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Innovation in the Rural Nonfarm Economy: Its Effect on Job and Earnings Growth, 2010-2014

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Abstract

Innovation—introducing new goods, services, or ways of doing business that are valued by consumers—is widely regarded as essential to dynamic and resilient local economies with long-term growth potential. However, innovation in the nonfarm rural economy has received relatively little attention. This report uses the first nationally representative sample of self-reported innovation at the U.S. establishment level to: (1) assess the level of innovation in rural establishments relative to their urban peers; (2) identify rural industries that are the most innovation-intensive; and (3) estimate how innovation at the local level may have affected the rate of recovery after the Great Recession.

Keywords: employment growth, wage growth, net establishment change, geography of innovation, self-reported innovation**,** data-driven decision making, survey methodology, latent class analysis

Acknowledgments

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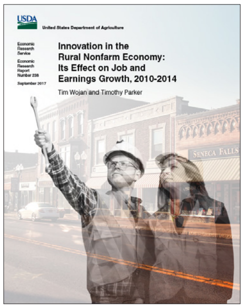


Innovation in the Rural Nonfarm Economy: Its Effect on Job and Earnings Growth, 2010-2014

Tim Wojan and Timothy Parker

What Is the Issue?

Innovation—introducing new goods, services, or ways of doing business that are valued by consumers—is regarded as essential to a dynamic and sustainable economy. Empirical evidence of innovation in agriculture and closely related industries is voluminous, but much less is known about innovation in the nonfarm economy of rural America.

The economic study of innovation has mainly relied on data from the congressionally mandated collection on patents, research and development (R&D) expenditures, and the training and employment of scientists, engineers, and technicians. While this R&D-based innovation has been critical to advances in many fields, a large number of advances are made outside R&D labs without the aid of highly trained scientists or dedicated R&D budgets. Instead, these innovations arise the way they always have, by individuals confronting problems and finding creative solutions, often described as grassroots or user innovation. In contrast to the rich sources of data and analysis on R&D-based innovation, grassroots or user innovation has been thinly studied. However, it may be more important to the dynamism of rural areas, given drawbacks of supporting R&D-based innovation. This study uses the 2014 Economic Research Service Rural Establishment Innovation Survey (REIS), the first nationally representative sample of self-reported innovation in rural areas of the United States, to examine the impetus, outcomes, and prevalence of rural innovation, both grassroots and R&D based.

The report further explores whether innovation-intensive industries and the more innovative rural regions recovered faster from the Great Recession of 2007 to 2009 by examining: (1) the rural industries that tend to support the largest share of innovators; (2) the employment trends of these innovation-intensive industries; and (3) employment, earnings, and establishment-formation trends in sub-State regions, based on the prevalence of innovators. The study population was limited to nonfarm tradable industries, that is, to those whose products are conducive to regional or international trade that provides growth opportunities beyond local markets.

What Did the Study Find?

Using a comprehensive definition of innovation— both grassroots and R&D based—the authors found that establishments in nonfarm tradable industries in urban areas were more likely than rural establishments to be classified as substantive innovators in 2014. This is consistent with earlier research that has found an urban innovation advantage. However, innovation rates are very similar among urban-rural establishments in manufacturing industries. Thus, the long-recognized urban innovation advantage appears partly attributable to industry distribution—innovation-intensive manufacturers make up a larger share of the urban economy. For service industries, however, innovation rates of rural establishments tend to lag their urban peers in the same service sector.

In both rural and urban areas, manufacturing makes up the bulk of the most innovative industries. Manufacturing industries with the highest share of substantive innovators in rural areas included pharmaceuticals, chemicals, computers, and plastics. Textile mills also had a high share of innovative establishments, likely because intense global competition makes it difficult for noninnovating firms to survive. The only tradable service-providing industries with a high share of substantive innovators in rural areas were telecommunications and wholesale electronic markets. In contrast, service industries in urban areas with a high share of innovators included broadcasting, data processing, web hosting and related services, air transportation, and business management establishments, among others. Innovation appears to be an increasingly broad-based phenomenon in urban areas, while in rural areas it remains centered around manufacturing.

Overall, in net employment growth, rural tradable industries described as innovation-intensive did not substantially outperform industries described as not innovation intensive. The net employment growth from innovation-intensive industries was 153,736 from 2010 to 2014 (+ 8.4 percent) compared to 130,345 (+ 5.36 percent) for noninnovation-intensive industries. Innovation-intensive industries facing severe import competition continued to lose employment in the post-recession recovery period, implying that factors other than innovation-intensity explain employment growth at the industry level. The regional analysis provides evidence, however, that innovation-intensity at the establishment level did have some positive impact on employment. Industries in all rural commuting zones dominated by substantive innovators (characterizing 648 of 2,570 commuting zone/industries, or 25.2 percent) added, on average, 100 more jobs from 2010 to 2014 than industries in all rural commuting zones characterized by noninnovators (which made up 956 of 2,570 commuting zone/industries, or 37.2 percent), while nominal innovators characterized the remaining 37.6 percent of commuting zone/industries.

How Was the Study Conducted?

This study relies on primary data collected by the REIS explicitly to examine innovation in business establishments. The REIS surveyed private businesses in nonfarm tradable industries with five or more employees in 2014.

A preliminary assessment of the importance of rural innovation to economic outcomes was based on industry and regional estimates of innovativeness derived from the survey data. These measures of innovativeness were then combined with data on employment, earnings, and establishment-formation trends from the Bureau of Labor Statistics Quarterly Census of Employment and Wages (QCEW) to examine whether innovative-intensive industries and more innovative rural regions recovered faster from the Great Recession.

The classification of industries as innovation-intensive was based on latent class analysis (LCA) of the innovation and auxiliary innovation questions in the 2014 REIS data. This allowed us to rank industries by the probability that a representative establishment was a substantive innovator, that is, demonstrating behavior consistent with both incremental and more wide-ranging innovation. The probability of being classified as a substantive innovator was also used to estimate the innovativeness of multi-county rural commuting zones. Unpublished QCEW data were used to track employment trends for innovation-intensive industries and to track employment, earnings, and establishment-formation trends for rural regions.

Innovation in the Rural Nonfarm Economy: Its Effect on Job and Earnings Growth, 2010-2014

Why Studying Rural Innovation Matters

Innovation is widely regarded as essential to dynamic and resilient local economies with long-term growth potential. Empirical evidence of innovation in agriculture and closely related industries is voluminous, but much less is known about innovation in the nonfarm economy of rural America.[1] In fact, the majority of scholarship on the geography of innovation has been dismissive of the innovative capacity of the rural nonfarm economy (World Bank, 2009; Carlino and Kerr, 2014). Central constructs such as the product life cycle, which assumes that all new, innovative products emerge first in cities and then filter down to less expensive rural production sites as products mature, or the Marshallian industrial district, where innovation relies on large pools of specialized labor, support models of urban innovation. This report provides empirical evidence of the extent of substantive innovation in rural areas, based on the first nationally representative sample of self-reported innovation in the tradable rural nonfarm sector, as well as offering a preliminary assessment of whether rural innovation matters for employment and wage growth.

Innovation and Innovation Activities, Outputs, and Outcomes

Innovation can be concisely described as the introduction of new goods, services, or ways of doing business that are valued by consumers. Innovations are much more than just new ideas. A new idea must be demonstrated as feasible in practice for doing something useful. In addition, these workable solutions or inventions need to be made available to consumers.

Innovation Activities are the things done by businesses for transforming new ideas into innovations. Many of the traditional measures of innovation activity include R&D and the staffing of scientific and engineering personnel. Innovation activities may include continuous improvement processes, data-driven decision making, and means of protecting intellectual property, which are investigated in this report.

Innovation Outputs – As an example, patents have been an important tool for protecting intellectual property and are often used as a measure of innovation. However, because a patent does not require demonstrating that the invention is valued by consumers, it can only provide an **output** measure of innovation activities.

[1]Throughout this report, we refer to metropolitan counties, as defined by the Office of Management and Budget, as "urban" and nonmetropolitan counties as "rural."

Innovation Outcomes are best assessed by how consumers value innovations in markets, which may include additions to consumer surplus from cost savings resulting from innovation. Whether something new is valued by consumers is demonstrated in measures of business performance such as market or export penetration, employment or productivity growth, or business resilience.

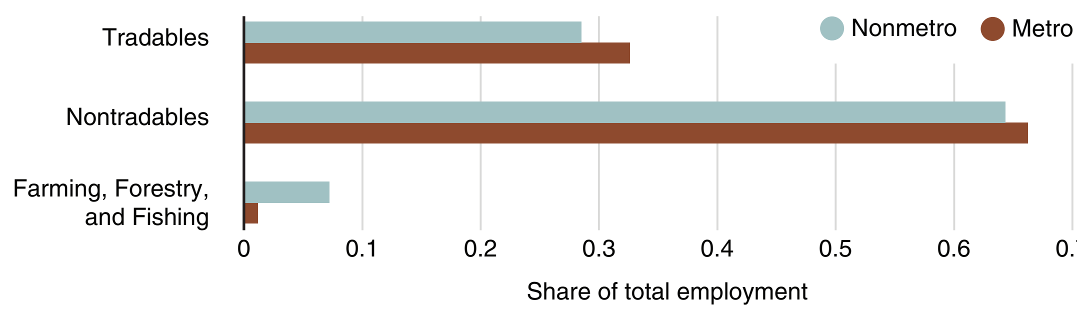
Where To Look for Innovative Rural Businesses

The focus on tradable sectors—identified by patterns of geographical concentration (Jensen et al., 2005)—is motivated by an assumed greater need for innovation to remain competitive. If rural tradable industries fail to innovate, then they are more likely to be supplanted by imports than are nontradable industries where imports are infeasible or cost-prohibitive.[2] Past studies consistently find much higher innovation rates in tradable industries (North and Smallbone, 2000; Boroush, 2010).

Tradable industries include mining; oil and gas; manufacturing; wholesale trade; transportation and warehousing; information; finance and insurance; professional, scientific, and technical services; management of companies (i.e., headquarters establishments); and performing arts and museums (Jensen et al., 2005). Nontradable industries include utilities; construction; retail trade; real estate; administrative and support services; educational services; health care and social assistance; accommodation and food services; public administration; and an "other services" category.

One highly tradable set of industries not included in the analysis includes the natural resource-based industries of farming, forestry, and fisheries. The choice was driven by the large amount of research on innovation in this sector and the annual collection of farming practices data in the Agricultural Resource Management Survey administered by ERS and the National Agricultural Statistics Service. The Government interest in reducing respondent burden argued against extending REIS to the farm sector. The employment shares for tradable, nontradable, and resource-based sectors in metro and nonmetro areas are provided in figure 1. Large increases in labor productivity in the natural resources sector over the past century explain the modest share of employment in the modern economy. In nonmetro areas, the employment shares in tradable (other than agriculture) and nontradable sectors are four and nine times that of the farming, forestry, and fisheries sector, respectively. Nontradables account for a larger share of employment in metro areas than in nonmetro areas, reflecting greater demand for activities serving large resident populations.

