other hand, the APE's for *reduced material/energy use per unit output* are about the same for urban moderately innovative and highly innovative firms (and not statistically significant for rural moderately innovative and highly innovative firms), and the APE's for *reduced labor cost per unit output* are only positive and statistically significant for urban highly innovative firms and rural moderately innovative. The results suggest that the alternatives to seeking IP protection, specifically for moderately innovative firms, may be more related to expanding and maintaining their customer base and improving conditions for workers, and less so on reducing costs. At the same time, rural and urban moderately innovative firms appear to be more in line with each other in terms of competitive pressures, compared to rural and urban highly innovative firms.

For urban firms, the *abandon innovation project* APE is largest for highly innovative firms while the APE for *incomplete innovation projects* is largest for moderately innovative firms. Considered together, these results may indicate a wiliness by highly innovative urban firms to pursue riskier projects or be more willing to let go of projects relative to moderately innovative firms. For example, since highly innovative firms pursue formal IP protection (this is what distinguishes them from moderately innovative firms), they may be better suited to know when to abandon or move on from unsuccessful projects. On the other hand, highly innovative urban firms may take on more innovation development projects compared to moderately innovative firms, and, thus, have more projects in their portfolios and to potentially abandon. For rural firms, the situation appears different in that moderately innovative rural firms may be more willing to take on riskier project or more willing to move on from unsuccessful projects compared to highly innovative rural firms. Additionally, and similar to the explanation of the first to sets of APE's discussed it may be this reflects reduced competitive pressures for highly innovative rural firms and potentially the specific industries that highly innovative rural firms enter. Neither of these APE's are statistically significant for minimally innovative firms and they are negative and statistically significant for non-innovative firms, which reinforces, the definitions of the minimally innovative and non-innovative firm categories. Unfortunately, the NSBC data does not provide greater detail in terms of the number or type of abandon and incomplete innovations.

The *train staff to develop innovations* APE is largest for moderately innovative firms (about 50% larger than the size as for highly innovative firms) and is the largest moderately innovative APE across all the other APE's. Thus, training staff to develop innovations is very important especially for moderately innovative firms. This results may be put into further context by considering the *share professionals at firm* results, which is positive and statistically significant only for the highly innovative firms. Combined, these two results imply that both rural and urban moderately innovative firms place greater emphasis on training employees after they join the firms compared highly innovative firms. Highly innovative firms also appear to place strong emphasis on training staff to develop innovations, but hiring professionals is also relevant and may reduce some of the need for training given the types of innovations sought by highly innovative firms (i.e., those more consistent in terms of IP protections). An additional variable to include in this discussion is *experienced difficulty hiring* which is only statistically significant for rural minimally innovative firms. This suggests that the differences in terms of hiring and training employees for moderately innovative and highly innovative firms are not necessarily due to a shortage of human capital, and more about the strategies pursued by the firms.

Turning to the characteristics variables, urban highly innovative firms appear to be larger than urban moderately innovative firms, and non-innovative firms appear to the largest in rural areas. Urban highly innovative firms appear more likely to provide health insurance for their employees. None of the APEs across urban or rural firm types for *firm age* or *average wage* are statistically significant. Highly innovative firms are more likely to conduct business via e-commerce, and the APE for *international sales* for urban highly innovative firms is about twice that for urban moderately innovative firms, but only slightly larger for rural highly innovative firms compared to rural moderately innovative firms. These last two results suggest that while moderately innovative firms may try to capitalize on expanding and maintaining their customer base, highly innovative firms may have broader reach in terms connecting to new customers domestically (via e-commerce) and globally (through international sales). The results also provide another example where rural highly innovative firms are less competitive than urban highly innovative firms. Interestingly, both the APEs for *internet sales* and *international sales* are negative and statistically significant for non-innovative firms. This suggests that the customer base for non-innovative firms is limited to domestic and, potentially, only local customers.

For the two sources considered in this study where firms get information on new opportunities, for highly innovative and moderately innovative urban firms other business people are important in this regard. This result is different compared to Huang, Arundel and Hollanders (2010), in that they reported R&D intensive firms rely on sourcing information from universities and non-R&D innovators relied on competitors and suppler. On the other hand, the APE for rural firms is not statistically significant. One explanation for this results is the higher concentration of firms in urban versus rural areas, and it could be another example of the spillover effect observed in urban areas but which is believed to be stifled in rural areas. For urban firms, universities appear to be about equal in terms of important sources of information on new opportunities for minimally innovative and moderately innovative firms, but not so for non-innovative (which is negative) or highly innovative firms (which is not statistically significant). For rural areas, universities appear to not be relevant in this regard for firm types 1-3 (the APE is also negative and statistically significant for non-innovative firms). For urban firms, these results differ from Huang, Arundel and Hollanders (2010) in that information from universities does not appear relevant to highly innovative firms, and information from other business people (e.g., competitors) appear more important to highly innovative firms than for moderately innovative firms. Referring back to the results from Lopez-Garcia and Montero (2012), who demonstrated the link between innovative behaviors and spillovers, the lack of statistical significance in the APE's for rural moderately innovative and highly innovative firms related to where firms get information on new opportunities may also be relevant in this regard. Combined with the other evidence provided above showing various way in which rural highly innovative firms behave differently than their urban counterparts, information from competitors and universities may be two kinds of spillovers of which rural highly innovative firms are at a disadvantage. On the other hand, rural moderately innovative firms do not differ nearly as much as their urban counter parts. Thus, these information sources may be less relevant to them.

