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The Importance of Education for the Unemployed

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INDIANA BUSINESS REVIEW

from Knowledge Creation to Innovation

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From the Editor

Cliché: knowledge is power. New cliché: knowledge is empowerment.

Both articles presented to you in this issue focus on knowledge and education. The first looks at "knowledge production" in our universities and the spillover effects that can be seen, most notably within an hour's drive of the institution. Indiana is shown to be uniquely situated in this regard, having its own top-tier universities and being so close to those in Chicago.

Knowledge, as measured by degree attainment, is once again shown to be empowering for those seeking to be re-employed, particularly after the latest recession—which for many didn't end until last year when businesses began hiring again in earnest. While many of our readers likely understand deeply the empowerment of education past high school, the article provides deeper analytical insights on the duration of unemployment when one does or doesn't advance skills that are in demand by employers.

Fair warning that there are—egads—formulas and caveats. These pages do, after all, provide research-based analysis, but in the context of things deemed important to our state.

Knowledge Creation and Innovation in the Hoosier State

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Like it or not, the global economy is increasingly knowledge-based. And, in the future, knowledge will become even more important. This article looks at the role that knowledge-producing institutions may play in creating a competitive region and enhancing economic performance.

Does knowledge production at institutions like universities or research and development (R&D) facilities lead to innovation? Does it lead to more innovative activities the closer one is to those knowledge anchor institutions?

It is often suggested that the intensity of knowledge production and its related innovative activities depends upon the geographic proximity of knowledge and information sources. On the other hand, with the rapid development of communication technologies, the importance of geographic proximity on innovative outcomes would be greatly reduced.

Does distance matter? This article proposes a measure for the importance of proximity to knowledge creation and explains how it may be useful for business and macroeconomic policies that relate to technological innovations. We use this measure to see if there is a geographic link between knowledge creation and innovation for Hoosiers.

Review on Knowledge and Proximity

Laboratories and universities that produce knowledge are tangible: One can count the number of scientists in white lab coats, the number of microscopes or length of a linear accelerator. One cannot see, much less count, the flow of knowledge. That said, the diffusion of knowledge is important for creating new products or services. Thus, academic researchers have been interested in measuring knowledge production and diffusion. Many of these researchers have used the number or rate of patents as a metric for knowledge creation (for example, Bontazzi & Peri, 2003; Jaffe, 1986; Jaffe et al., 1993).

According to Krugman (1991), knowledge flows are invisible: "They leave no paper trail by which they may be measured and tracked, and there is nothing to prevent theorists from assuming anything about them that she likes…" Tracking these invisible knowledge flows was pioneered by Jaffe (1986). Patent citations are something of a paper trail for knowledge spillovers. But using patent citations as a gauge to measure the spillover from creating knowledge and innovation is not perfect: "Only a small fraction of research output is ever patented. In particular, much of the results of very basic research cannot be patented" (Jaffe et al., 1993).

Proximity is also critical to the notion of knowledge spillovers. Many researchers explicitly incorporate geographic proximity into measuring the impact of knowledge creation sources. Knowledge is embedded in people and, as a result, the face-to-face interaction of people is needed in the exchange and diffusion of knowledge, for example, within professional associations and communities (Bontazzi & Peri, 2003; Pond et al., 2009).

There are several ways universities as knowledge producers can measure their potential or actual effect on innovation.

1. The number of STEM degrees an institution graduates. While many, if not most, of the graduates would get jobs far removed from the degree-granting university, the number of STEM graduates would reflect the STEM programs and faculty that would diffuse knowledge locally.
2. The number of patents that the university itself files.
3. The number of technology startups by faculty or students that can be attributed to the university. Many large universities support innovation centers and technology parks.
4. The level of research and development funding a university receives to conduct scientific exploration. University R&D expenditures may also help to develop collateral businesses, collaborative networks and supply chains in the surrounding area.

> **"It is often suggested that the intensity of knowledge production and its related innovative activities depends upon the geographic proximity of knowledge and information sources.**

Given that we are attempting to determine knowledge spillovers, university R&D expenditures may be the most direct and comprehensive metric for determining the level of innovative activities in a locale. The question then becomes, how far away are the effects of R&D expenditures felt? University knowledge creation may also spill over to neighboring counties or regions. Many researchers attempted to quantify such

Table 1: Data Sources and Summary Statistics

Description	Source	Mean	Std. Dev.	Min.	Max.
Output Measure					
Number of patents per 1,000 workers	3	0.30	0.31	0	1.92
Input Measures					
Knowledge Spillovers					
Has university R&D spending (0 or 1)	7	0.17	0.38	0	1
Knowledge spillovers with 50-mile cutoff	7, 11	34.85	28.47	0.00	188.00
Knowledge spillovers with 100-mile cutoff	7, 11	109.95	48.47	23.70	239.60
Knowledge spillovers with 250-mile cutoff	7, 11	293.42	57.70	174.10	410.20
Human Capital					
Population share of age 25 and older with bachelor's and above degrees	4, 8	0.11	0.05	0.05	0.35
Has STEM programs (0 or 1)	4	0.29	0.46	0	1
STEM graduates, share of population	4, 8	0.00	0.00	0.00	0.02
High-Tech Index					
Employment share in high-tech industries	2	0.05	0.03	0.00	0.19
Employment share in technology-related occupations	1	0.08	0.02	0.04	0.18
Has large high-tech firms (0 or 1)	9	0.23	0.42	0	1
Number of large high-tech establishments per 1,000 workers	2, 9	0.01	0.02	0	0.13
Number of small high-tech establishments per 1,000 workers	2, 9	1.50	0.67	0.00	4.84
Small high-tech establishment quotient	2, 9	0.99	0.15	0.00	1.18
Establishment Formation					
Share of establishment births	10	0.07	0.01	0.04	0.12
Share of employment from establishment births	10	0.03	0.01	0.01	0.06
Proprietorship					
Share of proprietorship relative to total employment	6	0.21	0.08	0.07	0.50
Venture Capital					
Has venture capital investment (0 or 1)	5	0.14	0.35	0	1
Venture capital per $1,000 GDP	5, 6	0.05	0.20	0	1.09
Population Density					
Population density (per square miles)	8	177.70	281.59	21.80	2279.60

N=92
Source: 1) IBRC Occupational Statistics, 2) IBRC QCEW-Complete Employment Estimates, 3) U.S. Patent and Trademark Office, 4) U.S. Department of Education (IPEDS), 5) ThompsonOne, 6) U.S. Bureau of Economic Analysis, 7) National Science Foundation, 8) American Community Survey (U.S. Census Bureau), 9) County Business Patterns (U.S. Census Bureau), 10) Business Dynamics Statistics (U.S. Census Bureau), 11) IBRC distance decay function

knowledge spillovers by constructing different measures that attenuate the R&D effects as the distance from the research university and its neighborhoods increases (Anselin et al., 1997, 2000; Audretsch et al., 2005; Fischer & Varga, 2003; Woodward et al., 2006).

Anselin and colleagues (1997) find that university R&D spillovers positively affect patent and innovation creation in the regions within the university's proximity extending over 50 miles. Woodward and colleagues (2006) suggest that the optimum radius for the effect of university R&D on new plant formation is 60 miles. The effect of distance, however, may also depend on the type of industry.

