Exploring innovation creation across rural and urban firms: Analysis of the National Survey of Business Competitiveness

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Towards a More Reliable Substantive Innovation Measure from Self-Reported Surveys: Hard Tests of the 2014 Rural Establishment Innovation Survey Latent Class Analysis

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ABSTRACT: A major impediment to discussion of grassroots innovation that is not science or engineering based is the reliability of self-reported innovation measures. The unexpected result that self-reported innovation rates can be high in regions characterized by thin markets and lower levels of technological development was of particular concern in the design of the Rural Establishment Innovation Survey (REIS) administered in the U.S. in 2014. The strategy used to generate more reliable substantive innovation rates for rural areas assumes that the population of firms is made up of subpopulations of substantive innovators, nominal innovators, and non-innovators. A set of auxiliary questions whose affirmative responses are thought to be associated with substantive innovation allow identifying these unobserved subpopulations. The usefulness of this approach for other self-reported innovations surveys is assessed by examining internal and external validity of subpopulation membership and the substantive innovator class. More reliable indicators of where substantive grassroots innovation takes place are essential for including innovation as a pillar of inclusive growth strategies.

The Importance of Measuring Innovation Wherever It Occurs

Innovation has been heralded as "the first step in winning the future,"[2] singled out as the only process capable of sustaining employment in high wage countries in an age of increasing globalization, and may become the primary activity that adds value to human capital as more cognitive and manual functions are automated through advances in robotics and artificial intelligence. The implication of these assertions is that innovation will need to become increasingly broad-based if it is to serve as a bulwark against international and technological competition.

From this perspective, the efforts of the OECD to develop guidelines and principles for the collection of information on broad-based innovation that extends beyond the conventional focus of science and engineering-based innovation appears particularly prescient. And yet the economic study of innovation is still dominated by a linear model of hard inputs such as science and engineering personnel, and R&D expenditures, motivated by the rational pursuit of monopoly profit where the output is most reliably represented by patents (Baumol 2010). If one were to draw a parallel between biological ecosystems and innovation ecosystems, one would be struck by the focus on a single taxonomic class in the latter. The activities of MAMILs (Middle-Aged Men in Labcoats) have become a preoccupation despite the acknowledgement that the linear model can only account for a subset of all innovation, disregarding the large number of

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[1] The opinions expressed in the paper are those of the author and are not attributable to the Economic Research Service or U.S. Department of Agriculture.

[2] President Barack Obama 2011 State of the Union Address

innovations that emerge from the application of creative thinking to solve vexing problems, often by non-specialists (Phelps 2013).

The huge advantages that the study of science and engineering-based innovation possess are a long history of data on intellectual property protections, reliable third parties that vouch for the originality and utility of these protections, and a plausible behavioral model based in neoclassical economics. The disadvantage of studying grassroots or user innovation begins with the need to purposefully collect these data. Self-reported innovation measures have been regarded with considerable skepticism in the U.S. A 2007 report by an advisory committee to the Commerce Department dismissed the EU Community Innovation Survey (CIS) as "very costly and ha[s] encountered both definitional and response rate problems" (U.S. Department of Commerce 2007 cited in Hill 2013). While the inclusion of CIS-like questions in the National Science Foundation Business R&D and Innovation Survey (BRDIS) is recognition of the need to collect more comprehensive data on innovation activities, a disciplinary interest in these data has yet to be demonstrated in the U.S.[3]

The large differences in self-reported innovation rates in a combination R&D/innovation survey like BRDIS compared with innovation only surveys such as the Community Innovation Survey have raised additional doubts about reliability (Gault 2013). OECD is currently engaged in extensive cognitive testing of alternative ways of eliciting more reliable self-reported innovation activity (Galinda-Rueda 2013). The logic behind this effort is that better cues or better defined conditional statements may produce better measures of substantive innovative activity than is currently possible with the more ambiguous questions about introduction of "new or significantly improved" produces, services, and processes.

The logic behind the approach investigated in this paper retains the original CIS questions but assumes that differentiating substantive from nominal innovators is possible by identifying establishment characteristics elicited with simple questions. If some combination of responses to these simple questions is highly correlated with substantive innovative activity then it may be possible to greatly improve the reliability of self-reported innovation surveys. This strategy was implemented in the 2014 Rural Establishment Innovation Survey administered by the Economic Research Service, a statistical agency of the U.S. Department of Agriculture. The relevant study population for the survey was establishments with 5 or more employees in potentially tradable, nonfarm sectors in both rural and urban areas. Given the novelty of this method the purpose of this paper is to critically assess the latent classes identified in the data and their productiveness in deriving more reliable measures of self-reported innovation.

Generating more reliable estimates of substantive innovative activity would be a worthy goal in itself. However, in the case of REIS more reliable estimates of innovative activity are essential to meaningful analysis due to a strong tendency in the literature to dismiss "rural innovation" as being either inconsequential or highly idiosyncratic. Conventional wisdom—borrowing much from the Marshallian industrial district construct—holds that rural firms are disadvantaged in

[3] The situation in Europe, with more than 20 years of data from the Community Innovation Survey, is very different. More than 50 academic papers a year are published using CIS data for analysis (Arundel and Smith 2013). Sanchez (2014) is one of the earliest examples of econometric analysis of the innovation questions included in BRDIS.

their innovative capacity due to thin final and intermediary markets, thin labor markets which complicates hiring specialized human capital, and much more sparse information environments which are less likely to benefit from spillovers of other proximate innovation activities. Findings from a conventional self-reported innovation survey that contradicted these priors would be easily dismissed. And yet, if the conventional wisdom is incomplete or incorrect then the innovative capacity of places and its implications for economic growth are likely to be poorly understood.

The Challenge of Accurately Measuring Substantive Grassroots Innovation
All innovation is dependent on the generation of novelty. Unfortunately, novelty generation by humans is characterized by a very low expected fitness (March 2010). The great majority of new ideas are bad, and most of these will never meet the criterion of being introduced to a market to meet the minimum requirement for being considered an innovation (Gault 2013). The essential problem for measuring substantive innovation is differentiating new ideas introduced to a market that may have a considerable impact from new ideas introduced to a market that have little or no impact.[4]

Science and engineering-based innovation research often circumvents this problem by relying on national patent offices as a highly selective sieve for differentiating potentially impactful novelty from mere newness. In contrast, self-reported innovation measures are wholly reliant on a survey respondent's interpretation of "new or significantly improved" in determining whether a business unit is innovative or not.

North and Smallbone (2000) attempted to assess the selectiveness of the self-reported sieve by requiring respondents that answered CIS innovation questions affirmatively to provide a description of that innovation. Industry experts then rated those descriptions as being either "Highly Innovative" or "Somewhat Innovative." More than half of the "innovative" firms were deemed to be only "Somewhat Innovative" by the industry experts, suggesting that self-reported innovation may be a poor proxy for substantive innovation. Arundel et al. (2013) used a similar strategy in an assessment of possible errors in the 2007 Innovation Census from Tasmania which confirmed that less than 10% of self-reported innovations were deemed to require substantial creative input from the respondent firm. This reinforces a seemingly wide gap in the criteria used to assess science and engineering-based innovation versus grassroots or user innovation.

While statistical agencies are justified in their pursuit of positive, objective measures of innovation that do not attempt to assess the quality or impact of innovations, this preference may pose problems for innovation policy where public investments are expected to affect outcomes that citizens care about such as employment, income, and competitiveness. The issue is even

[4] Measuring "substantive innovation" is somewhat different from the Oslo Manual interest in measuring innovation where the degree of novelty is assessed but the value or impact of an innovation is not considered. The interest of USDA in measuring substantive innovation is to determine whether firms in rural areas are constrained in innovation that leads to favorable market outcomes such as increased employment, increased productivity and wages, increased competitiveness, or increased firm resilience.

more critical in those areas where strong priors discount the very possibility of substantive innovation as is the case with rural innovation.