The last group of APE's are for the business environment, which are at the county-level of observation. In general, these appear not to be impactful in terms of innovation intensity level. However, there are a few exceptions for urban firms. First, the *share of the population foreign born* APE is positive and statically significant for highly innovative firms. This supports other literature that shows that immigrants make important contributions to firm innovation. Additionally, the *unemployment rate* APE is positive and statistically significant for urban moderately innovative firms, and the *total taxes per capita* APE is positive and statistically significant for the urban non-innovative firms. Regarding the unemployment rate, it may be that moderately innovative firms are more likely to be located in areas with higher unemployment. This may also indirectly reflect the skill-level of the local labor pool, which could be related to the suggestion that moderately innovative firms place more emphasis on training staff to develop innovations compared to hiring high-skilled labor. The total taxes per capita result may be related to the idea that non-innovative firms are more dependent on local and domestic markets compared to other firm-types. Therefore, higher taxes paid may equate to either larger number of local sales (sales taxes) or persons with higher incomes (higher property taxes) or a combination of both.

6. Summary and Conclusion

The goal of this paper is to compare firms' competitive behaviors and other characteristics across increasing (decreasing) levels of innovation activity, and determine if rural and urban firm differ (or are the same) at given levels innovation activity intensity. To achieve this goal, a revealed choice model was developed using responses from the 2014 NSBC conducted by the USDA ERS, which contains 10,952 firm-level observations and 257 variables, including 41 innovation related variables. The dependent variables, framed as a revealed choice, was constructed from 15 innovation metrics provided the NSBC, and distinguished between four types of firms including non-innovative, minimally innovative, moderately innovative, and highly innovative. More specifically, highly innovative firms are defined as those that invest resources to develop innovations (e.g., conduct in-house R&D), seek formal IP protection (e.g., apply for patents), and produce an innovative output (e.g., create a new good). Moderately innovative firms, invest resources to develop innovations and produce an innovative output (they do not seek formal IP protection), minimally innovative firms only produce an innovative output, and non-innovative firms do none of the activities used to distinguish the other three firm types.

There are four groups of results which are highlighted here, that may also be relevant in terms of developing policy prescriptions. First, results imply that highly innovative rural firms experience less competitive pressures compared to highly innovative urban firms and moderately innovative rural and urban firms. Reduced competitive pressures are likely the result of fewer highly innovative rural firms in a given region, but may also be related to perceptions about sources of information important for learning about new knowledge and innovative opportunities. Second, there is evidence showing highly and moderately innovative rural firms are impacted by limited access to spillovers in terms of implementing new innovative opportunities (recall that rural firms were much less likely than urban to offer green technology), and this may especially impact highly innovative rural firms as spillover are linked to innovation intensity. Thus, it is likely that both factor, less competitive pressures and restricted spillovers, impact highly innovative rural firms and this results in lower innovation rates as shown in figure 1.

Bridging the rural-urban innovation gap may entail bridging the gap in knowledge spillovers including the actual flows from innovation clusters or knowledge centers to innovative rural firms as the firms' perceptions regarding the importance of sources of knowledge and opportunities. The results show that the competitive behaviors of rural highly innovative firms are somewhat subdued, relative to rural moderately innovative firms and compared to the same scenarios among urban highly and moderately innovative firms. This appears to be associated with a combination of reduced competitive pressures restricted access to knowledge spillover. Policies should focus on greatly improving the knowledge exchange between knowledge centers, such as universities, which may also include helping moderately and highly innovative rural firms understand the value of such knowledge resources. Additionally, providing opportunities in which innovative rural firms can more directly interact and compete with urban innovative firms may also encourage innovations rates among highly innovative rural firms.

Third, moderately innovative firms appear to focus more, relative to highly innovative firms, on expanding and maintaining their customer base and improving worker satisfaction as competitive strategies. Such strategies identified in this study include increasing production capacity, increasing the variety of products sold, improving the responsiveness to customer needs, and improving the satisfaction of employees. Moderately innovative firms do not pursue formal IP protection but are closer in terms the importance placed on some forms of informal protections (such as first mover's advantage). Strategies directed toward expanding and maintaining customers could be viewed by moderately innovative firms as alternatives to the benefits of formal IP. The results showed that moderately innovative firms place less importance on internet and international sells relative to highly innovative firms. Helpful polices may include directing resources that help these firms engage more actively with customers via ecommerce and with the global market.