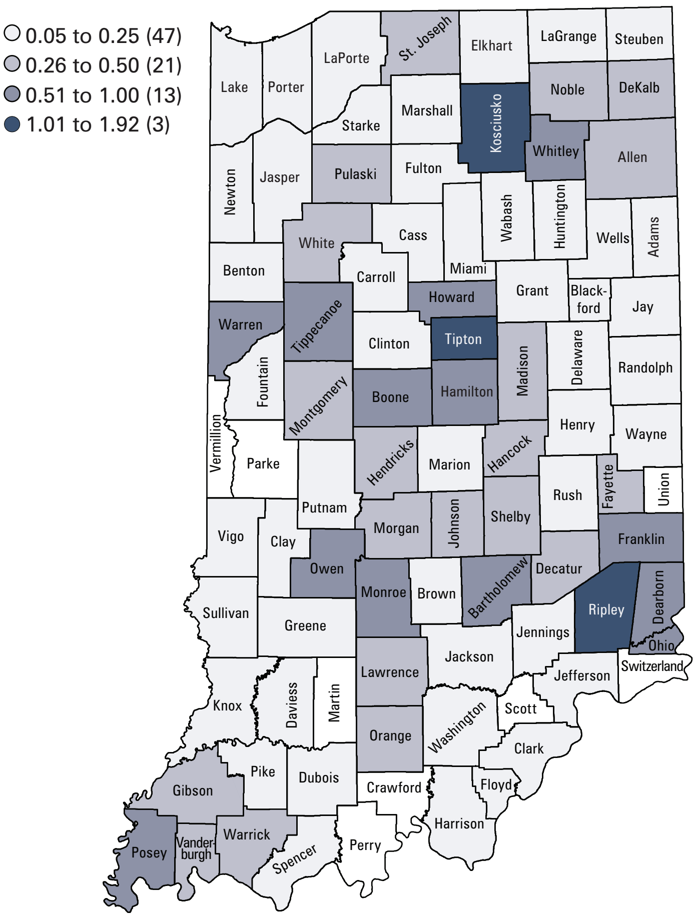
Empirical Analysis and Findings

The critical core assumption of the causal relationship is that R&D produces knowledge and knowledge promotes innovation and that innovative activities culminate in creating patents.

Thus, in our exploration of knowledge spillovers in Indiana, we use university R&D expenditures as the foundation for our metric of knowledge spillovers and use a decay function to reflect the diminishing influence of those expenditures—and, thus, the university—as the distance from the university increases. In other words, university-based knowledge has a positive spillover effect on innovation, which is measured by patenting activities.

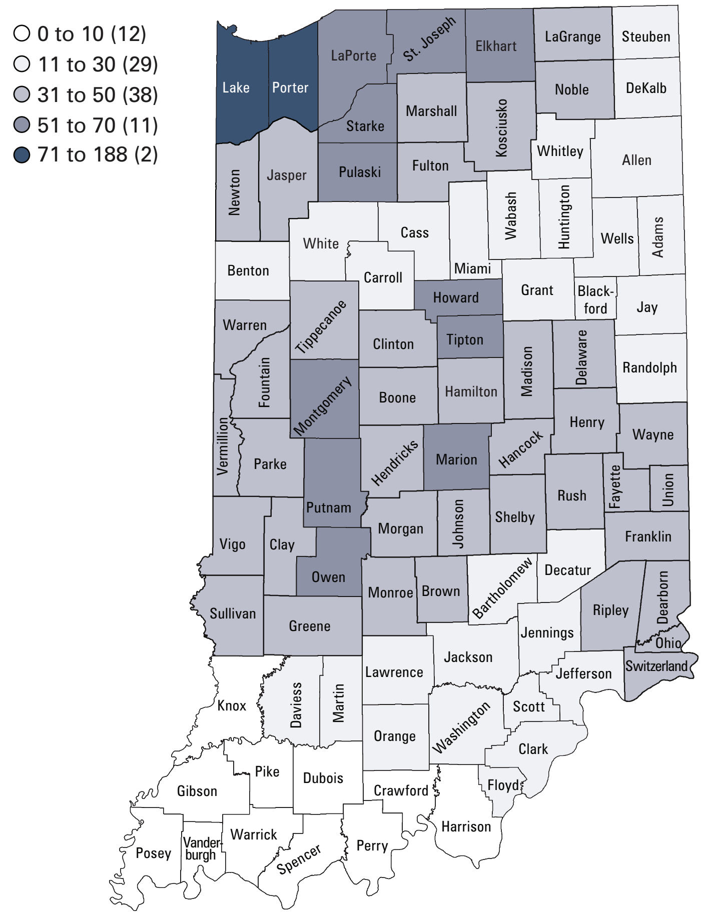
University-based knowledge spillovers are calculated using university R&D spending, weighted by the distance between the university and the center of the county selected. We incorporated R&D spending in the following

Figure 1: Number of Patents per 1,000 Workers, 2010-2011 Average



Source: IBRC, using U.S. Patent and Trademark Office data and IBRC QCEW-complete employment estimates

Figure 2: University-Based Knowledge Spillovers, 50-Mile Radius, 2011-2013 Average



Source: IBRC, using National Science Foundation data

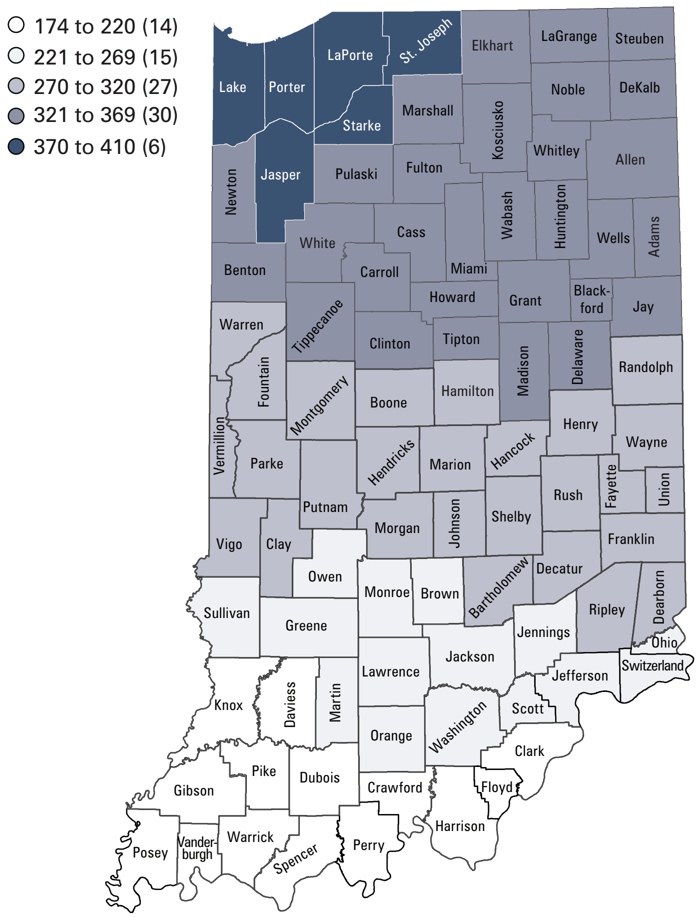
fields: engineering, geosciences, life sciences, math and computer science, and physical science. Higher scores represent regions close to universities with high R&D spending in the science and engineering fields. We tested for the effect of distance by using three distance thresholds for our knowledge spillover variable: within a 50-, 100- and 250-mile radius of the county with the university.

Another way to conceptualize the path from R&D to patents is a knowledge production function (KPF). A production function in economics is something like a recipe: Add inputs, like eggs and cheese, and you get an output, like an omelet. The KPF output is the number of patents generated in each Indiana county expressed as a linear combination of several input measures, one of which is university-based knowledge spillovers (KSPL). Other inputs include educational attainment of a county's population, the occupational mix, the number of (and the employment in) high-tech firms, and venture capital investment in the area. **Table 1** reports the complete list of inputs, data sources and summary statistics.

Figures 1 through **5** present key data for the state. **Figure 1** shows patent creation in the state, scaling the number of patents by the number of workers in the county. We see that the counties with the higher tech industries—medical devices, in particular—are the patenting hot spots. We also see that more rural counties with relatively few workers outshine many larger cities in the state. While university towns are well represented, it appears that patent rates are more strongly driven by industry, not academia.

