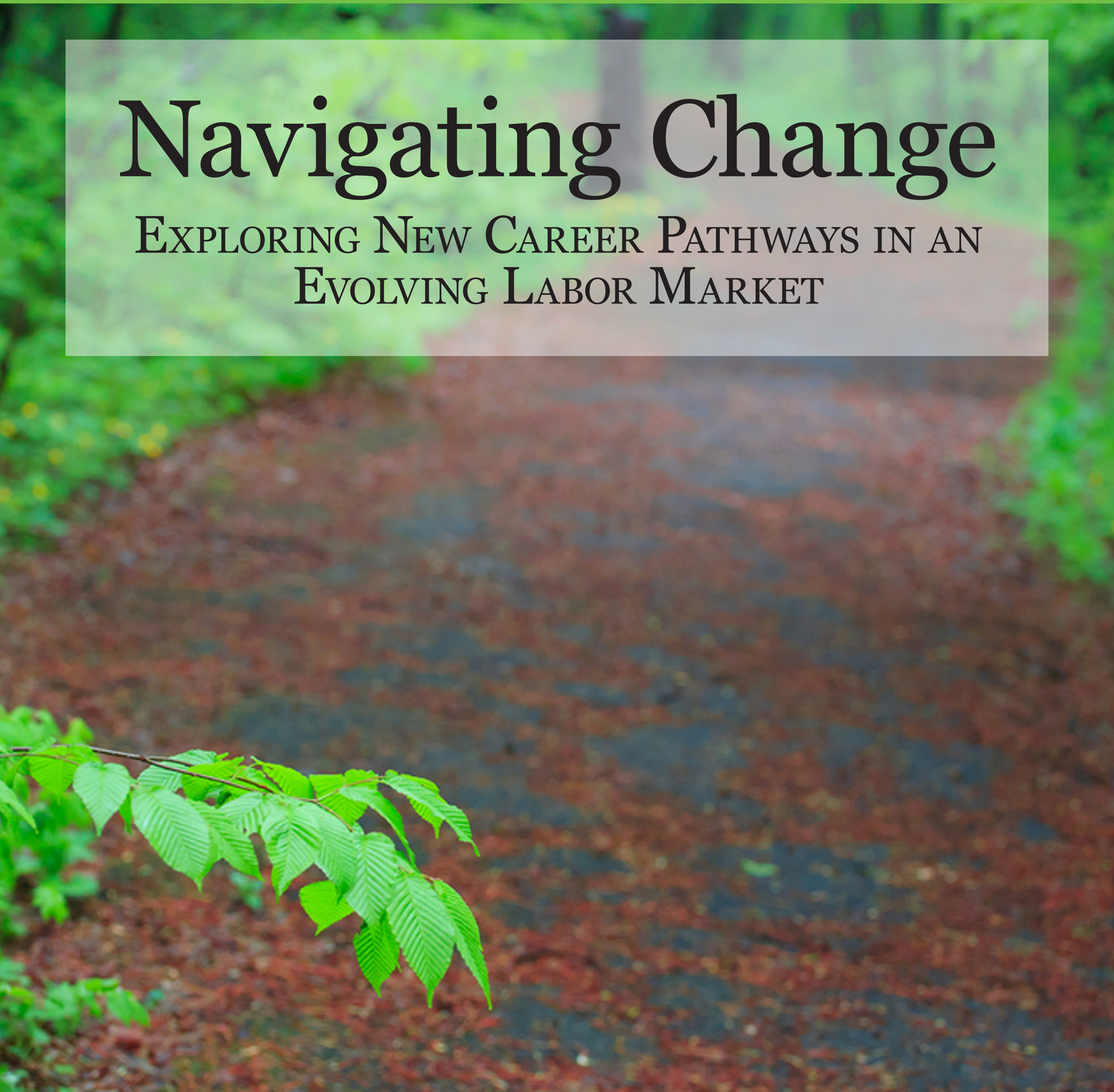
Navigating Change

Exploring New Career Pathways in an Evolving Labor Market



KELLEY SCHOOL OF BUSINESS
INDIANA UNIVERSITY
Indiana Business Research Center

INDIANA WORKFORCE DEVELOPMENT
AND ITS WorkOne CENTERS

Navigating Change

Exploring New Career Pathways in an Evolving Labor Market

Research conducted by the

Indiana Department of Workforce Development
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and

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Kelley School of Business, Indiana University

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DRIVING CHANGE
Greening the Automotive Workforce

September 2011

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For more information, visit www.drivingworkforcechange.org.

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Executive Summary

Before the Great Recession, the auto industry in Indiana, Michigan and Ohio was already in the throes of major restructuring—applying new technologies and production efficiencies, reducing costs, and modifying product lines to equal or beat global competitors. Add the dramatic economic downturn to the industry restructuring and the loss of jobs in the auto sector became a torrent.

Even if the national economic recovery had been strong, the tri-state economy would have been in a fundamentally different place. As the American auto sector works to establish its revival on firm footing, employment in the industry will not be sufficient to rehire all the dislocated workers. To address the large numbers of dislocated auto industry workers, Indiana, Michigan and Ohio formed the Driving Change research consortium with four overarching goals:

1. Chronicle the transformation from the old auto industry to a new, more efficient auto industry, focusing on the new skill and training requirements of the auto workforce

2. Identify the effects of this structural transformation on the auto parts supply chain workforce

3. Examine green job opportunities now and in the future as alternative career pathways for displaced workers

4. Identify the skills gap and the required educational and technical training needed for dislocated workers to transition into new occupations

The research documented in this report addresses the latter two goals: developing alternative career pathways and an easily understandable measure to communicate the estimated time needed to transition to a new occupation.[1] Given restructuring in the auto industry, many displaced workers need help to find suitable alternative jobs. The two-step pathway cluster and skills gap analyses developed in this study offer valuable guidance to displaced workers charting pathways to new career opportunities.

Pathway Cluster Analysis

Team assemblers and assemblers/fabricators were the two auto manufacturing occupations experiencing the largest job losses, accounting for more than 57,000 dislocated workers in the three states. More than 60 percent of these workers have only a high school education.

Where will these displaced workers find jobs in tomorrow's economy? How will they increase their training and skills in order to secure the jobs of the future? What are their alternatives? How can a dislocated worker plot a path to a new job that uses the skill set he or she has developed over the years?