Substantive Innovators as an Unobserved Subpopulation

Case study and anecdotal observations of rural innovative firms mesh well with the stylized fact that innovation is an activity observed mainly in the right tail of an empirical distribution (Marsilia and Salter 2005). If the rural population of firms is made up of a small contingent of highly innovative firms, a somewhat larger contingent of competent but only nominally innovative firms, and a large contingent of firms pursuing traditional cost-minimizing, routine production strategies thought to be emblematic of rural production, then the "representative" rural firm will appear to be an innovation laggard. Urban firms may appear to be "more innovative" on average but this may be more a function of many fewer laggards in urban areas (why would cost minimizing firms choose high cost locations?) than a function of what is happening in the right tail—a much more meaningful focus. Unfortunately, such fallacies of composition are so commonplace, the idea that substantive innovation might take place in rural areas is either dismissed (World Bank 2009) or never considered (Carlino and Kerr 2014).

Whether the right tail of the rural distribution contains an appreciable number of innovative firms—the minimum requirement for rural innovation to be a topic worthy of study—is an empirical question. The anecdotes and case studies provide the requisite condition: the existence of rural innovative firms is proof of possibility. Examples of both substantive innovation and disruptive innovation in rural areas are enough to establish the necessity for data to determine their frequency (see Freshwater 2012). These examples demonstrate that some rural firms possess the attributes and motivations required of innovative entrepreneurship (Baumol 2010). A rejoinder to this optimism is that "for example is not a proof." If innovative entrepreneurship in rural areas is a rare occurrence, dependent on a confluence of improbable events, it is a poor candidate for economic analysis or pragmatic policy initiatives.

A Survey Method for Differentiating Substantive Innovators from Nominal Innovators

The genesis of the strategy to be applied in the REIS to differentiate substantive from nominal innovators was contained within the CIS instrument. A CIS question asks if the business had failed or incomplete innovation projects over the study period. The purpose of the question in the EU survey is to distinguish innovators from non-innovators to allow non-innovators to skip over a number of questions only relevant to innovators. An additional value of this question is to potentially provide information to control for social desirability bias. Consider the case of a non-innovative firm answering any of the "new or significantly improved" questions affirmatively either because there is the expectation that the enumerator is seeking this response or because there is the sentiment that good firms innovate. When confronted by a question regarding failed or aborted innovation attempts, non-innovative firms are likely to answer negatively as this question provides no positive reinforcement for the respondent (see Q28 in Appendix). In contrast, a true innovator is more likely to recognize the role of failure in eventual success and thus is much more likely to acknowledge failure (Leoncini 2015).

The realization that respondents are motivated by many things other than providing wholly objective, accurate information to enumerators can confer considerable value to auxiliary questions (Tourangeau, Rips and Rasinski 2000).

The insight provided by this one question was that the experience of substantive innovation would likely result in responses to other simple questions that would differentiate them from respondents who had not struggled with the innovation process. Take the example of financing innovation projects. The difficulty of securing funds for innovation would be familiar to firms pursuing substantive innovation projects given the very serious asymmetric information problem facing potential lenders. Innovative firms that had experienced difficulty securing such funds in the past would recognize that the availability of such funds would be of great value to the firm. In contrast, non-innovating firms would put little value on such funds because its scarcity is irrelevant to the business. One survey strategy for revealing capital constraints is to pose a hypothetical money-dump question: "If excess funds were available how would they likely be used?" By including innovation projects as one use of funds the question should differentiate innovative firms that face this constraint regularly from non-innovating or nominally innovating firms who may be capital constrained but not innovation capital constrained (see Q34 in Appendix).

An establishment's approach to protection of intellectual property is also likely to differ between innovative and non-innovative firms. Patents have long been used to differentiate inventive firms from non-inventive firms. However, patents are clearly an incomplete measure of intellectual property protection as: 1) many economically valuable ideas are not patentable, 2) the expense of securing a patent may be deemed greater than the value of protection provided by a patent, or 3) other means of protection may be easier to enforce. The survey includes a question about intellectual property protections that are more general and less arduous than securing a patent that includes nondisclosure agreements, non-compete clauses or seeking remedies for misappropriation (see Q37 in Appendix). Non-innovative firms that are not actively engaged in the novel combination of ideas are much less likely to utilize trade secret protections, providing another dimension for differentiating substantive innovators from other firms.

Another strategy for designing auxiliary questions was to identify potential markers of "innovative firm DNA'—i.e., core skills or organizational culture possessed by innovative firms. A growing body of work by Nick Bloom, Erik Brynjolfsson and assorted co-authors makes the strong case that the inputs firms use to make decisions is a consistent marker of innovative firms (Bloom et al 2013; Bloom et al. 2012; Brynjolfsson et al. 2011). Firms that rely most heavily on data from all aspects of their business operation to make decisions are consistently found to be more productive and more innovative than firms with more modest demands for data. The survey thus includes questions about the use of Enterprise Resource Planning (ERP) software—an integrated set of applications businesses use to collect, store, manage, and interpret data from a large number of activities—that has been associated with induced innovation from Chinese import penetration (Bloom, Draca and Van Reenen 2016; see Q14 in Appendix). An organizational culture consistent with data driven decision-making mirrors the requirements for an effective total quality management system. So questions related to assessment of customer satisfaction, corrective action, and tracking human resource training are also included in the survey (see Q26, Q25 and Q13b in Appendix).

Uncovering Substantive Innovators in the Rural Establishment Innovation Survey

The unique approach for innovation surveys explored in REIS assumes that the population of establishments is made of functionally distinct but unobservable subpopulations. In contrast, the assumptions undergirding conventional innovation surveys either assumes a single population of establishments (or firms) or subpopulations that are observable based on the presence or absence of formal R&D expenditures. Innovative respondents in the conventional case are identified by their response to questions asking about "new or significantly improved" products, processes, practices or marketing methods. While questions related to the novelty of an innovation (new to firms, new to market, new to world), or the revenues attributed to innovative products, may be used to rate the importance or impact of innovations, responses to the innovation questions are otherwise assumed to be perfectly comparable. The subject-based identification of innovation is wholly reliant on the response to the "new or significantly improved" questions.

If establishments are in fact members of distinct subpopulations based on an organization's orientation towards innovation, then it is reasonable to assume that the responses to the "new or significantly improved" questions are not comparable. In this case, subject-based identification of substantive innovation is reliant on both responses to the "new or significantly improved" questions along with observable attributes or attitudes thought to be strongly associated with substantive innovation. The challenge statistically is moving from a single dimension for differentiating innovators from non-innovators to a multiple dimension construct, based on responses to the auxiliary questions outlined above.

The best explanation for why the strategy of using auxiliary questions to differentiate substantive innovators from other firms has not been used before is the incompatibility of most classification procedures with complex sampling design. Since most innovation surveys are conducted by national statistical agencies, statistical methods that cannot produce valid variance estimates are dismissed. Cluster analysis is widely considered to be an exploratory statistical method: "The term exploratory is important here because it explains the largely absent 'p-value', ubiquitous in many other areas of statistics. . . . Clustering methods are intended largely for generating rather than testing hypotheses" (Everitt 1993, p. 10). Because many classification methods rely on discrete group membership they may not be amenable to incorporating the sample weights in complex survey design that characterize every large data collection effort (Ackerman, et al. 2011).

Latent class or mixture models, which provide a probabilistic basis for identifying subpopulations, conceptually provided a plausible solution to the problem. The National Institute on Alcohol Abuse and Alcoholism funded development of a complex survey design module for MPlus software that could be used for latent class analysis on national health datasets (Muthen and Muthen 2010). Although latent class analysis procedures are available in other popular statistical packages such as Stata and SAS, the packages are not yet able to incorporate complex survey design capabilities that are available for other econometric procedures.