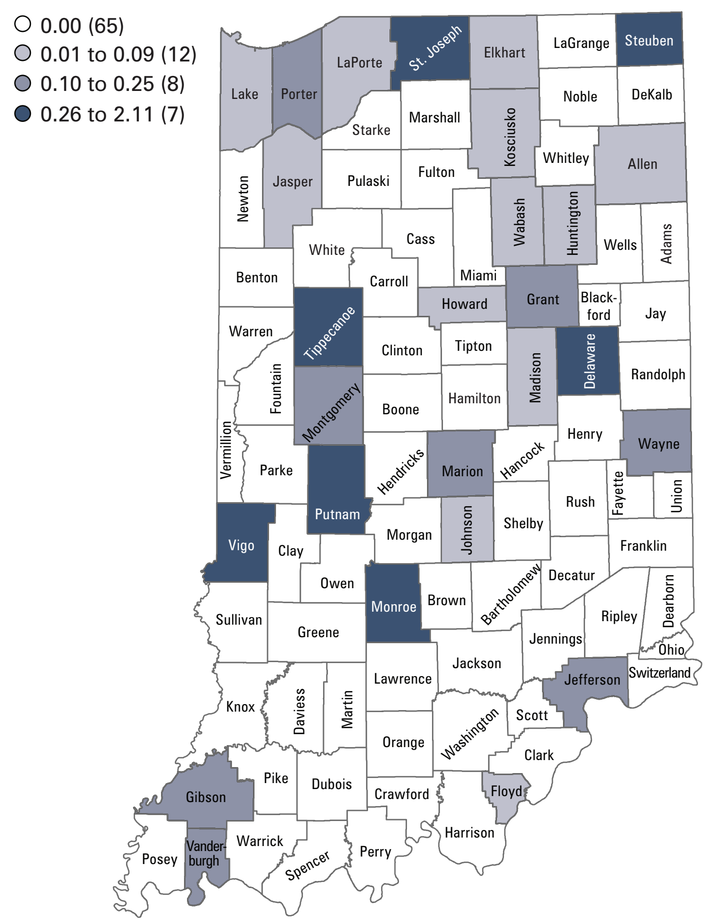
Figures 2 and **3** show two of the three distance threshold measures for university knowledge spillovers. For the 50-mile radius, we see that counties close to Chicago would be the region that, if proximity matters greatly, would benefit the most from the R&D and innovation activities in Chicagoland. Somewhat surprisingly, the two large state research

Figure 3: University-Based Knowledge Spillovers, 250-Mile Radius, 2011-2013 Average



Source: IBRC, using National Science Foundation data

Figure 4: STEM Degrees Awarded as a Percent of Total Population, 2010-2012 Average



Source: IBRC, using U.S. Department of Education (IPEDS) and U.S. Census Bureau (American Community Survey) data

"The effects of Chicago's university R&D overwhelm the effects of R&D at Indiana's universities, thus creating a gradual diminishing of the spillover score as one moves south through the state.

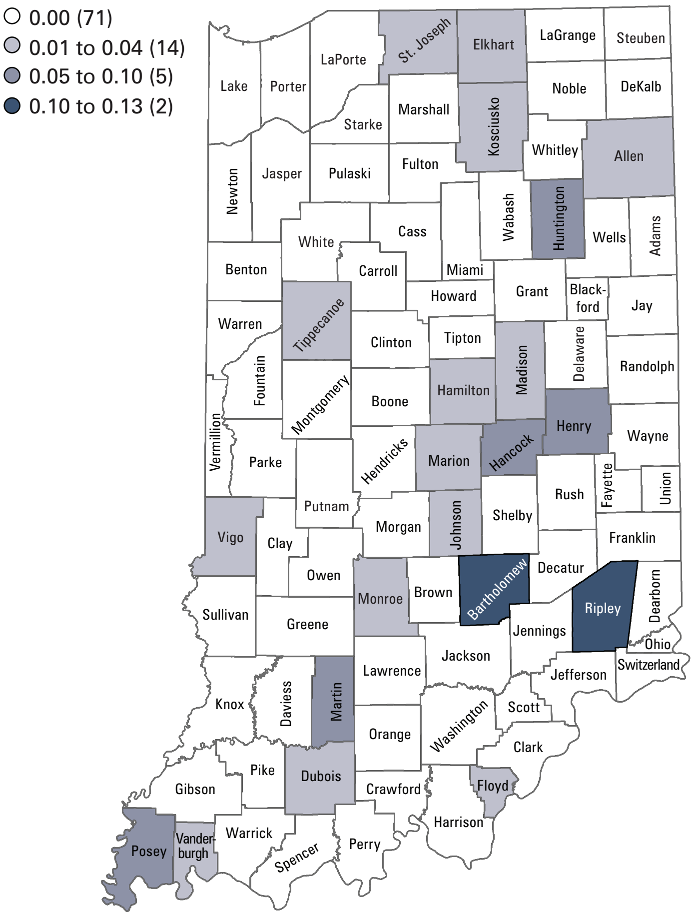
universities (Indiana University in Monroe County and Purdue University in Tippecanoe County) did not produce high scores in their respective home counties but rather seemed to "heat up" the counties where their expected spillover effects would overlap.

In **Figure 3,** we see what happens as we expand the expected scope of spillover effects. With a much larger radius, the effects of Chicago universities are felt in many more northern counties in Indiana, which get much higher spillover scores. Moreover, the effects of Chicago's university R&D overwhelm the effects of R&D at Indiana's universities, thus creating a gradual diminishing of the spillover score as one moves south through the state.

Figure 4 presents something of a proxy value for the science and technology activities in a county. The number of STEM degrees awarded as a proportion of the local population is a measure for the concentration of people who can create knowledge and, as a result, measures the potential or capacity to innovate new products, services and production processes. Not surprising, and in contrast to the knowledge spillover scores and patenting rates, the home counties of the universities in the state are the STEM graduate hot spots.

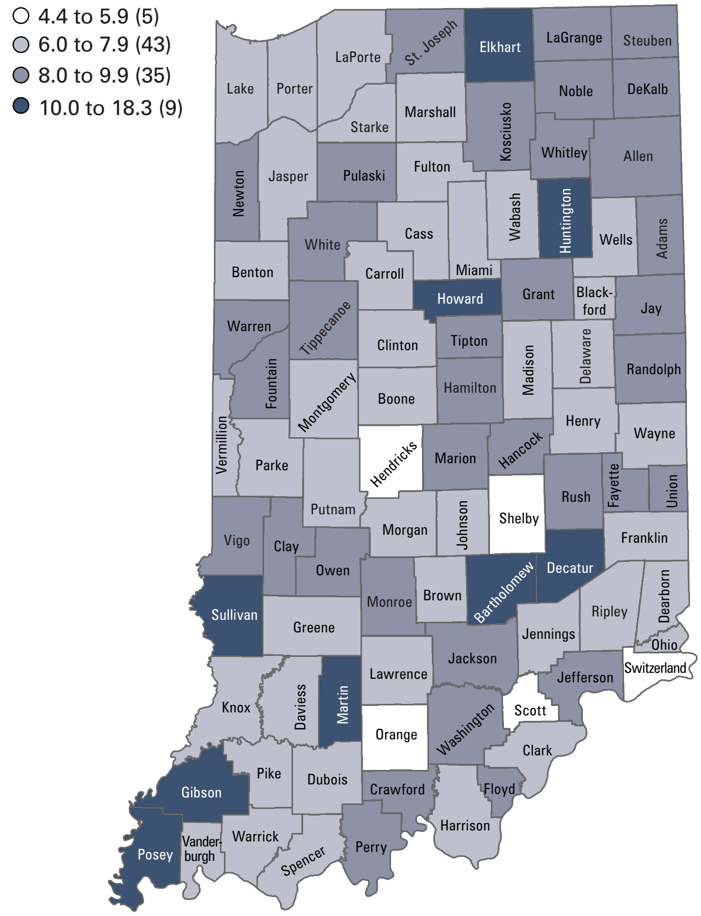
Figure 5 presents the relative concentration of high-tech firms employing over 500 people. Bartholomew and Ripley counties are dominated by Cummins and Hill-Rom, respectively. While Kosciusko County, also a high-tech