The operating principle for the pathway cluster concept is that workers will seek, and be most productive in, occupations that are most similar to their current or former jobs.

Pathway clusters are organized based not upon industries or functions, but upon the similarities and differences of worker and job characteristics. Most occupational matching tools and resources use knowledge, skills and abilities (KSAs) to direct someone from one type of job to another. Pathway clusters, on the other hand, use KSAs *and* work context, tools used and worker traits such as "highly social" or "attentive to detail" to determine the degree to which occupations are more or less similar.

Job transitions within a given cluster, therefore, would be easier than moving from one cluster to another.

[1] All Driving Change research findings, reports and resources are available at www.drivingworkforcechange.org.

Three key observations result from the pathway cluster analysis:

- The technique used to group occupations into pathway clusters breaks new ground. Pathway clusters differ from other approaches because they are not organized based upon industries, such as health care, or solely upon job functions, such as business administration. Rather, they take a wide range of job and worker attributes into account.

- While auto occupations are concentrated in the production, construction and engineering pathway cluster, there are dozens of occupations in other industries that may make good target occupations for a displaced worker.

- There are seven pathway clusters, and green occupations are well distributed throughout the pathway clusters.

Time to Transition

Knowing the alternative occupations that are most similar to one's current occupation—those in the same pathway cluster—is a good first step. A worker then needs to know the relative difficulty or ease in closing the skills gap between two occupations.

The skills gap is primarily a knowledge, or human capital, gap. Closing the knowledge gap may take months or years in the classroom earning credits and degrees, just as closing many types of skills gaps requires many months or even years as an apprentice.

The skills gap analysis measures the time to transition —the "trip time"—from one occupation to another based on differences in the knowledge/skill levels between the old and new job. The trip-time method compresses all the gaps in knowledge and skill between two occupations into a common numéraire, namely the preparation or retraining time it would take to change jobs. While the trip-time measure is not perfect, it is a great advance because it provides users an understandable measure of a worker's skills gap.

Because up-skilling entails increasing the level or mix of a worker's human capital, this report describes two essential online resources:

- Trip-time reports provide a displaced worker a set of suitable occupations based on the worker's earning history, occupation history and estimated level of preparation needed for the alternative occupations.

- A tri-state training program database of green and growing occupations complements the trip time results, so a worker can match the most suitable occupations with postsecondary educational, technical and vocational programs in his or her region.

These resources, tools and analysis are available online and free of charge, helping today's displaced workers in the tri-state region find suitable employment, but also serving as a foundation for expanding the workforce development toolkit in the future.

The Driving Change study has been a collaborative effort of workforce development agencies of Indiana, Michigan and Ohio and their strategic partners. This project was supported by a grant from the Employment and Training Administration of the U.S. Department of Labor. The research was conducted by the Indiana Business Research Center at Indiana University's Kelley School of Business and the Research and Analysis division of the Indiana Department of Workforce Development.

All Driving Change research findings, reports and resources are available at:

www.drivingworkforcechange.org

1. Introduction

The manufacturing sector, and the automobile industry in particular, was under stress well before the advent of the Great Recession. That massive economic downturn further altered the economic and workforce landscape. As the recession took hold, the manufacturing sector hemorrhaged middle class jobs at a staggering rate. While the sector has turned around at the time of this writing, a brief synopsis of the structural and cyclical forces that have contributed to changes in the auto sector is in order.

In 2009, automotive sales were only 10.4 million units—the worst year for the market in almost 30 years. The economies of the tri-state region—Indiana, Michigan and Ohio—depend heavily on automotive and parts production, accounting for 44 percent of all U.S. production in 2009 and nearly 47 percent in 2010. As a result, the automotive crisis and broader economic recession hit these three states particularly hard. While the U.S. transportation equipment manufacturing (TEM) industry, as measured by automotive and parts employment, declined 50.4 percent from the most recent peak employment in 2000 through 2010, automotive and parts employment in Indiana, Michigan and Ohio fell by 57.8 percent. In Michigan alone, industry employment contracted 64.1 percent.

The automotive industry's restructuring was well underway when the financial crisis hit in the fall of 2008. Already, many automotive manufacturing and supplier plants had been shuttered, and communities were dealing with the impact of thousands of workers who had been bought out, retired or laid off. The economic crisis and the subsequent government-orchestrated bankruptcies of both General Motors and Chrysler accelerated the workforce transition, leaving the industry forever changed. For many workers, their jobs were gone and they weren't coming back. For talented younger workers who might have considered an automotive career, the instability of the industry has led them to look elsewhere.

The automotive industry is also facing pressures to produce greener vehicles that meet higher fuel economy and greenhouse gas emission mandates, stricter safety regulations, and consumer demand for increased electronics content enabling greater safety, connectivity and entertainment. Developing, engineering and manufacturing these advanced vehicle technologies drive the transformation of the workforce and skill needs. In some cases, it means the industry is seeking new employees with a brand new set of skills. In others, it means upgrading the skills of the incumbent workforce to handle the increased complexity of the products and processes. Educating and training the automotive workforce is made all the more difficult as many internal corporate training programs have been cut back or suspended, partnerships with outside organizations and educational institutions were put on hold, and some workforce development efforts were shelved during the crisis.

The federal government has invested heavily in the resurgence of the automotive industry, and a large portion of the recent public and private automotive investments have been made in the three states of Indiana, Michigan and Ohio. The tri-state region has attracted new investments from existing employers, as well as new automotive-related industries such as energy storage and other recent entrants to the automotive market. In addition, new opportunities are arising in other sectors of the green economy. Investment drives innovation and ultimately results in more jobs. Although the automotive industry may never return to previous employment levels, there may be a future for substantial automotive and green employment in the tri-state region.

1.1 The Driving Change Research: Rationale and Objectives

The goal of the tri-state research consortium was to understand the specific nature of the auto industry transformation and skills relevant to efficient and renewable vehicle technologies and other career opportunities in the broader economy.

