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Business dynamics and economic performance in the Midwest

A look at the new Innovation 2.0

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The Indiana Business Research Center recently launched [Innovation 2.0](#). It is a rich compilation of a broad array of measures of innovation at the county, metropolitan statistical area (MSA) and economic development district levels nationwide. What follows is something of a case study for how a researcher might use the Innovation 2.0 data.

Inside Innovation 2.0

Innovation 2.0 provides a robust set of relevant measures of innovation and regional competitiveness that are constructed based on research pertaining to the forces and prerequisites of competitiveness and performance. The importance of

clusters to regional economic growth has been well-documented elsewhere. The regional competitive model that is advocated here focuses on the regional character of internally generated (i.e., internal to the region) growth through innovation and entrepreneurship. Put differently, fresh ideas and a propensity to take chances provide a fertile seedbed for innovation and a foundation to create new economic opportunities.

Innovation 2.0 is a web-based tool, available at www.statsamerica.org/ii2, for regional economic development practitioners to identify the innovation-based strengths and weaknesses of a regional economy. Many of the measures used gauge the foundational elements that are currently in place in the region for future, innovation-driven economic growth. Some of the measures gauge the degree to which the region is attractive to new talent and firms that may also enhance the regional economy, but those same measures of attractiveness are also measures for retaining current talent and firms.

Certain regional characteristics, in other words, work like gravity, keeping objects on the ground and pulling objects to the ground. It is hoped, therefore, that Innovation 2.0 is not primarily used to try to attract outside firms, resources and talent, but is used to identify indigenous sources of innovation and ways to fortify those sources. Encouraging homegrown entrepreneurs with personal commitments to the region, for example, is preferred over attracting talent with minimal personal investment in the region.

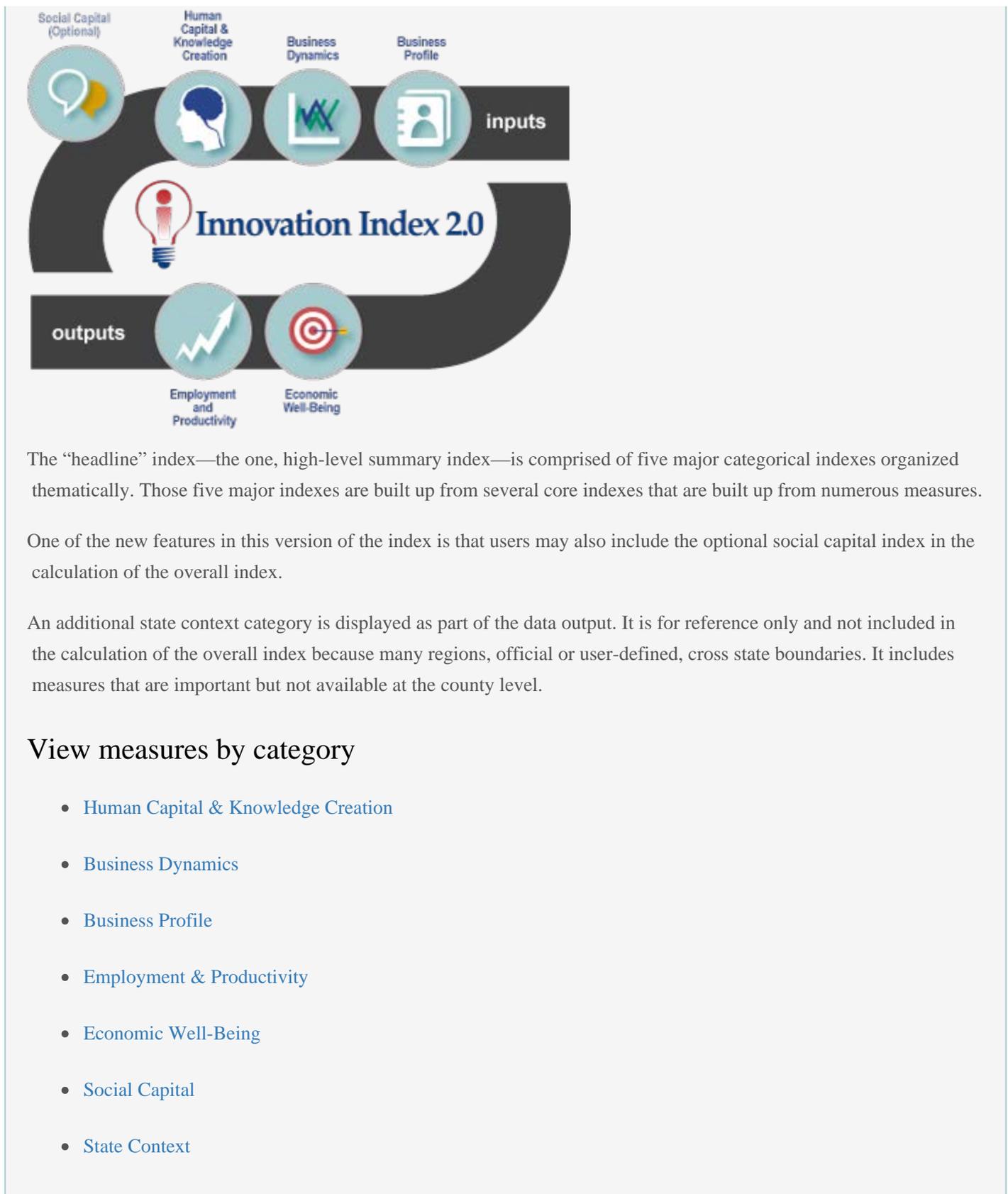
The index measure that is a key component of Innovation 2.0 is admittedly not perfect. Researchers have noted the pitfalls with creating indexes. For example, using indexes can result in a loss of variability and explanatory power through the grouping of data. This is something we will attempt to address later in the

article as we evaluate which regional characteristics are better equipped to explain MSA performance in the Midwest.

Imperfections aside, the Innovation Index version 2.0 presents a state-of-the-art measure of county and regional innovation capacity and performance. This index can serve as a valuable tool for policymakers and practitioners to quickly evaluate innovative capacity and potential. Economic development practitioners not only get a quick snapshot of how their region is doing in terms of innovation with the headline index, but they also have the ability to drill down and get dirty in the data to gain a better understanding about their region's strengths and weaknesses.

It is not surprising that developing data-driven regional development strategies requires data. The Innovation 2.0 project consolidates data from multiple public sources. The vast majority of the data items used in the Innovation Index are county-based and are available for download by county, MSA and other official statistical areas. The website currently aggregates the index components in an equal, unprejudiced manner. That is, the data are assembled thematically and with no judgment calls regarding what measures are the most relevant in terms of measuring innovation capacity.

The next step for the IBRC researchers is to conduct empirical analysis. This article is part of that next step, something of a case study in how a researcher or an economic development practitioner can use the Innovation 2.0 data to determine which factors are the most important in driving regional innovation and economic performance.



The “headline” index—the one, high-level summary index—is comprised of five major categorical indexes organized thematically. Those five major indexes are built up from several core indexes that are built up from numerous measures.

One of the new features in this version of the index is that users may also include the optional social capital index in the calculation of the overall index.

An additional state context category is displayed as part of the data output. It is for reference only and not included in the calculation of the overall index because many regions, official or user-defined, cross state boundaries. It includes measures that are important but not available at the county level.

View measures by category

- [Human Capital & Knowledge Creation](#)
- [Business Dynamics](#)
- [Business Profile](#)
- [Employment & Productivity](#)
- [Economic Well-Being](#)
- [Social Capital](#)
- [State Context](#)

The set of measures that comprise Innovation 2.0 is expansive (see sidebar), so we selected just a dozen or so measures of business dynamics and regional characteristics to see how they relate to important measures of regional

economic and innovation performance in order to keep the analysis and presentation manageable. For this analysis, we trimmed the number of regions to those MSAs in the Midwest, so we could focus on Indiana and neighboring states.

What follows is a discussion of the measures we used in this analysis and the motivation for including them in Innovation 2.0. The measures are categorized as either an input to innovation that may explain the performance, or an output that is an outcome of innovative activities.

Input measures

Inputs are those factors, influences or conditions that promote innovation and create knowledge. Input measures for Innovation 2.0 are categorized into two thematic categories: human capital and knowledge creation and business dynamics.

Human capital and knowledge creation are critical and typically explain much of why some regions prosper and others do not. But it is because education and knowledge building are the standard, default variables, that we decided to focus on regional business dynamics for the purpose of this analysis.

Business dynamics (in the form of entry and exit) is the mechanism by which outdated ideas and industry practices are replaced by new and potentially revolutionary ones. This process of creative destruction—a term and concept introduced by the economist Joseph Schumpeter—is the hallmark of a thriving and dynamic economy. This dynamic is at the heart of competition creating new industries, invigorating old ones and relegating inefficient practices to the pages of history. As such, exit and entry drive the growth and prosperity of individual firms, as well as the economy at large. This is a central focus of research in both

economics and management.