The general model is:

$$f(y) = \sum_{j=1}^{k} \pi_{j(\boldsymbol{z},\alpha_j)} p_{j(y;\boldsymbol{x}_j\beta_j,\varphi_j)}$$

> where y represents a response variable that is presumed to be generated by class specific probabilities (which is not the focus of the current paper); the number of classes in the mixture is denoted as k;
> the mixture probabilities πj can depend on regressor variables z and parameters α_j. The class distribution p_j can also depend on regressor variables in xj, regression parameters β_j, and possibly scale parameters φ_j (see Vermunt and Magidson 2004).

Differentiating a substantive innovator class is done by including categorical responses to the auxiliary questions as the z-vector over k = 3 possible classes.

Arriving at the final specification for the z-vector used to differentiate establishment subpopulations was accomplished with a minimal amount of "specification tests" to minimize the possibility that the resulting class structure was an artifact of the sample data. The principal exploratory tools used to confirm the utility of auxiliary question responses to differentiate unobserved subpopulations were sample means and the tetrachoric or polychoric correlations between these categorical variables.[5]

[5] Tetrachoric (for binary) and polychoric (for ordered categorical) correlations assume that unobserved normally distributed continuous variables underlie the observed categorical variables. These can be estimated in SAS using the POLYCHORIC option in the CORR procedure.

Table 1: Means of Categorical Variables Pertinent to Latent Class Analysis

Variable	Percent Affirmative	Percent Missing
Innovation Questions		
Q27a Goods New or Significantly Improved	60.51	33.97
Q27b Services New or Significantly Improved	70.8	18.34
Q27c New Methods for Producing Output	54.85	34.53
Q27d New Logistics or Distribution Methods	50.66	28.56
Q27e New Support Activities for Processes	58.38	23.87
Q27f New Marketing Methods	58.43	19.5
Auxiliary Questions		
Q28a Innovation Projects Abandoned	24.5	14.98
Q28b Innovation Projects Incomplete	33.32	14.28
Q34d Innovation Projects Capital Constrained (Definitely) [a]	28.87	20.38
Q37d Intellectual Property	28.32	16.68
Digital Technology		
Q14a Personal Computers	94.69	5.82
Q14b Broadband	98.63	8.75
Q14c E-commerce	52.53	11.55
Q14d E-procurement	82.54	9.74
Q14e Web Advertising	68.57	10.5
Q14f Direct E-mail Marketing	44.99	12.29
Q14g Social Media	57.75	11.21
Q14h Issued Smartphones	51.65	11.48
Q14i Radio Frequency Identification Readers	23.93	13.94
Q14j Industry Specific Software	81.49	10.19
Q14k Resource Planning Software	36.04	13.17
Q14l Logistics Software	20.47	14.67
Q14m Customer Relationship Software	28.66	13.69
Data Driven Decision-Making		
Q24 Document Best Practices	48.54	11.59
Q25 Monitor Customer Satisfaction (Regularly)[b]	39.30	10.77
Q26 Correct Problems re Complaints(Regularly) [b]	53.45	11.83
Q13B Track Employee Training	37.32	11.96

Source: 2014 ERS Rural Establishment Innovation Survey

[a] Alternative response categories include Not at All Likely, and Probably [b] Alternative response categories include Never, and Occasionally

Full sample containing metro and nonmetro establishments, weighted to represent population of U.S. establishments in nonfarm tradable sectors

The responses to the CIS innovations questions confirms the need for a more selective screen for substantive innovation. The good news is that the majority of establishments self-identify as innovators. The bad news is that the credibility of this self-identification is challenged by the 2011 BRDIS results that estimate the US firm innovation rate at 14.3% for all industries and 29.4% for manufacturing (Boroush and Jankowski 2016). Thus, it is somewhat encouraging that the first 4 auxiliary questions in Table 1 do not receive affirmative responses from more than a third of establishments, suggesting that these variables may be effective in differentiating substantive innovators from nominal innovators. Responses to the Digital Technology questions confirm that many of these technologies are widely utilized. ERP software has the strongest conceptual link to data driven decision-making in firms because it is the one technology that endeavors to compile, analyze and compare large amounts of data from disparate business activities (OECD 2016). Its association with innovation will be assessed before selection into the latent class analysis. Finally, questions related to management practices associated with data driven decision-making have a higher share of affirmative responses relative to the other target auxiliary questions. However, this is consistent with many otherwise non-innovative establishments pursuing continuous improvement or systematic quality assurance strategies. This distinction between protocols that firms use to incrementally improve their business and substantive innovation activities that may develop whole new methods or products points to the subjective nature of the “new or significantly improved” criterion.

The auxiliary variable that had the strongest association with the various innovation questions was the one related to trade secret protections (Q37D). The digital technology question most strongly associated with this variable was ERP software (Q14K). The one concern in using this variable in the latent class analysis is the introduction of an establishment size bias if the technology is rarely used in smaller establishments (those with 5-19 employees). However, the small firm sector has been aggressively targeted by ERP software publishers in recent years resulting in a usage rate of 28.4% in the survey, somewhat lower than the 36.0% for all establishments but prevalent enough to be considered a viable small establishment technology.

The preliminary latent class analysis included the follow variables in the z-vector: Q28a and b, Q34D, Q37D, Q14K, Q24-Q26, and Q13b. However, the one troubling result from the first cut was that 7% of establishments classified as “substantive innovators” had not answered any of the innovation questions affirmatively. The result raised the question of why even include the CIS questions in the survey if the auxiliary questions ostensibly did a better job of identifying innovative establishments. So the one revision to the z-vector after assessing the latent class structure was to include a variable to indicate if any of the CIS questions (Q27a-Q27f) were answered affirmatively.

The latent class structure using the full complement of auxiliary variables above is presented in Table 2. The first task in interpreting a latent class structure is to identify the salient characteristics that define each class. Using the means of the auxiliary variables provides a strong basis for identifying a Substantive Innovator class and a Non-innovator class. The remaining class shares some of the data driven decision making characteristics with the Substantive Innovator class but appears much more similar to the Non-innovator class with respect to the core auxiliary variables. We label this class Data Driven Nominal Innovators.

Table 2: Means of Auxiliary Variable by Latent Class Membership

(Percent of All Establishments)	Substantive Innovator (30.12%)	Data Driven Nominal Innovator (33.09%)	Non-Innovator (36.79%)
Abandoned and/or Incomplete Innovation	72.35%	16.72%	22.09%
Probably Use Surplus Funds for Innovation	46.86%	47.55%	30.85%
Most Definitely Use Surplus Funds for Innovation	47.07%	16.34%	17.11%
Intellectual Property Protections	55.79%	13.28%	13.45%
Use ERP Software	52.49%	37.12%	15.74%
Track Employee Training	58.78%	45.48%	10.30%
Monitor Customer Satisfaction Regularly	56.19%	50.88%	3.18%
Monitor Customer Satisfaction Occasionally	37.56%	44.21%	36.53%
Fix Customer Complaint Problems Regularly	64.33%	70.89%	17.43%
Fix Customer Complaint Problems Occasionally	28.76%	29.12%	66.73%
No Reported Innovations	0.89%	30.95%	58.01%

Source: 2014 ERS Rural Establishment Innovation Survey

The large differences in means across the classes are not that surprising given that is the central objective of the algorithm. The more critical check at this point is whether the class structure seems to make sense both in terms of how respondents answered other relevant questions in the survey and with respect to the collection of industries within each class—that is, are establishments in innovation intensive industries more likely to be members of the Substantive Innovator class?

Is the Class Structure Consistent with Survey Responses Not Included in the LCA?

The Innovation-Related Activities included in CIS and REIS survey instruments provide a natural first step for assessing whether the differences in establishment attributes produced in the LCA extend to other attributes strongly associated with innovation. Responses in the first 4 items in Table 3 include only those establishments that had reported one or more innovations.