In order to more effectively serve the large numbers of dislocated auto industry workers and those at risk of losing their jobs, Michigan, Ohio and Indiana formed the Driving Change research consortium to investigate this matter and provide analysis to:

- Chronicle the structural transformation of the auto industry to the “new” auto industry and identify new skill and training requirements
- Identify the auto parts supply chain impact of auto industry structural transformation
- Find alternative career path opportunities for dislocated auto and auto parts workers for jobs in demand, with an emphasis on those in the green economy
- Determine current and projected skill gaps of the auto and auto parts workforce and the required training needed to compete for jobs in demand and green job opportunities

This report focuses on the two latter items on the research agenda.

The report first answers the question: who are the displaced workers? It presents the demographic characteristics of the displaced workers. Then the report examines those industries to which former autoworkers have migrated since 2005. Third, data are reported on occupations in demand today and those with the brightest prospects for the future. Organized around the themes of jobs in the automobile sector, the green economy and other growing occupations, the chapter presents possible career options for displaced workers and others entering the job market.

The next chapters address the question: how does one transition to the occupations with the brightest prospects? The displaced autoworker has a certain skill set based upon his or her prior occupation. Does that skill set match the needs of the growing occupations? How can one make that assessment? What additional skills or training does one need to transition to occupations that are green, expected to grow or both?

The career pathway clusters and the skills gap resources are presented in chapters 4 and 5. Chapter 4 describes how the pathway clusters work and how they would be used. Pathway clusters are novel in that they are not organized around a particular industry such as health care or functions such as business administration. Instead, pathway clusters are organized around broad similarities and differences between occupations.

Chapter 5 addresses the issues of time and difficulty to switch to a different occupation. The goal of the research team was to boil down the complex components of a worker’s skills, an occupation’s needs and the mechanisms needed to move from one occupation to another into a single dimension: time. The research team developed a time-to-transition measure—“trip time”—that could inform a worker’s decision about which career pathway to follow.

Finally, an important goal for the Driving Change project was to develop a resource to help displaced workers plot a path, in some cases a green path, to a new future. For the dislocated autoworker (or any dislocated worker), the question of how to move from Point A to Point B is far from academic. Training dollars are of little use in workforce development efforts if they fail to move an individual closer to re-employment in a career with a future. This new pathway cluster analysis and use of trip time as a simple measure to gauge the ease or difficulty of career alternatives will help these dislocated workers make decisions about which transitions are the most feasible.

These resources, tools and analyses are available online and free of charge, helping today’s displaced workers in the tri-state region find suitable employment, but also serving as a foundation for expanding the workforce development toolkit in the future.

2. Mapping Job Change

The auto industry has experienced tremendous pressure in recent years, undergoing both structural and cyclical change. The industry has been restructuring its products and how it manufacturers those products. It also suffered greatly due to the Great Recession, the economic downturn that resulted in auto sales dropping from 17 million units in 2006 to about 10.5 million units in 2009.

The tri-state region of Indiana, Michigan and Ohio hemorrhaged jobs and experienced severe employment losses between June 2006 and June 2009. More than 232,000 jobs in manufacturing motor vehicles, parts, and bodies and trailers were lost—over 46 percent of the total auto industry workforce.

Between June 2009 and June 2010, all three states experienced an employment recovery as automakers have retooled and reorganized their businesses. Motor vehicle manufacturing added back 16,800 jobs and motor vehicle parts manufacturing added 25,400 over the year. That said, the modest rate of economic growth during the recovery has done little to offset the huge job loss of the previous three years.

An important component of the research for the Driving Change project was to identify the occupations most affected by economic disruptions and production transformation in the auto industry. The research team used a three-pronged approach to identify, cross-validate and analyze the most significantly affected jobs in the auto sector.

The first method constructed a tri-state composite staffing pattern in the auto sector for 2006 and 2009. Using data from the Bureau of Labor Statistics (BLS) Occupational Employment Statistics (OES) program, the research team estimated the occupational mix, or staffing pattern, for the auto industries in the tri-state region. The staffing patterns were then used to assess the level and direction of employment change for occupations within the transportation equipment manufacturing (TEM) industry, which is the shorthand industry title including motor vehicle manufacturing, motor vehicle body and trailer manufacturing, and motor vehicle parts manufacturing.[2]

For the second approach, the research team used Indiana-specific employment change over the same period for the TEM industry plus the engine (e.g., diesel engines for heavy-duty trucks), turbine and power transmission equipment manufacturing industry (referred to as "TEM-plus"). Because the Indiana-based research team had access to confidential Indiana data for detailed occupations and industries, they were able to cross-check the aggregate, sector-level staffing patterns with detailed, sub-sector data.

The third prong examined the self-reported occupations of long-term unemployment insurance claimants in Indiana who had been separated from TEM-plus.

The primary "take-away" from this chapter is that the auto workforce has become slightly older and more male. Policymakers and workforce development officials should also be concerned that a large majority of those who have been out of work for a long time have only a high school diploma. This will likely present a significant challenge for implementing education and retraining programs targeted to help displaced workers transition to new jobs.

2.1 Job Change by Occupation

Table 1 presents the top 20 occupations that lost auto sector jobs in the tri-state region from 2006 to 2009. The top two occupations with the greatest job reductions were team assemblers and assemblers and fabricators (all other), accounting for 25 percent of the observed job losses. Given the ambiguity of the "all other" category, along with some evidence

[2] Strictly speaking, according to the North American Industry Classification System (NAICS), TEM also includes aerospace products and parts, railroad rolling stock manufacturing, ship and boat building, and other transportation equipment manufacturing, but these sub-sectors were not included in our study scope.