Figure 1
2014 Employment shares in tradable, nontradable, and resource industries

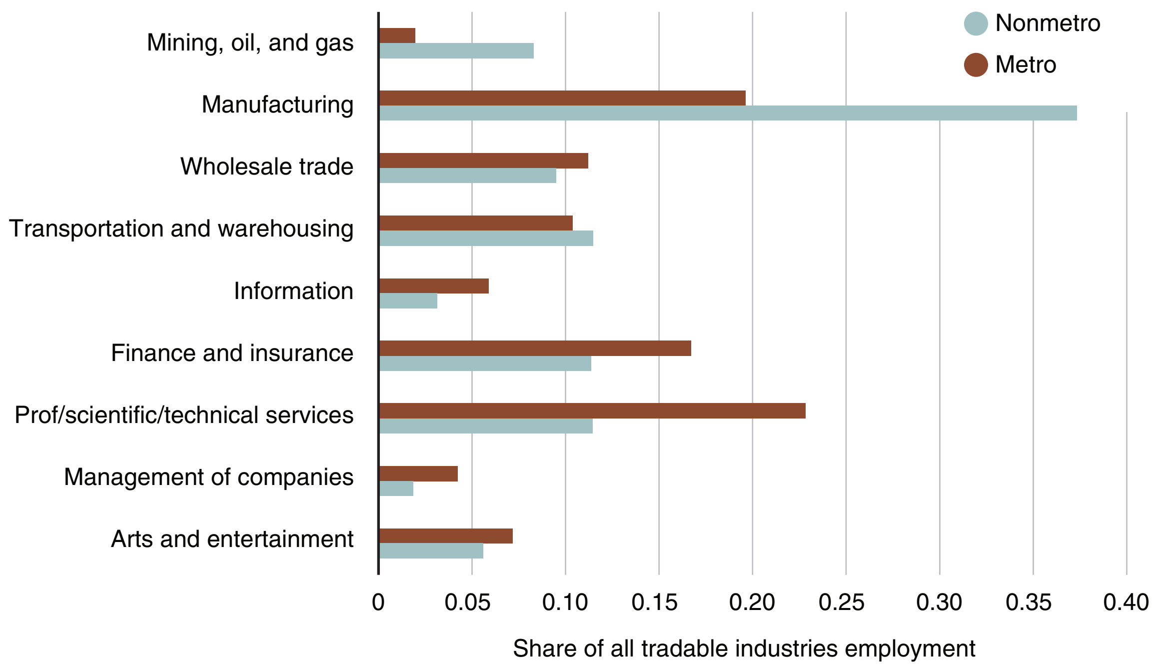


Note: Tradables include mining, manufacturing, wholesale trade, transportation, information, professional/scientific/technical services, management of companies, performing arts organizations and museums. Nontradables are all industries not included in tradables or farming, forestry, and fishing. Metro and nonmetro areas correspond to the Office of Management and Budget February 2013 Metropolitan Area criteria.
Source: USDA, Economic Research Service analysis of Bureau of Economic Analysis Regional Data, Table CA25N.

[2]The focus on tradable sectors in this report does not diminish the essential role that nontradable sectors play in the rural economy. In addition, because these activities are provided nearly everywhere, a lack of innovation could be detrimental to the long-term prospects of a local economy if its absence caused relative prices for these nontradables to rise over time.

Figure 2 shows a rural concentration in goods-producing industries and an urban concentration in service-providing industries within the tradable sector, based on employment shares. Goods-producing industries include mining, oil and gas, and manufacturing; service-providing industries include information, professional, scientific, and technical services; finance and insurance; and arts and entertainment. Wholesale trade and transportation and warehousing demonstrate a more even metro/nonmetro split. The nonmetro share of employment in manufacturing is notable, more than three times larger than any other nonmetro tradable sector. The nonmetro manufacturing share is also nearly twice the size of the metro manufacturing share. However, in metro areas, professional, scientific and technical services is the tradable sector employing the most workers. The composition of the manufacturing sector warrants special attention, given its rural concentration and the assumption that traditional, low-tech industries dominate there.

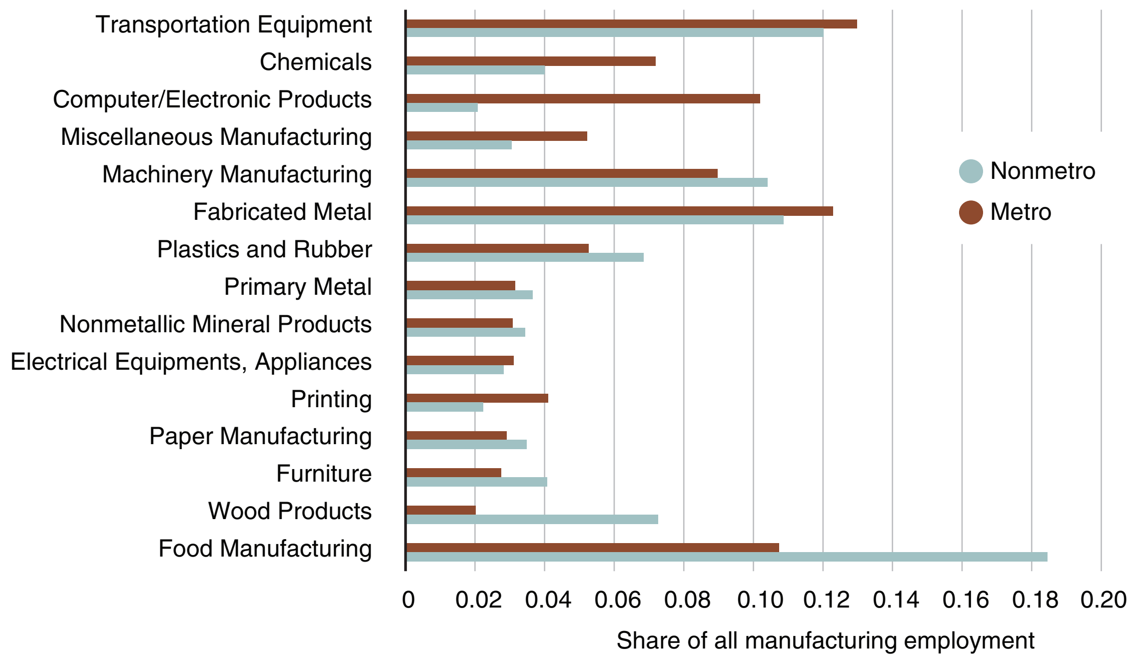
Figure 2
2014 Employment shares across all tradable industries



Note: Metro and nonmetro areas correspond to the Office of Management and Budget February 2013 Metropolitan Area criteria.
Source: USDA, Economic Research Service analysis of Bureau of Economic Analysis Regional Data, Table CA25N.

Figure 3 shows an urban manufacturing specialization in high-tech industries and a rural specialization in food industries, consistent with expectations. The first four sets of bars are innovation-intensive industries as identified by the National Science Foundation (NSF), based on R&D expenditures and patent applications. While the metro and nonmetro shares of manufacturing employment in transportation equipment are roughly the same, the share of nonmetro manufacturing employment in computers and electronic products, chemicals, and miscellaneous manufacturing is considerably less than the metro share. The middle bars in the figure are all fairly similar. The slightly higher share of nonmetro employment in machinery manufacturing is notable, as this industry is often the source of process innovations that can impact the entire manufacturing sector. At the bottom of the figure are food manufacturing and wood products, which—not surprisingly—demonstrate a significant nonmetro specialization relative to metro areas. The expectation that metro manufacturing is more concentrated in innovation-intensive industries (as defined by NSF), while nonmetro manufacturing is more concentrated in traditional, low-tech industries, is borne out. However, innovation-intensive industries account for a fifth of the nonmetro manufacturing employment (compared to more than a third in metro areas), and metro and nonmetro employment shares over the majority of the remaining industries are similar.

Figure 3
Share of total manufacturing employment by 3-digit NAICS industry, 2014



Note: Metro and nonmetro areas correspond to the Office of Management and Budget February 2013 Metropolitan Area criteria.
Source: USDA, Economic Research Service analysis of Bureau of Economic Analysis Regional Data, Table CA25N.

Figure 3 raises questions that this analysis can answer, including:

- Are rural establishments in innovation-intensive industries, as identified by the NSF, in fact innovative when a more comprehensive definition of innovation is used? And how does this broader innovation rate compare between urban and rural establishments?

- Does a more comprehensive measure of innovation fill gaps in our understanding of phenomena in the dominant food manufacturing industry and manufacturing sector, and for tradable sectors as a whole, that are not evident in R&D expenditures and patent applications data?

How To Identify Innovative Rural Businesses

Looking beyond the hard innovation inputs and outputs such as R&D expenditures, patents, and science, technology, engineering, or mathematics (STEM) workers to arrive at a more comprehensive measure of innovation has been a considerable challenge (see Box, The History of Innovation Surveys). The approach used in the 2014 Rural Establishment Innovation Survey (REIS) is depicted in figure 4, which identifies subpopulations based on two thresholds or rungs of an innovation ladder. The questions used to elicit information for classifying respondents into these subpopulations are provided in Appendix A.

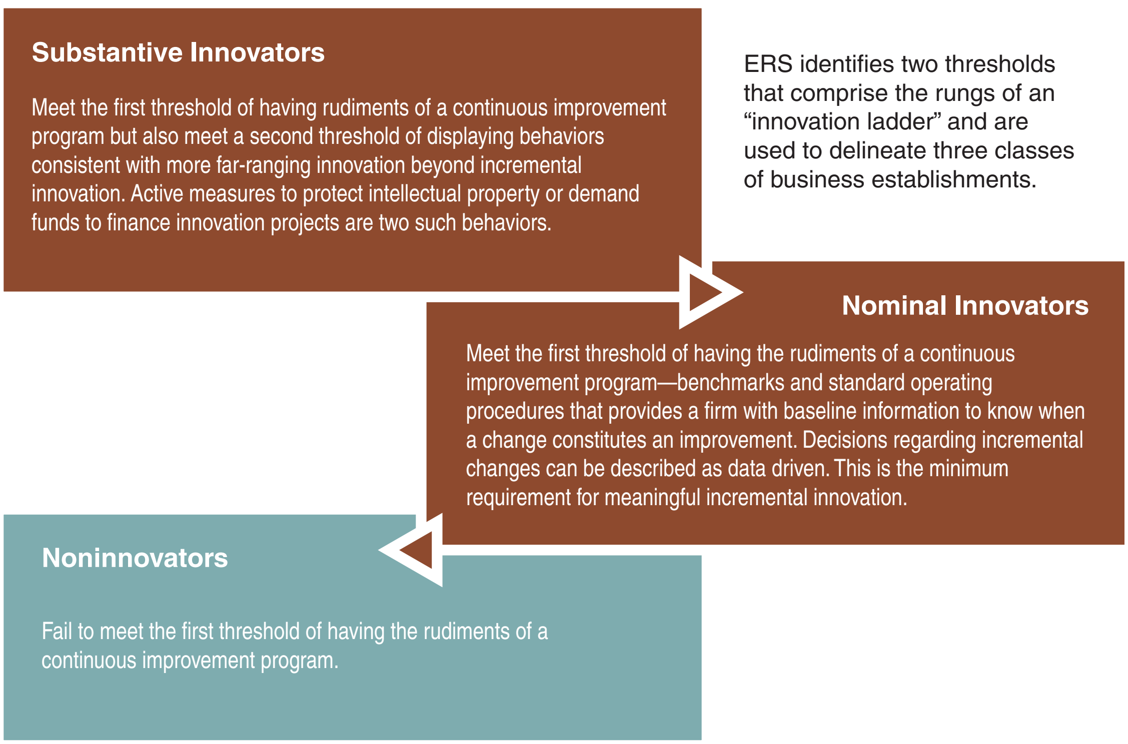
The History of Innovation Surveys

The conventional notion of R&D-based innovation, highly dependent on science and engineering inputs, has been the central focus of Federal data-collection activities. Since the 1950s, the National Science Foundation (NSF) has had a congressional mandate to collect data on research and development (R&D) expenditures, patents applied for and granted, and the employment and training of scientists, engineers, mathematicians, and other technical workers. The majority of this type of innovation activity occurs in R&D labs, which are concentrated primarily in the largest metropolitan areas.

Recognizing that the conventional notion of innovation was incomplete, the NSF expanded its annual Survey of Industrial Research and Development to include questions on the introduction of new or significantly improved products, services, and processes. The redesign of the survey was strongly influenced by the decades-long effort at the Organisation for Economic Co-operation and Development (OECD) to develop a more comprehensive definition of innovation and provide guidance on how to collect relevant data. That guidance has been used in the European Union's Community Innovation Survey—administered independently by member countries—since its inception in 1992. The revised NSF survey was renamed the Business Research & Development and Innovation Survey (BRDIS). This annual survey of companies provided the first view of the prevalence of a more comprehensive notion of innovation in the United States in 2009 (Boroush, 2010). However, three attributes of BRDIS make it less amenable to examining rural innovation explicitly. First, as a company survey, the geography of innovation is only identifiable for single-unit firms, which may not be representative of the economywide phenomenon. Second, because a primary objective of the survey is to provide accurate estimates of R&D expenditures, companies with formal R&D budgets are sampled with certainty. This means that single-unit firms—particularly single-unit rural firms—make up a relatively small share of the sample, resulting in larger sampling errors for these firms. Finally, self-reported innovation rates in a combined R&D/innovation survey such as BRDIS tend to be much lower than self-reported rates in standalone innovation surveys such as the European Union's Community Innovation Survey (CIS) (Gault, 2013; Wilhemsen, 2012). Because respondents to BRDIS are being asked questions about formal R&D budgets and the hiring of scientists and engineers, they may be more likely to interpret the innovation questions as pertaining to R&D-based innovation only, with resultant underreporting of grassroots or user innovation.