In particular, an expanding body of research focuses on the geographic dimension of entry and exit, the effect on the formation and growth of firms, and the associated implications for local and national economies. As older, inefficient and marginally productive capital is destroyed, new, efficient and productive capital is created. This implies that productivity variability is likely linked closely to job reallocation, as workers matched with unproductive capital lose their jobs and new, more productive couplings of labor and capital are made.

Table 1 shows all the variables, and the data sources, that we investigated. Using averages of multiple years reduced the cyclical effects of the Great Recession and smoothed the sometimes erratic nature of patent and FDI data. For more information on the measures, the source data and the Innovation Index 2.0 calculations, please see the report, “[Driving Regional Innovation: The Innovation Index 2.0](#).”¹

Table 1: Business dynamics and regional characteristics driving innovation (explanatory variables)

Variable name	Variable description
<i>estBr</i>	Establishment Births to Total Establishments (2007 to 2011)
<i>esttrBr</i>	Traded-Sector Establishment Births to Total Establishments (2007 to 2011)
<i>jobBr</i>	Jobs Attributed to Births to Total Employment (2007 to 2011)
<i>estBd</i>	Change in Establishment Births to Total Establishments (average for years 2007 to 2011)
<i>estX2C</i>	Establishment Expansions Divided by Contractions (2007 to 2011)
<i>estB2D</i>	Establishment Births Divided by Deaths (2007 to 2011)
<i>trestdyna</i>	Traded-Sector Establishment Dynamics: The sum of births and expansions divided by deaths and contractions (2007 to 2011)
<i>ttlSestqt</i>	High-Tech Industry Early-in-Life-Cycle Establishment Ratio: The proportion of high-tech industry establishments that are less than 5 years old (2007 to 2011)
<i>FDIinv2labf</i>	FDI Investment Index, Foreign Source: Ratio of dollars of greenfield investment to total FDI investment (2007 to 2011)

<i>FDIinv2labUS</i>	FDI Investment Index, National Source: Ratio of greenfield investment by new
<i>avgSest</i>	Average Small Establishments: The number of small establishments with less
<i>avgLest</i>	Average Large Establishments: The number of large establishments with 500
<i>prpr</i>	Proprietorship Rate: The number of nonfarm proprietors divided by the total nu
<i>prprd</i>	Change in Proprietorship Rate: The change in the proprietorship rate, showing

Source: Indiana Business Research Center

Establishment formation and dynamics

Some researchers have emphasized technological and knowledge requirements that have changed, or even destroyed, the economic viability of a region's industries, firms and jobs. But then again, these changes also present the opportunity to create new industries, firms and jobs. Labor churn improves productivity. Labor churn is an indicator that members of the workforce are bettering their employment situation. That is, workers move to more desirable and higher-wage jobs. In the same way, churn—whether measured by new businesses being established or by existing businesses expanding their workforce—provides an indicator that the region is undergoing positive economic change.

There are also churn measures that focus on employment, not establishment, counts.

In recent decades, the U.S. economy has shown secular declines in employment and business dynamics. This decline in dynamism has been well documented in the analysis of job creation rates, job destruction rates and startup entry rates. Decker et. al (2014) note that while the job creation rate averaged 18.9 percent in the late 1980s, it declined to an average 15.8 percent for the 2004–2006 period preceding the Great Recession. Similarly, the job destruction rate fell from 16.1 percent in the late 1980s to 13.4 percent in the mid-2000s.

Furthermore, Hyatt and Spletzer (2013) find evidence that the decline in employment dynamism has accelerated since 1998.

While the levels of each measure vary across sources depending on the scope and the definition used in the configuration of the relevant database, scholars find consistent downward trends in employment and business dynamics indicators. In their 2012 paper, Reedy and Strom find downward trends since the 2000s for job creation rates, business survival rates and business births (among others).

These findings contrast with the work of Hathaway, Schweitzer and Shane (2014) who focus on the rise in the number of new establishments opened by existing businesses. While they recognize the declining rate of new firm formation and the declining contribution to employment by new firms, they notice a simultaneous rise in new outlet formation and in the job creation rate at new outlets. Thus, establishment formation may—yea verily does—overstate the entrepreneurial dynamic because establishment births don't measure business formation exclusively. Rather, the measure melds business formation and business outlet expansion together.

The Great Recession elicited a wealth of research on the effects of the recession on employment and business dynamics statistics. Economic theory suggests that recessions are periods of accelerated productivity-enhanced reallocation or “cleansing.” Foster, Grim and Haltiwanger (2013) found that job creation fell much more dramatically than in prior recessions and job destruction increased less than in prior recessions. Even though productivity-enhancing reallocation was more intense in previous recessions, reallocation in the first decade of the 2000s was still productivity enhancing since less-productive establishments were more likely to exit, while the more-productive establishments were more likely to grow.

Given the wealth of research published in recent years on this topic, it is surprising to notice the lack of regional research and the lack of understanding on what is driving this decline in business dynamics. Hathaway and Litan (2014) are among the few that study the issue of declining dynamism from a regional perspective. They find that the downward trend in business dynamics is pervasive across all 50 U.S. states and in over 300 metropolitan areas since 1978. Decker et al. (2014) find that the changing firm-age distribution—more mature firms—explains a great deal of the slower pace of business dynamics.

Foreign direct investment attractiveness

Foreign direct investment (FDI) flows are relevant to innovation for at least two reasons. First, there is a transfer of knowledge, technology and know-how when an outside firm enters a regional market or adds to the production portfolio of that region. Second, it says something about the openness of a region's economy and community and whether a region is "business friendly." A possible third benefit is that many FDI greenfield investments represent large expenditures, showing that the incoming firm is either expanding or restructuring to improve productivity.

Foreign direct investment increases competition and gives rise to positive technological externalities and spillovers, thereby raising dynamic efficiency. Researchers have measured the amount of knowledge transfer and spillovers, and have found benefits in backward linkages. Often these studies look at FDI impacts in developing countries since those effects are more observable; however, even multinational firms that invest in the U.S. experience knowledge spillovers both from and to the investing firm. The knowledge spillover/transfer can happen in multiple ways: demonstration effects, worker mobility and vertical linkages. Demonstration effects occur when the host country's firms

mimic and reverse engineer a multinational firm's products and practices. Worker mobility or turnover occurs from the multinational firm training its employees then subsequently losing them to startups, other businesses or entrepreneurial ventures. Vertical linkages with multinational firms cause increased local firm productivity due to knowledge spillovers.

Within Innovation 2.0, the FDI data are related to greenfield investments and plant and equipment expansions. This concept does not include the majority of FDI flows that are related to mergers and acquisitions. These data are announced FDI investments that may or may not be realized. The data are treated, however, as though all announcements are realized.

Average small establishments

Small firms, it can be argued, are highly adaptable and can easily change their processes to incorporate new ideas. In recent years, high merger rates between small and large firms have coincided with increased technological influence of small firms. Some evidence, however, suggests these acquisitions may not be significant sources of innovation for large firms.

Average large establishments

Theoretically, a higher proportion of large businesses, defined as establishments with 500 or more employees, would positively contribute to innovation through the increased availability of funds for research and development, as well as the resources to directly employ scientists rather than hire out research services. Available data, however, do not identify whether, or the degree to which, an establishment is engaged in innovative activities. It may be that one establishment has a large, low-skilled operation while innovative activities for the same firm occur at a different location.

High-tech industry early-in-life-cycle establishment ratio

Clusters of innovative activity are closely tied to the stages of an industry's life cycle. The propensity to innovate varies depending on if the industry is in a birth, growing, maturing or declining stage. Specifically, during the early stages of an industry life cycle, there is an increase in the entry of new firms and a high amount of innovative activity.

During the early stages of an industry life cycle, new and smaller businesses have an advantage: They are better at utilizing R&D resources and turning them into innovative activity. Research shows that the type of innovation depends on how a firm is able to absorb knowledge. It is important to look at clusters of small firms, especially in the high-tech industry sectors, to understand and predict where innovation comes from. Not only do small firms incorporate R&D, but they are able to utilize knowledge from other small firms. Indeed, in the first stages of the industry life cycle, there are more inter-industry spillovers. Therefore, it is important to have a cluster of small firms in a variety of industries to encourage knowledge sharing and more innovations.

In addition to the distinction made between new firms, establishments and outlets, researchers have emphasized the difference between *small* and *young* firms. Until recently, research on employment and business profiles provided great attention to the role of small businesses in the U.S. economy. It was often argued that small businesses were the primary source of job creation. Today, however, much more attention and recognition is given to the contribution of young firms to job creation.

In 2011, Neumark, Wall and Zhang found, without consideration for firm age, an inverse relationship between net growth rates and firm size based on the National Establishment Time Series (NETS). They concluded that small firms

contributed disproportionately to net job growth. Two years later, Haltiwanger, Jarmin and Miranda (2013) used firm-age data and found no systematic relationship between firm size and growth when controlling for firm age.