Table 1: Tri-State Occupational Employment Loss in Transportation Equipment Manufacturing, 2006 to 2009

Occupation Code	Title	Loss	Industry Loss Rank	Percent of Auto-Related Loss
00-0000	**Total, All Occupations**	**-232,335**		**100%**
51-2092	Team Assemblers	-32,876	1	14%
51-2099	Assemblers and Fabricators, All Other	-24,527	2	11%
51-9199	Production Workers, All Other	-9,676	3	4%
51-4031	Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic	-8,146	4	4%
51-9061	Inspectors, Testers, Sorters, Samplers, and Weighers	-7,432	5	3%
51-1011	First-Line Supervisors/Managers of Production and Operating Workers	-6,940	6	3%
51-4041	Machinists	-6,823	7	3%
51-4111	Tool and Die Makers	-6,728	8	3%
17-2199	Engineers, All Other	-6,585	9	3%
17-2112	Industrial Engineers	-5,224	10	2%
53-7051	Industrial Truck and Tractor Operators	-5,019	11	2%
49-9042	Maintenance and Repair Workers, General	-3,531	12	2%
49-9041	Industrial Machinery Mechanics	-3,401	13	1%
17-2141	Mechanical Engineers	-3,362	14	1%
51-4121	Welders, Cutters, Solderers, and Brazers	-3,277	15	1%
53-7062	Laborers and Freight, Stock, and Material Movers, Hand	-3,150	16	1%
51-4072	Molding, Coremaking, and Casting Machine Setters, Operators, and Tenders, Metal and Plastic	-3,106	17	1%
13-1199	Business Operations Specialists, All Other	-3,097	18	1%
51-4081	Multiple Machine Tool Setters, Operators, and Tenders, Metal and Plastic	-2,830	19	1%
47-2111	Electricians	-2,792	20	1%

Note: Shaded rows indicate occupations where workers have experienced extended unemployment.

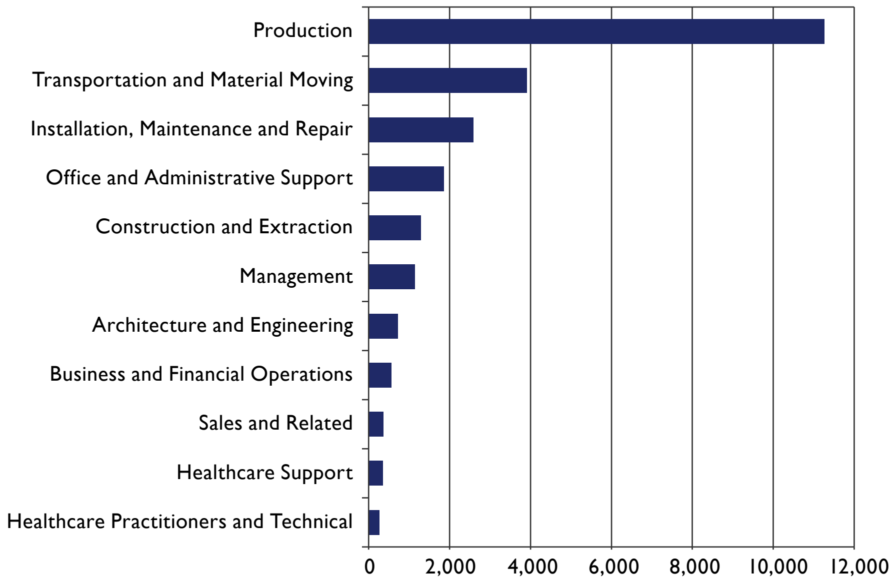
Source: Indiana Department of Workforce Development, using QCEW and OES data

of jobs shifting from one of these categories to the other for the same employer, one may reasonably argue that a single occupation accounted for a quarter of the industry job loss from 2006 to 2009. This consolidated job classification represents more than 57,000 dislocated workers in the three states. If O*NET occupational survey demographics for team assemblers also apply to assemblers and fabricators, more than 60 percent have only a high school education—a troubling statistic.

The 12 shaded rows in **Table 1** indicate that autoworkers in these occupations have experienced long-term unemployment.[3] The fact that these are long-term claimants also *implies* that autoworkers in these occupations are having difficulty finding work in other industries. Either demand for labor in these occupations in other industries is also low—a plausible hypothesis given the massive economic downturn—or there are other structural obstacles that hinder a worker's transition from one industry

3 Long-term claimants are those who exhausted the "normal" unemployment insurance benefits and have continued to draw unemployment benefits via the Federal Emergency Unemployment Compensation program. Analysts selected an unduplicated cadre of claimants from Indiana's TEM-plus sector (transportation equipment manufacturing plus engine, turbine and power transmission equipment manufacturing), who received unemployment benefits between July 1, 2009, and June 30, 2010.

Figure 1: Long-Term Indiana Claimants by Broad Occupational Category



Source: Indiana Department of Workforce Development, using Indiana unemployment claims data

to another. Appropriate policy responses might thus aim to increase inter-industry labor flexibility by concentrating retooling and retraining resources on those 12 occupations.

2.2 Demographics and Education for Displaced Workers

Demographic data for the whole tri-state region were unavailable at the time of this writing, so the research team analyzed Indiana's long-term unemployment claimant data as a proxy to gain insights on the dislocated workforce. Sixty-seven percent of the dislocated workforce is male. This is not surprising, given that the overall workforce for this industry is roughly 75 percent male. Self-reported occupations for these workers are concentrated in production and transportation and material moving occupations, but they span a wide gamut of broad occupational groups, as shown in **Figure 1**.

Seventy-five percent of these displaced workers have a high-school education or less (see **Figure 2**).

In addition, more than 47 percent are over the age of 45, as shown in **Figure 3**. Since many of these workers have not been inside a classroom for decades, retraining for an alternate career may pose a daunting challenge.

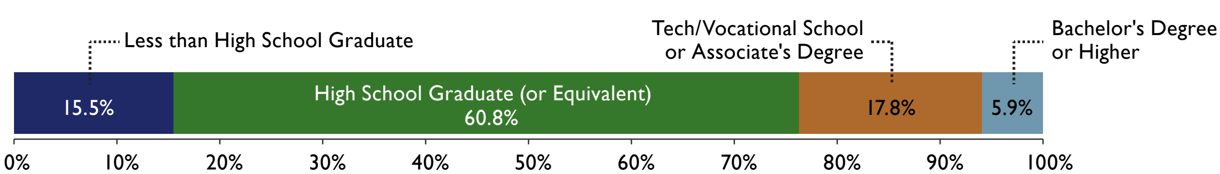
All told, job losses were not proportional across age and sex in the tri-state region (see **Table 2**). In terms of sheer numbers, male autoworkers bore the brunt of the absolute job loss and men in their prime earning period of 45-54 years of age were hardest hit. However, on a percentage basis, both men and women in the 25-34 year old age bracket experienced the largest job losses. The remaining auto sector workforce has become, on average, older and more male, a phenomena partially explained by seniority and union rules.