Fourth, there appears to be a difference between highly innovative and moderately innovative firms in the way that human capital for each is managed. For highly innovative firms, especially those in urban areas, a highly educated and skilled labor pool is of great importance to develop new innovations. On the other hand, moderately innovative firms place the highest emphasis on training staff to develop innovations. This is no to say that moderately innovative firms do not hire high-skilled workers or that highly innovative firms do not train their staff to develop innovations. Instead, moderately innovative firms appear to be more endogenously focused regarding where the innovation training for their workers is developed. This difference could be related to the kinds of innovations developed by each firm type, or it could also be related to the locations of these firms regarding the quality of the labor pool. To aid highly innovative rural firms, policies should be directed at improving the labor pool in terms of increasing the amount of high skilled labor and the number of professional. For moderately innovative rural firms, resources directed at helping firms train workers to develop new innovations would be beneficial.

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Table 1. Description of MNL model variables

Variable name	Description	Source
First mover on new innov.	Was the first in market to offer new good or service	NSBC
Offer green tech/innov.	Goods or services related to renewables, energy efficiency, or conservation	NSBC
Incr. var. goods/services	Increased the variety of goods or services offered	NSBC
Incr. prod. capacity/serv. prov.	Increased capacity of production or service provision	NSBC
More responsive to customers	Reduced time to respond to customer needs	NSBC
Improved worker satisfaction	Improved worker satisfaction or reduced worker turnover	NSBC
Red. mat./energy per unit output	Reduced materials and energy required per unit output	NSBC
Red. labor cost per unit output	Reduced labor costs per unit output	NSBC
Abandon innov.	Abandon innovation activity	NSBC
Have incomplete innov. project	Has incomplete innovation activity	NSBC
Train staff to devel. Innov.	Trains staff to develop or introduce innovations	NSBC
Total # employees	Number of full- and part-time employees at the firm	NSBC
Firm age (years)	Number of years firms has been in operation	NSBC
Average wage ($)	Average wages of non-salaried employees at the firm	NSBC
Provide health insurance	Offers employees a health insurance plan	NSBC
Share professionals at firm (%)	Share of employees that are classified as professional employment	NSBC
Internet sales	Sold goods or services via e-commerce	NSBC
International sales	Sold at least 1% of goods or services internationally	NSBC
Get new info from other bus. peop.	Gets information on new opportunities from other business people	NSBC
Get new info from universities	Gets information on new opportunities from universities	NSBC
Experienced difficulty hiring	Experienced difficulty hiring between 2011-2013	NSBC
Share high-tech firms	Share of high-tech firms in county, 2013	CBP/NSF
Variety of high-tech industries	Variety of high-tech industries in county, 2013	CBP/NSF
Share professionals in labor mkt	Share of professionals in labor force in county, 2013	ACS
Share labor with bach. degree	Share of labor force with at least a bachelor's degree in county, 2013	ACS
Share pop foreign born	Share of foreign born persons in county, 2013	ACS
Unemployment rate	County-level employment rare 2013	BLS
Total taxes per capita	Total local sales and property taxes paid in 2012	Skidmore

Table 2. Summary statistics of dependent variables used in MNL model

Variable Name	Mean	Std. Dev.
First mover on new innov.	0.302	0.459
Offer green tech/innov.	0.274	0.446
Incr. var. goods/services	0.551	0.497
Incr. prod. capacity/serv. prov.	0.443	0.497
More responsive to customers	0.416	0.493
Improved worker satisfaction	0.481	0.500
Red. mat./energy per unit output	0.197	0.398
Red. labor cost per unit output	0.263	0.440
Abandon innov. project	0.187	0.390
Have incomplete innov. project	0.255	0.436
Train staff to devel. Innov.	0.386	0.487
Total # employees	46.902	244.220
Firm age (years)	32.122	27.777
Average wage ($/hour)	16.006	22.394
Provide health insurance	0.702	0.457
Share professionals at firm (%)	0.218	0.341
Internet sales	0.398	0.490
International sales	0.214	0.410
Get new info from other bus. peop.	0.067	0.250
Get new info from universities	0.489	0.500
Experienced difficulty hiring	0.227	0.419
Share high-tech firms	5.769	2.924
Variety of high-tech industries	19.044	10.982
Share professionals in labor mkt	7.325	3.620
Share labor with bach. degree	9.693	3.795
Share pop foreign born	5.821	6.959
Unemployment rate	7.115	2.261
Total taxes per capita	1.478	0.759