Reedy and Strom (2012) follow this age-focused trend by studying young firms by their age cohorts. They find that while young firms (and establishments) that survive their first two years continue to grow and add new jobs, the rate of their employment addition has been declining for business cohorts since 1994. But this is not the whole story. While most startups exit within their first 10 years, and firms that survive remain small, a small fraction of young firms become high-growth firms, making a substantial contribution to job creation. In fact, approximately 20 percent of U.S. gross job creation is attributed to business startups and 50 percent of job creation is attributed to high-growth firms—which are disproportionately young. Along the same lines, DynEmp, a new OECD project on the dynamics of employment, highlighted that firms five years of age or younger were the primary source of job creation in 18 countries throughout the 2000s due to the role of startups and high-growth young firms.

Proprietorship

Entrepreneurship is a complex, multifaceted concept and, in an ideal world, there would be a census of entrepreneurs to gauge the true concentration of those who drive business formation and start-up companies. Many definitions exist and multiple aspects of entrepreneurship are recognized in the literature.

Researchers, depending on their conceptualization of entrepreneurship, tend to study either entrepreneurship's characteristics (e.g., innovation and growth) or outcomes (e.g., ownership and value creation).

Given the lack of consensus on how to measure entrepreneurship and that a

headcount of entrepreneurs is not available, we consider proprietorship as a proxy. Proprietorship captures the ownership aspect of entrepreneurship. It does overstate entrepreneurial activity, however. An entrepreneur would not likely purchase a hair salon or carpet cleaning franchise that has been in business for decades, while a proprietor who is interested in being one's own boss would. Entrepreneurs are dependent on capital to create and develop new businesses. Therefore, also included is a measure of local availability of capital. If a region contains many banks that are spending their funds locally, entrepreneurs will be more able to receive loans for their projects.

Researchers commonly rely on self-employment and proprietorship rates in studies of entrepreneurship due to the availability and consistency of state and national data. Research using U.S. data suggests that proprietorship is associated with greater job growth and that this effect is stronger for metropolitan counties and in times of national economic expansion. Romero and Martínez-Román (2012), exploring the determinants of innovative proprietorship, identify three levels of key factors influencing innovation in small business: the personal characteristics of the self-employed individual, the characteristics of the organization and the characteristics of the external environment.

In regard to the study of entrepreneurship and its connection to innovation, the use of the proprietorship rate is not without its limitations. All proprietors are not necessarily entrepreneurs in the traditional sense. Proprietors do not need to operate or manage their own business to qualify as such for tax purposes, nor is it the case that all proprietors have created what they claim today to be their business. Proprietors who are entrepreneurs are also not necessarily innovators. Unfortunately, it is impossible to tease out innovative entrepreneurs from non-innovative entrepreneurs using proprietorship data. Proprietorship data includes

part-time business owners, “hobby” business owners, as well as proprietors that double as wage and salary employees. Additionally, these measures do not account for the continuation or dissolution of proprietorships. Thus, the rate of proprietorship does not differentiate between new and old entrepreneurial activity, nor does it differentiate between innovative and non-innovative entrepreneurial ventures.

Outputs

Outputs are the direct outcomes and economic improvements that result from innovation activities. **Table 2** presents the dependent, or the performance variables, and the data sources that we used to measure innovation outcomes. For more information on the measures, the source data and the index calculations, please see the “[Driving Regional Innovation](#)” report.

Table 2: Performance variables measuring innovation (dependent variables)

Variable name	Variable definition
<i>GDP2emp</i>	Gross Domestic Product per Worker: Economic output per worker (2008 to 2012)
<i>GDP2empd</i>	Change in GDP per Worker: The increase (or decrease) in current-dollar GDP per worker (2008 to 2012)
<i>ttlpat</i>	Total Number of Patents Awarded (2008 to 2012)
<i>pat2emp</i>	Total Number of Patents Awarded per 1,000 Workers (2008 to 2012)

Source: Indiana Business Research Center

Gross domestic product

GDP per worker is the single most important measure of productivity available. Innovative products or processes would not be undertaken if the action would not increase wages or profits. We incorporate the current level of a county’s economic success (one might say that GDP per worker funds wages, benefits, profits and returns to intellectual property) by comparing the size of the economic pie, and also include a measure for growth in worker productivity (or,

put another way, the rate at which the pie is growing).

Patents

Patents are critical for measuring regional innovation as they represent current innovation and predict future technology and know-how developments.

Only utility patents are used. Utility patents are items intended to serve a function—in contrast to design patents, which are nonfunctional in nature and include such things as new computer fonts. Recalled patents and statutory invention patents are also excluded.

Patent counts are not water-tight measures for innovation activities in a region, particularly in areas where a single firm overwhelms the total patent count, such as Eli Lilly, the pharmaceutical giant headquartered in Indianapolis. The data also do not indicate where a patent is applied, in contrast to where the technology or intellectual property was developed—patent making versus patent using. For example, a new polymer could be developed (and patented) in New Jersey but it can be used in the manufacture of water purification equipment in Wisconsin. Arguably, both constitute innovation. Patent using, however, can only be implied by matching the technology class of a patent with a particular industry classification.

Which measures matter most?

The foregoing discussion presented the motivation or rationale for the subset of 14 of the Innovation 2.0 measures that drive or explain innovative activities. The question then becomes: Which of these measures matter most?

We conducted a statistical analysis of MSAs in the Midwest to begin the process of empirically verifying the measures in Innovation 2.0. In this and subsequent

analyses, we will strive to determine which economic dynamics, demographic forces and regional characteristics have the strongest influence on regional innovation and economic growth.

Using four of our performance measures (i.e., dependent variables), we assessed the degree to which our explanatory measures explain the variation in regional (MSA) performance. Put colloquially, we ran four models, one for each of the performance measures. The analysis consisted of two steps. For the first step, we used all of the 14 explanatory variables described above. Then we truncated the set of explanatory variables if they could not be statistically confirmed as having an influence on our performance measures. That is, only those variables that were statistically significant were retained.²

The first round of regressions containing all explanatory variables are shown in **Table 3**.

Table 3: Regression results (all variables) for Midwest metropolitan statistical areas

	Model 1 (Total patents)	Model 2 (Patents per 1,000 workers)	Model 3 (GDP per worker)	(Ch
<i>estBr</i>	-3289.342 (4487.697)	-2.863 (9.546)	-312119.077 (160802.924)	
<i>esttrBr</i>	3297.017 (2895.057)	17.117** (6.206)	152025.844 (115581.665)	
<i>jobBr</i>	-1530.750 (6993.783)	-22.558 (17.103)	233982.274 (146055.679)	
<i>estBd</i>	044.366 (628.789)	0.705 (1.219)	14007.686 (17004.025)	
<i>estX2C</i>	-857.335 (684.385)	-0.165 (1.278)	-5925.709 (28644.743)	
<i>estB2D</i>	-709.891 (492.087)	-1.480 (1.004)	-3443.295 (18479.085)	
<i>trestdyna</i>	796.526 (435.791)	0.829 (1.064)	4178.153 (21381.109)	
<i>FDlinv2labUS</i>	0.000 (0.000)	0.000 (0.000)	0.006 (0.003)	

<i>FDInv2labf</i>	-0.000 (0.000)	0.000 (0.000)	-0.005 (0.017)
<i>ttlSestqt</i>	2152.706*** (476.274)	0.168 (0.338)	29569.355*** (7646.720)
<i>avgSest</i>	1.366 (1.144)	-0.002 (0.001)	-19.188 (26.223)
<i>avgLest</i>	90.016 (87.526)	0.036 (0.149)	7115.931** (2238.645)
<i>prprd</i>	193.517 (667.559)	-0.624 (1.047)	16379.169 (24352.678)
<i>prpr</i>	804.128 (1385.186)	0.804 (1.486)	11948.386 (36330.482)
<i>Constant</i>	-902.788 (475.639)	0.865 (0.656)	63416.714*** (10685.662)
N	93	93	93
Adjusted R ²	0.624	0.128	0.373

Note: Standard errors in parentheses. Statistically significant results are shown in bold.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: Indiana Business Research Center

The second round of regression models are presented in **Table 4**.³ The degree to which the models explain the variation in the performance of the MSAs—the explanatory power of the models—ranges from poor to moderately high, as indicated by the adjusted R² values.