2.3 Finding Work—Autoworker Re-employment

As the economy turns around, many displaced autoworkers will be re-employed in the industry. Some workers have already been recalled or secured new employment within the sector. Others will have to move into different industries.

This section explores whether and where affected autoworkers found re-employment five years later. By taking a snapshot of employment in the transportation equipment manufacturing (TEM) sector from the first quarter of 2005 and locating the

Figure 2: Long-Term Claimants by Educational Attainment



Source: Indiana Department of Workforce Development, using Indiana unemployment claims data

Table 2: Auto Sector§ Employment Change by Sex and Selected Age Brackets for the Tri-State Region, 2006 to 2009

		Second Quarter 2006		Second Quarter 2009		2006-2009 Change		
Category	Age Group	Employment	Percent of Employment	Employment	Percent of Employment	Employment Loss	Percent Loss	Employment Share Point Change
Total	**14-99**	**499,200**	**100.0%**	**315,400**	**100.0%**	**-183,800**	**-36.8%**	
Male	**14-99**	**368,900**	**73.9%**	**236,200**	**74.9%**	**-132,700**	**-36.0%**	**1.0**
	25-34	68,800	13.8%	38,500	12.2%	-30,300	-44.0%	-1.6
	35-44	99,400	19.9%	68,100	21.6%	-31,300	-31.5%	1.7
	45-54	112,200	22.5%	77,600	24.6%	-34,600	-30.8%	2.1
	55-64	61,500	12.3%	38,800	12.3%	-22,700	-36.9%	0.0
Female	**14-99**	**130,300**	**26.1%**	**79,200**	**25.1%**	**-51,100**	**-39.2%**	**-1.0**
	25-34	25,600	5.1%	13,000	4.1%	-12,600	-49.2%	-1.0
	35-44	37,500	7.5%	23,100	7.3%	-14,400	-38.4%	-0.2
	45-54	41,000	8.2%	27,100	8.6%	-13,900	-33.9%	0.4
	55-64	18,200	3.6%	12,200	3.9%	-6,000	-33.0%	0.2

§ Auto sector defined as TEM-plus.

Source: U.S. Census Bureau, Local Employment Dynamics

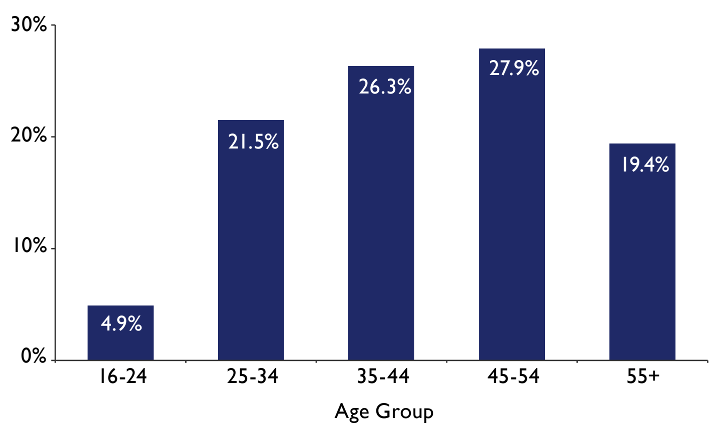
industry employing these workers five years later, researchers can answer the questions about the industry "migration" of the displaced autoworkers. Did the workers remain in TEM? If so, are they with the same or a different employer? To what extent did they migrate out of TEM?

2.3.1 Methodology

Using Indiana unemployment insurance administrative data, the research team established an initial universe of autoworkers by extracting wage records from the first quarter of 2005 for employers in TEM.[4] Some workers were employed in more than one industry during the base reference quarter in 2005. In that event, the worker was assigned an industry on the basis of the wage record with the greatest wage.

The initial pool of autoworkers was then matched against all employer wage records for the first quarter of 2010. Again, some multiple matches for the same worker were discovered and the employer record with the highest wage was used to determine the worker's 2010 industry employment. Some wage record matches included employer account information that did not identify an industry; these are the "No NAICS Match" records. Workers who had a wage record in the first quarter of 2005 but not in the first quarter of 2010 were listed as "No Wage Match." Some possible reasons for not having a wage match involve workers who are unemployed, self-employed or retired, became disabled, returned to school, or are employed

Figure 3: Long-Term Claimants by Age Group



Source: Indiana Department of Workforce Development, using Indiana unemployment claims data

4 Namely, motor vehicle manufacturing, motor vehicle body and trailer manufacturing, and motor vehicle parts manufacturing—NAICS industry sectors 3361, 3362 and 3363, respectively.

in an organization that is not subject to wage reporting.

2.3.2 Findings

There were 142,219 autoworkers—from all occupations including production, administration, management and engineering—in Indiana in the first quarter of 2005. **Table 3** presents the top 10 three-digit NAICS industries where these workers were employed five years later. The table shows that nearly 40 percent were still in the auto sector, but at least 19 percent had found new work outside TEM. The industry "no NAICS match" indicates that the displaced worker was employed in the first quarter of 2010, but the records do not identify the industry. Nearly 32 percent of the TEM workers did not have wage matches and one may surmise that a significant percentage of them were not employed in the first quarter of 2010.[5]

Table 3: Indiana Autoworker Migration: Sub-sectors in 2010 Employing TEM Workers from 2005

NAICS Code	Subsector	Workers	Percent
336	Transportation Equipment Manufacturing	56,740	39.9
n/a	No Wage Match (no wage record in 2010)	45,090	31.7
n/a	No NAICS Match (2010 industry not identified)	13,206	9.3
561	Administrative and Support Services	3,490	2.5
332	Fabricated Metal Product Manufacturing	1,891	1.3
611	Educational Services	1,171	0.8
333	Machinery Manufacturing	1,042	0.7
722	Food Services and Drinking Places	995	0.7
423	Merchant Wholesalers, Durable Goods	986	0.7
326	Plastics and Rubber Products Manufacturing	922	0.7

Note: Data are for the first quarter of each year.