Table 3. Correlation matrix of MNL variables

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28
1 First mover on new innov.	1.00																											
2 Offer green tech/innov.	0.20	1.00																										
3 Incr. var. goods/services	0.41	0.22	1.00																									
4 Incr. prod. capacity/serv. prov.	0.31	0.26	0.43	1.00																								
5 More responsive to customers	0.26	0.22	0.35	0.41	1.00																							
6 Improved worker satisfaction	0.26	0.22	0.36	0.40	0.40	1.00																						
7 Red. mat./energy per unit output	0.22	0.23	0.23	0.35	0.29	0.30	1.00																					
8 Red. labor cost per unit output	0.23	0.18	0.25	0.36	0.30	0.29	0.50	1.00																				
9 Abandon innov.	0.23	0.11	0.21	0.19	0.15	0.10	0.15	0.16	1.00																			
10 Have incomplete innov. project	0.23	0.13	0.26	0.23	0.20	0.14	0.15	0.16	0.51	1.00																		
11 Train staff to devel. Innov.	0.38	0.24	0.39	0.35	0.31	0.31	0.24	0.24	0.25	0.30	1.00																	
12 Total # employees	0.04	0.03	0.00	0.03	0.01	-0.01	0.06	0.05	0.04	0.03	0.04	1.00																
13 Firm age (years)	-0.02	-0.01	-0.02	-0.06	-0.01	-0.04	0.00	-0.01	-0.04	-0.03	0.02	0.06	1.00															
14 Average wage ($)	-0.01	0.02	-0.01	0.01	-0.01	-0.01	0.00	-0.01	0.00	-0.01	-0.01	0.04	-0.02	1.00														
15 Provide health insurance	0.07	0.09	0.10	0.11	0.09	0.08	0.08	0.08	0.06	0.08	0.13	0.09	0.10	0.04	1.00													
16 Share professionals at firm (%)	0.01	-0.02	-0.01	-0.02	-0.03	0.00	-0.05	-0.06	0.02	0.03	0.06	-0.05	-0.08	0.05	0.03	1.00												
17 Internet sales	0.17	0.06	0.16	0.12	0.11	0.08	0.10	0.10	0.11	0.12	0.12	-0.01	0.01	-0.01	0.05	-0.05	1.00											
18 International sales	0.21	0.13	0.19	0.22	0.19	0.13	0.21	0.21	0.14	0.21	0.19	0.07	-0.05	0.00	0.14	-0.02	0.15	1.00										
19 Get new info from other bus. peop.	-0.01	-0.01	-0.01	0.00	-0.02	0.00	-0.01	0.00	-0.02	-0.02	-0.03	-0.02	-0.05	0.00	-0.04	-0.04	0.03	0.04	1.00									
20 Get new info from universities	-0.01	-0.01	0.06	0.04	0.03	0.05	-0.04	0.03	0.03	0.02	-0.02	-0.06	-0.08	0.00	0.00	-0.02	0.07	0.02	0.15	1.00								
21 Experienced difficulty hiring	0.07	0.07	0.06	0.08	0.06	0.03	0.04	0.02	0.07	0.07	0.06	-0.01	-0.02	0.02	0.01	-0.01	0.06	0.02	0.01	0.05	1.00							
22 Share high-tech firms	0.00	-0.04	-0.01	-0.01	-0.02	-0.01	-0.04	-0.03	0.04	0.04	0.01	0.01	-0.15	0.04	0.06	0.15	-0.02	0.06	-0.01	0.03	-0.06	1.00						
23 Variety of high-tech industries	0.01	-0.04	0.01	0.00	0.01	-0.02	-0.02	-0.02	0.06	0.05	0.02	0.02	-0.14	0.04	0.10	0.14	0.01	0.10	-0.01	0.04	-0.09	0.70	1.00					
24 Share professionals in labor mkt	0.00	-0.05	0.00	-0.02	-0.03	-0.03	-0.03	-0.02	0.06	0.06	0.02	0.01	-0.16	0.04	0.06	0.16	0.01	0.09	-0.02	0.04	-0.08	0.74	0.73	1.00				
25 Share labor with bach. degree	0.02	-0.03	0.03	0.00	-0.02	-0.01	-0.03	-0.02	0.06	0.07	0.03	-0.01	-0.11	0.05	0.07	0.16	0.02	0.08	-0.03	0.02	-0.06	0.66	0.59	0.70	1.00			
26 Share pop foreign born	0.01	-0.04	-0.01	-0.01	-0.01	-0.01	-0.03	-0.02	0.04	0.03	0.00	0.01	-0.14	0.03	0.03	0.11	0.00	0.06	0.00	0.02	-0.05	0.56	0.61	0.59	0.40	1.00		
27 Unemployment rate	-0.02	0.00	-0.03	-0.02	-0.01	-0.03	0.01	0.02	-0.01	0.00	-0.01	0.01	-0.01	-0.03	-0.03	-0.03	0.00	0.01	0.00	0.01	-0.02	-0.19	-0.01	-0.04	-0.35	0.04	1.00	
28 Total taxes per capita	0.00	-0.02	0.00	-0.01	-0.01	-0.01	-0.02	-0.03	0.02	0.03	0.02	-0.02	-0.03	0.03	0.04	0.09	-0.02	0.04	-0.02	0.01	-0.01	0.39	0.30	0.39	0.52	0.38	-0.22	1.00