Table 4: Regression results (select variables) for Midwest metropolitan statistical areas

	Model 1 (Total patents)	Model 2 (Patents per 1,000 workers)	Model 3 (GDP per worker)	(Cha
<i>estBd</i>	888.908* (421.195)			
<i>estB2D</i>	-705.771* (350.141)			
<i>ttlSestqt</i>	2220.399*** (444.906)		30809.292*** (6069.521)	
<i>avgSest</i>	1.464 (0.737)	-0.002 (0.001)		
<i>esttrBr</i>		14.129* (5.491)		

<i>jobBr</i>		-23.248 (12.708)	281766.530* (128409.315)
<i>estBr</i>			-110275.314 (60727.306)
<i>avgLest</i>			7156.816*** (1576.860)
<i>Constant</i>	-713.449* (311.475)	0.826* (0.391)	59996.573*** (3641.662)
N	93	93	93
Adjusted R ²	0.648	0.175	0.414

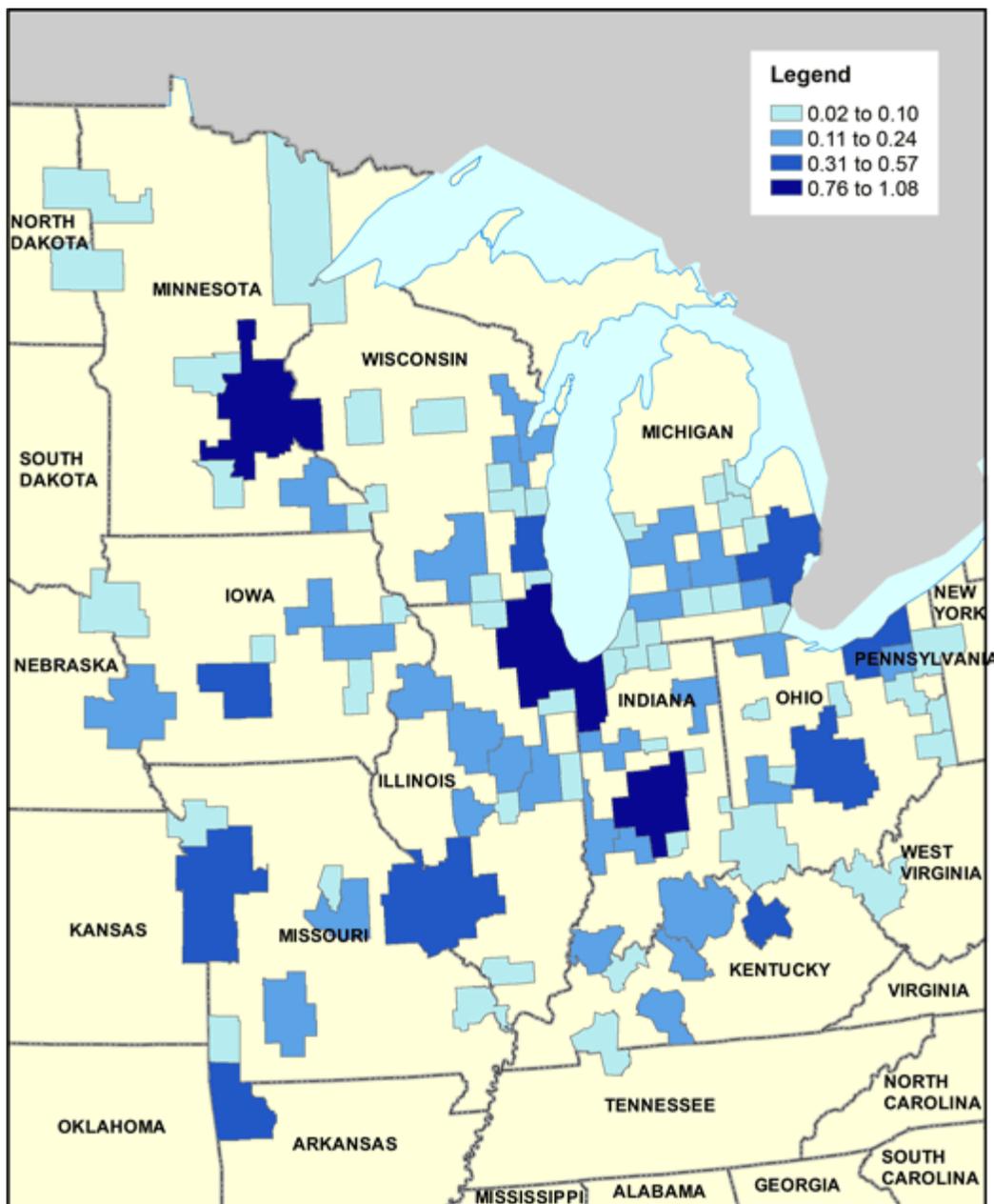
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Standard errors in parentheses. Statistically significant results are shown in bold.

Source: Indiana Business Research Center

In the two models with the highest R², the high-tech industry early-in-life-cycle establishment ratio was shown to have the strongest relationship with innovation outputs in terms of both standardized effect size and statistical significance. This makes sense intuitively as those firms that are at the leading edge of technology are also the firms that are in the high-growth stage. **Figure 1** shows this ratio across the Midwestern MSAs.

Figure 1: High-tech industry early-in-life-cycle establishment ratio for Midwestern MSAs, 2008 to 2012



Source: Indiana Business Research Center

Model 1 (Total patents)

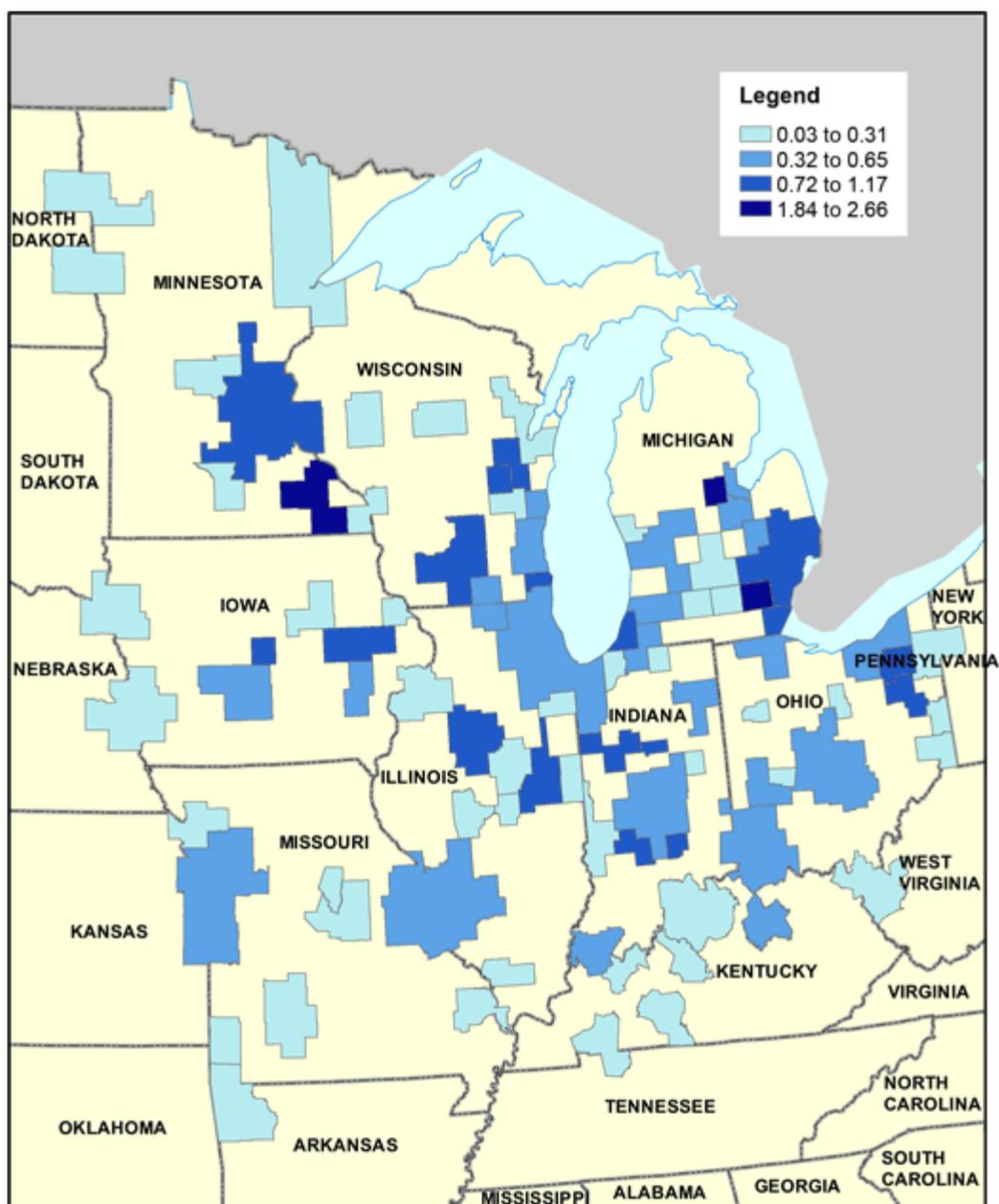
Model 1 describes total patents as a function of change in establishment births, establishment birth-to-death ratio, high-tech industry early-in-life-cycle establishment ratio, and average small establishment size. Of these, the high-tech establishment ratio has the strongest positive association with patent totals. The establishment birth-to-death ratio, a measure of establishment churn or “creative destruction,” appears to have a negative relationship with patenting activity, suggesting that creative destruction may not be positively associated with

patenting activity. This model accounts for 64.8 percent of the variation in total patents across Midwestern regions, implying that approximately one-third of regional variation in patenting is driven by factors not included in the model.