While it is unexpected that some respondents classified as non-innovators engaged in innovation-related activities, the percentage of affirmative responses is close to a third or less than for the substantive innovator class. A closer examination of "non-innovators" reporting in-house R&D appears warranted. When the items pertain to the full sample the differences in percentage between substantive innovators and non-innovators are by factors ranging from 4 to 8. "Registered an Industrial Design" is the rarest of all the items included for all classes in the table and it is also the item that provides the greatest contrast between substantive innovators and the other two classes. The table provides strong evidence that the differences in responses to the auxiliary variables used in the LCA are capturing something real in the innovation orientation of the various classes.

Table 3: Percent Responding Affirmatively to Innovation-Related Activity Questions by Latent Class

	Substantive Innovators	Data Driven Nominal Innovators	Non-Innovators
In-house R&D*	68.39%	36.34%	25.01%
In-house Design*	52.42%	28.88%	18.93%
Purchase or License Patents*	17.38%	6.02%	4.69%
Innovation Related Market Research*	61.34%	34.36%	23.12%
Participated in a Patent Application	16.63%	2.31%	3.02%
Registered an Industrial Design	8.35%	1.10%	0.96%
Registered a Trademark	30.97%	6.15%	5.66%
Produce Material Eligible for Copyright	31.23%	8.31%	8.11%
Used Borrowed Funds for Innovation Projects	27.41%	11.16%	6.02%
Used Borrowed Funds for Intangible Investments	21.51%	6.09%	3.44%

*percent of respondents that answered at least one innovation question affirmatively

Source: 2014 ERS Rural Establishment Innovation Survey

Hard Tests of the Protocol

The hardest test of the protocol will not be possible for another couple years once sufficient data to assess individual establishment performance are available. Clearly, if establishments classified as substantive innovators have higher levels of employment or productivity growth, faster rates of penetrating export markets, or prove to be more resilient than their nominal or non-innovating peers, then the classification will have effectively captured the dimensions of innovation that matter most for favorable economic outcomes.

In the meantime, self-reported outcomes do provide a hint of what the hard data on establishment performance may show. The results presented in Table 4 confirm that substantive innovators perceive themselves as performing better on all of the outcome dimensions asked about.

Table 4: "In the past 3 years, has the business…"

	Substantive Innovators	Data Driven Nominal Innovators	Non-Innovators
Increased variety of goods or services offered	85.53%	63.84%	48.32%
Increased market share or entered new markets	77.98%	55.86%	41.24%
Begun exporting goods or services	20.22%	8.85%	6.27%
Reduced time responding to customer needs	67.59%	53.07%	33.15%
Reduced labor cost per unit output	45.50%	28.37%	19.09%
Reduced materials and energy required per unit output	33.66%	20.97%	10.51%

Source: 2014 ERS Rural Establishment Innovation Survey

The problem with assessing the utility of the latent class structure only using responses to other questions in the survey is the absence of any external measure of innovativeness. While it is reasonable to assume that "innovativeness" is the dimension captured by the LCA, the results reported above might also be consistent with isolating dimensions of "optimism" or "self-importance." A more stringent test is to use information external to the survey instrument such as comparing the industry distribution of substantive innovators with known innovation-intensive industries. If ostensible substantive innovators are much more likely to be in innovation-intensive industries defined by hard data such as patents and R&D expenditures, then this would provide prima facie evidence of the validity of the class structure. While we do not expect a perfect rank order correlation between innovative intensive industries defined by REIS and those defined by National Science Foundation statistics, a strong positive correlation suggests that these measures are capturing different aspects of an innovation dimension.

We present external validation at the most detailed NAICS industry level using data on patent applications, patents awarded and R&D expenditures (Shackelford 2013). This classification singles out the most innovation intensive industries at the 4-digit level, collapses 2 or 3 4-digit industries into a single category for some other innovation intensive industries, and collapses the remainder of industries into 2-digit or other aggregate composite classifications.

The validation exercise applied to the most aggregate industry classification (2-digit NAICS) produced strong rank order correlations but with some notable differences (Table 5). Manufacturing ranks first in the 3 NSF metrics for innovation intensiveness. However, the share of manufacturing establishments classified as substantive innovators in REIS only earns a second place behind Information (NAICS 51). For the remainder of industries the NSF patent applications ranking matches that found in REIS, resulting in a Spearman rank order correlation of 0.943. So at the coarsest level the survey methodology does appear to be capturing many of the empirical regularities but with manufacturing falling from the top spot.

Table 5: External Validation of Latent Class Structure Using NSF 2-digit NAICS Rankings

		National Science Foundation			REIS	
NAICS	2-digit NAICS category	Rank of Patent Applications Per Establishment	Rank of Patents Issued Per Establishment	Rank of R&D Expenditures Per Establishment	Percent of Establishments in Substantive Innovator Class	Rank
31–33	Manufacturing	1	1	1	34.21	2
51	Information	2	2	2	36.28	1
54	Professional/scientific/technical services	3	4	4	29.98	3
42	Wholesale trade	4	3	6	28.96	4
48–71	Non-manufacturing industries	5	6	5	26.17	5
21	Mining	6	5	3	16.79	6
	Rank Order Correlation with REIS Rank	0.943***	0.829**	0.543		

Source: Shackelford (2013) and 2014 ERS Rural Establishment Innovation Survey
Asterisk represents significance at 0.01 (***), and 0.05 (**) level.

A harder test is to examine the rank order correlation at the most disaggregated level provided by NSF. Table 6 provides the NSF ranking of 4-digit NAICS industries that are most innovation intensive, along with the ranks of more aggregate categories such as All Other Manufacturing. One problem introduced by the more disaggregated analysis is a decline in the cell size used to estimate the percent of establishments classified as substantive innovators. Thus ranking is less robust due to the increase in sampling error. However, the correlation with the NSF patent application industry ranking is 0.348 (significant at the 0.16 level), suggesting some correspondence between the rankings. The two top ranked industries by NSF essentially switch places in the REIS ranking. However, the next tier of industries do not match up, with the NSF ranking staying with hi-tech manufacturing but the REIS ranking picking up professional/technical/scientific services. These industries account for some of the largest discrepancies between the REIS and the NSF rankings. NAICS 3342 (Communications Equipment) is ranked as high as second with respect to R&D expenditures but comes in last in the REIS ranking. But this is most likely due to a very small cell size compounded by the fact that the innovative establishments identified in the survey were located in nonmetro counties that were oversampled. If that industry is removed from the analysis the rank order correlation increases to 0.433 (significant at the 0.05 level). The NSF and REIS rankings at the lower end of the scale are fairly close with the exception of NAICS 5415 and 5417 noted above, and some information industries (51) other than software publishers (5112). As with the more coarse exercise discussed above, the REIS protocol appears to produce ranking somewhat similar to conventional measures but with notable differences.

Table 6: External Validation of Latent Class Structure Using NSF 4-digit NAICS Rankings

		NSF			REIS	
NAICS	4-digit NAICS category	Rank of Patent Applications Per Establish-ment	Rank of Patents Issued Per Establish-ment	Rank of R&D Expenditures Per Establish-ment	Percent of Establish-ments in Substantive Innovator Class	Rank
3254	Chemicals: Pharmaceuticals and medicines	1	4	1	52.72	2
3345	Computer and electronic products: Navigational/measuring/electromedical/control instruments	2	7	8	54.41	1
3364	Aerospace products and parts: All	3	5	3	31.37	12
3344	Computer and electronic products: Semiconductor and other electronic components	4	1	4	42.43	6
3341, 3343, 3346	Computer and electronic products: Computer equipment/other electronic products	5	2	5	34.57	10
5112	Information: Software publishers	6	6	6	35.92	8
3342	Computer and electronic products: Communications equipment	7	3	2	6.43	18
3251	Chemicals: Basic chemicals	8	8	9	17.12	17
325_	Chemicals: Other	9	10	10	48.87	5
3391	Medical equipment and supplies: All	10	11	12	27.39	15
5417	Professional/scientific/technical services: Scientific research and development services	11	12	11	51.72	3
3361–3363	Automobiles/bodies/trailers/parts: All	12	9	7	34.87	9
31__-33__	Manufacturing nec, other: All	13	13	13	33.44	11
51__	Information: Other information, other	14	14	15	36.31	7
5415	Professional/scientific/technical services: Computer systems design and related services	15	15	14	51.06	4
5413	Professional/scientific/technical services: Architectural/engineering/related services	16	16	16	28.51	13
54__	Professional/scientific/technical services: Other	17	17	17	24.28	16
21-23 42–81	Nonmanufacturing nec, other: All	18	18	18	27.77	14
	Rank Order Correlation with REIS Rank	0.348	0.164	0.195		
	Rank Order Correlation with REIS Rank excluding 3342	0.433**	0.326	0.389*		

Source: Shackelford (2013) and 2014 ERS Rural Establishment Innovation Survey
Asterisk represents significance at 0.05 (**), and 0.10 (*) level.