Table 5. Summary statistics of variables used for construction of choice options

Variable Name	Mean	Std. Dev.
In house R&D	0.3196	0.4663
Buy R&D	0.0893	0.2851
In house design	0.2593	0.43828
Buy design	0.2774	0.4477
Purchase knowledge	0.1754	0.3802
Patent application	0.0497	0.2172
License patent	0.0605	0.2384
Industrial design	0.0238	0.1525
Trademark	0.0836	0.2768
Copyright	0.1012	0.3016
New good	0.3673	0.4821
New service	0.5301	0.4991
New manuf. Method	0.343	0.4747
New logistics	0.3061	0.4609
New support	0.3746	0.4841

Table 6. Correlation matrix of MNL variables used to construct dependent variable choices

	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	In house R&D	1.00														
2	Buy R&D	0.32	1.00													
3	In house design	0.53	0.23	1.00												
4	Purchase knowledge	0.29	0.31	0.28	1.00											
5	Buy design	0.31	0.26	0.37	0.34	1.00										
6	Patent application	0.29	0.17	0.23	0.14	0.17	1.00									
7	Industrial design	0.19	0.17	0.18	0.13	0.13	0.49	1.00								
8	Trademark	0.29	0.18	0.29	0.18	0.23	0.38	0.36	1.00							
9	Copyright	0.29	0.17	0.32	0.21	0.23	0.25	0.25	0.39	1.00						
10	License patent	0.24	0.24	0.23	0.28	0.20	0.47	0.29	0.27	0.18	1.00					
11	New good	0.43	0.19	0.44	0.21	0.23	0.24	0.17	0.26	0.25	0.20	1.00				
12	New service	0.26	0.18	0.26	0.25	0.21	0.06	0.06	0.11	0.19	0.13	0.27	1.00			
13	New manuf. method	0.41	0.20	0.37	0.23	0.21	0.20	0.15	0.20	0.19	0.19	0.49	0.28	1.00		
14	New logistics	0.26	0.19	0.26	0.25	0.21	0.08	0.08	0.14	0.15	0.15	0.23	0.35	0.32	1.00	
15	New support	0.35	0.23	0.31	0.31	0.25	0.13	0.12	0.17	0.17	0.17	0.28	0.40	0.35	0.46	1.00

Table 7. Frequency (%) of innovation activities by firm type , region

Variable		Type 0 firm		Type 1 firm		Type 2 firm		Type 3 firm	
		Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural
Initial input	In-house R&D	0.0%	0.0%	0.0%	0.0%	57.0%	58.7%	81.5%	77.5%
	Purchased R&D	0.0%	0.0%	0.0%	0.0%	16.1%	14.3%	29.3%	22.9%
	In-house design	0.0%	0.0%	0.0%	0.0%	45.9%	44.4%	66.7%	69.8%
	Purchased knowledge	0.0%	0.0%	0.0%	0.0%	34.1%	29.7%	49.0%	44.0%
	Purchased design	0.0%	0.0%	0.0%	0.0%	47.7%	49.5%	73.1%	70.4%
Intermediate output	Applied for patent	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	27.3%	29.3%
	Registered industrial design	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	15.5%	12.9%
	Registered trade mark	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	50.6%	43.3%
	Copyright	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	61.0%	52.8%
	Licensed patent	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	29.5%	36.2%
Final output	Produced new/improved good	0.0%	0.0%	33.2%	31.2%	50.8%	54.1%	71.3%	75.9%
	Produced new/improved service	0.0%	0.0%	71.9%	75.0%	76.0%	72.6%	78.1%	74.6%
	Used new manufacturing method	0.0%	0.0%	31.6%	31.5%	50.4%	51.6%	60.4%	65.7%
	Use new logistics method	0.0%	0.0%	35.5%	34.6%	44.3%	43.7%	50.8%	52.5%
	Used new support method	0.0%	0.0%	44.1%	36.5%	59.4%	54.8%	69.5%	63.1%
Number firms		690	1848	431	1563	675	2160	498	997
% NSF high-tech industries[a]		25.8%	13.5%	20.2%	9.8%	26.8%	17.9%	41.8%	22.5%

[a.] See NSF (2017) for a list of the 4- and 6-digit NAICS codes classified as high-tech.