Model 2 (Patents per 1,000 workers)

Model 2 scales the number of patents to the size of the regional economy (the number of workers) to describe patenting activity as a function of traded-sector establishment birth rates, jobs attributed to births and average small establishment size. This model has low explanatory power, accounting for only 17.5 percent of the variation in patents per worker. It is likely that rates of patents per worker in Midwestern regions are driven primarily by factors unrelated to regional business dynamics as measured in this study. **Figure 2** displays the patent rate across the Midwest.

Figure 2: Patents per 1,000 workers for Midwestern MSAs, 2008 to 2012



Source: Indiana Business Research Center

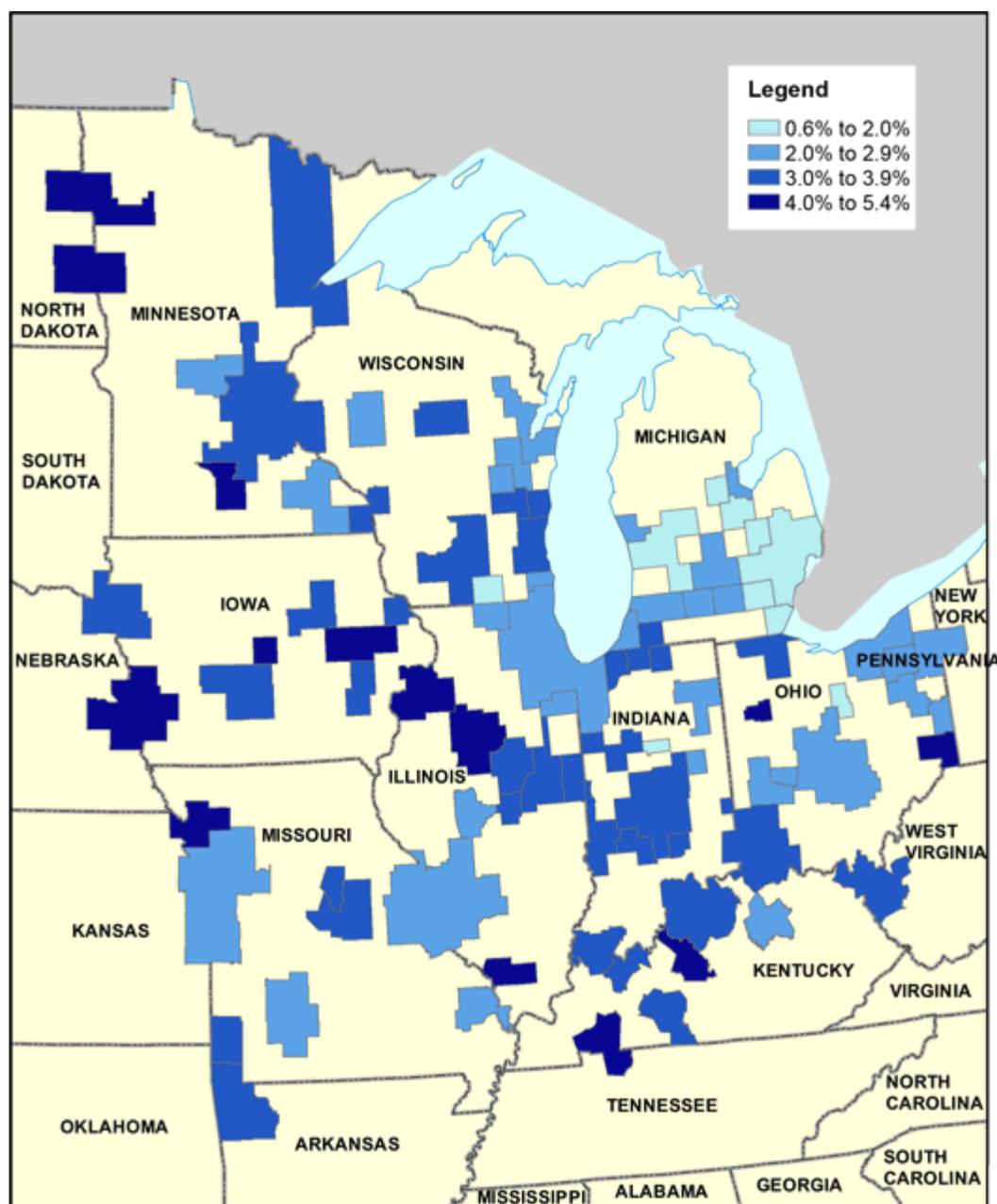
Model 3 (GDP per worker)

Model 3 describes GDP per worker as a function of change in establishment births, jobs attributed to establishment births, high-tech industry early-in-life-cycle establishment ratio and average large establishments. As with total patenting activity (Model 1), the high-tech industry variable has the strongest positive effect on GDP per worker. This model accounts for 41.4 percent of the variation in GDP per worker across Midwestern regions, giving the model moderate practical significance.

Model 4 (Change in GDP per worker)

Model 4 describes the change in GDP per worker (which is shown in **Figure 3**), our measure for productivity growth, as a function of traded-sector establishment births, change in establishment births, establishment birth-to-death ratio (a creative-destruction proxy) and average large establishments. Interestingly, all of these variables except establishment birth-to-death ratio are shown to have a negative relationship with the change in GDP per worker.

Figure 3: Annual average change in GDP per worker for MSAs in the Midwest, 2002 to 2012



Source: Indiana Business Research Center

However, this model has relatively low explanatory power (adjusted $R^2 = 27.4$ percent), implying that the statistical analysis of GDP per worker could be improved through a more complete and relevant array of explanatory variables or more advanced methodology. One may note that the negative relationship between all the explanatory variables (except birth-to-death ratio) may point to the fact that these economic phenomenon do not necessarily boost productivity. Large firms may lag in raising wages and profits. New establishments may not be the most productive relative to other businesses. On the other hand, in regions where business formation exceeds business destruction, the productivity of the new establishments more than compensates for the lost productivity of the disappearing (and underproductive) establishments.

These models were tested for violations of the general linear regression model.⁴ Because several of the variables or measures within Innovation 2.0 are multiple variations on a theme that a practitioner may wish to explore, there may be an issue of too much overlap among some of the variables. For example, there is a pairwise correlation coefficient of 0.90 between the establishment births and establishment birth-to-death ratio variables.

It is possible that these models are incompletely specified in terms of explaining the drivers of regional innovation in the Midwest. The Innovation Index 2.0 contains many other variables, including education and demographic variables, that also influence patenting activity and GDP per worker. Future studies building on our simple example will incorporate these and other variables to create a more complete picture of regional innovation.

Importantly, these models do not indicate a causal relationship between these

innovation inputs and outputs as defined in this study. Only Model 1 is able to explain more than half of the variation in an innovation output using the selected suite of Innovation 2.0 variables. Furthermore, there is the “which came first” concern associated with this simple ordinary least squares (OLS) regression methodology. For example, we see a strong positive relationship between high-tech early-in-life-cycle establishments and innovation outputs. This might imply that a region with many innovative new businesses will see higher patenting rates as a result of those businesses. Or, it may be that a high concentration of patenting activity in a region precedes the birth of new establishments. Our averaged measures and linear regression models seek to broadly describe regional innovation characteristics in terms of inputs and outputs.

While we cannot make any causal inferences using these models, we can conclude that there is great potential for empirical analysis of regional innovation using our Innovation 2.0 data set and linear regression methodology, as even this simplistic approach reveals intriguing relationships between innovation variables across Midwestern regions. For example, it appears that high-tech early-in-life-cycle establishments (*ttlSestqt*), establishment birth rates in the traded industries (*esttrBr*) and the large establishment ratio quotient (*avgLest*) can help to explain some of the variation in innovative performance in these regions.

To help bring the analysis closer to Indiana, we looked at how five of the most populous Indiana cities (MSAs) performed on these three variables and the change in GDP per worker (*GDP2empd*), comparing them to the top and bottom MSAs in the Midwest. **Table 5** ranks the top and bottom among the 93 Midwest MSAs for the four selected economic indicators.

The Indianapolis MSA in particular ranks well for two indicators (third and

fourth, respectively), reflecting the recent establishment growth in high-tech and traded sectors. MSAs in Indiana in general rank relatively well compared to other Midwestern states. Columbus and Kokomo reflect that they are large company towns, even for the Midwest, as both are in the top five MSAs for average large establishments per 10,000 workers. In terms of GDP per worker, Indiana cities are in the middle of the pack, while Michigan was still reeling from the Great Recession given the range of years ending in 2012.