Figure 5: Number of Large High-Tech Establishments per 1,000 Workers, 2012-2013 Average



Source: IBRC, using U.S. Census Bureau (County Business Patterns) data and IBRC QCEW-complete employment estimates

Figure 6: Employment Share (Percent) in Technology Occupations, 2013



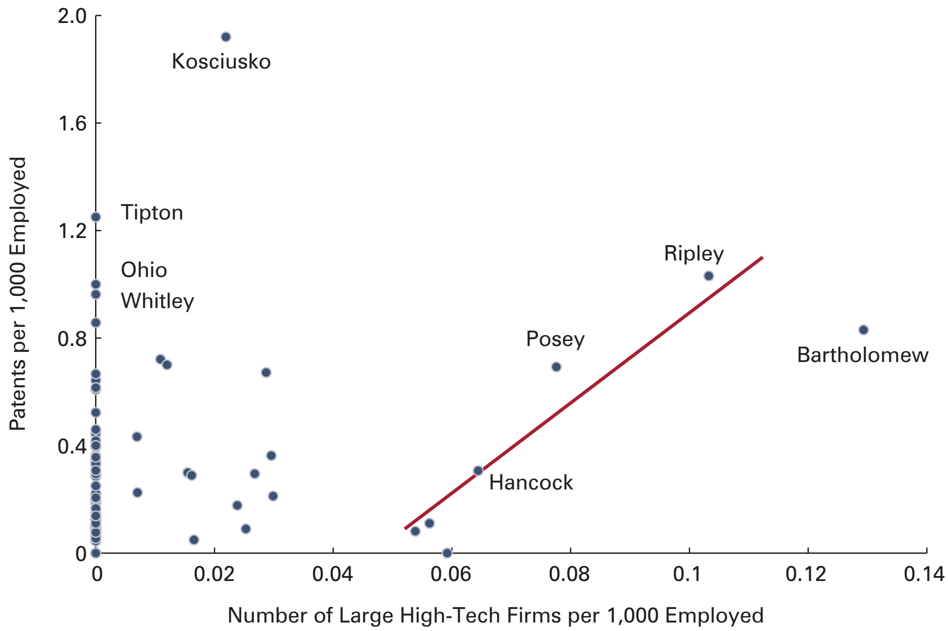
Source: IBRC, using U.S. Census Bureau (County Business Patterns) data and IBRC QCEW-complete employment estimates

heavyweight, has a wide array of firms of many different sizes, it is about three times the size of Ripley County, thus lowering the overall value for this measure. **Figure 6** shows the concentration of high-tech employment. It may be akin to the employment of STEM occupations. We see that Martin County, home to the Naval Surface Warfare Center (NSWC) Crane Division and its associated research labs, is a high-tech occupation hot spot. Next door, Orange County, a tourist destination, has a low concentration of STEM-type occupations. We may also see that many counties are home to "advanced manufacturing" facilities (which include many automobile manufacturers) that employ an assortment of technicians and engineers.

Our KPF analysis is exploratory. By all appearances, several Indiana counties are special cases that cloud the investigation. After several iterations of analysis, we excluded four counties from the analysis: Kosciusko, Lake, Porter and Martin. These counties are outliers for our statistical analysis, but they rather make the case that R&D and proximity to concentrations of scientific activities drive innovation (more on this later).

For several of the KPF inputs in the statistical model, we used both binary (i.e., either one or zero) and level variables. For example, if an institution in a county awarded any STEM degrees, it would be coded with a one (1) and a zero (0) if not. The level variable for STEM graduates would be the number of degrees awarded. The use of the binary measure is due to most of the counties in the state not having tertiary educational institutions awarding STEM degrees. The level measure is used to see if there is "power in numbers," to put it colloquially. The level measure shows the strength of the variation in STEM degrees awarded and whether it explains any variation in the number of patents within the distance thresholds.

FIGURE 7: Relationship between Large High-Tech Establishments and Patent Rates in Indiana Counties



Note: Patent data are 2010-2011 averages and large high-tech firm data are 2012-2013 averages.
Source: IBRC, using IBRC QCEW-complete employment estimates and U.S. Patent and Trademark Office data

TABLE 2: How Distance Affects the University-Based Knowledge Spillovers on Patents in Indiana

Knowledge Spillover	Knowledge Spillover Impact Factor
50-mile cutoff	0.00277
100-mile cutoff	0.00027
250-mile cutoff	0.00020

N = 88
Source: Indiana Business Research Center

Table 2 summarizes the empirical results. Our main hypothesized driver of innovation—university-based knowledge spillovers—does appear to have a positive effect on patents, although its impact is marginal. Distance also seems to matter. Consistent with previous research, the spillover score measured using the smallest radius (50 miles) has the greatest and the most significant effect on patents. As distance increases to 100 and 250 miles, the effect diminishes. We see this phenomenon graphically in **Figures 2** and **3**. The 50-mile spillover scores in **Figure 2** show a few counties with strong proximity values, while the 250-mile spillover scores show a smoother and more intense dispersion. (One could attribute the fact that these effects cannot be statistically confirmed using the standards of academic practice to the fact that our data set was limited to only Indiana counties. That said, the results of the strength of the knowledge spillover score's impact based on distance is encouraging.)

As noted above, we tested other potential drivers of innovation in a county (or region). The variable that has the most statistically confirmed positive effect on patents is the number of large high-tech firms (technically, high-tech establishments). For counties that have large high-tech establishments, our model estimated that the number of patents created would increase by five for every 1,000 employees in those large high-tech firms. STEM graduates and educational attainment (i.e., the share of bachelor's degrees and above) both have

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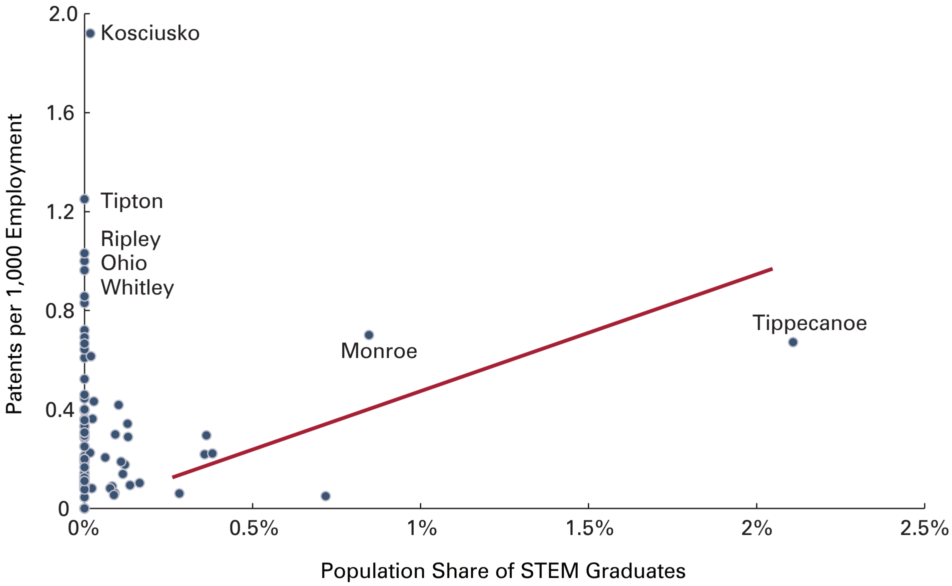
significantly positive effects on patent creation.