Table 8. Average partial effects from MNL model

Variable	Type 3	Type 2	Type 1	Type 0
Innovative behaviors				
First mover on new innov.	0.06153 ***	0.11934 ***	0.01082 ***	-0.19169 ***
Offer green tech/innov.	0.04168 ***	0.08335 ***	-0.08856 ***	-0.03646 ***
Incr. var. goods/services	0.02615 ***	0.04997 ***	0.01518 ***	-0.09130 ***
Incr. prod. capacity/serv. prov.	0.01787 ***	0.08946 ***	-0.05796	-0.04937 ***
More responsive to customers	-0.00044	0.04651 ***	-0.01498	-0.03109 ***
Improved worker satisfaction	-0.00561	0.03346 ***	-0.00926	-0.01859 **
Red. mat./energy per unit output	0.03863 ***	0.05836	-0.09226 ***	-0.00473
Red. labor cost per unit output	0.01878 ***	0.04141 **	-0.03962	-0.02057 **
Abandon innov. project	0.03711 ***	0.04889 ***	-0.01375	-0.07225 ***
Have incomplete innov. project	0.04724 ***	0.08182 ***	-0.04979	-0.07927 ***
Train staff to devel. Innov.	0.09134 ***	0.34621 ***	-0.24693	-0.19062 ***
Characteristics				
Total # employees	0.00011 ***	-0.00013 ***	-0.00003	0.00005 **
Firm age (years)	-0.00009	-0.00036	0.00035	0.00011
Average wage ($/hour)	-0.00003	0.00024	-0.00026	0.00005
Provide health insurance	0.04241 ***	0.01948	-0.05290 ***	-0.00899 *
Share professionals at firm (%)	0.07237 ***	0.01621	-0.08715 ***	-0.00143
Internet sales	0.02703 ***	-0.01037	0.00404	-0.02070 ***
International sales	0.08517 ***	0.09051 ***	-0.10276 *	-0.07292 ***
Get new info from other bus. peop.	0.03906 **	0.01314	-0.04444	-0.00776
Get new info from universities	-0.00377	0.00151 *	0.02483 ***	-0.02257 ***
Experienced difficulty hiring	-0.00754	-0.00684	0.02503 **	-0.01066
Business environment				
Share high-tech firms	-0.00083	0.00765 *	-0.00501	-0.00181
Variety of high-tech industries	0.00010	0.00015	-0.00136	0.00112 *
Share professionals in labor mkt	0.00412 *	-0.00424	-0.00005	0.00017
Share labor with bach. degree	0.00157	0.00207	-0.00089	-0.00276 *
Share pop foreign born	0.00156	-0.00040	-0.00145	0.00030
Unemployment rate	-0.00238	0.01048 ***	-0.00549	-0.00260 ***
Total taxes per capita	0.00575	-0.01492 ***	0.00064 *	0.00854 ***
# obs.	8862			
R-square	0.62			
Log likelihood	-7378			