Conversely, the innovation rates in standalone surveys (which investigate self-reported innovation without the in-depth questions on R&D-based innovation characterizing EU Community Innovation Surveys) may be inflated by the absence of set criteria for defining innovation. A study examining innovation rates of rural firms in the United Kingdom modified the CIS questions by asking respondents to describe the innovations that prompted them to state they had introduced new or significantly improved products over the past 3 years (North and Smallbone, 2000). The descriptions were then graded by industry experts as either being "highly innovative" or "somewhat innovative." Close to half (49 percent) of all firms self-reported as introducing an innovation, but fewer than a quarter (24 percent) of all firms had their innovations classified as "highly innovative." The challenge facing standalone innovation surveys is finding a way to differentiate self-reporting firms that are highly innovative from those that that are only somewhat or nominally so.

Figure 4
Substantive Innovators, Nominal Innovators, and Noninnovators



Characteristics of Innovators

Table 1 demonstrates clear distinctions between the Substantive Innovator, Nominal Innovator, and Noninnovator subpopulations in the 2014 REIS data identified through Latent Class Analysis.[3] The results reported are for the entire sample from nonfarm tradeable industries that include establishments in both metropolitan and nonmetropolitan counties. Substantive innovators are identified least frequently, making up 30.1 percent of establishments with five or more employees. Data-driven nominal innovators make up 33.1 percent of establishments, while noninnovators make up the

[3]The Latent Class Analysis method is explained in Appendix A.

largest share at 36.8 percent. The justification for the names given to these groups is based on the characteristics that typify each business type. A significant majority of establishments classified as substantive innovators report abandoned and/or incomplete innovation projects (72.3 percent) or efforts to protect intellectual property (55.8 percent). In contrast, only a relatively small minority of both noninnovators and nominal innovators answered any of these questions affirmatively. The share of establishments that would probably use surplus funds for additional innovation projects was fairly similar across business types. However, very few substantive innovators said they would not use surplus funds for innovation projects, while the share that would definitely use funds for this purpose was three times that of the nominal and noninnovator establishments.

Table 1

Responses to questions regarding more far-ranging innovation by innovator class

	Substantive Innovator (Percent)	Nominal Innovator (Percent)	Noninnovator (Percent)
Percent of all establishments	30.12 (1.04)	33.09 (1.06)	36.79 (1.09)
Abandoned and/or incomplete innovation	72.35 (1.65)	16.72 (1.06)	22.09 (1.91)
Probably use surplus funds for innovation	46.86 (2.16)	47.55 (2.27)	30.85 (2.30)
Most definitely use surplus funds for innovation	47.07 (2.16)	16.34 (1.75)	17.11 (2.02)
Intellectual property protections	55.79 (2.08)	13.28 (1.26)	13.45 (1.43)

Standard error in parentheses.

Note: Percentages pertain to all tradable, nonfarm industries included in the survey.

Source: USDA, Economic Research Service (ERS) analysis of the 2014 ERS Rural Establishment Innovation Survey.

Data in the 2014 ERS Rural Establishment Innovation Survey (REIS)

REIS data were collected in the 2014 calendar year using a multimode design, allowing respondents to complete the survey via mail, internet, or telephone. The multimode approach was used to compensate for rapidly declining response rates of voluntary telephone surveys. The final response rate was 22.4 percent. The sample was drawn from the Business Registry maintained by the Bureau of Labor Statistics (BLS) as part of the Quarterly Census of Employment and Wages—a cooperative program with State employment security departments, based on administrative Unemployment Insurance records. A proprietary business registry was used for four States that do not allow BLS to share these data with other Federal agencies.

The population of interest was all private business establishments with five or more employees in nonfarm tradable industries. Tradable industries—that is, industries that might plausibly serve consumers or businesses some distance from a physical business location—are identified by patterns of geographical concentration (Jensen et al., 2005). In contrast, nontradable industries will be uniformly present nearly everywhere. Tradable industries in the survey include Mining (NAICS 21), Manufacturing (NAICS 31-33), Wholesale Trade (NAICS 42), Transportation (NAICS 48), Information (NAICS 51), Finance (NAICS 52), Professional Services (NAICS 54), Management of Businesses Headquarters (NAICS 55), and Performing Arts and Museums (NAICS 71).

Development of the survey involved input from academics, other Federal agencies, and nonprofit organizations with an interest in innovation and business development. In addition, the survey authors referenced work on self-reported innovation surveys by the European Union. The Organization for Economic Cooperation and Development (OECD) was also consulted regarding development of the Oslo Manual, which provides guidance on designing self-reported innovation surveys (OECD/Eurostat 2005). No one in individual EU countries was consulted, but surveys and research using the data were referenced.

The minimum required sample size—information collection that would minimize respondent burden but allow valid analysis of relatively rare occurrences such as rural patenting—was determined in consultation with the Office of Management and Budget. The 10,911 usable observations in the dataset provide adequate sample size to investigate these phenomena. Three-quarters of the sample is made up of establishments in nonmetro counties, while the remaining quarter of establishments in metro counties allows a reliable means of comparison.

With respect to continuous improvement and data-driven decisionmaking variables (table 2), the attributes of the noninnovator establishments appear quite different from those of the substantive or nominal innovators. The percentage of substantive and nominal innovators using enterprise resource planning software, tracking employee training, or regularly monitoring customer satisfaction or fixing customer complaints is substantially higher than it is for noninnovators. Fewer than 1 percent of the establishments classified as substantive innovators did not report any new or significantly improved products, services, or processes over the past year. The majority of establishments classified as noninnovators did not report any innovations over the past 3 years, but a substantial minority (42 percent) did.[4] The fact that a relatively high share of ostensible noninnovators reported new or significantly improved products or processes over the past 3 years reinforces the need for validating the innovation classification, using establishment-level performance measures when available.

[4]The novelty of a product innovation provides a gauge of how substantive the innovation may be. That is, an establishment may report introducing a new or improved product that merely imitates a competitor's product. In contrast, being the first to introduce a new product or improvement in the market is more in line with the notion of substantive innovation. In REIS, establishments classified as noninnovators that also reported a product innovation were less likely "to start selling any new or significantly improved goods or services" before their competitors (43 percent) than substantive innovators (78 percent) or nominal innovators (58 percent).

Table 2

Responses to questions regarding continuous improvement and data-driven decision making by innovator class

	Substantive Innovator (Percent)	Nominal Innovator (Percent)	Noninnovator (Percent)
Percent of all establishments	30.12 (1.04)	33.09 (1.06)	36.79 (1.09)
Use enterprise resource planning software	52.49 (2.17)	37.12 (2.09)	15.74 (1.59)
Track employee training	58.78 (2.01)	45.48 (1.99)	10.30 (0.82)
Monitor customer satisfaction regularly	56.19 (2.10)	50.88 (2.07)	3.18 (0.24)
Monitor customer satisfaction occasionally	37.56 (2.07)	44.21 (2.05)	36.53 (2.12)
Fix customer complaint prob-lems tegularly	64.33 (1.83)	70.89 (1.93)	17.43 (1.14)
Fix customer complaint prob-lems occasionally	28.76 (1.83)	29.12 (1.93)	66.73 (1.79)
No reported Innovations	0.89 (0.17)	30.95 (1.79)	58.01 (1.73)

Standard error in parentheses.

Note: Percentages pertain to all tradable, nonfarm industries included in the survey.

Source: USDA, Economic Research Service (ERS) analysis of the 2014 ERS Rural Establishment Innovation Survey.

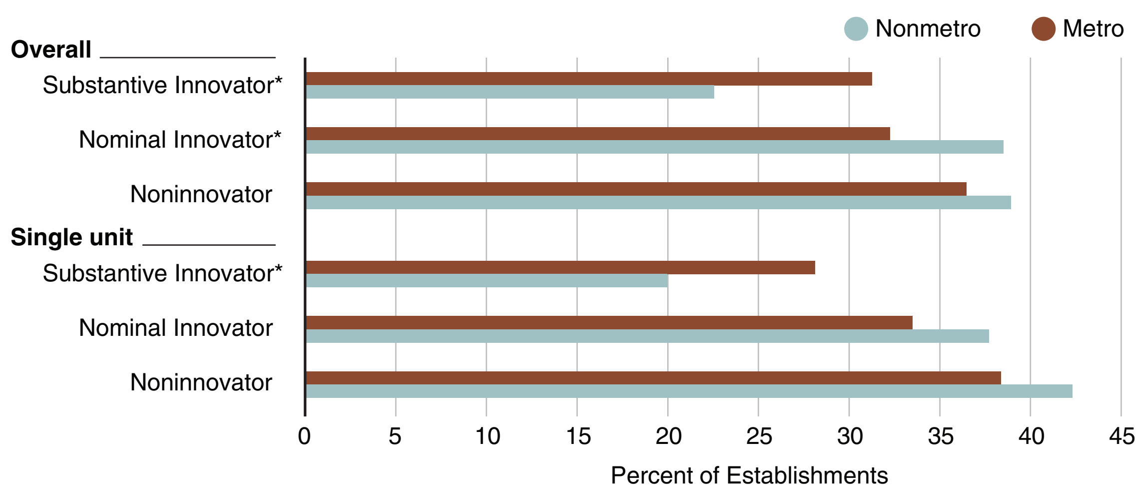
The Most Innovative Rural Industries

The substantive, nominal, and noninnovator groups were identified for the whole sample from tradable industries, including both metropolitan and nonmetropolitan establishments. These groups are defined solely by responses to the self-reported innovation and auxiliary questions, without reference to geography. Which leads to the empirical questions: What percentage of rural establishments are substantive innovators? How does this compare with the percentage of substantive innovators in metropolitan areas?

Figure 5 provides estimates of these percentages, weighted to be representative of the U.S. population of establishments with five or more employees in tradable, nonfarm industries, broken out by both settlement type (nonmetro/metro) and establishment type (single-unit or multi-unit firm; see Appendix table 1 for more information). These initial findings from the 2014 REIS data are consistent with previous studies showing a higher prevalence of substantive innovators in metro areas, to be expected given potential innovation advantages of denser networks of businesses and consumers that characterize urban locations. Roughly 3 of 10 metro establishments are classified as substantive innovators compared with approximately 2 of 10 nonmetro establishments. The metro-nonmetro differences in innovation are considerable but less than commonly assumed.[5] One possible explanation for higher-than-anticipated rates of rural innovation is that branch plants of multi-unit firms located in rural areas adopt the innovative orientation of the parent company. Instead of a measure of "rural innovation," these findings may merely reflect "innovation of branch plants located in rural areas." The second set of bars in figure 5 provide information to test that conjecture. The nonmetro single-unit rate of 19.96 percent is near the overall nonmetro rate of 22.56 percent—that is, the 2 in 10 description applies to wholly rural firms.