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Comparing Rural and Urban Innovation Rates

Up to this point the assessment of the protocol has utilized data from the whole sample. Indeed, the protocol assumes that the subpopulations share similar attributes irrespective of where they are located. Which leads to the critical empirical question: How prevalent are rural substantive innovators?

Before looking at the distribution of substantive innovators in rural (nonmetro) and urban (metro) areas, it is important to gain an appreciation for how foreign the concept of rural innovation is to the economic study of innovation. In their recent study of Innovation and Agglomeration, Carlino and Kerr (2014) do not even mention the possibility of innovation in rural or nonmetro areas. Similarly, the World Bank's report on *Reshaping Economic Geography*, though actually mentioning rural areas, imposes the assumption that all innovation happens in urban areas. The view from the Brookings Institution, the National Bureau of Economic Research and the overwhelming majority of innovation researchers is that rural innovation is rare enough to be of no economic significance. That is a long way of saying that the discipline's prior belief on the rural share of substantive innovators is that it is negligible.

Table 7 provides estimates of the share of substantive innovators in rural and urban areas that is representative of the population of establishment with more than 5 employees in tradable non-farm sectors. Roughly 3 out of 10 urban establishments are classified as a substantive innovator (31.27%) compared with a little more than 2 out of 10 rural establishments sharing the distinction (22.56%). While there appears to be a clear urban advantage it is not overwhelming as commonly assumed. Looking across the classes it is interesting to note that the rural deficit in substantive innovators is split between a larger share of both nominal innovation and non-innovators.

Table 7: Prevalence of Substantive Innovators in Metro and Nonmetro Areas

	Substantive Innovators	Data Driven Nominal Innovators	Non-Innovators
Nonmetro	22.56	38.52	38.92
Metro	31.27	32.26	36.47
Small Establishment			
Nonmetro	18.02	38.29	43.69
Metro	26.00	33.18	40.83
Medium Establishment			
Nonmetro	28.53	41.12	30.35
Metro	41.10	31.96	26.94
Large Establishment			
Nonmetro	52.14	29.99	17.87
Metro	48.36	22.97	28.67
Hi-tech Manufacturing			
Nonmetro	44.04	29.53	26.43
Metro	35.56	30.26	34.19
Hi-tech Services			
Nonmetro	32.71	26.75	40.54
Metro	40.41	24.21	35.38

Source: 2014 ERS Rural Establishment Innovation Survey

Working down the table we see that both small (fewer than 20 employees) and medium (20-99 employees) sized rural establishments are less likely to be substantive innovators than their urban peers. And consistent with expectations, non-innovators make up a larger share of rural establishments in all but the large establishment category. The high share of substantive innovators in the large establishment category in both rural and urban areas is suggestive of a potential bias in the protocol that will be investigated below.

The best evidence that the rural innovation disadvantage may be compositional—that is, explained by a lower share of innovation intensive industries in rural areas—is provided by the bottom four rows of Table 7. For hi-tech manufacturing (defined here as the industries tracked separately by NSF in their 4-digit NAICS series, the remainder being the category of all other manufacturing) the rural share actually exceeds the urban share. For hi-tech services (the four digit industries within NAICS 51 and 54 tracked separately), the urban advantage is again evident. The implications for the study of rural innovation are encouraging as the phenomenon appears to be pronounced in some sectors despite lower levels of substantive innovation across the rural economy as a whole.

The analysis so far has relied on defining class membership discretely. However, this represents a loss of information since the LCA provides a probability of membership in each class, with the highest membership probability defining class membership for each respondent. Because the number of establishments for any given industry is not large, the share of establishments classified as substantive innovators might vary a lot due to sampling error. In addition, because the classification as a substantive innovator is probabilistic, a highly innovative industry where all the establishments in the top quartile are almost assuredly substantive innovators may rank similarly to a marginally innovative industry where establishments in the top quartile only have a 50-50 chance of being true substantive innovators. That is, membership in the substantive innovator group only requires that probability of membership is higher than for the nominal or non-innovator group. Finally, if we assume that the innovativeness of an industry will be defined mainly by the right tail of the firm distribution, a focus on the top industry quartile is warranted. Thus, the probability that the establishment in the 75th quantile of an industry distribution is a substantive innovator provides much more information on industry innovation intensity than does the percent of establishments classified as substantive innovators. We use this more information rich measure for identifying innovation intensive industries in rural and urban areas.

A useful threshold for identifying innovation intensive industries is where the probability of the 75th quantile establishment being a substantive innovator exceeds 60%. Conceptually, the focus on the top quartile makes sense as we anticipate that innovation is not a commonplace occurrence. Empirically, this 60% threshold identifies a natural gap in the data for both metro and nonmetro establishments. The nonmetro and metro rankings are provided in Table 8, that includes both the probability of the 75th quantile establishment and the share of all establishments in the industry classified as substantive innovators.