Statistical significance is denoted as * ≤ 10%, ** ≤ 5%, *** ≤ 1%

Table 9. Average partial effects from MNL model

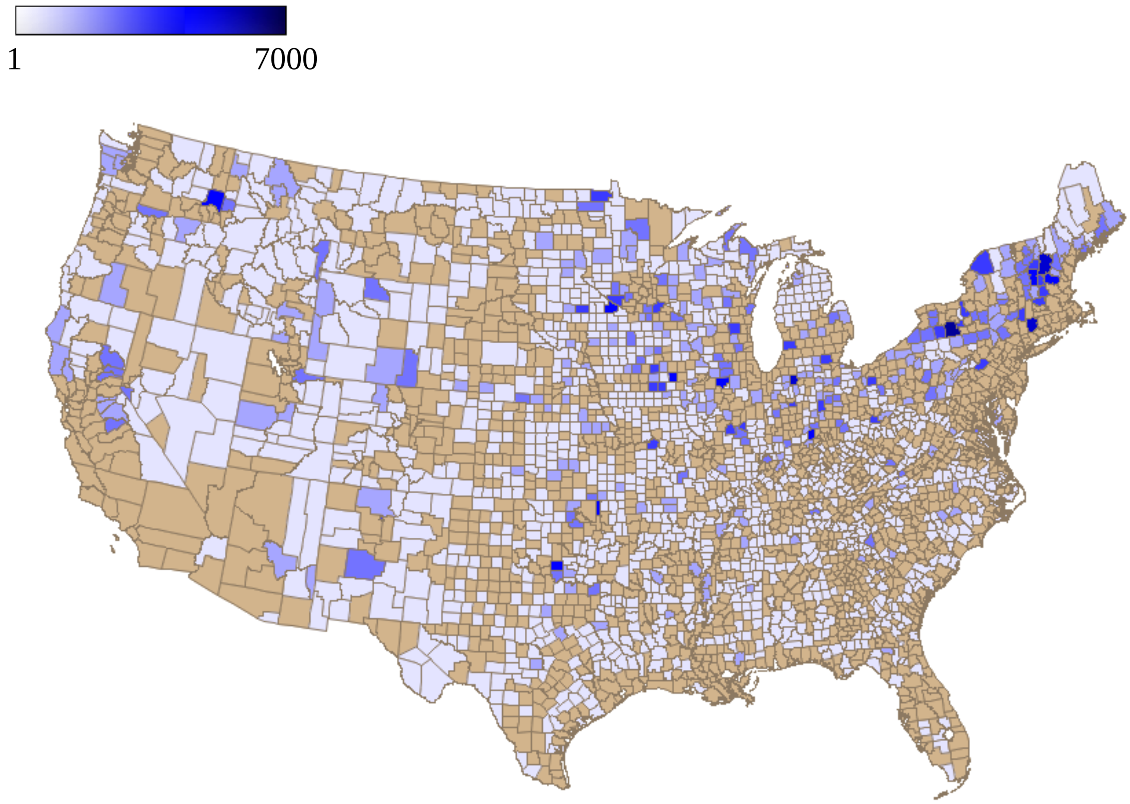
Variable	Type 3	Type 2	Type 1	Type 0
Innovative behaviors				
First mover on new innov.	0.26665 ***	0.24437 ***	0.13155 ***	-0.64257 ***
Offer green tech/innov.	0.12539 ***	0.10999 ***	-0.01430	-0.22108 ***
Incr. var. goods/services	0.12279 ***	0.16635 ***	0.03969	-0.32883 ***
Incr. prod. capacity/serv. prov.	0.07924 **	0.11635 ***	0.00100	-0.19659 ***
More responsive to customers	0.02145	0.08775 ***	0.01201	-0.12121 **
Improved worker satisfaction	0.02442	0.06100 **	0.01075	-0.09616 **
Red. mat./energy per unit output	0.07464 *	0.07268 *	-0.07989 **	-0.06743
Red. labor cost per unit output	0.05429 *	0.04887	0.01924	-0.12239 **
Abandon innov. project	0.17673 ***	0.10345 **	-0.01470	-0.26548 ***
Have incomplete innov. project	0.12668 ***	0.14613 ***	0.05547	-0.32827 ***
Train staff to devel. Innov.	0.26549 ***	0.36962 ***	-0.07736 *	-0.55776 ***
Characteristics				
Total # employees	0.00031 ***	-0.00024 **	0.00008	-0.00015 *
Firm age (years)	-0.00059	-0.00026	0.00034	0.00052
Average wage ($/hour)	0.00006	-0.00115	0.00018	0.00091
Provide health insurance	0.11846 ***	0.01159	-0.02140	-0.10865 **
Share professionals at firm (%)	0.18983 ***	-0.02718	-0.09110 **	-0.07155
Internet sales	0.05656 **	0.01275	0.03198	-0.10129 **
International sales	0.18879 ***	0.07757 **	-0.03118	-0.23517 ***
Get new info from other bus. peop.	0.14503 ***	0.11018 **	-0.13136 ***	-0.12385 *
Get new info from universities	0.00192	0.05783 **	0.05205 **	-0.11179 ***
Experienced difficulty hiring	0.01306	-0.03832	-0.01222	0.03747
Business environment				
Share high-tech firms	-0.00745	0.00789	0.00731	-0.00775
Variety of high-tech industries	-0.00212	-0.00264	-0.00078	0.00554
Share professionals in labor mkt	0.00474	-0.01315	-0.00468	0.01309
Share labor with bach. degree	0.00997	0.01099	-0.00296	-0.01800 *
Share pop foreign born	0.00391 *	-0.00012	-0.00166	-0.00213
Unemployment rate	0.00087	0.02089 **	-0.00878	-0.01297
Total taxes per capita	-0.02112	-0.04377	-0.02361	0.08850 *
# obs.	2294			
R-square	0.63			
Log likelihood	-2135			