Figure 5

Substantive, nominal, and noninnovator rates by metro and single-unit status

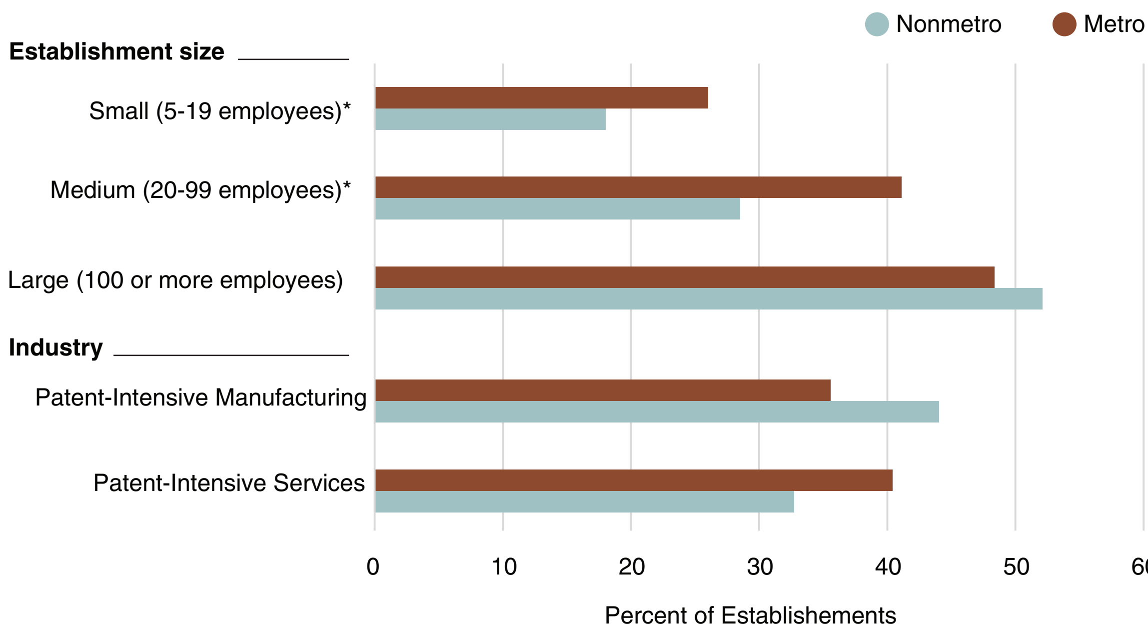


Note: Asterisk indicates that nonmetro and comparable metro estimate are statistically different at the 5% level. Percentages pertain to all tradable, nonfarm industries included in the survey.
Source: USDA, Economic Research Service (ERS) analysis of the 2014 ERS Rural Establishment Innovation Survey.

[5]Per capita patenting rates in large urban areas are six times the per capita patenting rates in nonmetro areas, leading many to conclude that invention—which often serves as a proxy for innovation—is a rare rural phenomenon (Wojan, Dotzel, and Low, 2015).

In figure 6, a preliminary look at substantive innovators by size distribution of establishments and industry group suggests that these differences may reflect more about the influence of establishment size or industrial composition than the relative innovativeness of urban and rural establishments within a size category or an industry. The percent of small (5-19 employees) and medium (20-99 employees) metro establishments classified as substantive innovators is larger than for their nonmetro peers. However, the difference in this regard between large metro and nonmetro establishments is not statistically significant. Similar results characterize nonmetro establishments in R&D/patenting-intensive manufacturing and services.[6] Substantive innovation rates identified in REIS are relatively high in industries classified as innovation intensive using R&D expenditures or patenting, but the data cannot confirm that the metro percent is higher than for the nonmetro peers.

Figure 6
Substantive innovator rates by metro status, establishment size, and patenting-Intensive industries



Note: *indicates that nonmetro and comparable metro estimate are statistically different at the 5% level. Percentages pertain to all tradable, nonfarm industries included in the survey.
Source: USDA, Economic Research Service (ERS) analysis of the 2014 ERS Rural Establishment Innovation Survey, Shackelford (2013).

[6]R&D/patenting-intensive manufacturing and services for the purposes of this report are those industries with high rates of patent applications, patents awarded, and/or high shares of R&D expenditures as compiled by the National Science Foundation (Shackelford, 2013). Chemicals (NAICS 325), Transportation Equipment (NAICS 336), Computer and Electronics Products (NAICS 334), and Medical Equipment and Supplies (NAICS 3391) comprise R&D/patenting-intensive manufacturing. Information (NAICS 51) and Professional/Scientific/Technical Service (NAICS 54) comprise R&D/patenting-intensive services. A 2012 report by the Economics and Statistics Administration and the United States Patent and Trademark Office (ESA/USPTO) identified a similar set of patent-intensive industries in manufacturing, with some notable differences. Using a patents-per-job measure rather than the NSF patents-per-establishment measure, NAICS 325, 334, and 3391 were identified as patent-intensive but NAICS 336 was not. The ESA/USPTO also identified NAICS 333 (Machinery) and NAICS 335 (Electrical equipment, appliance, and components) as patent-intensive. The ESA/USPTO report did not examine patent intensity in nonmanufacturing industries, but it did identify NAICS 51 and 54 as being copyright-intensive industries. So the NSF collection of R&D/patenting-intensive industries could also be classified as intellectual-property-intensive. An international study of R&D intensity in OECD member countries reinforces the NSF and ESA/USPTO findings: all of the industries cited in these reports are classified as having either "high R&D" or "medium-high R&D" intensity (Galindo-Rueda and Verger, 2016).

We define innovation-intensive industries as those where the probability of the 75th quantile establishment being a substantive innovator is 60 percent or greater. The justification for these somewhat arbitrary thresholds is derived from the assumption that substantive innovation is a business characteristic that is not commonly observed; thus the focus on the top quarter of the distribution. Requiring the substantive innovator probability at the 75th quantile to be at least 60 percent ensures somewhat better than even odds that the top quarter of establishments are in fact substantive innovators. This guards against the possibility that an industry with 25 percent or more of its establishments classified as substantive innovators may actually have a much smaller share of establishments that are truly in that category. Empirically, the 60-percent threshold identifies a natural gap in the data for both metro and nonmetro establishments. The nonmetro and metro rankings are provided in table 3, which includes the probability of the 75th quantile establishment, the percentage of all establishments in the industry classified as substantive innovators, and the percentage of all establishments that self-report at least one innovation over the 3 years prior to the survey.[7]

Table 3 reveals that several industries facing substantial international competition over the past decade rank high in innovation-intensiveness. Induced innovation—where competitive pressures increasingly make innovation a necessity for survival—appears to be prevalent in Textile Mills (313), Apparel (315), and Paper (322) in both rural and urban areas (see also Bloom et al., 2016). In fact, all textile mill establishments in urban areas in the survey were classified as substantive innovators. Industries expected to rank high in innovation intensity include chemicals, computer and electronic products, and transportation equipment,[8] and this was true in both urban and rural areas. The biggest difference between urban and rural areas is the dominance of manufacturing in rural areas, with a very limited number of service-providing 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), resulting in a significantly larger number of urban industries meeting the threshold. It is notable that Publishing (which 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.

Table 3 also includes a column showing the percentage of establishments within each 3-digit industry code that self-reported a product, service, process, logistical, or marketing innovation in the 3 years prior to the survey. The relatively high self-reported rates for industries with low percentages of substantive innovators are particularly striking. These numbers are not directly comparable to other studies that have investigated self-reported innovation rates such as that by North and Smallbone (2000), who looked only at product innovations (goods or services). Whether the protocol to identify substantive innovators is actually capturing an innovation construct that affects economic outcomes is examined next.

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[7]Table 3 provides concrete examples of why the protocol chosen is more informative than simply selecting industries that have the highest share of establishments classified as substantive innovators. The nonmetro Pipeline Transportation industry has 40 percent of its establishments classified as substantive innovators, placing in the top 10 of nonmetro industries with respect to this metric. However, the probability of the 75th quantile establishment being a substantive innovator is only 50.7 percent, roughly even odds. This means most of the remaining Pipeline Transportation establishments below the 75th quantile classified as substantive innovators have less than a 50-percent chance of being a true substantive innovator. In comparison, the nonmetro Transportation Equipment industry has roughly the same share of establishments classified as substantive innovators, but the probability that the 75th quantile establishment is a true substantive innovator is 72.9 percent.

[8]In addition to including aerospace, Transportation Equipment (NAICS 336) also includes the automotive industry, which funds R&D expenditures per establishment at a significantly higher rate than manufacturing as a whole. Patents issued per establishment in the automotive industry are also high relative to all other manufacturing.

Table 3
2014 Innovation-intensive industries in nonmetro and metro areas using latent class analysis

Nonmetro					Metro				
NAICS	Industry	Pr. 75th Perc.*	% Subst. Innov.	% Self-Rep. Innov.	NAICS	Industry	Pr. 75th Perc.*	% Subst. Innov.	% Self-Rep. Innov.
313	Textile Mills	0.986	61.91	100	515	Broadcasting	0.996	39.58	57.3
334	Computer and Electronic Products	0.927	48.52	71.31	322	Paper Manufacturing	0.974	56.65	67.02
326	Plastics and Rubber	0.915	49.01	78.93	324	Petroleum and Coal	0.974	34.38	34.38
325	Chemical	0.915	41.96	73.45	313	Textile Mills	0.956	100	100
322	Paper Manufacturing	0.89	44.9	79.6	518	Data Processing, Hosting	0.943	60.24	76.62
335	Electrical Equipment, Appliance	0.887	41.47	69.3	487	Scenic and Sightseeing Trans.	0.908	26.21	26.21
339	Miscellaneous Manufacturing	0.867	46.19	87.38	336	Transportation Equipment	0.896	38.67	67.33
333	Machinery Manufacturing	0.84	42.24	80.06	326	Plastics and Rubber	0.891	41.9	73.87
324	Petroleum and Coal	0.774	48.02	56.28	334	Computer and Electronic Products	0.865	40.13	67.02
315	Apparel	0.741	36.24	74.05	481	Air Transportation	0.856	44.4	69.58
336	Transportation Equipment	0.729	39.32	80.43	519	Other Information Services	0.856	54.29	86.66
517	Telecommunications	0.69	35.39	89.2	323	Printing	0.815	32.64	74.03
311	Food Manufacturing	0.682	32.01	81.23	335	Electrical Equipment, Appliance	0.815	38.65	78.1
331	Primary Metal	0.681	33.57	76.47	333	Machinery Manufacturing	0.814	42.73	77.3
487	Scenic and Sightseeing Trans.	0.671	35.4	83.33	331	Primary Metal	0.793	46.67	84.89
425	Wholesale Electronic Markets	0.67	30.68	67.76	315	Apparel	0.787	45.2	68.11
312	Beverage and Tobacco	0.658	32.49	84.77	425	Wholesale Electronic Markets	0.787	30.67	67.85
518	Data Processing, Hosting	0.625	38.19	63.73	522	Credit Intermediation	0.783	49.99	80.98
332	Fabricated Metal	0.597	28.66	73.42	311	Food Manufacturing	0.765	35.23	73.79
481	Air Transportation	0.596	28.1	56.33	339	Miscellaneous Manufacturing	0.738	29.88	70.1
314	Textile Product Mills	0.541	31.42	74.76	332	Fabricated Metal	0.719	34.84	69.89
316	Leather	0.519	26.96	90.14	424	Nondurable Goods Wholesalers	0.7	31.4	76.6

Table 3
2014 Innovation-intensive industries in nonmetro and metro areas using latent class analysis - *continued*

Nonmetro					Metro				
NAICS	Industry	Pr. 75th Perc.*	% Subst. Innov.	% Self-Rep. Innov.	NAICS	Industry	Pr. 75th Perc.*	% Subst. Innov.	% Self-Rep. Innov.
486	Pipeline Transportation	0.507	40.57	55.59	712	Museums, Historical Sites	0.7	32.19	73.86
711	Performing Arts Companies	0.502	28.2	83.47	551	Management of Companies	0.693	36.88	66.55
712	Museums, Historical Sites	0.498	26.98	79.44	314	Textile Product Mills	0.69	28.44	85.82
519	Other Information Services	0.495	26.96	84.59	488	Transportation Support Activities	0.677	38.4	71.77
511	Publishing Industries	0.437	23.61	80.62	541	Prof./Scientific/ Technical Services	0.674	31.21	70.06
515	Broadcasting	0.411	20.04	72.61	325	Chemical	0.671	39.28	82.6
551	Management of Companies	0.411	22.05	68.22	511	Publishing Industries	0.648	33.05	79.24
323	Printing	0.394	20.87	71.28	711	Performing Arts Companies	0.611	32.32	72.41
327	Nonmetallic Mineral Products	0.351	16.95	64.68	423	Durable Goods Wholesalers	0.604	29.8	73.54
424	Nondurable Goods Wholesalers	0.348	19.85	71.1	213	Support Activities Mining	0.566	30.49	34.14
423	Durable Goods Wholesalers	0.342	21.15	71.21	517	Telecommunications	0.566	37.18	73.75
337	Furniture	0.333	20.89	80.97	312	Beverage and Tobacco	0.541	26.82	80.64
522	Credit Intermediation	0.322	18.03	73.51	524	Insurance Carriers	0.489	23.71	67.06
321	Wood Products	0.316	22.06	63.7	321	Wood Products	0.487	21.93	59.14
541	Prof./Scientific/ Technical Services	0.313	19.82	68.69	483	Rail Transportation	0.309	0	79.27
212	Mining	0.255	21.5	61.07	484	Water Transportation	0.193	14.98	47.14
524	Insurance Carriers	0.251	17.84	63.05	523	Securities, Commodity Contracts	0.121	15.59	57.7
488	Transportation Support Activities	0.223	15.33	68.2	512	Motion Picture/ Sound Recording	0.106	11.9	58.9
213	Support Activities Mining	0.207	13.19	48.77	327	Nonmetallic Mineral Products	0.072	12.11	51.17
512	Motion Picture/ Sound Recording	0.155	1.35	79.26	337	Furniture	0.043	8.24	54.39