Table 8: Innovation Intensive Industries in Nonmetro and Metro Areas

Nonmetro				Metro			
NAICS	Industry	Pr. 75th Perc.*	%Subst. Innov.	NAICS	Industry	Pr. 75th Perc.*	%Subst. Innov.
313	Textile Mills	0.986	61.91	515	Broadcasting	0.996	39.58
334	Computer and Electronic Products	0.927	48.52	322	Paper Manufacturing	0.974	56.65
326	Plastics and Rubber	0.915	49.01	324	Petroleum and Coal	0.974	34.38
325	Chemical	0.915	41.96	313	Textile Mills	0.956	100
322	Paper Manufacturing	0.890	44.9	518	Data Processing, Hosting	0.943	60.24
335	Electrical Equipment, Appliance	0.887	41.47	487	Scenic and Sightseeing Trans.	0.908	26.21
339	Miscellaneous Manufacturing	0.867	46.19	336	Transportation Equipment	0.896	38.67
333	Machinery Manufacturing	0.840	42.24	326	Plastics and Rubber	0.891	41.9
324	Petroleum and Coal	0.774	48.02	334	Computer and Electronic Products	0.865	40.13
315	Apparel	0.741	36.24	481	Air Transportation	0.856	44.4
336	Transportation Equipment	0.729	39.32	519	Other Information Services	0.856	54.29
517	Telecommunications	0.690	35.39	323	Printing	0.815	32.64
311	Food Manufacturing	0.682	32.01	335	Electrical Equipment, Appliance	0.815	38.65
331	Primary Metal	0.681	33.57	333	Machinery Manufacturing	0.814	42.73
487	Scenic and Sightseeing Trans.	0.671	35.4	331	Primary Metal	0.793	46.67
425	Wholesale Electronic Markets	0.670	30.68	315	Apparel	0.787	45.2
312	Beverage and Tobacco	0.658	32.49	425	Wholesale Electronic Markets	0.787	30.67
518	Data Processing, Hosting	0.625	38.19	522	Credit Intermediation	0.783	49.99
332	Fabricated Metal	0.597	28.66	311	Food Manufacturing	0.765	35.23
481	Air Transportation	0.596	28.1	339	Miscellaneous Manufacturing	0.738	29.88
314	Textile Product Mills	0.541	31.42	332	Fabricated Metal	0.719	34.84
316	Leather	0.519	26.96	424	Nondurable Goods Wholesalers	0.700	31.4
486	Pipeline Transportation	0.507	40.57	712	Museums, Historical Sites	0.700	32.19
711	Performing Arts Companies	0.502	28.2	551	Management of Companies	0.693	36.88
712	Museums, Historical Sites	0.498	26.98	314	Textile Product Mills	0.690	28.44
519	Other Information Services	0.495	26.96	488	Transportation Support Activities	0.677	38.4
511	Publishing Industries	0.437	23.61	541	Prof./Scientific/Technical Services	0.674	31.21
515	Broadcasting	0.411	20.04	325	Chemical	0.671	39.28
551	Management of Companies	0.411	22.05	511	Publishing Industries	0.648	33.05
323	Printing	0.394	20.87	711	Performing Arts Companies[T]	0.611	32.32
327	Nonmetallic Mineral Products	0.351	16.95	423	Durable Goods Wholesalers	0.604	29.8
424	Nondurable Goods Wholesalers	0.348	19.85	213	Support Activities Mining	0.566	30.49
423	Durable Goods Wholesalers	0.342	21.15	517	Telecommunications	0.566	37.18
337	Furniture	0.333	20.89	312	Beverage and Tobacco	0.541	26.82
522	Credit Intermediation	0.322	18.03	524	Insurance Carriers	0.489	23.71
321	Wood Products	0.316	22.06	321	Wood Products	0.487	21.93
541	Prof./Scientific/Technical Services	0.313	19.82	483	Rail Transportation	0.309	0
212	Mining	0.255	21.5	484	Water Transportation	0.193	14.98
524	Insurance Carriers	0.251	17.84	523	Securities, Commodity Contracts	0.121	15.59
488	Transportation Support Activities	0.223	15.33	512	Motion Picture/Sound Recording	0.106	11.9
213	Support Activities Mining	0.207	13.19	327	Nonmetallic Mineral Products	0.072	12.11
512	Motion Picture/Sound Recording	0.155	1.35	337	Furniture	0.043	8.24
484	Truck Transportation	0.147	11.12	485	Truck Transportation	0.036	10.7
485	Ground Passenger Transportation	0.147	8.45	211	Oil and Gas	0.013	7.54
483	Water Transportation	0.100	0	525	Funds, Trusts,	0.007	0
523	Securities, Commodity Contracts	0.084	20.7	212	Mining	0.006	19.91
211	Oil and Gas	0.043	3.41	316	Leather	0.006	0
482	Rail Transportation	0.037	0				

Source: 2014 ERS Rural Establishment Innovation Survey

** Probability that establishment in the 75th percentile is classified as a Substantive Innovator*

Perhaps the most surprising finding in Table 8 is the high placement of industries that have been subject to severe import penetration over the past decade. Induced innovation appears to be prevalent in Textile Mills (313), Apparel (315), and Paper (322) as a means of survival in both rural and urban areas. In fact, in urban areas the survey was unable to identify any textile mill establishments that were not substantive innovators (see Bloom et al. 2016 regarding induced innovation from trade). Innovation intensive industries expected to place high include chemicals, computer and electronic products, and transportation equipment, and this was true in both urban and rural areas. The biggest differences between urban and rural areas is the dominance of manufacturing in rural areas at the top of the table with a very limited number of services-producing industries exceeding the Pr = 0.60 threshold. In contrast, the innovation-intensive industries in urban areas are split equally between manufacturing (15) and services (15), which also explains why urban areas have a significantly larger number of industries meeting the threshold. It is notable that Publishing (that includes software publishing), Professional/Technical/Scientific Services, and Management of Companies (i.e., headquarters establishments) in rural areas failed to meet the threshold, and the share of establishments in these industries classified as substantive innovators was very close to the rural average. All of these industries did meet the threshold in urban areas. So while innovation appears to be an increasingly broad-based phenomenon in urban areas, the rural phenomenon remains centered around manufacturing.

The Added Value of Probabilistic Classification

Once economic performance data are available for establishments in the dataset, the probability of being classified as a substantive innovator should provide considerable empirical leverage for assessing the importance of innovation to economic outcomes. In fact, the construct goes a long way in resolving one of the more problematic aspects of the subject-based approach to the study of innovation—the need to define innovative status in two mutually exclusive categories based on responses to a very limited number of questions. In this exercise, LCA uses theoretically motivated auxiliary questions to provide an information-rich basis for developing degrees of belief regarding the innovativeness of any single respondent.

We test the potential value of that leverage by inferring the retrospective employment performance of more innovative and less innovative establishments in our dataset. We do this by estimating class membership probabilities for every county-industry pair present in the REIS dataset. Although our dataset includes less than 6% of the population of rural establishments and about 0.3% of the population of urban establishments in tradeable sectors, comparing the industry employment performance in recovery from the Great Recession based on the average innovativeness of establishments in each county in the dataset may reveal the value of innovation to economic resilience. The analysis is expected to be plagued by a large amount of sampling error as the "innovativeness" of a county-industry will often be defined by a single data point, and very rarely by more than a couple. However, since the number of establishments in each county-industry will also tend to be small, even a single data point may be informative. The regression will be weighted by employment size as it is reasonable to assume that large innovative establishments will have a larger impact on local employment growth in recovery than small innovative establishments.

This exercise also allows a direct comparison between the potential explanatory power of the LCA method of probabilistic classification versus the traditional Community Innovation Survey method of dichotomous classification. A recent paper by Capello and Lenzi (2014) computed a regional innovation rate by estimating the share of firms that had introduced a new product or service in the past 3 years using the CIS 2004 data for Europe. The study found that innovation measured this way was a more powerful predictor of GDP growth than R&D expenditures. We can produce a parallel statistic from REIS for county-industries to compare with the probabilistic measure. These shares of innovative establishments will be either 0 or 100% for those county-industries with a single establishment, so the smaller sample size of REIS relative to the 2004 CIS may be particularly problematic. The empirical question is whether the LCA methodology is sufficiently more powerful to produce statistically significant results.

Table 9 provides the coefficient estimates regressing the county-industry probabilities or county-industry innovative shares against employment change in the recovery from the Great Recession between 2009 and 2014. The simplest regression model is used to guard against concerns that the results are cherry-picked from a large number of specification tests. The only other variables included in the regression are 3-digit NAICS dummy variable to control for industry effects, and county population (nneither shown). Two of the regressions using the probability of class membership are statistically significant: a county-industry probability of being classified as a substantive innovator was positively associated with employment growth while the county-industry probability of being classified as a nominal innovator was negatively associated with employment growth. Neither of the coefficients for the share introducing new products or services or the probability of being classified as a non-innovator were statistically significant.

Table 9: Regressions of County-Industry Employment Growth, 2009-2014

Variable	Parameter Estimate	Standard Error	t Value	Pr > |t|
Probability Substantive Innovator	82.69	43.02	1.92	0.0546
Share Introducing New Products or Processes	-60.61	37.88	-1.60	0.1097
Probability Nominal Innovator	-116.0698	54.081	-2.15	0.0319
Probability Non-Innovator	-14.59	54.01	-0.27	0.7870

Source: 2014 ERS Rural Establishment Innovation Survey

Coefficient estimates for intercept, population, and industry controls not reported

Too much should not be made of a retrospective association. Since a 2014 value for the explanatory variable is being regressed against a change from 2009 to 2014 it becomes clear that the results cannot be used to claim that the probability of being a substantive innovator either explains or causes faster employment growth during periods of economic recovery. However, the result is suggestive of a more reliable or less noisy measure of innovation that policymakers and citizens care about—innovation that contributes to more resilient firms. Causal analysis should be possible when economic performance measures become available for the establishments in REIS over the next couple years.