Table 5: Ranking of top, bottom and five most populous Indiana MSAs in the Midwest for four selected variables

	Top Midwest MSAs	Bottom Midwest MSAs
High-tech industry early-in-life-cycle establishment ratio	(1) Minneapolis-St. Paul-Bloomington, MN-WI	(93) La Crosse-Onalaska, WI-M
	(2) Chicago-Naperville-Elgin, IL-IN-WI	(92) Danville, IL
	(3) Indianapolis-Carmel-Anderson, IN	(91) Grand Forks, ND-MN
	(4) Columbus, OH	(90) Lima, OH
	(5) Detroit-Warren-Dearborn, MI	(89) Dubuque, IA
Traded sector establishment births	(1) Fayetteville-Springdale-Rogers, AR-MO	(93) Weirton-Steubenville, WV-O
	(2) Ann Arbor, MI	(92) Huntington-Ashland, WV-K
	(3) Columbia, MO	(91) Wheeling, WV-OH
	(4) Indianapolis-Carmel-Anderson, IN	(90) Decatur, IL
	(5) Chicago-Naperville-Elgin, IL-IN-WI	(89) Battle Creek, MI
Average large establishments	(1) Columbus, IN	(93) Cape Girardeau, MO-IL
	(2) Oshkosh-Neenah, WI	(92) St. Joseph, MO-KS
	(3) Sheboygan, WI	(91) La Crosse-Onalaska, WI-M
	(4) Kokomo, IN	(90) Grand Forks, ND-MN
	(5) Weirton-Steubenville, WV-OH	(89) Fargo, ND-MN
Change in GDP per worker	(1) Peoria, IL	(93) Flint, MI
	(2) Ames, IA	(92) Saginaw, MI
	(3) Grand Forks, ND-MN	(91) Ann Arbor, MI
	(4) Cedar Rapids, IA	(90) Mansfield, OH
	(5) Fargo, ND-MN	(89) Kokomo, IN

Note: Indiana MSAs are shown in bold in the top MSA/bottom MSA columns.

Source: Indiana Business Research Center

Conclusion

Innovation 2.0 utilizes a vast amount of data to create tools for economic development practitioners to help guide their strategic planning. The motivating principle is that innovation helps to energize a regional economy. We have summarized the rationale for including many concepts and measures in a broad measure of innovation.

We also performed simple statistical modeling to try and determine what forces and phenomenon help to explain why some Midwestern MSAs performed well in terms of innovation and productivity growth and others did not. We narrowed a slate of 14 business profile and dynamics variables—possible forces and phenomenon—down to just a handful. We found that these factors were not particularly good in explaining innovation and economic performance in the Midwest.

The analysis moved from simply providing a theoretical rationale for what drives innovation to what matters more based on empirical relationships. This last step, we hope, provides something of a case study in how to use the Innovation 2.0 data that serves as the foundation for the index.

What do the data—the evidence—tell us about the direction we should go or the policies we should pursue? Does the fact that the three bottom MSAs in the Midwest for births of establishments in traded industries are in the Appalachian region of Kentucky, Ohio and West Virginia tell us something about that region's possible future? Does it say anything about possible vulnerabilities if a small region is dominated by a few large firms?

Innovation 2.0 provides a set of analytic tools, available at <http://statsamerica.org/ii2/>, that can help regional leaders reach a strong consensus on regional strategic direction. One can use data and analytical tools as corrective lenses to see and understand a region's weaknesses, strengths and potential. In this way, data and analysis can inform stakeholders' collective action toward a common vision and can guide complex decision-making at a regional level.

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Notes

1. Indiana Business Research Center, "Driving Regional Innovation: The Innovation Index 2.0," August 2016, <http://statsamerica.org/ii2/reports/Driving-Regional-Innovation.pdf>.
2. These were significant at the $p < 0.10$ level.
3. They are significant at the $p < 0.05$ level.
4. All models were calculated using robust standard errors to account for any potential heteroscedasticity in the error terms. Variance inflation factors (VIFs) indicate that there may be an issue of near multicollinearity between the establishment births and establishment birth-to-death ratio variables in Models 1 and 4. Interestingly, the parameter estimates for these variables have opposite signs in the models where they appear—it may be that these measures cancel one another out to some degree in a simple OLS approach such as ours.

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Where did they go? Industrial change and worker transitions

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The February 2016 announcement that Carrier Corporation was moving their operations from the west side of Indianapolis to Mexico angered affected workers, frustrated policymakers and surprised people in both Indiana and the nation. Many have wondered: What will become of those workers?

We can shed some light on what the future may hold for such dislocated manufacturing workers with a retrospective look at the recent past. We investigated the dynamics of change in Indiana manufacturing employment pre- and post-recession. The years between 2003 and 2014 were chosen and we focused on these questions:

1. As the sector shed jobs, did the displaced workers transition to markedly different industries?
2. Did they go back to school or participate in job-training programs offered by the government?

3. If so, how did those actions affect their subsequent employment in Indiana?

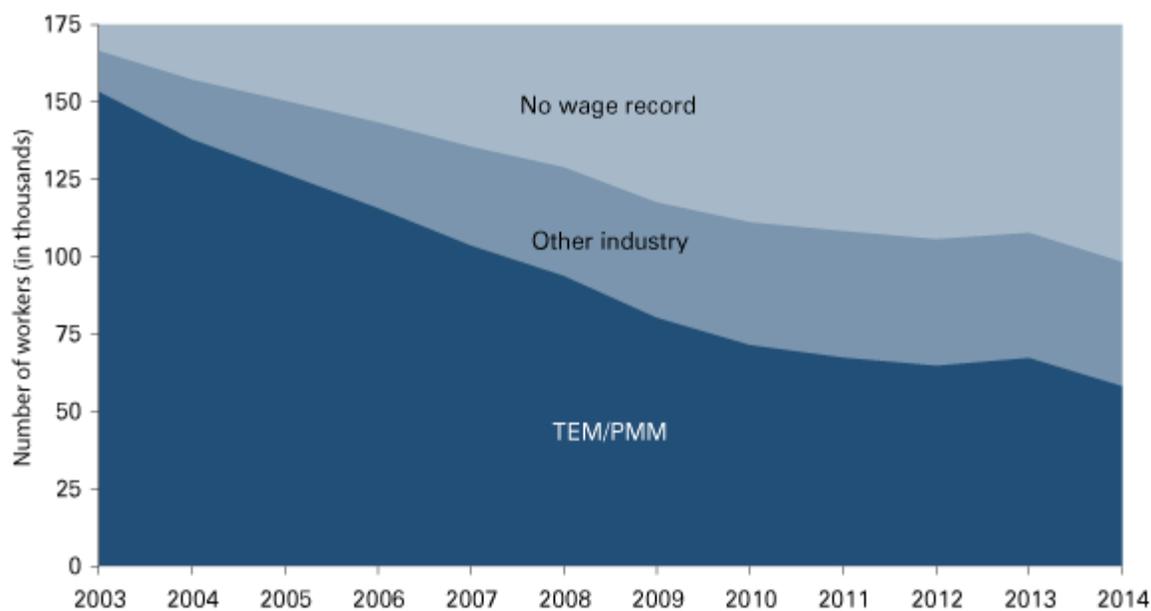
To identify worker transitions (and as part of the Workforce Data Quality Initiative of the U.S. Department of Labor's Employment and Training Administration), we used integrated administrative data from the Indiana Department of Workforce Development (IDWD) and the Commission for Higher Education. The resulting data set included unemployment insurance claims, quarterly industry and worker status, and degree attainment from Indiana's public colleges and universities. A cohort of workers was created for those employed in two of Indiana's most significant manufacturing industries—transportation equipment (TEM) and primary metals (PMM)—from 2001 through 2002 (eight quarters). The resulting cohort size of 174,865 was tracked from 2003 through 2014, and we followed changes in employment, industry and the pursuit of postsecondary public higher education.

Tracking transitions

Many of the original cohort workers continued to work in TEM and PMM between 2003 and 2014, while others switched to different manufacturing industries or to an industry outside the manufacturing sector. Some no longer appeared on an Indiana payroll. Due to the current limitations of these administrative data, we can only suggest that the latter found jobs in another state, stopped working altogether due to retirement or other factors, became self-employed, or perhaps even died.

Over the span of 12 years, we can quantify that, from the original cohort of workers (174,865), 33 percent were still working in TEM or PMM by 2014. Another 23 percent had transitioned to either another manufacturing industry or another sector, and by 2014, 44 percent of the original group had no Indiana payroll record (see **Figure 1**).