Table 3

2014 Innovation-intensive industries in nonmetro and metro areas using latent class analysis *- continued*

Nonmetro					Metro				
NAICS	Industry	Pr. 75th Perc.*	% Subst. Innov.	% Self-Rep. Innov.	NAICS	Industry	Pr. 75th Perc.*	% Subst. Innov.	% Self-Rep. Innov.
484	Truck Transportation	0.147	11.12	55.59	485	Truck Transportation	0.036	10.7	38.97
485	Ground Passenger Transportation	0.147	8.45	52.67	211	Oil and Gas	0.013	7.54	49.68
483	Water Transportation	0.1	0	35.44	525	Funds, Trusts,	0.007	0	0
523	Securities, Commodity Contracts	0.084	20.7	69.72	212	Mining	0.006	19.91	49.88
211	Oil and Gas	0.043	3.41	46.05	316	Leather	0.006	100	
482	Rail Transportation	0.037	0	100					

Note: * Probability that establishment in the 75th percentile is classified as a substantive innovator.
Source: USDA Economic Research Service (ERS) analysis of the 2014 ERS Rural Establishment Innovation Survey.

Employment, Wage, and Establishment Trends in Innovation-Intensive Industries and Regions, 2010-2014

The concentration of rural innovation in manufacturing industries suggests that a link between innovation and employment growth may be difficult to uncover, given the overall decline in manufacturing employment since 2000 and modest employment gains in recovery from the Great Recession. More pointedly, the process of induced innovation suggested by high innovation rates in textile mills and apparel establishments in table 3 suggests a complicated relationship between innovation and employment growth. Any association may be masked by productivity-enhancing innovations that reduce the demand for labor.

Ideally, examination of the relationship between innovation and desired outcomes such as growth of employment, productivity, wages, exports, or survivability would take place at the establishment level. For example, whether innovation provides a bulwark against substantial import competition can be empirically tested by comparing the survival rates of, say, apparel establishments to see whether more innovative ones were more likely to stay in business than less innovative peers. These analyses are planned once several years of outcome and performance data become available. In the meantime, empirical analysis is limited to retrospective employment performance by industry and by employment, wage, and net establishment formation performance by region.

Four dominant employment trends are possible:

- Innovation-intensive industries may demonstrate positive employment growth in recovery, which would support an innovation-led growth interpretation of the data but would also be consistent with a favorable demand shock, such as an increase in world prices for industry output.
- Alternatively, innovation-intensive industries might also demonstrate negative employment growth in recovery, which could support several interpretations of the data, including induced innovation or high rates of labor-saving innovation.
- Positive employment growth for industries that are not innovation-intensive would be consistent with a favorable demand shock or very low rates of labor-saving innovation.
- Finally, negative employment growth for industries that are not innovation-intensive is consistent with low competitiveness.

The objective of examining these trends is not to provide a definitive explanation for differences in employment growth performance during the recovery, but rather to identify those industries most likely to be contributing to innovation-led growth in rural areas and to examine the industry-level relationship between innovation and employment growth during recovery from the Great Recession.

The tendency for most rural innovation-intensive industries to be in manufacturing is reflected in table 3. Table 4 provides the employment growth rate in recovery from 2010 to 2014 for nonmetro areas. Some of the rural innovation-intensive manufacturing industries displayed robust employment growth in recovery, including transportation equipment, beverages, and machinery manufacturing. Employment growth in several innovation-intensive industries, including these manufacturing subsectors and several service subsectors (scenic and sightseeing tours, data hosting and electronic wholesale markets) surpassed the losses in several other innovation-intensive industries (including several manufacturing subsectors and telecommunications) in the recovery. This interpretation of innovation in manufacturing being associated with faster rates of employment growth is further reinforced by considering the composition of less innovative industries contributing to growth. In the top left column of table 4, the only manufacturing industries are wood products and nonmetallic mineral products. All other less innovative manufacturing industries lost employment during recovery.

Table 4
Employment growth in recovery (2010-2014)* by innovation intensiveness for nonmetro industries

Positive employment growth in recovery			
Not innovation-intensive		Innovation-intensive	
Growth Hypotheses: Commodity Price-Driven Growth; Limited Labor Saving Productivity Growth		Growth Hypothesis: Innovation-Led Growth	
Mining Support Activities	57%	Transportation Equipment	28%
Water Transportation	36%	Beverages and Tobacco	25%
Oil and Gas	28%	Machinery Manufacturing	16%
Pipeline Transportation	21%	Scenic and Sightseeing Trans	15%
Other Information Services	15%	Fabricated Metal	15%
Museums Historical Sites	14%	Data Processing Hosting	14%
Rail Transportation	14%	Primary Metal	11%
Transportation Support Services	13%	Plastics and Rubber	10%
Securities/Commodity Contracts	12%	Chemicals	4%
Durable Good Wholesalers	12%	Petroleum and Coal	4%
Truck Transportation	11%	Electrical Equipment	4%
Ground Passenger Transportation	9%	Wholesale Electronic Markets	3%
Management of Companies	9%	Food Manufacturing	2%
Wood Products	7%	Miscellaneous Mfg	1%
Prof/Sci/Tech Services	2%		
Nonmetallic Mineral Prods	1%		
Net Jobs Added	165,135		173,024
2010 Employment	1,374,858		1,573,786
Overall Growth Rate	12.03%		10.99%

Table 4
Employment growth in recovery (2010-2014)* by innovation intensiveness for nonmetro industries - *continued*

Negative employment growth in recovery			
Not innovation-intensive		Innovation-intensive	
Growth Hypothesis: Low Competitiveness		Growth Hypotheses: Induced Innovation or Labor-Saving Innovation	
Furniture	0%	Textile Mills	0%
Nondurable Goods Wholesalers	0%	Paper Manufacturing	-4%
Performing Arts Organizations	0%	Computer and Electronics	-6%
Insurance Carriers	0%	Telecommunications	-9%
Mining	-1%	Apparel	-29%
Leather	-2%		
Air Transportation	-5%		
Credit Intermediation	-5%		
Motion Picture/Recording	-6%		
Printing	-7%		
Textile Product Mills	-7%		
Broadcasting	-9%		
Publishing Industries	-15%		
Net Jobs Lost	-35,050		-19,288
2010 Employment	1,055,292		255,813
Overall Growth Rate	-3.32%		-7.54%

*The national recovery started in June 2009, according to the National Bureau of Economic Research Business Cycle Reference Date. The period of analysis used to examine growth in recovery begins in 2010, the year that the majority (36 out of 46) of rural industries examined in this study experienced a trough in employment.
Source: USDA, Economic Research Service (ERS) 2014 ERS Rural Establishment Innovation Survey and U.S. Bureau of Labor Statistics, Quarterly Census of Employment and Wages 2010 and 2014.

Any link between industry innovativeness and employment growth in nonmanufacturing industries during the recovery is much more difficult to discern from table 4. Service-providing industries do predominate in the left column of industries that are not innovation-intensive. However, the industries with the fastest rates of growth tend to be in resource extraction or transportation industries. Service-providing industries that were not innovation-intensive displayed some of the fastest rates of decline, including publishing industries and broadcasting. While some metropolitan service-providing industries mirrored declines in the 2010-2014 period (publishing, broadcasting, and telecommunications), motion picture/recording, performing arts organizations, and insurance carriers demonstrated employment growth, contrasting with rural employment declines. Growth in professional, scientific, and technical services was much more robust in metro areas than in rural areas. The story of employment growth is much more complex than a simplistic assumption of overall decline in goods-producing industries—perhaps induced by more rapid productivity increases—and growth in service-providing industries. However, it does appear that the innovation-intensiveness of an industry is more likely to positively impact employment growth in rural manufacturing than rural services.

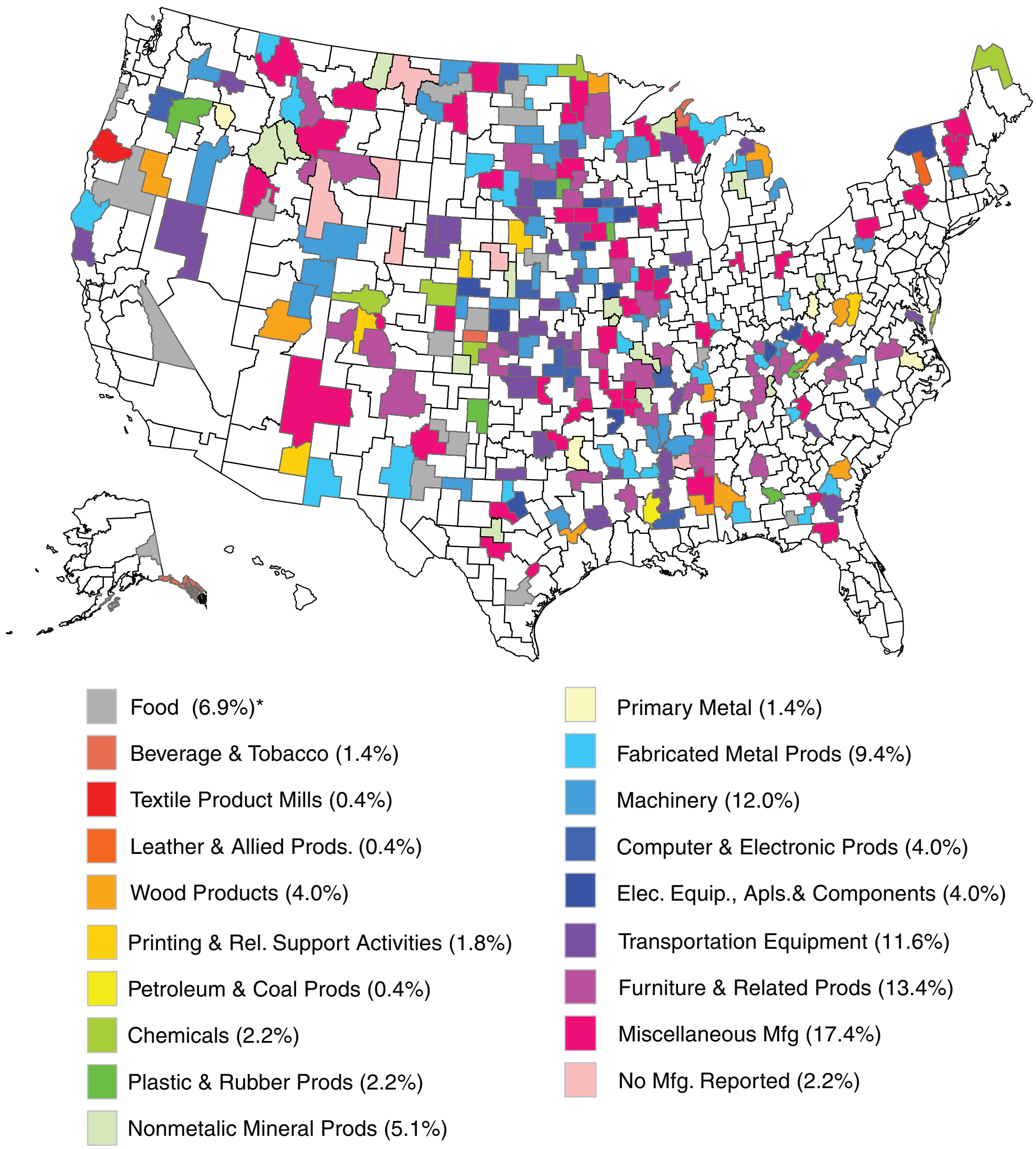
At the industry level, it does appear that innovation-intensive manufacturing industries recovered faster from the Great Recession than rural manufacturing industries that were not innovation intensive when employment is used as a gauge.[9] A question likely to be of greater interest to rural residents is whether a higher share of innovative establishments in the local economy—regardless of industry—contributed to a faster rate of recovery. Just as the data provided by REIS can be used to estimate the innovativeness of an industry, we can also use these data to estimate the innovativeness of a sub-State rural region. And since regional innovativeness estimated from 2014 data should be relatively persistent, retrospective employment, wage, and net establishment growth trends in recovery from the Great Recession may be informative while we await the availability of annual performance data in the years after 2014. The technical details of this exercise are explained in Appendix C.