Source: Indiana Department of Workforce Development

Table 4: Breakout of Transportation Equipment Manufacturing Re-Employment: Industry Groups in 2010 Employing TEM Workers from 2005

NAICS Code	Subsector	Workers	Percent
3363	Motor Vehicle Parts Manufacturing	31,903	56.2
3362	Motor Vehicle Body and Trailer Manufacturing	16,090	28.4
3361	Motor Vehicle Manufacturing	8,375	14.8
3364	Aerospace Product and Parts Manufacturing	245	0.4
3366	Ship and Boat Building	94	0.2
3369	Other Transportation Equipment Manufacturing	32	0.1
3365	Railroad Rolling Stock Manufacturing	1	0.0
Totals		**56,740**	**100.0**

Source: Indiana Department of Workforce Development

Administrative and support services was the next largest industry employing the 2005 autoworkers five years later. Over three-quarters of these people were employed in the employment services industry, which includes employment placement agencies, temporary help services, and professional employer organizations. Indiana's manufacturing sector, including TEM, makes extensive use of these temporary and leased employees.

Another destination industry of interest is education services. While less than 1 percent of the total number of autoworkers in the 2005 cadre, it still accounts for almost 1,200 worker placements. About 70 percent of these workers were employed in elementary and secondary schools and were concentrated in TEM-intensive regions such as Howard, Elkhart, Allen and St. Joseph counties. Most of the remaining former workers working in NAICS 611 found jobs in postsecondary institutions.

As shown above, about 40 percent of TEM workers in early 2005 were employed in TEM in early 2010.

[5] The method used does not allow one to know whether these workers had intermittent employment before the 1st quarter of 2009.

Table 4 shows the TEM employment breakdown with greater industry detail. Of the 56,740 workers from the original autoworker pool of 2005 who were also employed in the TEM industry in 2010, 99.4 percent of these workers were concentrated in the traditional auto industries of motor vehicle parts manufacturing, motor vehicle body and trailer manufacturing, and motor vehicle manufacturing. There were, however, minor movements to other, closely related TEM industries, but these other specialized industries did not appear to offer re-employment opportunities for a significant number of ex-autoworkers.

Table 4 shows that there was not a great deal of shifting within the TEM industry groups, but workers may have changed companies within a NAICS classification. The question is then: of the 142,219 TEM workers in 2005 how many changed employers?

Table 5 shows that a surprising number of workers remained in the sector, but with different employers.

Table 5: Employer Outcomes of TEM Worker Migration from 2005 to 2010

	Same Employer	Different Employer
TEM	21.9%	18.0%
Not TEM	0.3%*	28.2%

* Indicates that the employer changed industries
Note: The remaining 31.7 percent of TEM workers had no wage match for 2010.

Source: Indiana Department of Workforce Development

Of the original 2005 autoworker cohort, 21.9 percent stayed in TEM with the same employer in 2010, while 18 percent remaining in TEM changed employers. A very small percentage of the autoworker cohort stayed with the same employer but moved outside the industry. The typical autoworker migration was not only out of TEM, but also away from the same employer.

Dislocated autoworkers not only had to find new jobs, they also had the challenge to maintain their level of income. The TEM sector across its constituent occupations—production, engineering, management, etc.—tends to outpace other industries' average wages. As a result, the typical displaced autoworker that found employment in another industry saw his or her paycheck shrink. Migrating workers lost, on average, 29 percent of their earning power by moving from TEM to non-TEM industries.[6] Clearly, the average dislocated autoworker pays a steep price when transitioning to another industry.

2.4 Finding Work—Prospects for the Future

As a result of the Great Recession and industry restructuring, the employment picture in the automobile sector, as with manufacturing and construction in general, is grim. Over a third of the auto workforce lost their jobs from 2006 to 2009.

The auto sector is hiring again and has recalled some workers, but at a relative trickle. The uptake rate is not yet sufficient to rehire all those that lost their jobs because of the economic whirlwinds of the last several years. Where will a majority of the unemployed find jobs, given that being rehired may not be a realistic option?

As this chapter closes, one gets the distinct sense that the dislocated autoworker is in a conundrum. The jobs in the industry just are not there in sufficient numbers. Even if there are jobs in other sectors, the average job elsewhere does not pay as well by a substantial margin. What is the dislocated worker to do?

The next chapter begins to plot a path to viable occupation alternatives.

[6] This is based on the weighted-average wage for 2005 of the top 10 leading non-TEM industries to which autoworkers migrated. The 29 percent would reflect the average autoworker losing a TEM job and immediately being employed and earning the average wage of the top 10 non-TEM destination industries. It is a wage comparison within 2005 and does not account for changes in wages over time or for changes in the price level (inflation). The average annual wage in TEM for the second and third quarters of 2005 was $64,650 and the weighted average wage of the top 10 non-TEM destination industries for the same time period was $46,090. The weighting is based on the number of migrating workers.

3. Occupations of Opportunity

For the displaced autoworker, finding the best occupation to pursue may be difficult. Workers may need a great deal of assistance to identify and secure their next job. This chapter seeks to reveal occupations of opportunity for these displaced workers. The chapter starts with the level of demand for green automotive occupations, then identifies the growing occupations in the tri-state region (both green and non-green) and wraps up with a more localized focus, portraying how sub-state regional job prospects can differ from statewide projections.

3.1 Green Automotive Occupations

In order to gauge the labor demand in the tri-state area, the research team used the Conference Board's Help Wanted Online (HWOL) database to capture the job postings in the fourth quarter of 2010. These jobs were subsequently matched with O*NET's classifications of green occupations, the Center for Automotive Research (CAR) list of auto occupations, BLS' projected employment to 2018 and BLS/OES' 2009 employment and wages. Not all of the occupations and data are consistent across these databases; only 19 green automotive occupations were consistent across all data sources, the top 15 of which are displayed in **Table 6**. Of the top 15 occupations,

Table 6: Tri-State Top 15 Green Auto Occupation§ Postings and Expected Job Change to 2018