One input that has significantly negative impacts on patents is proprietorship. Upon reflection, that general proprietorship has negative effects is not surprising given that we control for the concentration of small high-tech establishments. Another measure, the relative strength of a county in terms of its small businesses in high-tech sectors, which is shown to have a positive effect on patents, picks up the positive influence of proprietorship—albeit for a subset of proprietors. Other negative, statistically relevant variables also include the binary measures, such as producing STEM graduates, having university R&D spending and the presence of large high-tech firms, as well as population density. But while these variables may pass statistical relevance, the size of the negative effects are much smaller than the size of the positive effects associated with high-tech firm size and STEM graduates. For those interested in the statistical details, please see the online appendix at www.ibrc.indiana.edu/ibr/2016/spring/appendix.html.

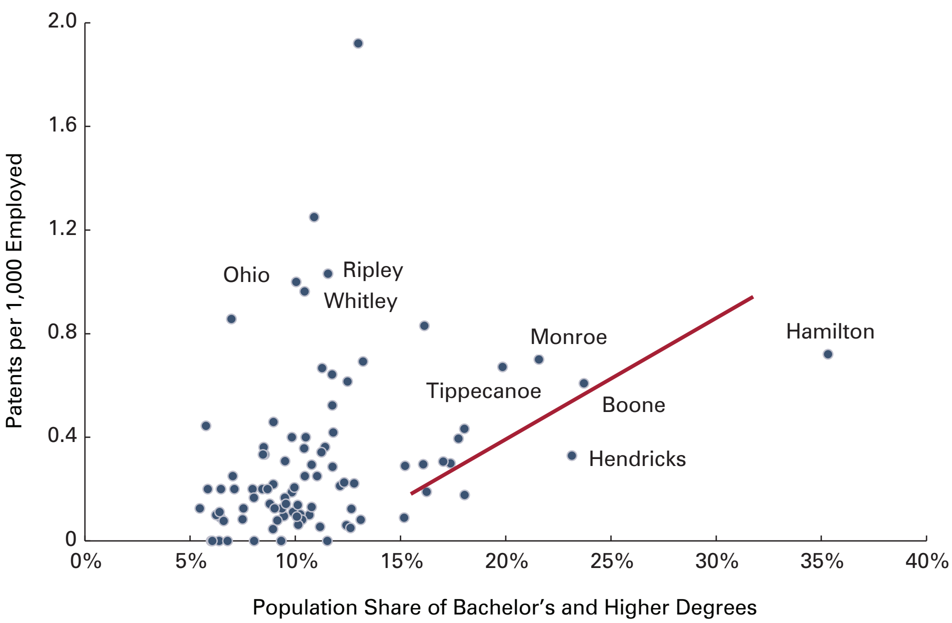
Figures 7 through **9** present selected results from the analysis. Several researchers have hypothesized that large firms would be relatively more innovative because deeper pockets give them the resources to commit to R&D. Our

Figure 8: Relationship between STEM Graduates and Patents in Indiana Counties



Note: Patent data are 2010-2011 averages and STEM graduates are 2010-2012 averages.
Source: IBRC, using IBRC QCEW-complete employment estimates, U.S. Patent and Trademark Office and U.S. Department of Education (IPEDS) data

Figure 9: Relationship between Educational Attainment (Bachelor's Degree and Above) and Patents in Indiana Counties



Note: Patent data are 2010-2011 averages and educational attainment data are for 2013.
Source: IBRC, using IBRC QCEW-complete employment estimates, U.S. Patent and Trademark Office and U.S. Census Bureau (American Community Survey) data

results seem to bear this out. **Figure 7** shows that the association between patents and large high-tech firms is clearer for counties that have relatively higher numbers of large high-tech firms. But the relationship between large high-tech firms and patents isn't hard and fast. Understanding how Ohio County does relatively well in terms of patent rates warrants further investigation.

Figure 8 shows that counties that produce STEM graduates don't necessarily produce the most patents. In general, no clear association exists between patents and the share of STEM graduates. However, a positive linear relationship can be seen for a few counties that have STEM programs—mainly Tippecanoe and Monroe counties. The takeaway here is that our STEM graduate hypothesis cannot be supported.

Figure 9 shows no obvious association between patents and the share of college degrees in general. That said, there is a positive linear relationship for a subset of counties that have relatively higher shares of college degrees and higher patenting rates.

Discussion and Conclusion

Our results are tempered by the fact that our analysis is restricted to Indiana, a relatively small, and perhaps unrepresentative, data set. Because our data set is small, the influence of standout counties is even more strongly felt. Kosciusko, Lake, Porter and Martin counties were standouts. Lake and Porter are close enough to Chicago and its endowment of top-shelf universities which, added to its proximity to Notre Dame, resulted in particularly high knowledge spillover scores. Kosciusko County is home to a high concentration of medical device manufacturing and all of the collateral R&D and patenting. Kosciusko is off the charts, as the array of maps indicate. Martin County, home to NSWC Crane, is an engineering hot spot and as a result, is off the charts in terms of STEM occupations. Crane is not, however, a patenting hot spot—or so it may appear. Patented technology developed at Crane is attributed and filed under the Secretary of the Navy. In other words, the link between patents and the location of the technology development is broken. (With more effort, one could

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re-establish this link with a deeper dive into the patent filings.)

It has been said that cities (as in large cities) are places where ideas (and hence creativity and innovation) go to procreate. If one were to roughly equate innovation with patents (and not all do), we see that the state is something of a curious outlier. Relatively low population density regions in the state are the locations that have high patent rates: Bartholomew, Kosciusko, Martin, Monroe, Riley and Tippecanoe counties. The policy implications are uncertain. Hoosiers, however, can feel pretty good that STEM density trumps population density. Maintaining this advantage should be on the screen of policymakers in the state.

In conclusion, innovation in Indiana, as measured by patenting activities, benefits from university-based knowledge spillovers. That said, innovation in Indiana is largely driven by counties like Bartholomew and Ripley that have large high-tech establishments. Counties such as Tippecanoe and Monroe, home to the state's flagship public universities that produce numerous STEM graduates, also benefit from high concentrations of human capital. ❑

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View the complete regression results at www.ibrc.indiana.edu/ibr/2016/spring/appendix.html.

The Importance of Education for the Unemployed

Based on a working paper

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What is the short-term influence of education in the re-employment market? Does it help people regain employment after receiving unemployment insurance benefits?

To answer these questions, this analysis uses unique employment and unemployment claims data and a simple model. The model attempts to determine which factors impact the relative wage of the person emerging from unemployment and the duration of unemployment. The results emphasize the relative short-term importance of education on the ability of an unemployed individual to successfully navigate the re-employment market. Higher levels of education increase the chance an unemployed person will emerge with a comparable wage and reduce the time required to find new employment.

Unemployment can have a devastating impact both on a household and the general economy. The loss of income has an immediate effect in the reduction of consumer spending. However, the increase in uncertainty for the household can have a multiplier effect on the reduction of consumer spending. A household that endures unemployment is likely to significantly cut spending, often in excess of the loss of income due to the uncertainty, and the resumption of spending can lag after the return of income. The psychological impact of unemployment on a household can have a significant impact on the broader economy. For this reason, economists have long sought better information on the dynamic influences of the re-employment market. It is in society's best interest for the newly unemployed to quickly navigate the re-employment market and re-emerge with the best wage outcome possible. The study examines factors, within the constraints of data availability, to determine which influences impact both the wage that someone will receive and the duration of unemployment. In particular, this article will examine the impact of education on the unemployed.

Researching the possible link between wage achievement in the labor market and education levels is well established in academic literature. The link is built on the commonly accepted idea of imperfect substitution between the work and the availability of skills in the labor market. The labor market maintains a positive wage bias in favor of skills and increased human capital. There is a large and consistent body of literature establishing a connection between wages and years of schooling as overviewed by Card (1999).

It is also argued from a dynamic perspective that wage inequality should decrease with increasing levels of education (Tilak, 1989). In the short term, higher wages are afforded positions requiring more skill. As more people pursue these positions and educational levels increase, the supply of higher skilled workers increase. The increase in supply puts downward price pressure on high-skilled jobs, which lowers wages. At the same time, fewer people pursuing low-skilled jobs push wages higher. From this dynamic perspective, education will cause wages to converge. This view is summarized and empirically shown in data prior to 1970 between white- and blue-collar employees by Goldin and Margo (1992).