The unit of analysis for this exercise is the 3-digit NAICS industry within each nonmetro commuting zone. A commuting zone is a collection of counties where some residents of one county in the zone are likely to work in adjoining counties. A map of nonmetro commuting zones, identified by the manufacturing industry with the largest employment, is provided in figure 7. Examining the relative innovativeness, employment growth, wage growth, and net establishment change for industries within each commuting zone individually provides two important benefits for examining these characteristics for nonmetro commuting zones as a whole. First, the wide variation in employment growth by industry in table 4 suggests the importance of an apples-to-apples comparison. An industry/commuting zone unit of analysis allows us to compare employment and wage growth within apparel, transportation equipment, wood products, or any other industry. For example, a commuting zone with a high concentration of apparel firms would not be comparable to a commuting zone with a high concentration of wood product firms—differences in employment or wage growth are much more likely to be due to an unfavorable or favorable industrial mix rather than differences in innovativeness. Second, the relative innovativeness of a local industry is likely to be more clearly defined than the relative innovativeness of a local economy. For example, we would

[9]ESA/USPTO (2012) provides corroborating evidence that "intellectual property (IP) intensive" industries also added jobs faster in the early stages of the recovery from 2010 to 2011 than industries that were not IP intensive: "1.6 percent rise in employment in IP-intensive industries outpacing the 1.0 percent increase in non-IP-intensive industries. Breaking IP-intensive industries out into constituent parts uncovers 2.4 percent job growth in copyright-intensive industries, 2.3 percent growth in patent-intensive industries, and 1.1 percent growth in trademark-intensive industries."(p. 41)

not necessarily expect insurance carriers in Silicon Valley to be more innovative than peers in other regions just because Silicon Valley is home to highly innovative computer and software companies. One drawback of using commuting zone geography is that nonmetro counties that are part of metropolitan commuting zones are excluded from the analysis.

Figure 7
Dominant manufacturing sectors for rural commuting zones, 2014



Note: * Percent of rural commuting zones. Note: Industry identified for each nonmetro commuting zone corresponds to the 3-digit NAICS with the most employment. No dominant industry is identified for commuting zones containing at least one metropolitan county.
Source: USDA, Economic Research Service using Bureau of Labor Statistics' Quarterly Census of Employment and Wages data.

Results that estimate the employment, weekly wage growth, or net establishment changes associated with being classified as a substantive innovator or nominal innovator in each nonmetro commuting zone by industry are reported in table 5. These estimates are relative to being classified as a noninnovator. The results demonstrate a clear employment growth advantage for commuting zones that contain establishments more likely to be substantive innovators. The added employment growth when all establishments in an industry were substantive innovators was 162 jobs for each commuting zone-industry, controlling for 3-digit NAICS industry and the population size of the commuting zone. The magnitude of this effect (22 percent of the average 2010 commuting-zone industry employment baseline) is attributable to what employment performance is being compared to: a scenario in which all establishments in the commuting zone/industry are noninnovators. If the effect is instead computed at the 90th percentile commuting zone representing high levels of the explanatory variables (but not assuming extreme values), then the difference in employment growth is 123 jobs or 17 percent of the 2010 baseline. The magnitude of the estimate for nominal innovators is also large, but much less precise than the substantive-innovator estimate.

Table 5

Association between estimated substantive/nominal innovator probability and employment/average weekly wage growth and net establishment change in commuter zone/industries

Probability establishments in commuting zone/industry are:	Employment growth 2010-2014 (number of jobs)	Average weekly wage growth 2010-2014 (dollars)	Net establishment change 2010-2014 (no. of establishments)
Substantive innovators	161.81 (0.0002)	\$6.81 (0.4947)	3.171 (0.0145)
Nominal innovators	61.26 (0.2150)	\$25.67 (0.0220)	0.8361 (0.5660)
Adjusted R^2	0.2970	0.0796	0.2144
N	2,499	2,498	2,477

Source: 2014 Economic Research Service Rural Establishment Innovation Survey and Bureau of Labor Statistics' Quarterly Census of Employment and Wages 2010 and 2014. Intercept, 3-digit NAICS-level industry controls and control for commuting zone population size not reported. Probability establishments in commuting zone/industry are noninnovators, the excluded category. P-values in parentheses.

For the average weekly wage growth equation, this pattern is reversed: the coefficient estimate for the Nominal Innovator variable is \$25.67, whereas the estimate for Substantive Innovators is \$6.81 but is not statistically significant. These findings do not support a simple linear relationship where both employment and wage growth increase with the degree of innovativeness. However, these findings are consistent with the types of business strategies that might characterize an "exemplary" Nominal Innovator or an exemplary Substantive Innovator. Recalling how these classifications were derived, the exemplary Nominal Innovator would have all the rudiments of a continuous improvement program but would not engage in activities associated with more far-ranging innovation. One could think of these businesses as pursuing the most efficient implementation of a fixed product or service line. For these businesses, one would expect to see a modest increase in employment as the economy recovered. But the most notable expected difference with noninnovators not actively engaged in continuous improvement would be in the wages paid to workers. In contrast, the exemplary Substantive Innovator that demonstrated both rudiments of a continuous improvement program and all the behaviors consistent with more far-ranging innovation could be thought to pursue efficient implementation over a changeable product or service line, perhaps exploring novel opportunities. The most notable expected difference with noninnovators would be greater flexibility to exploit emerging demands, manifest as much faster rates of employment growth in recovery.

This interpretation of the data is reinforced by estimating the effect of substantive and nominal innovation probabilities on net change in the number of establishments. The commuting zone containing exemplary substantive innovator establishments would have an additional 3.17 establishments in the commuting zone/industry over the period of recovery relative to a commuting zone with exemplary noninnovator establishments. In contrast, a commuting zone containing exemplary nominal innovator establishments would not differ from the noninnovator commuting zone. Net establishment change is more difficult to interpret than employment or wage growth as it is a combination of new-establishment births and establishment deaths. Whether substantive innovator commuting zone/industries are better in generating new start-ups or better at keeping incumbents in business is impossible to tell from these data. Given the very different firm-formation dynamics across the set of detailed industries, it is possible that both phenomena were in play. The implication from this retrospective analysis is that a strong innovation orientation in the local economy is likely to support net establishment growth.

Conclusions: Rural Innovation and Economic Impact

The findings in this report regarding the prevalence of rural innovation challenge the conventional wisdom that rural nonfarm innovation is relatively rare and idiosyncratic (World Bank, 2009; Carlino and Kerr, 2014). Our analysis does support conventional wisdom to the extent that substantive innovation rates in rural areas lag that of urban areas. This finding is to be expected, given likely innovation advantages of denser networks of businesses and consumers that characterize urban locations. However, this general result masks important details of the rural innovation economy. In innovation-intensive manufacturing industries, rural establishments are at least as likely to be classified as substantive innovators as their urban peers.

A critical question for rural stakeholders is whether innovation in rural establishments translates into significant economic impacts. The definitive answer will not be available for a few more years, when it will become possible to link the 2014 REIS data on innovation by individual establishments to other post-REIS establishment-level data on their economic performance. Findings in future research that establishments classified as substantive innovators in 2014 demonstrate faster rates of employment, increased earnings per job, or productivity growth; are more successful in penetrating export markets; or are more likely to survive relative to their nominal innovator or noninnovating peers would identify benefits in promoting innovation in the rural economy. However, different types of innovation may have countervailing economic impacts. For example, process or logistical innovations that result in greater automation or offshoring are more likely to be associated with productivity increases and employment losses, while product innovations that expand markets are more likely to result in employment gains. Data on rural innovation may enable researchers to tease out the causes underlying different economic outcomes.

Examining employment and wage growth and net establishment change retrospectively—using a new approach to identify more innovative industries and regions—provides the first hint of what the later analysis may show. The industry-level analysis confirmed that many factors other than innovation-orientation are likely to explain employment growth performance in economic recovery.

But the empirical analysis did uncover some interesting phenomena. The innovation-intensiveness of some industries facing strong import competition was surprising, given the low-tech characterization of textiles, apparel, and paper manufacturing (Boroush, 2010; OECD, 2003). This may be the result of a process of induced innovation, where firms that fail to innovate are forced to exit. That hypothesis will be testable when several years of performance data become available for the establishments studied in the REIS. Employment losses in other innovation-intensive industries raise the question of whether process innovations tend to be associated with lower levels of employment—a hypothesis that will also be testable with establishment-level performance data (Hall et al., 2008; Vivarelli and Pianta, 2000). For manufacturing more generally, innovation appears to be important to competitiveness, as only two manufacturing industries classified as not innovation-intensive demonstrated employment growth in recovery from the Great Recession (Wood Products and Nonmetallic Mineral Products (e.g., sand, gravel, and stone)). Employment growth in these industries during the recovery is consistent with a return to homebuilding after both demonstrated large employment losses from 2007 to 2010. Excluding these two industries allows a more definitive verdict: within manufacturing, only innovation-intensive industries added jobs in the recovery.

A clearer connection between innovation and employment and wage growth in recovery emerged from the regional analysis. Using nonmetro commuting-zone industries as the unit of analysis, it was possible to isolate the effects of the innovation orientation of establishments in the local economy from the local industrial structure while examining changes in employment, average weekly wages, and the number of establishments between 2010 and 2014. On average, employment across all industries and regions examined would have increased by 162 jobs if populated exclusively by exemplary substantive innovator establishments relative to being populated exclusively by exemplary noninnovator establishments. This difference in employment growth—roughly 22 percent of the average 2010 commuting-zone industry baseline—should be regarded as an upper bound as it is unlikely that these exemplary cases are commonly observed. However, the contribution of substantive innovator establishments to a faster rate of employment growth in the recovery is evident in the data. Commuting zones populated by substantive innovators were also more likely to demonstrate growth in the number of business establishments relative to commuting zones populated by noninnovators. The effect of nominal innovators was more distinct in the analysis of growth in average weekly wages. In this evaluation, the growth of average weekly wages in a commuting zone populated by exemplary nominal innovators would have outpaced a commuting zone populated by exemplary noninnovators by roughly $26 (27 percent of the average weekly wage growth of $96 from 2010 to 2014 or 3.1 percent of the 2010 average weekly wage baseline).

Taken together, the results from the commuting-zone industry analysis suggest that innovation is an important factor explaining greater economic dynamism in local rural economies. While it is too early to identify specific establishment-level innovation strategies associated with job generation, wage growth, productivity increases, export growth, or survivability that will require establishment-level performance data, this preliminary analysis supports the hypothesis that continuous improvement programs, data-driven decision making, and more far-ranging innovation activities were associated with faster recovery from the Great Recession.

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Appendix A: Using Latent Class Analysis To Increase Reliability of Self-Reported Innovation Measures

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 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.[10] While questions related to the novelty of an innovation (new to firm, new to markets served, 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.

If establishments are, in fact, members of distinct subpopulations based on an organization's orientation toward 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 specific questions in REIS to elicit this information are:

Questions used to identify rudiments of a continuous improvement program:

Q26. How often are processes changed to fix problems identified through customer complaints?