Figure 1: Cohort employment by dominant industry



n=174,865

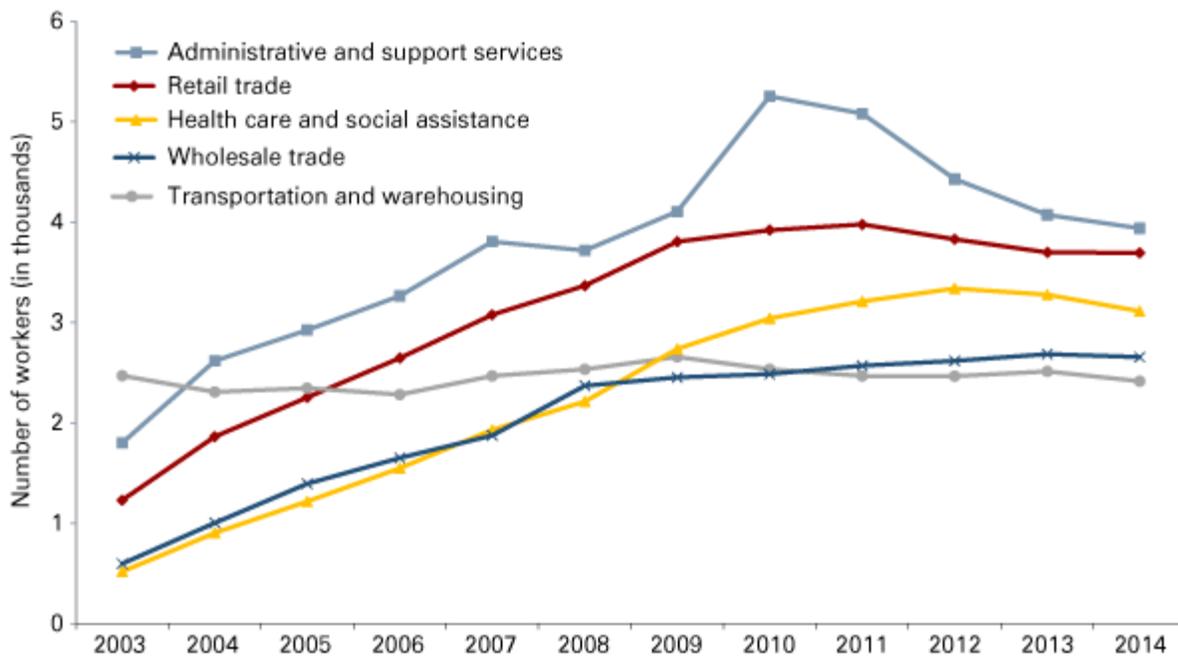
Note: The dominant industry is the industry in which a worker is employed for the majority of quarters in a given year. (If a person worked the same number of quarters in multiple industries, then we used the industry from the last quarter.)

Source: IBRC, using data from the Indiana Department of Workforce Development

By 2014, 16 percent of the original group was working outside of the manufacturing sector. **Figure 2** shows the most common sectors to which these workers transitioned, which included:

- Administrative and support services
- Retail trade
- Health care and social assistance

Figure 2: Top sectors (other than manufacturing) to which the cohort transitioned



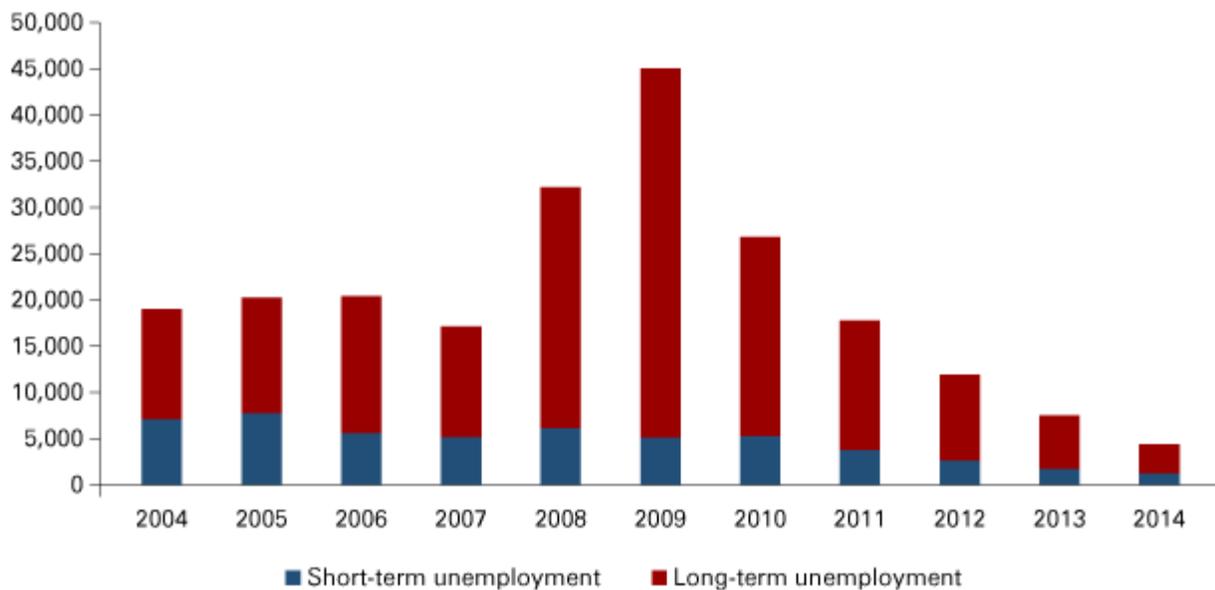
n=174,865

Source: IBRC, using data from the Indiana Department of Workforce Development

Unemployment experience

It is no surprise that unemployment among our cohort peaked during the recession (see **Figure 3**). In 2009, approximately 45,000 of the original TEM/PMM cohort workers received paid unemployment benefits. Over the span from 2004 to 2014, 43 percent of the cohort workers (75,729) received paid unemployment at least once. (Unemployment claims only became available in the database in 2004; thus the slight shift in the time span for unemployment experience.)

Figure 3: Cohort unemployment claimants



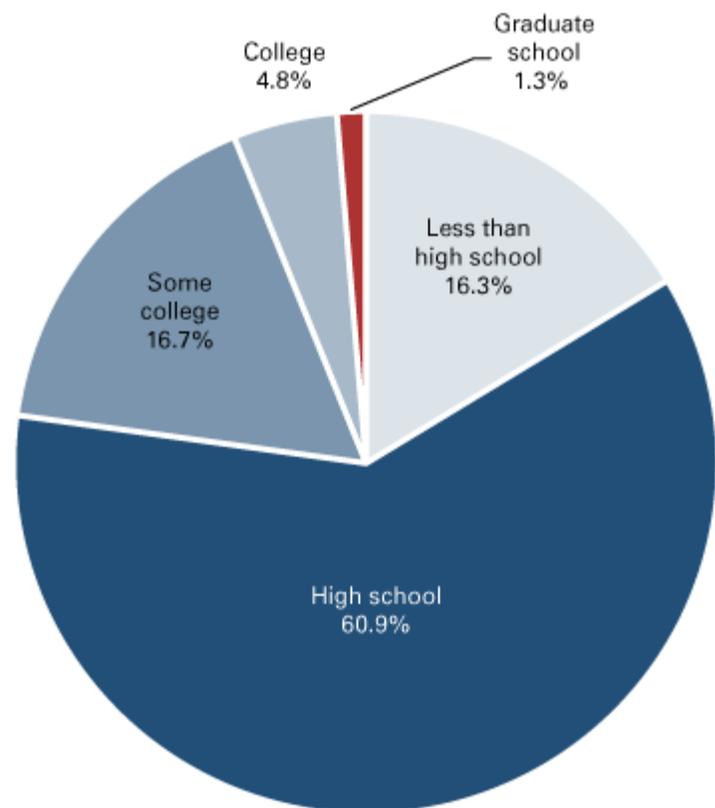
n=174,865

Note: Long-term unemployment is defined as receiving unemployment benefits for more than one month during the year.

Source: IBRC, using data from the Indiana Department of Workforce Development

Of the cohort workers who received unemployment benefits between 2004 and 2014, the majority indicated high school as their highest education attainment (61 percent), as shown in **Figure 4**.