Teulings (1995, 2005) attempts to bridge the gap between short-term and long-term dynamic trends by explaining that highly educated people are more skilled in complex jobs and, thus, demand higher salaries. In the longer term, the increased supply of highly educated people puts pressure on wages of the complex jobs or pushes the highly educated into jobs of lower wages with fewer skill requirements. Thus, the effect of education on income is positive as a first-order condition, but negative as a second-order condition.

Others disagree with the notion of long-term dynamic wage convergence and decreased wage disparity. Acemoglu (2002) argues that diminishing returns to education are not likely to exist. The increase in human capital due to education will induce greater levels of investment in technology, which promotes innovation. Innovation is a positive externality derived from education, which reduces the potential for diminishing returns to education. This argument is consistent with research using data after 1970 that indicates increasing wage inequality in the labor market due to skill requirement differentiation (Blackburn, 1990; Bound & Johnson, 1992; Karoly, 1992; Katz & Murphy, 1992; Kosters, 1991). This also includes general equilibrium models linking education and human capital development to increasing disparity (Mehta, 2000).

Another possible explanation for the observed increase in income inequality after 1970 is job mix. Thurow (1987) and Revenga (1992) suggest that high-wage job creation (such as manufacturing jobs) is in decline, while low-wage job creation (such as service-based jobs) is increasing. This change in the mix of job creation suppresses low-skilled wages and maintains a high-wage disparity. This view of job creation and wage growth is not universally accepted (Dickens & Lang, 1985, 1987).

This article adds to the existing literature by examining whether the link between wages and education extends into the re-employment market. Once factors of influence are identified, better policies can be initiated that can expedite the ability of the unemployed to attach with a job from the re-employment market. The twin goals of the unemployed person are to find a new position quickly and receive an adequate wage. This study helps to identify the influences that achieve these outcomes.

Methodology

This study uses a unique longitudinal data set that includes de-identified Indiana unemployment claimant data that have been linked to Indiana wage reporting records and public university education records. A random identifier is applied and the researcher never has access to identified data, insuring record anonymity. Only aggregate results are provided with the study. Unfortunately, many of the potential records are incomplete and do not contain complete information on the variables of interest. These incomplete records were discarded. Over the six years of collection, 342,890 records contain complete information on the desired variables. The first year had the most observations at approximately 30 percent, while the remaining years each represented about 15 percent of observations. The number of records collected from each of the years is provided in the summary statistics in **Table 1**.

The study uses data for individuals applying for Indiana unemployment insurance (UI) benefits from 2004 through 2009 that had been successfully matched with corresponding wage and education records. Individuals with wage data before (starting first quarter of 2004) and after UI claims (ending fourth quarter of 2009) are included.

Individuals without wage matches are excluded from the study since the study is focused on reintegration. This undoubtedly includes those unable to find work in addition to those moving for work outside Indiana for which wage records are unattainable. These individuals did not have available data and are beyond the reach of this study.

The total time spent collecting UI benefits is captured and measured as the total number of weeks of UI benefits received. This includes all benefits (including state and federal regular and extended benefit programs). Individuals entering the study period already collecting benefits or those exiting the study period collecting benefits are excluded from evaluation. The major objective of the study is to determine factors of influence on post-claim wages and claim duration. It is, therefore, essential to establish observations with clean wage records before and after the UI claim. Therefore, only records with known starting and ending dates in the UI claims system are relevant to the study.

Several considerations are required in working with the claims matched to wage data, given availability constraints. The available wage data are presented in quarterly aggregates. For each record, no information is provided to delineate part-time labor, full-time labor, weeks worked or the number of hours worked within the quarter. Given it unlikely that people separate or reintegrate into the labor market precisely on the first day of the respective quarters, a potential for measurement error exists. To accommodate this potential error and reduce its possible impact, the study uses an average of the second and third quarters directly preceding separation and the second and third quarters directly following workforce reintegration. Thus, the quarterly wage directly preceding

Table 1: Summary Statistics

	Mean	Std. Dev.
Observations	**342,890**	
Wage Difference *	-1,149.46	6,048.00
Total Weeks Claimed	18.00	16.01
Quarterly Wage before Claim **	7,681.60	6,275.25
GDP (in millions of chained 2009 dollars)	273,479.70	6,105.40
Age Re-Employed	40.38	12.23
Gender - Male	0.5669	0.4954
Race		
White	0.0835	0.3711
African-American	0.1104	0.3133
Education (Highest Attainment)		
Doctorate Degree	0.0066	0.0808
Master's Degree	0.0172	0.1301
Bachelor's Degree	0.0960	0.2947
3 Years of College/Tech/Vocational	0.0216	0.1454
2 Years of College/Tech/Vocational or Associate Degree	0.1312	0.3377
1 Year of College/Tech/Vocational	0.0766	0.2659
High School Graduate/Equivalent	0.5292	0.4991

* Difference between quarterly wages before claim and after re-employment (second and third quarter averages)
** Second and third quarter average before unemployment
Source: Author's calculations

entry into the claims system and the quarterly wage directly after reintegration into the labor market are discarded. They are discarded due to the high likelihood that the quarterly wage is only a partial quarter and under-represents actual earnings. The average of the second and third quarters of wages is a better indication of wages before entry and exit of the claims system.

In order to understand the impact of unemployment on wages, the study examines the wage difference between when an individual enters the claims system against when they reintegrate into the labor market. The wage difference is calculated using the average wages post-UI claim minus the calculated average wages pre-UI claim.

Wage Difference =
(Avg. 2nd and 3rd Qtr Wages Post-UI Claim)
– (Avg. 2nd and 3rd Qtr Wages Pre-UI Claim)

A positive difference is reflective of higher wages in the new position, while a negative difference indicates a decrease in wages.

The explanatory variables are a collection of other available variables in the matched data set. The first variable is the wage before unemployment. This variable is a control to help account for factors beyond the scope of available data. This is the average wage of the second and third quarters directly before entry into the claims system.

The economic condition of the state is also an important influence on the health of the labor market and the ability of an individual to navigate the unemployment market. Indiana's gross domestic product (GDP) for each year of the study is used (in millions, chained 2009 dollars), using U.S. Bureau of Economic Analysis data.

The influence of age is evaluated. The age of re-employment variable is computed as the difference between the year of workforce reintegration and the birth year. Only those ages 18 through 100 were considered for the study. Records outside of this range were dropped from evaluation, as they are either outside the scope of the study or likely the result of invalid data. The age variable is also a proxy for experience. The more experienced a worker, the greater the potential for enhanced skills and desirability. However, there are diminishing returns to age/experience, as some skills and physical abilities deteriorate with age. To account for the potential non-linear influence of age and experience, the age variable is also squared.

Demographics and race are incorporated to the extent that the data allow. A binary gender variable was used with positive being an indication of male. Race binary variables are created, but complete separation is limited with data. The data provide for three binary options: African-American, other and white.

Binary variables ascertain the influence of educational attainment. The data provide the highest level of achievement by applicant during the claims period. The assignment of educational level is valid regardless of whether it is obtained prior to or during the study period. The educational achievement levels are:

- High School Graduate or Equivalent
- 1 Year of College or Technical/ Vocational School
- 2 years of College, Technical/ Vocational School or Associate Degree
- 3 years of College or Technical/ Vocational School
- Bachelor's Degree
- Master's Degree
- Doctorate Degree

As part of the unemployment application process, a claimant completes a profile when registering for benefits. The profile includes a Standardized Occupational Code (SOC) for the occupation from which the applicant is separated. Unfortunately, SOC information is not available for applicant positions when a claimant is successful and re-enters the workforce.