Rank	Description	HWOL Green Postings[1]	10-Year Expected Growth[2]	Postings-to-Employment Ratio[3]	Mean Wage[4]
1	Industrial Engineers	10,960	14.2%	1 : 3	$75,476
2	Mechanical Engineers	6,626	6.0%	1 : 7	$78,759
3	First-Line Supervisors/Managers of Production and Operating Workers	6,525	-5.2%	1 : 12	$55,964
4	Maintenance and Repair Workers, General	5,004	10.9%	1 : 25	$36,712
5	Electrical Engineers	2,901	1.7%	1 : 4	$76,464
6	First-Line Supervisors/Managers of Mechanics, Installers, and Repairers	2,677	4.3%	1 : 15	$59,704
7	Machinists	2,307	-4.6%	1 : 28	$38,823
8	Computer-Controlled Machine Tool Operators, Metal and Plastic	1,713	6.6%	1 : 16	$35,287
9	Electronics Engineers, Except Computer	1,444	0.3%	1 : 6	$81,587
10	Inspectors, Testers, Sorters, Samplers, and Weighers	1,368	-3.6%	1 : 43	$35,354
11	Industrial Machinery Mechanics	878	7.3%	1 : 37	$48,450
12	Electrical and Electronic Equipment Assemblers	856	-14.7%	1 : 16	$28,369
13	Industrial Engineering Technicians	801	6.6%	1 : 14	$48,006
14	Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic	534	-14.1%	1 : 80	$32,306
15	Team Assemblers	330	0.0%	1 : 467	$31,731

§ Auto occupation is defined by CAR

[1] Source: HWOL, Quarter 4, 2010; N=131,248; Green jobs comprised 22.1 percent of all posted occupations.

[2] Source: BLS; Projections from 2008 to 2018 are for the parent, six-digit SOC. HWOL and O*NET now report occupations at the eight-digit SOC level. As a result, those occupations listed in this table are at the more detailed, eight-digit SOC while the projection figures are for the parent six-digit SOC. Hence the projection is for a group of similar occupations and not the specific occupation listed in the table.

[3] Source: IBRC using HWOL and BLS/OES data

[4] Source: 2009 OES data from BLS

one-third are engineers or technicians, and the remainder are managers or production occupations. Some of the top 15 green auto occupations have bright prospects for the future, but BLS forecasts that several of these occupations will decline in the coming decade.

Despite the increased focus on green occupations and the greening of the auto sector, not all occupations within the auto industry will be uniformly affected by the greening of the industry. Engineers, technicians and technologists are most likely to face significant change in the skills needed to accomplish their jobs. Production line workers, on the other hand, would require minimal on-the-job training to acquire the skills needed to handle the new green tasks. The focus panels conducted by CAR indicated that future engineers would need a systems approach to engineering rather than the traditional insular disciplinary perspective.[7]

3.1.1 What Does a Green Auto Job Mean?

The research team wove labor force data together from several different sources, as mentioned above. While BLS may forecast the demand for occupations across a broad array of industries for the entire nation, occupation projections for a specific sector may differ. As the auto industry transforms, so will the mix of occupations employed in the industry. In anticipation of these changes, the Center for Automotive Research compiled a list of auto occupations that they predict will grow in the auto sector in the future (see **Table 7**). A majority of these future occupations are engineers, technologists, and technicians who specialize in electricity. While standard auto occupations (e.g., industrial truck and tractor operators) still exist, the CAR occupation list emphasizes highly skilled occupations that will be needed as the industry transforms.

These CAR future auto industry jobs were placed in the O*NET categories of green occupations. O*NET categorizes green jobs into three categories: green new and emerging, green increased demand, and green enhanced skills.

Green New and Emerging: Newly generated occupations resulting from the green economy and technologies. The output of the green economy and green technologies is sufficient to create the need for unique work and worker requirements. These are entirely novel occupations arising from the green economy, but they could be an outgrowth of an existing occupation.

Green Increased Demand: Occupations in increased demand due to the green economy and technologies. Expanding green economic output simply increases the employment demand for an existing occupation. It does not entail significant changes in the work and worker requirements. The work context may change, but the tasks themselves do not. An example is the increased demand for heating and ventilation installers that replace the energy-efficient furnaces and air conditioning units more frequently because these units are not as durable as the older furnaces.

Green Enhanced Skills: The requirements of green economic output and technologies change an existing occupation. The change may be reflected in the necessary skills, knowledge or credentials to execute the occupation's purpose. This effect may or may not result in an increase in employment demand for the occupation. Architecture is such a field. The occupation now requires increased knowledge about energy efficient materials and construction, as well as skills associated with integrating green technology into the aesthetic design of buildings. The essential purpose of the occupation remains the same, but tasks, skills, knowledge and external elements (such as credentials) have expanded.

[7] Driving Change Consortium, "Driving Workforce Change: Regional Impact and Implications of Auto Industry Transformation to a Green Economy," a report prepared for the Employment and Training Administration, U.S. Department of Labor, May 2011, www.drivingworkforcechange.org/reports/DrivingWorkforceChange.pdf.

Table 7: Future Auto Occupations by Green Category

Not Green§

- Quality Control Systems Managers
- Computer Hardware Engineers
- Product Safety Engineers
- Materials Engineers
- Drafters, all other
- Rolling Machine Setters, Operators, and Tenders, Metal and Plastic
- Model Makers, Metal and Plastic
- Patternmakers, Metal and Plastic
- Civil Engineering Technicians
- Non-Destructive Testing Specialists
- Urban and Regional Planners
- Foundry Mold and Coremakers
- Plating and Coating Machine Setters, Operators, and Tenders, Metal and Plastic
- Metal Workers and Plastic Workers, all other
- Electrical and Electronics Repairers, powerhouse, Substation, and Relay
- Electronic Equipment Installers and Repairers, Motor Vehicles
- Automotive Body and Related Repairers
- Automotive Glass Installers and repairers
- Bus and Truck Mechanics and Diesel Engine Specialists

New and Emerging

- Biofuels Production Managers
- Biochemical Engineers
- Validation Engineers
- Manufacturing Engineers
- Mechatronics Engineers
- Microsystems Engineers
- Photonics Engineers
- Nanosystems Engineers
- Automotive Engineering Technicians
- Electrical Engineering Technologists
- Electronics Engineering Technologists
- Manufacturing Engineering Technologists
- Mechanical Engineering Technologists
- Fuel Cell Technicians
- Nanotechnology Engineering Technologists
- Nanotechnology Engineering Technicians
- Electromechanical Engineering Technologists