Figure 4: Education level of cohort unemployment claimants (self-reported at time of filing for unemployment), 2004 to 2014



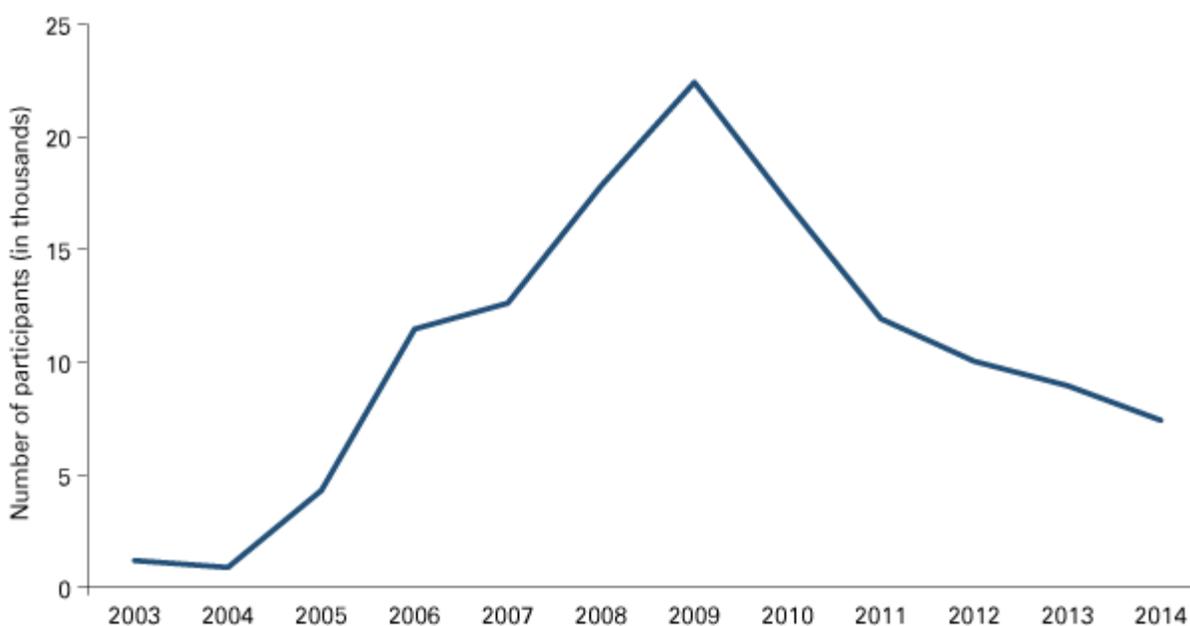
n=222,368 (this is the sum of paid unemployment filings for the cohort)
Source: IBRC, using data from the Indiana Department of Workforce Development

Job assistance programs

One-third of the original cohort, or 57,845 workers, enrolled in job assistance programs managed by the Indiana Department of Workforce Development.

Figure 5 shows the number of cohort workers enrolled in job programs between 2003 and 2014.

Figure 5: Cohort enrollment in job assistance programs



n=174,865
Source: IBRC, using data from the Indiana Department of Workforce Development

After exiting the job assistance program(s), 57 percent returned to the manufacturing sector, while the remainder transitioned to the administrative and support, retail, or health care and social assistance sectors.

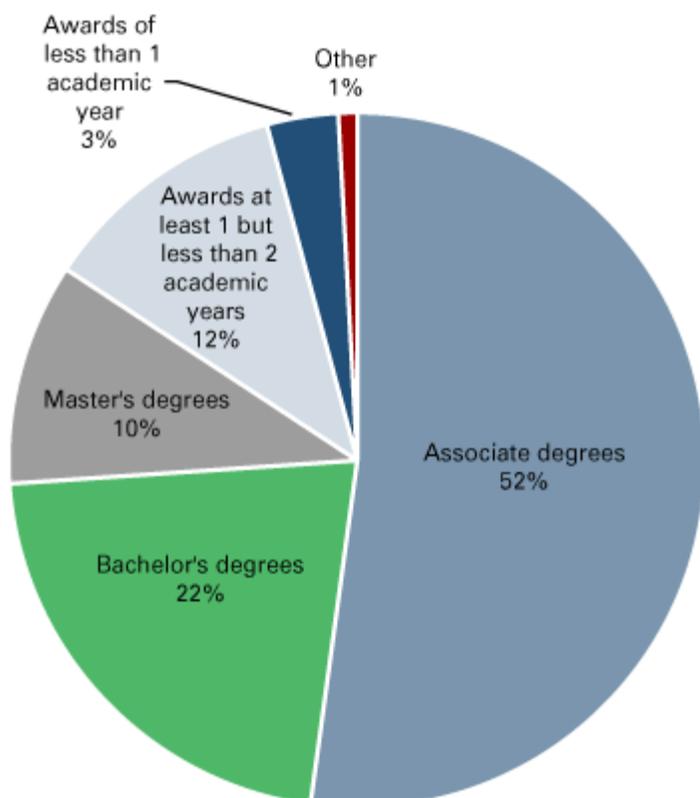
Education

Among the initial cohort of 174,865 workers in TEM/PMM, about 5,000 (3 percent) graduated from a public college or university in Indiana between 2003 and 2014.¹ It bears noting that the data set included only graduation from an Indiana public institution, while some workers in the cohort may have attained

certifications or degrees from private colleges, proprietary schools, colleges in other states or online.

Of this group pursuing postsecondary public education, 52 percent earned an associate degree (see **Figure 6**).

Figure 6: Postsecondary degrees earned by the TEM & PMM cohort graduates, 2003 to 2014



n = 5,041

Source: IBRC, using data from the Indiana Commission for Higher Education

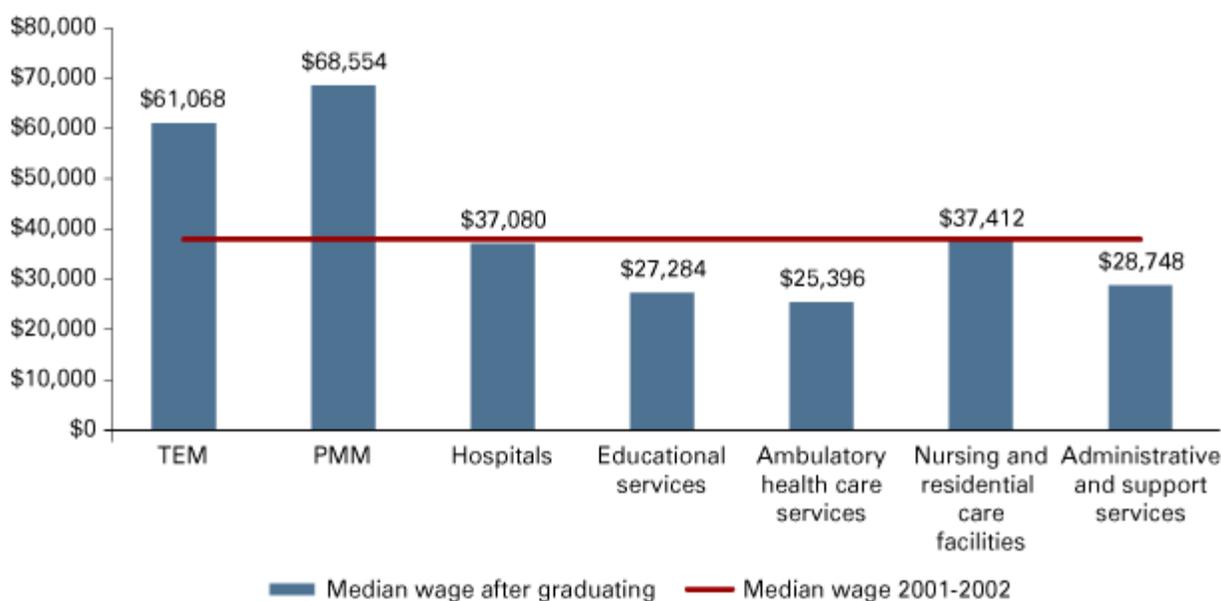
Most common fields of study? Business, health professions and engineering technologies topped the list. Both men and women pursued business-related degrees in similar numbers, but three times as many women received degrees in health professions, while engineering technology degrees were predominantly received by men.

The age profile of this group was dominated by 30-somethings (39 percent), followed by those in their 40s at 33 percent. (Note that these are the age ranges

when they received their degree.) Only 9 percent of the graduates were under age 30, and these individuals were more likely to pursue degrees in engineering and computer and information sciences.

One year post-graduation, most of these workers found jobs in manufacturing, health care and social assistance, and educational services. For the graduates who returned to the manufacturing sector, half returned to TEM and a fourth to PMM. Notably for them, this was also where the highest median wages one year post-graduation were to be found (see **Figure 7**).² Why transition to another industry like health care or education services when higher wages are to be had in manufacturing?

Figure 7: Annualized median wage one year after graduating for top industries



n = 5,041

Note: No adjustments were made for inflation.

Source: IBRC, using data from the Indiana Department of Workforce Development

Conclusion

By tracking a cohort of workers in these two significant Indiana manufacturing industries over 12 years, we found a strong and persistent tendency to re-enter the manufacturing sector and, in particular, the TEM and PMM originating

industries of the cohort. This held true after unemployment due to layoffs or closings and even after pursuing a college degree or certificate.

With high wages, it isn't difficult to see why workers returned to these industries, which have recovered a significant share of the jobs lost during the Great Recession. We look to conduct additional research to expand on the education component of this work and to flesh out the effect of training and college on wages. We also anticipate that as states throughout the Midwest, including Indiana, continue to pursue cross-state data sharing, that we may then be able to chart the work and education pathways more fully post-recession and post-college.

Notes

1. The data set used did not include the initial enrollment date, so it is unknown whether degrees were pursued part-time or full-time.
2. Wage information for the graduates includes only those who worked in one industry for three consecutive quarters out of six in the year and a half after graduating. The wages are annualized using the wages earned in the middle quarter.

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