Finally, yearly binaries are created as an additional control. These binaries should account for influences such as yearly trends in wage differences. Additionally, as the wage data are in nominal terms, the yearly binaries should account for any inflationary influence.

In extracting the data, filters were used to exclude every-year claimants as these records could bias results. Some industries routinely discharge individuals for a short period of time with the expectation that they will be re-hired. As these individuals should not be considered truly unemployed, including their data could distort the results.

An Ordinary Least Squares (OLS) regression model was constructed to test for influences on the wage differential of individuals moving through the re-employment market and the time required.

Results

Tables 2 and **3** indicate the influence of the independent variables in wage differences and weeks of benefit collections, respectively, for individuals participating in the UI system. Variables statistically significant at the 1 percent level are discussed.

The wage of someone prior to entering the re-employment market has a significant influence both on the time required to find a new position and the subsequent wage. The higher the salary was before the unemployment insurance claim, the more time it took to find and accept a new position. The lower the salary, the less time it took to find and accept a position. Higher wage earners find it more difficult to emerge from unemployment with a comparable wage and take longer to find a new position.

Table 2: Wage Difference Results for UI Claimants

Observations F-Value Prob>F R^2	Coeff.	Std. Error	342,890 3198.19 0.0000 0.2717 |t|	p
Quarterly Wage Before Claim **	-0.541	0.002	340.73	0.000 *
GDP (in millions of chained 2009 dollars)	-0.095	0.002	-52.57	0.000 *
Age Re-employed	229.20	4.76	48.11	0.000 *
Age Re-employed Squared	-2.65	0.06	-47.31	0.000 *
Gender - Male	932.71	20.70	45.05	0.000 *
Race - White	312.88	24.08	12.99	0.000 *
Education				
Doctorate Degree	1,088.56	112.74	9.66	0.000 *
Master's Degree	1,829.39	74.55	24.24	0.000 *
Bachelor's Degree	1,556.60	40.59	38.35	0.000 *
3 Years of College/Tech/Vocational	646.58	65.56	9.86	0.000 *
2 Years of College/Tech/Vocational or Associate Degree	902.49	35.95	25.11	0.000 *
1 Year of College/Tech/Vocational	450.48	41.11	10.96	0.000 *
High School Graduate/Equivalent	297.70	28.25	10.54	0.000 *
SOC Coded Occupations				
Management	-362.31	47.52	7.62	0.000 *
Business and Financial Operations	-333.67	58.19	5.73	0.000 *
Computer and Mathematical	161.63	84.65	1.91	0.056
Architecture and Engineering	706.74	75.12	9.41	0.000 *
Life, Physical, and Social Services	-174.81	174.07	1.00	0.315
Community and Social Services	-908.36	105.66	8.60	0.000 *
Legal	-188.17	154.11	1.22	0.222
Education, Training, and Library	-747.36	77.80	9.61	0.000 *
Arts, Design, Entertainment, Sports, and Media	-788.13	93.10	8.46	0.000 *
Healthcare Practitioners and Technical	167.66	68.68	2.44	0.015
Healthcare Support	-611.19	62.08	9.85	0.000 *
Protective Service	-1,209.50	109.98	11.00	0.000 *
Food Preparation and Serving Related	-1,163.52	53.32	21.82	0.000 *
Building and Grounds Cleaning and Maintenance	-1,088.66	65.13	16.72	0.000 *
Personal Care and Service	-863.04	95.17	9.07	0.000 *
Sales and Related	-766.03	47.29	16.20	0.000 *
Office and Administration Support	-660.08	43.98	15.01	0.000 *
Farming, Fishing, and Forestry	-837.70	153.24	5.47	0.000 *
Construction and Extraction	600.40	45.25	13.27	0.000 *
Installation, Maintenance, and Repair	488.07	49.66	9.83	0.000 *
Production	225.53	35.65	6.33	0.000 *
Transportation and Material Moving	-11.51	42.31	0.27	0.786
Military Specific	-2,367.24	149.21	15.87	0.000 *
Years				
Year 2004	-1,088.81	27.06	40.24	0.000 *
Year 2005	-1,045.68	28.17	37.12	0.000 *
Year 2006	-636.42	30.35	20.97	0.000 *
Year 2007	Omitted			
Year 2008	718.53	33.74	21.29	0.000 *
Year 2009	Omitted			
Constant	23,756.14			

* Significant at the 1 percent level
** Second and third quarter average before unemployment
Source: Author's calculations

Table 3: Weeks of Benefits Results for UI Claimants

Observations F-Value Prob>F R^2			342,890 3008.83 0.0000 0.2692	
	Coeff.	**Std. Error**	**|t|**	**p**
Quarterly Wage Before Claim**	0.00002	4.70E-06	4.21	0.000 *
GDP (in millions of chained 2009 dollars)	0.00038	5.34E-06	70.37	0.000 *
Age Re-employed	0.456	0.014	32.36	0.000 *
Age Re-employed Squared	-0.004	0.000	24.92	0.000 *
Gender - Male	-0.654	0.061	10.68	0.000 *
Race - White	-0.534	0.071	7.50	0.000 *
Education				
Doctorate Degree	-2.34	0.33	7.01	0.000 *
Master's Degree	-0.92	0.22	4.18	0.000 *
Bachelor's Degree	-0.91	0.12	7.62	0.000 *
3 Years of College/Tech/Vocational	0.15	0.19	0.77	0.444
2 Years of College/Tech/Vocational or Associate Degree	0.29	0.11	2.74	0.000 *
1 Year of College/Tech/Vocational	0.67	0.12	5.49	0.000 *
High School Graduate/Equivalent	0.00	0.08	0.01	0.993
SOC Coded Occupations				
Management	12.40	0.14	88.21	0.000 *
Business and Financial Operations	11.46	0.17	66.58	0.000 *
Computer and Mathematical	10.67	0.25	42.62	0.000 *
Architecture and Engineering	10.91	0.22	49.12	0.000 *
Life, Physical, and Social Services	11.45	0.51	22.24	0.000 *
Community and Social Services	9.31	0.31	29.78	0.000 *
Legal	11.36	0.46	24.91	0.000 *
Education, Training, and Library	10.02	0.23	43.56	0.000 *
Arts, Design, Entertainment, Sports, and Media	11.52	0.28	41.84	0.000 *
Healthcare Practitioners and Technical	11.07	0.20	54.49	0.000 *
Healthcare Support	11.94	0.18	65.01	0.000 *
Protective Service	12.24	0.33	37.62	0.000 *
Food Preparation and Serving Related	9.16	0.16	58.10	0.000 *
Building and Grounds Cleaning and Maintenance	11.52	0.19	59.82	0.000 *
Personal Care and Service	10.26	0.28	36.44	0.000 *
Sales and Related	10.84	0.14	77.48	0.000 *
Office and Administration Support	13.76	0.13	105.78	0.000 *
Farming, Fishing, and Forestry	11.05	0.45	24.37	0.000 *
Construction and Extraction	12.37	0.13	92.40	0.000 *
Installation, Maintenance, and Repair	12.24	0.15	83.33	0.000 *
Production	10.65	0.11	101.02	0.000 *
Transportation and Material Moving	12.93	0.13	103.28	0.000 *
Military Specific	11.73	0.44	26.57	0.000 *
Years				
Year 2004	10.46	0.08	130.63	0.000 *
Year 2005	5.85	0.08	70.16	0.000 *
Year 2006	2.84	0.09	31.62	0.000 *
Year 2007	Omitted			
Year 2008	1.95	0.10	19.50	0.000 *
Year 2009	Omitted			
Constant	-110.15			

* Significant at the 1 percent level
** Second and third quarter average before unemployment
Source: Author's calculations