The statistical power of this exercise was not expected to be high given the large amount of sampling error. This makes some of the results for major economic sectors with smaller sample sizes even more surprising. And the results also help ameliorate possible criticism of the conventional CIS measure of innovation. Table 10 presents the coefficient estimates for the substantive innovator probability and new product/process share variables for fiber industries (textiles, apparel and leather), food industries (including beverages), and information industries (publishing including software, data processing). The coefficient estimates from other major sectors were not statistically significant. The effect of innovation on employment growth in the fiber industries is of considerable interest given continued rapid rates of employment decline overall and the appearance of a high degree of induced innovation. The parameter estimate on the substantive innovator probability variable is positive and large but not statistically significant. In contrast, there is a significant association between the share of establishments introducing new products or processes and employment growth. For food industries both measures of county-industry innovativeness are negatively associated with employment growth. This would be consistent with either greater labor-saving productivity increases in more innovative food manufacturers—particularly acute due to income inelastic demand—or more innovative establishments concentrating in niche markets. In the latter case, the largest employment gains might occur in staple and commodity suppliers as aggregate demand is restored. Finally, both measures are strongly associated with more rapid rates of employment growth in recovery for the information sector. The difference in magnitude between the probability measure and the share measure is considerable, which is something of a mirror image of the result for the fiber sector. The latent class analysis may do a better job of differentiating substantive innovators from nominal innovators in industries with high levels of new product introduction. In traditional industries with anticipated low levels of innovation, the simple self-reporting of new products or processes may pick-up the salient differences that matter for faster employment growth in recovery.

Table 10: Regressions of County-Industry Employment Growth, 2009-2014, Selected Sectors

Industrial Sector	Variable	Parameter Estimate	Standard Error	t Value	Pr > |t|
Fiber	Probability Substantive Innovator	38.64	132.15	0.29	0.7709
Fiber	Share Introducing New Products or Processes	484.33	83.795	5.78	<.0001
Food	Probability Substantive Innovator	-146.081	52.49	-2.78	0.0057
Food	Share Introducing New Products or Processes	-110.174	52.933	-2.08	0.0383
Information	Probability Substantive Innovator	412.369	76.328	5.40	<.0001
Information	Share Introducing New Products or Processes	200.25	62.53	3.20	0.0015

Source: 2014 ERS Rural Establishment Innovation Survey
Coefficient estimates for intercept, population, and industry controls not reported

Soft Tests of Potential Bias in the Protocol

Given that the primary motivation for developing and administering the REIS emerged from concern about innovative activity that might otherwise be overlooked, it is important to investigate whether the innovation measure may systematically favor some establishment characteristics that in reality are weak determinants of innovative activity. Hard tests of potential bias will not be possible until individual establishment performance data are available. For example, are there groups of high performing establishments not classified as substantive innovators explained by attributes not included in the LCA? In the meantime, we can conduct some soft tests that might be suggestive of potential problem areas to focus on when better data become available.

The size of the establishment having an undue influence on a respondent's classification as a substantive innovator was a concern throughout development of the survey. The potential source of bias is clearest in the inclusion of Enterprise Resource Planning software in the z-vector of the LCA. While this technology is present in 69% of the largest establishments (> 100 employees), only about a quarter of small establishments (5-19 employees) utilize the technology. Most tellingly, utilization of the technology is also strongly associated with the reported employment size within each establishment size strata. So establishments with 5 employees are less likely to use the technology than establishments with 10 or 15 employees. Other variables used in the z-vector that appear to have a within strata employment size bias for small and medium sized establishments include the use of trade secret protection (Q37D) and tracking employee training (Q13b). The possibility that the protocol misses some highly innovative microenterprises that are recent start-ups will need to be thoroughly investigated.

The first two rows of Table 11 include regression results summarizing the tendency for the protocol to favor larger employers within the small and medium establishment size strata. Comparing the magnitude of the coefficients suggests a potentially serious problem: in small establishments the effect of employment on the probability of being classified as a substantive innovator is four times larger than that in medium-sized establishments. However, the association between employment size and innovation also holds for the self-reported innovation measures in the last four rows: whether the establishment introduced a new product or process of the last 3 years or whether the establishment increased the variety of products sold. So not only are the smallest establishments in the small establishment stratum less likely to be classified as substantive innovators, they are also less likely to self-report innovations. Both results are consistent with the existence of a significant share of "lifestyle entrepreneurs" in the small establishment stratum whose primary objective is sustaining a business rather than growing a business. This possibility does not let us conclude that the LCA protocol is biased in ascribing substantive innovator status to larger establishments as larger establishments may, in actuality, have a higher likelihood of being innovative.

Table 11: The Association between Employment Level and Innovation within Employment Size Strata

Dependent Variable	Independent Variable	Parameter Estimate	Standard Error	Pr > |t| or Pr > ChiSq	Odds Ratio
PrSubstantive Innovator (5-19 Emp)	Employment	0.0123	0.00104	<.0001	N/A
PrSubstantive Innovator (20-99 Emp)	Employment	0.0031	0.000375	<.0001	N/A
New Product or Process (1-0) (5-19 Emp)	Employment	0.0545	0.000692	<.0001	1.056
New Product or Process (1-0) (20-99 Emp)	Employment	0.00185	0.000234	<.0001	1.002
Increased Variety of Products (1-0)) (5-19 Emp)	Employment	0.0402	0.000741	<.0001	1.041
Increased Variety of Products (1-0)) (20-99 Emp)	Employment	0.00928	0.000261	<.0001	1.009

Source: 2014 ERS Rural Establishment Innovation Survey
Coefficient estimates for intercept and industry controls not reported

Our final test for bias examines possible discrepancies between the protocol's prediction of substantive innovator status and self-reported innovation by industry strata. Clearly, if the protocol does a better job of predicting self-reported innovation status in some industries than others, then the possibility that some elements of the LCA z-vector are irrelevant for some industries—or the z-vector is missing an element critical to innovation in some industries—will need to be examined. Table 12 present results from logistic regressions where self-reported innovation (introduced a new product or process in last three years) is predicted by the probability of being classified as a substantive innovator for each industry stratum. Since self-reported innovation is used in the LCA it is not surprising that all of the estimates are highly significant. The magnitude of the estimates is very large in all cases such that a very high probability of being classified as a substantive innovator nearly guarantees an affirmative response to the CIS questions. Management of Companies (headquarters establishments) produced the smallest parameter estimate resulting in an odds ratio of 59. The interpretation of this is that a headquarters establishment with a probability of 1 of being a substantive innovator would be 59 times more likely to report a product or process innovation relative to a headquarters establishment with substantive innovator probability of 0. Most industries have an odds ratio greater than 999.99. While difference in magnitudes across the industry strata suggest taking a closer look at the protocol in Management of Companies, Finance, and Wholesale Trade, the results do not provide evidence of a systematic industry bias in the LCA protocol.

Table 12: The Association between the Probability of Being Classified as a Substantive Innovator and Self-Reported Product or Process Innovation, by Industry Strata

Industry	Parameter Estimate	Standard Error	Pr > ChiSq	Odds Ratio	% Concordant
Mining	20.3685	0.7050	<.0001	>999.999	91.5
Manufacturing	8.4635	0.0664	<.0001	>999.999	90.9
Wholesale Trade	6.6181	0.0446	<.0001	748.531	87.2
Transportation	13.6471	0.1295	<.0001	>999.999	89.7
Information	22.0687	0.2918	<.0001	>999.999	90.5
Finance	5.5315	0.0353	<.0001	252.526	90.7
Prof/Tech/Scientific Services	7.1372	0.0416	<.0001	>999.999	87.0
Management of Companies	4.0809	0.0791	<.0001	59.199	90.1
Performing Arts and Museums	7.4217	0.2440	<.0001	>999.999	90.0

Source: 2014 ERS Rural Establishment Innovation Survey
Coefficient estimate for intercept not reported

How Reliable Measures of Rural Innovation Can Aid Rural Policy
Rural development problems in OECD countries could be productively understood as problems of allocative efficiency in the twentieth century. Redundancies in the agricultural sector due to mechanization were absorbed by diversification of the rural economy. This filtering down of industry to lower order places provided a plausible model for development through the 1990s (Rosenfeld and Wojan 2016). However, the unexpectedly rapid modernization in low labor-cost developing countries combined with increasing opportunities for substituting capital for labor throughout the world paints a picture of perpetual redundancies for rural areas in a purely allocative economy. Nonetheless, some prominent approaches to regional development maintain the assumption that resource allocation is adequate to resolve the problems of growth and development in all lower order places (World Bank 2009). In this view, the problems of innovation-led growth are seemingly unique to major urban centers.