___ Never ___ Occasionally ___ Regularly

Q25. How often does this business monitor customer satisfaction through analysis of complaints, customer satisfaction surveys, focus groups, or other methods?

___ Never ___ Occasionally ___ Regularly

Q13. Does this business have written position descriptions?

Are training requirements documented in those position descriptions?

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

___ Yes ___ No

Question used to identify data-driven decision making:

[10]The idea that an establishment's orientation to innovation is likely to be more complex and nuanced than revealed in response to questions regarding the introduction of "new or significantly improved" products, services, or processes over the past 3 years have been examined in both the CIS and BRDIS, using factor analysis (e.g., Sanchez, 2014; Frenz and Lambert, 2009). Factor analysis in these studies is used to reduce the relatively large number of innovation inputs and outputs reported by respondents into a much smaller set of innovation modes—collections of innovation practices that tend to be found together.

Q14. Are the following technologies currently used at this business? …

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)

___ Yes ___ No

Questions used to identify more far-ranging innovation initiatives:

Q28. In the past 3 years, did this business have any improvement or innovation activities that were…

Abandoned ___ Yes ___ No Incomplete ___ Yes ___ No

Q37. In the past 3 years, did this business…

Use trade secret protections (e.g., nondisclosure agreements, noncompete clauses, or sought remedies for misappropriation)

___ Yes ___ No

Q34. In the current environment, if excess cash were available, how likely is it that these funds would be used to…

Fund additional innovation projects

___ Not at all likely ___ Probably ___ Most definitely

At least one positive response to the following questions used to identify self-reporting innovators:

Q27. In the past 3 years, did this business…

Produce any new or significantly improved goods? Provide any new or significantly improved services? Introduce new or significantly improved methods of manufacturing or producing goods or services? Introduce new or significantly improved logistics, delivery, or distribution methods for your inputs, goods, or services? Introduce new or significantly improved support activities for your processes? Introduce new or significant improvements in your marketing methods?

The rationale behind development and selection of these questions is provided in Appendix B.

Statistically, the challenge is moving from a single dimension for differentiating innovators from noninnovators to a multiple dimension construct, based on responses to the survey questions above.

Latent class or mixture models provide a probabilistic basis for identifying subpopulations and are flexible enough to allow statistical analysis when data are collected using complex survey design.

The probabilistic parameterization of the model requires two types of categorical variables—observed or manifest indicator variables and unobserved or latent variables—and two types of parameters—latent class and conditional probabilities (see McCutcheon, 2002). The manifest indicator variables in the present analysis include categorical responses to continuous improvement, data-driven decision making, and more far-ranging innovation questions. The assumption is that the relationship between these manifest variables can be explained by the latent variable—in this case, innovator class membership. For ease of exposition, if we assume our single latent variable (innovator class membership) X is explained by two manifest variables (A and B), then the latent class model can be expressed as the product of the latent class probabilities (π^{X}_{t}) and conditional probabilities ($\pi^{A|X}_{it}, \pi^{B|X}_{jt}$):

$$\pi^{ABX}_{ijt} = \pi^{X}_{t}\,\pi^{A|X}_{it}\,\pi^{B|X}_{jt}$$

In this report, the latent variable (X) is innovator class membership (1 = substantive innovator, 2 = nominal innovator, and 3 = noninnovator). One of the manifest indicator variables (A) is the use of intellectual property protections other than patents or copyright (i = 1, used; i = 2, not used). The conditional probability $\pi^{A|X}_{11}$ is the probability that a substantive innovator selected at random used intellectual property protections.

The explicit latent class analysis model estimated with question numbers referencing the survey questions above is:

$$\pi^{Q_{26}\,Q_{25}\,Q_{13}\,Q_{14}\,Q_{28}\,Q_{37}\,Q_{34}\,Q_{27}\,X}_{ijklmnopt} = \pi^{X}_{t}\,\pi^{Q_{26}|X}_{it}\,\pi^{Q_{25}|X}_{jt}\,\pi^{Q_{13}|X}_{kt}\,\pi^{Q_{14}|X}_{lt}\,\pi^{Q_{28}|X}_{mt}\,\pi^{Q_{37}|X}_{nt}\,\pi^{Q_{34}|X}_{ot}\,\pi^{Q_{27}|X}_{pt}$$

If the latent variable were, in fact, observed, the probabilistic parameterization would merely be a logistic regression on categorical independent variables. Since this is not the case, the latent class structure must be found using an iterative, maximum-likelihood estimation protocol called expectation-maximization. The simplest way to think of this protocol is as a logistic regression with missing data in the dependent variable. The expectation step of the protocol computes the expected value of the log of the likelihood function, conditional on initial parameter estimates and observed data. The maximization step updates values of the parameter value to maximize the likelihood function. The expectation step is then repeated with these updated values. This iterative process continues until a predefined level of precision is reached.

Arrival at the final selection of manifest indicator variables used to differentiate establishment subpopulations was accomplished with a minimal amount of “specification tests” to reduce 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.[11]

The latent class probabilities for the three subpopulations and their associated standard errors are provided in Appendix table 1, broken out by metro and nonmetro location and whether the establishment comprises a single-unit firm or is part of multi-unit business.

The latent class probabilities for the three subpopulations and their associated standard errors are provided in Appendix Table 2, broken out by establishment size and for establishments in patenting intensive industries.

[11]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.

Appendix Table 1

Distribution of substantive, nominal, and noninnovators by nonmetro and metro location and establishment type

	Substantive innovator (percent)	Nominal innovator (percent)	Noninnovator (percent)
Percent of all nonmetro establishments	22.56* (0.59)	38.52* (0.71)	38.92 (0.70)
Percent of all metro establishments	31.27 (1.21)	32.26 (1.24)	36.47 (1.24)
Percent of all nonmetro single-unit firms	19.96* (0.67)	37.73 (0.84)	42.31 (0.84)
Percent of all metro single-unit firms	28.12 (1.42)	33.48 (1.48)	38.39 (1.49)
Percent of all nonmetro part of multi-unit firm	28.66* (1.19)	41.52* (1.36)	29.82 (1.25)
Percent of all metro part of multi-unit firm	39.61 (2.37)	32.16 (2.36)	28.22 (2.21)

Standard error in parentheses. * indicates that nonmetro and comparable metro estimate are statistically different at the 5% level.

Note: Percentages pertain to all tradable, nonfarm industries included in the survey.

Source: USDA, Economic Research Service analysis of 2014 ERS Rural Establishment Innovation Survey.

Appendix Table 2

Distribution of substantive, nominal, and noninnovators in nonmetro and metro locations by establishment size and by R&D/patenting-intensive industries

		Substantive innovators (percent)	Data-driven nominal innovators (percent)	Noninnovator (percent)
Small establishment (5-19 employees)	Nonmetro	18.02* (0.71)	38.29* (0.89)	43.69 (0.89)
	Metro	26.00 (1.49)	33.18 (1.59)	40.83 (1.62)
Medium establishment (20-99 Employees)	Nonmetro	28.53* (1.16)	41.12* (1.32)	30.35 (1.21)
	Metro	41.10 (2.25)	31.96 (2.16)	26.94 (1.95)
Large establishment (100 or more employees)	Nonmetro	52.14 (2.32)	29.99 (2.16)	17.87 (1.78)
	Metro	48.36 (4.17)	22.97 (3.26)	28.67 (4.19)
R&D/patenting-intensive manufacturing (NAICS 325, 334, 336, and 3391)	Nonmetro	44.04 (2.95)	29.53 (2.68)	26.43 (2.67)
	Metro	35.56 (4.77)	30.26 (4.63)	34.19 (5.05)
R&D/patenting-intensive services (NAICS 51 and 54)	Nonmetro	32.71 (2.71)	26.75 (2.60)	40.54 (2.78)
	Metro	40.41 (2.98)	24.21 (2.54)	35.38 (2.84)

Standard error in parentheses. * indicates that nonmetro and comparable metro estimate are statistically different at the 5% level.

Note: Percentages pertain to all tradable, nonfarm industries included in the survey.

Source: USDA, Economic Research Service analysis of 2014 ERS Rural Establishment Innovation Survey, Shackelford (2013).

Appendix B: Eliciting Information To Differentiate Substantive Innovators From Nominal Innovators and Noninnovators

The implicit assumption in traditional analysis is that all business establishments can be thought of as members of a single population. While observable differences between business establishments make heterogeneity across characteristics clear, the single-population assumption requires that responses to various stimuli that underlie behavior are homogenous, or at least can be productively approximated by the behavior of the average or representative establishment.

The assumption undergirding the development of the REIS was that the population of establishments is comprised of subpopulations based on an establishment's orientation toward innovation. Thus, not only will establishments differ in terms of many observable characteristics, but also with respect to their motivations and capabilities to innovate. However, unlike the observable characteristics, an establishment's orientation towards innovation is unobserved.

The possibility of identifying these subpopulations depends on the association between this unobserved or latent innovation orientation and behaviors or attitudes that can be observed. Beginning with incremental innovation—that is, small changes in process or methods that may improve the effectiveness of the business unit—the assumed minimal set of required behaviors includes regularly collecting information on business operations. REIS contains a series of questions to determine whether the respondent establishment supports the rudiments of a continuous improvement or quality assurance program. The requirement to "say what you do and do what you say" is central to these programs. This requirement cannot be met if employees are not trained to faithfully perform their job duties. The survey asks if the training requirements for each job are documented and whether training that individual employees receive is tracked.

Because business establishments cannot guarantee performing as promised 100 percent of the time, any failure provides a valuable source of information for improving business operations. Thus, continuous improvement and quality assurance programs require explicit procedures for taking corrective actions in response to a failure to perform as promised. The survey asks how frequently this type of information is used by the establishment to change business processes.

The final management practice considered as a rudiment to continuous improvement or quality assurance programs is whether data on customer satisfaction are collected. These data provide critical information for improving the business, and the survey asks if various methods are used to acquire it. Establishments answering that they regularly track employee training, correct processes to address performance failures, and track customer satisfaction demonstrate behaviors consistent with a commitment to incremental innovation. Establishments that failed to implement these management practices might also be interested in incremental innovation; lacking these practices, however, they would be unable to differentiate an objectively better process from a stroke of good luck. Different responses to these three questions should thus enable identifying both establishments with a latent orientation toward incremental innovation and those incapable of an organized pursuit of incremental innovation.

The management practices above are consistent with an overall business strategy of "data-driven decision making." A body of empirical research provides evidence that the most innovative and productive firms are ravenous consumers of data about their internal operations, as well as about the markets they serve (Bloom et al., 2013; Brynjolfsson et al., 2011). The ability to collect, compile, and analyze these data are a function of both management practices, as discussed above, and technology. The technology that best exemplifies a data-driven approach to management is enterprise resource planning (ERP) software. These resource planning systems integrate data and analysis from accounting, logistics, human resources, sales management, and customer relationship applications to establish valid baselines, identify performance gaps or successes, and allow data-rich scenario analysis (Bloom et al., 2016). Software companies have aggressively targeted smaller and medium-sized enterprises for these products, ensuring that data-driven management technologies are applicable to the full set of establishment size classes included in REIS. Although REIS includes questions on the use of a wide variety of information and communications technologies, the focus on ERP software to identify establishments with a commitment to innovation is compelling. The one caveat is that adoption of a particular technology does not guarantee how that technology is used. But because it is an enabler of data-driven decision making, the adoption of ERP software would help to reinforce the innovation orientation of an establishment.

To differentiate incremental innovators from establishments pursuing more far-ranging innovation—that is, innovation that is not merely a minor modification to an existing product or process but that entails considerable rethinking of interacting components or processes—we assume establishments pursuing this heightened innovation will have unique experiences that can be elicited with simple questions.

Innovation is often described as a process of trial and error, where some hunches are dead ends and some are productive mistakes that lead to eventual success. Substantive innovators are more likely to acknowledge failed, aborted, or incomplete innovation activities because they recognize the value of initial failures in the process of innovation. In contrast, a respondent from an establishment that has not struggled with the innovation process is much less likely to acknowledge abandoned or incomplete innovation activities (see Leoncini, 2016). The simple question, "In the past three years, did this business have any improvement or innovation activities that were … Abandoned? ... Incomplete?" provides this information.