Statistical significance is denoted as * ≤ 10%, ** ≤ 5%, *** ≤ 1%

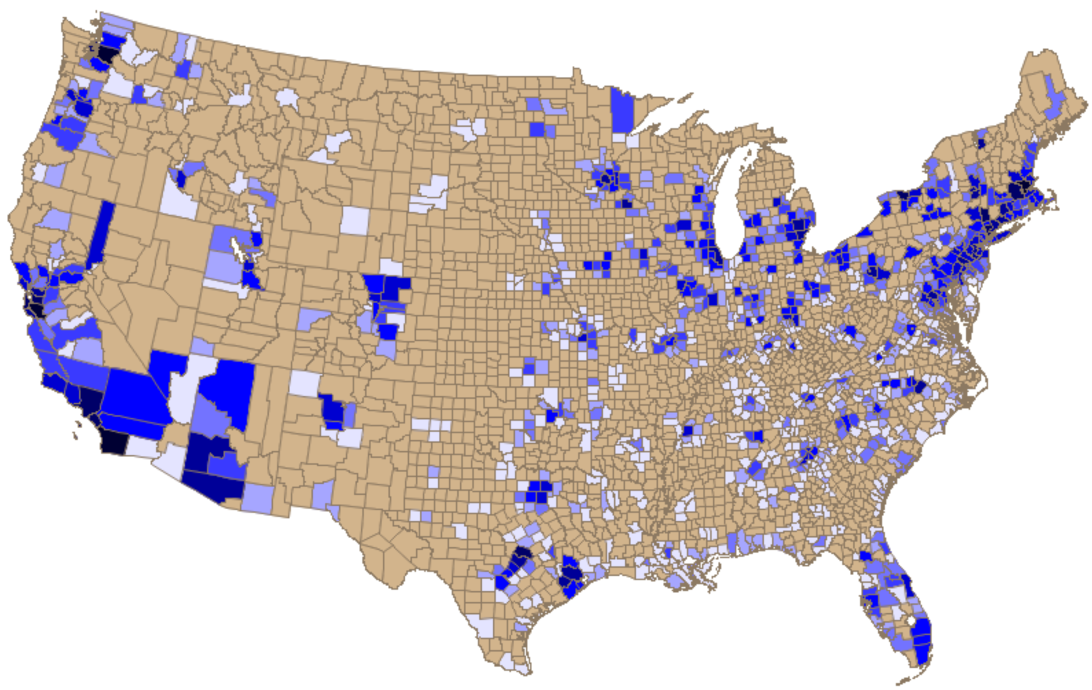
Table 10. Average partial effects from MNL model

Variable	Type 3	Type 2	Type 1	Type 0
Innovative behaviors				
First mover on new innov.	0.15520 *	0.23893 **	0.11649	-0.51062 **
Offer green tech/innov.	0.06511 *	0.07702 **	-0.05397	-0.08815 **
Incr. var. goods/services	0.07209 *	0.09867 *	0.07273	-0.24349 **
Incr. prod. capacity/serv. prov.	0.04179	0.09984 ***	-0.01343	-0.12820 **
More responsive to customers	0.01496	0.05717 **	0.01155	-0.08367 **
Improved worker satisfaction	-0.00424	0.03915 **	0.00627	-0.04118
Red. mat./energy per unit output	0.05026	0.02207	-0.06327 **	-0.00906
Red. labor cost per unit output	0.03307	0.04398 *	-0.02919	-0.04785
Abandon innov. project	0.05764 *	0.08177 *	0.04827	-0.18769 **
Have incomplete innov. project	0.10036 *	0.11301 **	-0.00480	-0.20857 **
Train staff to devel. Innov.	0.21108 *	0.39840 ***	-0.05344	-0.55605 ***
Characteristics				
Total # employees	0.00024	-0.00006	-0.00054 **	0.00037 *
Firm age (years)	-0.00019	-0.00035	0.00021	0.00033
Average wage ($/hour)	-0.00063	0.00048	-0.00011	0.00026
Provide health insurance	0.04992	0.00772	-0.03661 *	-0.02103
Share professionals at firm (%)	0.06963 *	0.00268	-0.06872 *	-0.00359
Internet sales	0.04733 *	0.00737	0.00362	-0.05832 **
International sales	0.13877 *	0.11671 **	-0.04645	-0.20903 **
Get new info from other bus. peop.	0.03831	-0.02189	-0.00484	-0.01158
Get new info from universities	0.00928	0.01413	0.02505	-0.04846 *
Experienced difficulty hiring	-0.01000	0.01507	0.03187 *	-0.03694
Business environment				
Share high-tech firms	0.00469	0.00626	-0.00452	-0.00644
Variety of high-tech industries	0.00011	-0.00093	-0.00177	0.00258
Share professionals in labor mkt	0.00595	-0.00432	-0.00060	-0.00103
Share labor with bach. degree	0.00259	0.00337	0.00037	-0.00632
Share pop foreign born	0.00243	-0.00379	-0.00067	0.00202
Unemployment rate	-0.00220	0.00790	-0.00016	-0.00554
Total taxes per capita	0.00263	-0.01866	0.00049	0.01554
# obs	6568			
R-square	0.55			
Log likelihood	-5112			

Statistical significance is denoted as * ≤ 10%, ** ≤ 5%, *** ≤ 1%



Patents in rural counties



Patents in metro counties

Figure 1. County-level patent applications per 100 firms in rural and urban (metro) areas, averaged for the period 2011-2015

Source: Constructed from US Patent and Trademark Office, US Census County Business Patterns, and USDA Economic Research Service data