The regional development approach espoused by the OECD rejects the premise that innovation is a phenomenon limited to large cities. *Promoting Growth in All Regions* (OECD 2012) provides empirical evidence that dynamic growth characterizes different places throughout the settlement hierarchy. The book also discusses the policy framework best able to exploit these diverse growth opportunities comprised of place-based approaches to multi-level governance. A central tenet of this approach is that:

> the knowledge needed to fully exploit the growth potential of a place and to design tailor-made institutions and investments is not readily available – whether held by the state, large corporations, or local agents – and must be produced anew through a participatory and deliberative process involving all local and external actors. (Barca, McCann and Rodriguez-Pose 2012 p. 147)

It is through this deliberative process that locales are able to resolve the very serious problems of coordination that emerge from the conditions of novelty characterizing any innovative economy—problems that are assumed away in a focus on allocative efficiency (Wojan Forthcoming).

Thus from a macro level the existence and prevalence of innovation in more peripheral areas is critical to getting the policy framework right. Using hard measures of science and engineering-based innovation such as R&D and patents, the verdict was seemingly unequivocal that innovation was overwhelmingly an urban phenomenon. And yet even this evidence is debatable. For example, recent analysis demonstrating that conventional per capita patenting rates are confounded by a composition factor that substantially reduces the reputed urban patenting advantage—that is, when patenting rates are computed using the regional population that might plausibly contribute to patenting. In fact, patenting rates in some rural areas are higher than half of the global cities in the U.S. when computed on this population, named the inventive class (Wojan, Dotzel and Low 2015). Measures of grassroots innovation further further suggest there is not an urban monopoly on innovation. Research by Capello and Lenzi (2014) confirms that many peripheral regions are disadvantaged in knowledge creation activities. However, innovation as measured by the CIS was found to have a larger impact on GDP growth than R&D expenditures, was present in many peripheral regions, and had its largest impact where knowledge creation activities were limited. The preliminary findings from REIS presented here confirm that substantive innovation is not only taking place in rural areas, but that innovation rates within innovation intensive industries are surprisingly similar across rural and urban areas. All of these findings reinforce the OECD's prescription for place-based regional policy that is able to address problems that emerge from innovation-led growth.

At the micro or mesa level, more reliable measures of grassroots innovation have the potential to both expand our view of the possibilities of rural development that is constrained by the urban, high-tech focus of current innovation research, and to directly investigate the efficacy of policy to promote rural innovation. Much rural policy is premised on the need to ameliorate or allay market failures that can plague more sparsely settled locales. Current research using REIS is examining: 1) whether substantive rural innovators have a harder time securing borrowed funds and whether loan guarantee programs are filling a possible credit gap; and 2) the knowledge management strategies used by rural innovators and the role that ICT infrastructure plays in lessening the disadvantages of distance. The health of the innovation ecosystem in rural areas is being examined from a number of perspectives to better understand community level characteristics that may impede or facilitate innovation. Preliminary analysis has identified a strong association between the design orientation of an establishment and its innovation orientation, similar to findings in a recent OECD study (Galindo-Rueda and Millot 2015). Whether this design orientation is associated with community indicators of creative milieu may provide explicit evidence of an arts-innovation nexus that has long been suggested by various associations but has eluded empirical verification (Florida 2002, Wojan, et al. 2007). In this way, microdata on innovation in rural areas has the potential to provide evidence for current policies such as creative placemaking that have proven difficult to evaluate (Markusen and Gawda 2010).

Conjectures about a possible arts-innovation nexus is in many way diametrically opposed to the concrete, material approach to innovation embodied in the linear model. In place of easily observed inputs like STEM employees and R&D expenditures producing easily observed outputs such as patents one will need to struggle with the cognitive processes that are the true source of innovation. For this endeavor to be potentially fruitful, measures of innovation will need to be more reliable than the subjective assessment of the ambiguous phrase "new or significantly improved." The protocol discussed in this paper that relies both on self-reported innovative activity and attributes thought to be strongly associated with substantive innovation is an attempt to increase the importance of the subject in the subject-based study of innovation. Preliminary findings support the validity of the assumptions used in developing the survey, confirming a strong association between self-reported innovation and probabilistic classification as a substantive innovator, a loose correspondence between innovation intensive industries ranked by science and engineering based measures and innovation intensive industries ranked by the protocol, and a suggestive association between the innovativeness of local industry and employment growth in recovery from the Great Recession. Harder tests of the protocol await—particularly with respect to the ability of the innovation measure to predict more favorable economic outcomes—but this first assessment bodes well for the rigorous analysis of grassroots innovation in both rural and urban areas.

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Appendix: Selected Questions from the 2014 Rural Establishment Innovation Survey (administered under the title "National Survey of Business Competitiveness")

28. In the past 3 years, did this business have any improvement or innovation activities that were…

	Yes	No
a. Abandoned	O 1	O 2
b. Incomplete	O 1	O 2

34. In the current environment, if excess cash were available, how likely is it that these funds would be used to…

	Not at all likely	Probably	Most definitely
a. Provide additional training of workers	O 1	O 2	O 3
b. Repay debt	O 1	O 2	O 3
c. Provide a reserve or cushion	O 1	O 2	O 3
d. Fund additional innovation projects	O 1	O 2	O 3
e. Fund additional investment projects, such as replacing old equipment or for expansion	O 1	O 2	O 3

37. In the past 3 years, did this business…

	Yes	No
a. Register an industrial design	O 1	O 2
b. Register a trademark	O 1	O 2
c. Produce materials eligible for copyright	O 1	O 2
d. Use trade secret protections (e.g., non-disclosure agreements, non-compete clauses, or sought remedies for misappropriation)	O 1	O 2

14b. Are the following technologies currently used at this business?

	Yes	No
b. Broadband or high speed internet	O1	O2
c. Sale of products or services over the Internet (e-commerce)	O1	O2
d. Supplies purchased over the Internet (e-procurement)	O1	O2
e. Web advertising	O1	O2
f. Direct e-mail marketing	O1	O2
g. Social media (e.g., LinkedIn or Facebook)	O1	O2
h. Business issued smartphones to workers	O1	O2
i. RFID readers, barcode, or optical scanners (e.g., Radio Frequency Identification)	O1	O2
j. Computer software specifically designed for your business or industry	O1	O2
k. An integrated enterprise resource planning system (e.g., SAP or Microsoft Dynamics, or Oracle Applications that include accounting, logistics, human resources, sales management, along with other functions)	***O1***	***O2***
l. Stand-alone supply chain or logistics management software	O1	O2
m. Stand-alone customer relationship management software	O1	O2

25. How often does this business monitor customer satisfaction through analysis of complaints, customer satisfaction surveys, focus groups, or other methods?

O1 Never
O2 Occasionally
O3 Regularly

26. How often are processes changed to fix problems identified through customer complaints?

O1 Never
O2 Occasionally
O3 Regularly

24. Does this business require workers to document good work practices and lessons learned?

O1 Yes
O2 No

13. **Does this business have written position descriptions?**

O₁ Yes
O₂ No → **Skip to question 14a**

13a. **Are training requirements documented in those position descriptions?**

O₁ Yes
O₂ No → **Skip to question 14a**

13b. **Does this business track whether workers complete or if they have already completed these training requirements?**

O₁ Yes
O₂ No