Because the success of innovation projects is never assured—and because it is very difficult for an outsider to assess a firm's likelihood of success—raising capital for innovation projects is always a challenge. Again, these constraints are likely to be well known to firms actively engaged in innovation projects and little known to firms that have never needed to fund innovation activities. In the survey, respondents are asked how they would allocate an unexpected surplus across competing uses, including paying down debt, setting aside a reserve, funding worker training, funding additional investment projects such as the replacement of old equipment or expansion, or funding additional innovation projects. The choice is not exclusive, but by selecting the last option, establishments will be indicating past capital constraints with respect to funds for innovation. Establishments that are not substantive innovators are much less likely to indicate innovation-related funding constraints.

Patents—the legal protection of new inventions that may be economically valuable—have played a central role in the study of innovation. However, patents may be too exclusive, while also including some new ideas with little or no economic value. To address the problems that not all innovative ideas that add value are patentable and that the costs of obtaining a patent may exceed the benefits, the survey also asks about less arduous means of protecting intellectual property. These can include trade-secret protections, nondisclosure agreements, noncompete clauses, or attempted remedies for misappropriation. Establishments that are actively introducing new products or ways of doing things are much more likely to possess unique intellectual property that needs protecting. Therefore, responses to this question should also help distinguish substantive innovators from nominal or noninnovators.

Appendix C: Estimating the Association Between Regional Innovativeness and Retrospective Employment Growth, Average Weekly Wage Growth, and Net Establishment Change

The innovation-intensiveness of an industry was defined earlier by the innovation-intensiveness of the top quarter of industry establishments (table 3). That is, substantive innovation is assumed to be a characteristic of exemplary—rather than representative—establishments. The distribution of these exemplary establishments over space may not be uniform, giving rise to particular rural regions with a concentration of innovative establishments and other rural regions with a dearth of them. To examine this issue, we aggregate counties into functional Commuting Zones—groups of counties that are economically integrated by commuter flows (Autor and Dorn, 2013). Aggregating counties this way increased the number of observations per region and thus increases the reliability of substantive innovator estimates for each region relative to a county-level analysis.

Given the large variation in employment growth across 3-digit NAICS industries, an informative analysis of the potential impact of regional innovation will need to control for local industrial structure. We do this by estimating regional innovation at the 3-digit industry level. Every establishment in the REIS has an estimated probability of being a member of the substantive innovator, the nominal innovator, or the noninnovator subpopulation. For each commuting zone, we estimate the probability that the average establishment in a given 3-digit industry is a substantive innovator, nominal innovator, or noninnovator, based on estimates of establishments in REIS, weighted by reported employment size for each establishment. There are 354 Commuting Zones that contain only nonmetro counties, and the REIS sample covers 45 3-digit NAICS industries. The total number of observations available for the analysis (n) is thus the number of commuting zone/industries that have respondents in the REIS data and that had employment, wage, or establishment data from the Quarterly Census of Employment and Wages in 2014.

One potential weakness of this approach is the relatively high degree of sampling error of these weighted regional probabilities. Given the small number of surveyed establishments in any commuting zone/industry, the sample may not be truly representative of the innovation orientation of the local collection of establishments. That is, the luck of the draw may result in a significantly larger share of substantive innovators relative to noninnovators in the sample than is true in the local economy, or vice versa. However, since these sampling errors will be random, the analysis will provide unbiased estimates of the association between innovation and employment growth, wage growth, or net establishment change. The major implication of increased sampling error is a reduction in the statistical power of the analysis. That is, the larger sampling error will decrease the likelihood of detecting an association between innovation and employment or wage growth if it truly exists.

The specification of the weighted ordinary least squares regression model is:

$$\Delta y = \alpha + x\beta + z\gamma + \varepsilon$$

where Δy= an n x 1 vector of the change in employment, average weekly wages, or number of establishments between 2010 and 2014 for each commuting zone/industry;

α = an intercept;

x = an n x 2 matrix of the estimated commuting zone/industry probabilities that the representative establishment is a substantive innovator and a nominal innovator;

β = a 2 x 1 vector of estimated coefficients of the employment, average weekly wage, or net establishment impact from the estimated substantive and nominal innovator probabilities (relative to noninnovator probability excluded category);

z = an n x 46 matrix including controls for 3-digit industries and commuting zone population size in 2000;

γ = a 46 x 1 vector of estimated coefficients of industry and population control variables; and

ε = an n x 1 vector of disturbance terms.

The regression is weighted by the respective 2009 3-digit industry employment in the respective commuting zone. The full sets of α, β and γ estimated coefficients are provided in the following table.

Appendix Table 3

Association between estimated substantive/nominal innovator probability and regional performance metrics (2010-14)

Variable	Employment growth estimate (jobs)	Employment growth p-value	Wage growth estimate (dollars)	Wage growth p-value	Net establishment change estimate (establishments)	Net estab. change p-value
Intercept	544.0741	0.0003	-3.0080	0.9297	10.8347	0.0146
Prob. Substantive Innovator	161.8145	0.0002	6.8112	0.4947	3.1709	0.0145
Prob. Nominal Innovator	61.2577	0.2150	25.6713	0.0220	0.8361	0.5660
CZ Population 2000	-0.0011	<.0001	-0.0002	0.0001	<.0001	<.0001
212 Mining (except Oil and Gas)	-893.7415	<.0001	122.8746	0.0010	-19.5047	<.0001
213 Support Activities for Mining	1481.3379	<.0001	256.5556	<.0001	41.5840	<.0001
311 Food Manufacturing	-489.0497	0.0016	71.8518	0.0410	-7.1382	0.1183
312 Beverage and Tobacco Product Manufacturing	-331.5939	0.1956	60.1223	0.3009	2.2919	0.7623
313 Textile Mills	-430.7021	0.5032	21.8316	0.8811	-6.4924	0.7371
314 Textile Product Mills	-538.9254	0.0965	24.8603	0.7353	-8.2296	0.3895
315 Apparel Manufacturing	-490.2665	0.3574	54.9182	0.6495	-7.3906	0.6380
316 Leather and Allied Product Manufacturing	-657.5796	0.2125	116.0810	0.3319	-6.9930	0.6529
321 Wood Product Manufacturing	-456.6535	0.0044	91.2758	0.0121	-8.8768	0.0604
322 Paper Manufacturing	-530.3770	0.0547	109.8050	0.0794	-5.6172	0.4899
323 Printing and Related Support Activities	-589.8201	0.0031	72.2399	0.1104	-8.6042	0.1429

Appendix Table 3
Association between estimated substantive/nominal innovator probability and regional performance metrics (2010-14) - *continued*

Variable	Employment growth estimate (jobs)	Employment growth p-value	Wage growth estimate (dollars)	Wage growth p-value	Net establishment change estimate (establishments)	Net estab. change p-value
324 Petroleum and Coal Products Manufacturing	-492.0567	0.2730	379.9901	0.0002	-7.0144	0.5960
325 Chemical Manufacturing	-494.2261	0.0101	130.8829	0.0027	-7.3818	0.1931
326 Plastics and Rubber Products Manufacturing	-253.2823	0.1371	50.0816	0.1949	-7.6558	0.1274
327 Nonmetallic Mineral Product Manufacturing	-435.9790	0.0234	132.8806	0.0023	-7.1452	0.2067
331 Primary Metal Manufacturing	-467.2164	0.0435	180.6677	0.0006	-5.9534	0.3834
332 Fabricated Metal Product Manufacturing	-308.6098	0.0509	94.0709	0.0087	-7.1785	0.1234
333 Machinery Manufacturing	-356.2261	0.0264	100.5578	0.0058	-8.2983	0.0794
334 Computer and Electronic Product Manufacturing	-574.2205	0.0072	79.8762	0.0991	-6.9456	0.2698
335 Electrical Equipment, Appliance, and Component	-391.8669	0.0466	54.2320	0.2247	-6.4957	0.2632
336 Transportation Equipment Manufacturing	493.6128	0.0024	69.9389	0.0583	-6.1901	0.1971
337 Furniture and Related Product Manufacturing	73.9809	0.6717	52.7681	0.1828	-6.8900	0.1808
339 Miscellaneous Manufacturing	-347.2006	0.0556	145.8559	0.0004	-7.9611	0.1366
423 Wholesalers, Durable Goods	-409.2201	0.0086	124.3648	0.0004	-6.0644	0.1866
424 Wholesalers, Nondurable Goods	-505.5889	0.0011	100.4171	0.0043	-8.4619	0.0638
425 Wholesale Electronic Markets	-535.6831	0.1296	210.3652	0.0087	-5.7210	0.5829
481 Air Transportation	-577.2477	0.1707	48.2375	0.6138	-9.1637	0.4607
484 Truck Transportation	-384.9729	0.0137	105.5726	0.0029	-3.5503	0.4403
485 Transit and Ground Passenger Transportation	-468.3922	0.0585	39.1410	0.4857	-6.4310	0.3771
486 Pipeline Transportation	-581.6315	0.4704	650.3034	0.0004	-10.3778	0.6622
487 Scenic and Sightseeing Transportation	-481.8717	0.2130	34.2822	0.6960	-10.7011	0.3508
488 Support Activities for Transportation	-619.7130	0.0056	33.4046	0.5104	-5.3669	0.4159
511 Publishing Industries (except Internet)	-520.0797	0.0064	80.2570	0.0635	-7.9810	0.1556
512 Motion Picture and Sound Recording Industries	-483.8949	0.2875	38.5035	0.7091	-6.7163	0.6166

Appendix Table 3

Association between estimated substantive/nominal innovator probability and regional performance metrics (2010-14) *- continued*

Variable	Employment growth estimate (jobs)	Employment growth p-value	Wage growth estimate (dollars)	Wage growth p-value	Net establishment change estimate (establishments)	Net estab. change p-value
515 Broadcasting (except Internet)	-489.8940	0.0795	60.0537	0.3431	-7.3045	0.3750
517 Telecommunications	-584.5308	0.0031	120.9138	0.0069	-8.2502	0.1562
518 Data Processing, Hosting, and Related Services	-514.6609	0.7782	-117.4911	0.7769	-8.1087	0.8842
519 Other Information Services	-465.7695	0.4046	51.4486	0.6849	-4.5989	0.7860
522 Credit Intermediation and Related Activities	-530.7961	0.0009	107.7422	0.0030	-9.7675	0.0386
523 Securities, Commodity Contracts, and Other Financial Investments and Related Activities	-499.6884	0.4874	557.6334	0.0006	-5.3294	0.8016
524 Insurance Carriers and Related Activities	-510.9933	0.0049	113.9929	0.0057	-7.0238	0.1898
541 Professional, Scientific, and Technical Services	-474.4193	0.0018	127.0539	0.0002	-0.5107	0.9093
551 Management of Companies and Enterprises	-335.9057	0.0565	185.9530	<.0001	-5.3284	0.3050
711 Performing Arts	-703.5573	0.0156	7.0234	0.9152	-11.7371	0.1711
712 Museums	-478.9778	0.1202	30.4646	0.6630	-5.5030	0.5482
Adjusted R-Squared	0.2970		0.0796		0.2144	

Source: 2014 USDA, Economic Research Service Rural Establishment Innovation Survey and U.S. Bureau of Labor Statistics' Quarterly Census of Employment and Wages 2010 and 2014.

Appendix Table 4

Descriptive statistics for the dependent and x variables for the regression above

Variable	N	Mean	Std. Dev.	Minimum	Maximum
Employment growth 2010-14 (jobs)	2,503	137.573	14,878.32	-2,619.00	9,270.00
Avg. weekly wage growth 2010-14 (dollars)	2,500	95.759	2,950.74	-1,611.15	1,821.00
Net establishment change 2010-14 (establishments)	2,479	2.118	415.127	-46	276
Prob. substantive innovator	2,511	0.288	6.435	0.00000002	0.996
Prob. nominal innovator	2,511	0.367	5.585	0.00000022	0.994
Prob. noninnovator	2,511	0.344	6.839	0.00000084	0.999

Source: 2014 USDA, Economic Research Service Rural Establishment Innovation Survey and U.S. Bureau of Labor Statistics' Quarterly Census of Employment and Wages 2010 and 2014.