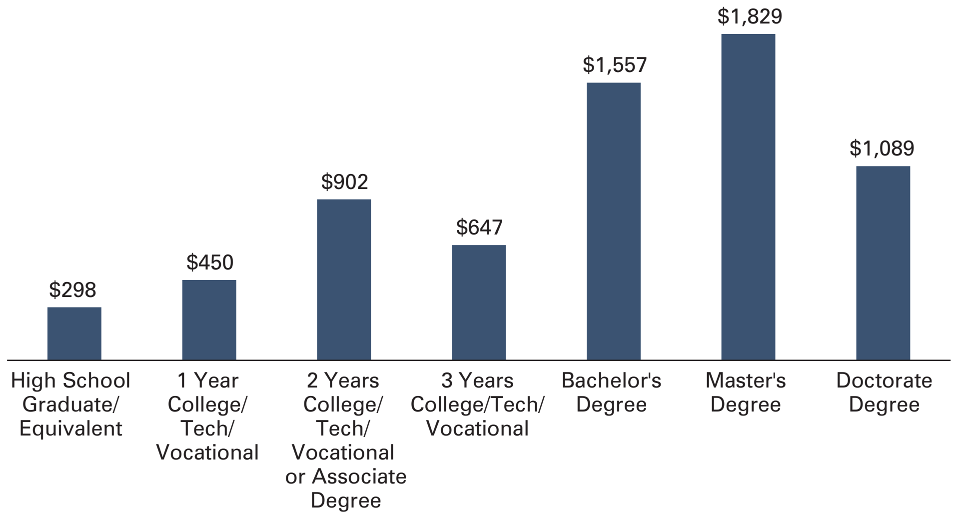
The GDP variable is significant in both the wage after unemployment and the time elapsed to find new employment (that is, weeks of benefits) models. The variable coefficient is negative in the wage difference model and positive in the weeks of benefit model. Initially, this might seem counterintuitive. One could reasonably expect that a better economy should expand wage potential and reduce the length of unemployment.

However, the results suggest the opposite effect. It is possible that selection bias is causing this result. When the economy is strong, only the weakest elements of the workforce will disconnect and enter the re-employment market. Their perceived weakness is a signal to the labor market about their potentially being lower quality. These individuals will find re-entry more difficult in terms of wage and timing. In a poor economy, separation from a company is more likely and even good candidates can find themselves unemployed. In a poor economy, the business perception of those unemployed might be better.

The influence of age, as a proxy for experience, is shown to be both significant and non-linear. In the wage difference model, the coefficient for the age of re-employment variable is significant and positive. The coefficient of the squared variable is significant and negative. Age and experience make a worker more desirable; however, this influence is diminishing. The positive influence of age on post-UI claim wages appears to peak around age 45. After age 45, diminishing returns set in and the wage of a person emerging from claims decreases. The re-employment market is biased against those both younger and older.

The influence of age on weeks of claim benefits is also significant and non-linear, but the results are slightly different than the influence on wages. In the weeks of benefits model, the coefficient for the age of re-employment is positive. The coefficient for the squared variable is negative. However, the magnitude of the squared coefficient is small. Therefore, through the effective range of employment, the weeks to find new employment increases. As a person ages, it is increasingly difficult to navigate the re-employment market and more time is required.

Figure 1: Influence of Education on Quarterly Wage in the Re-Employment Market



Note: All values shown are significant at the 1 percent level.
Source: Author's calculations

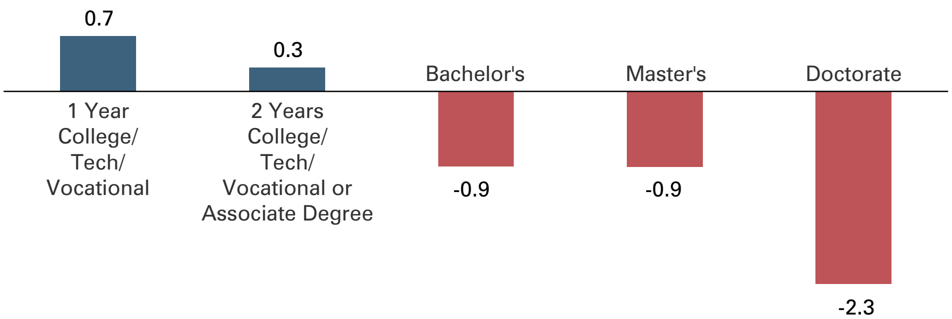
The race and gender coefficients are significant and positive in the wage difference model. They are significant and negative in the weeks of benefits model. The results indicate a measureable difference observed in the re-employment market with regard to gender and racial variables, favoring white and male claimants.

The link between education and the ability of an individual to navigate the re-employment market is both significant and pronounced. The variable coefficients for education levels are all significant and positive in the wage difference model. The magnitudes of the coefficients are large. In general, the more education one receives, the higher the wage one will receive directly emerging from unemployment. In terms of quarterly income, the boost in income for a person with a master's degree is $1,829 in that first position post-unemployment compared to someone with an education less than a high school degree. A high school degree is worth a boost of $298 per quarter in the re-employment market compared to someone with less than a high school degree. This research indicates an immediate return to education for those in the re-employment market. These results are consistent with prior research on the immediate impact of education. This analysis examines the short-term individual impact of education in re-employment wages and does not address the longer term impact of macro dynamics and the potential for long-term wage disparity convergence.

Figure 1 shows education's impact on the re-employment market and the potential of wage adjustment. The results also indicate the importance of degree completion. A two-year associate degree is valued more by the post-unemployment job market than partial degrees at one or three years.

The link between education and weeks of benefits is not as strong as it was in the wage difference model. The variable coefficients for education levels are mostly significant in the weeks of benefits model. However,

FIGURE 2: Influence of Education on Time Spent Unemployed: Effect on Weeks of Unemployment



Note: High school and three years of college or technical/vocational school are not significant at the 1 percent level. All values shown are significant at the 1 percent level.
Source: Author's calculations

the signs are varied and the magnitude is small. The general trend is that higher levels of education will result in less time unemployed. A person with a higher level of education may find work a week or two quicker than someone with low levels of education (see **Figure 2**).

The SOC variable results vary. While the coefficients of the SOC variables are significant, the magnitude varies in sign and size in the wage difference model. Some industries, such as engineering and heavy construction, do well in maintaining wages in re-employment (quarterly wage increases of $706 and $600, respectively), while those leaving the military or in the food service industry do poorly (quarterly wage decreases of $2,367 and $1,163, respectively).

The results in the weeks of benefit model are also varied. While most are significant, there is little variation in magnitude. The duration of unemployment is only modestly impacted by the type of industry.

There exists an endogenous link between education and occupation. For example, it is likely that a physician with many years of education will maintain a higher salary than a lower skilled worker. The higher wage compensates the individual for the effort and sacrifice to achieve the level of education required for such a position—in addition to the opportunity cost of lost wages over the years obtaining the education. Simply ignoring this potential source of unobserved heterogeneity can bias estimation results (Baltagi, 1995). An individual's wage is both a function of the individual and the firm. Since firm-specific data are not available, the inclusion of occupational variables helps control for the influence of this unobserved behavior. Without the occupational code, it would be more difficult to note whether the education is responsible for wage increases or simply correlating with higher wage occupations (such as physicians).

The year variables are controls and attempt to capture influences not expressed by the other variables. Two of the yearly variables are omitted in the study results due to collinearity. The year variables are significant in both models, suggesting temporal influence not captured elsewhere.

Conclusion

The empirical results of historically linked unemployment and wage data confirm the importance of education and its immediate positive impact on wages in the re-employment market. While unemployment has a negative influence on wages, these effects can be somewhat mitigated with higher levels of education. In navigating the re-employment market, not only do higher levels of education present the best opportunity to achieve the best wage outcome when emerging with a new position, but also that a person is likely to find that job quicker. Compared to someone who did not complete a high school education, the value of a bachelor's degree in the re-employment is a quarterly wage increase of about $1,557. For a high school degree, the quarterly wage increase is $298 for the first position emerging from unemployment. A person will also find the position on average about one week faster with a bachelor's degree compared to a high school degree. ❑

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