Increased Demand

- Stationary Engineers and Boiler Operators
- Industrial Truck and Tractor Operators
- Chemical Technicians
- Commercial and Industrial Designers
- Electricians
- Millwrights
- Electrical Power-line Installers and Repairers
- Helpers--Installation, Maintenance, and Repair Workers
- Power Distributors and Dispatchers
- Power Plant Operators
- Chemists
- Materials Scientists
- Chemical Engineers

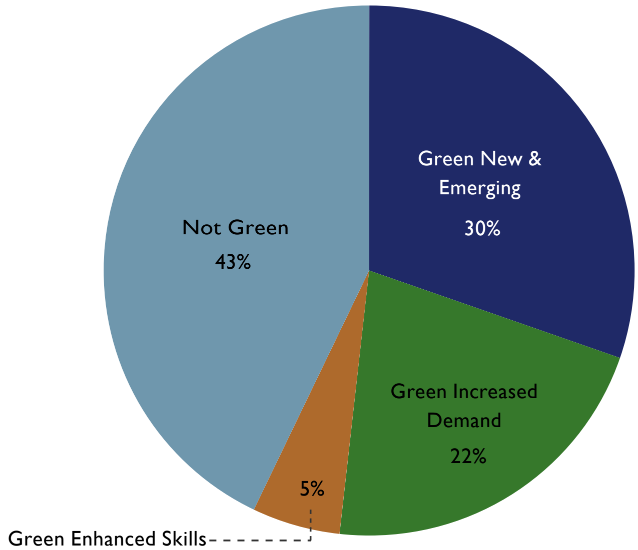
Enhanced Skills

- Environmental Engineers
- Environmental Engineering Technicians

§ O*NET does not classify these auto occupations as green.

Source: IBRC, using Center for Automotive Research and O*NET data

Figure 4: Potential Future Auto Occupations



Source: IBRC, using Center for Automotive Research and O*NET data

As **Figure 4** shows, over half of the future auto occupations—not the number of people employed in these jobs but the number of occupation titles—are considered green (57 percent), with the bulk of these considered new and emerging occupations. These new and emerging occupations are unique and have unique worker requirements that official data sources have not yet been able to document. It is likely these occupations have evolved from other engineering and environmental occupations. That said, they may also be completely original in their development and requisite skills.

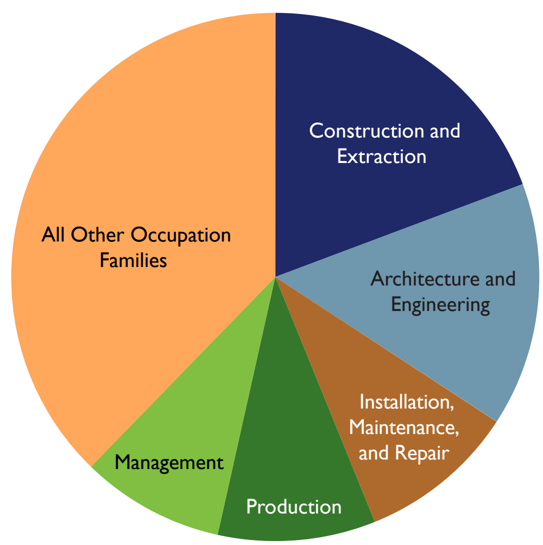
3.2 Green and Growing Occupations

At the time of this writing, the auto industry is hiring again, but not at rates sufficient to absorb all the displaced autoworkers. Displaced autoworkers, therefore, may choose to look for employment outside of the auto industry and, most likely, high-wage/high-demand occupations will be of great interest. For simplicity, these high-wage/high-demand occupations are referred to simply as "growing" occupations.

In keeping with the green theme of the Driving Change research, the research team wanted to distinguish between green and non-green occupations that are growing. **Figure 5** shows the leading green job families[8] that are expected to grow in the tri-state region. Of the 371 unique occupations in the tri-state region that are growing, only 17 are green. The construction and extraction job families have the most green and growing occupations in the three states. Architecture and engineering occupations were the second-largest job family.

Table 8 shows the top 15 green and growing occupations in the tri-state area based on the number of job postings recorded by HWOL in the fourth quarter of 2010. Of the top 15 green and growing occupations, only two are considered part of the auto industry (industrial engineers and computer-controlled machine tool operators, metal and plastic). The average wage of the top 15 occupations was $61,900 and the occupations had an average expected growth of 13.2 percent. The ratio of HWOL postings to jobs reflects the relative strength of the job postings to the number employed in 2009. Therefore, from the list, one can see that marketing managers are in relatively high demand as there was a posting for every two marketing manager jobs.

Figure 5: Distribution of Tri-State Green and Growing Occupations by Job Family§



§ O*NET groups occupations into "job families" based upon work performed, skills, education, training, and credentials.

Source: Indiana, Michigan and Ohio Labor Market Information offices

8 O*NET groups occupations based upon work performed, skills, education, training and credentials into "job families."

Table 8: Tri-State Top 15 Green and Growing Occupations Projected to 2018

Rank	Description	HWOL Postings[1]	Total Employment 2009[2]	10-Year Expected Growth[3]	Postings-to-Employment Ratio[4]	Mean Wage[5]
1	Truck Drivers, Heavy and Tractor-Trailer	16,343	164,770	12.9%	1 : 10	$39,190
2	Industrial Engineers	10,960	221,484	9.7%	1 : 3	$75,476
3	Marketing Managers	5,919	9,530	7.4%	1 : 2	$106,051
4	Public Relations Specialists	1,826	17,310	18.0%	1 : 9	$51,630
5	Training and Development Specialists	1,794	18,050	20.0%	1 : 10	$53,051
6	Comp. Software Engineers, Systems Software	1,377	19,780	23.7%	1 : 14	$81,926
7	Financial Analysts	1,284	14,050	14.4%	1 : 11	$74,050
8	Construction Laborers	1,013	56,490	14.5%	1 : 56	$36,989
9	Civil Engineers	970	15,110	18.8%	1 : 16	$72,232
10	Industrial Engineering Technicians	801	144,070	4.6%	1 : 14	$48,006
11	Construction Managers	674	14,670	13.4%	1 : 22	$93,401
12	Personal Financial Advisors	669	8,520	24.7%	1 : 13	$91,046
13	Computer-Controlled Machine Tool Operators, Metal and Plastic	534	104,719	1.8%	1 : 80	$32,306
14	Construction and Building Inspectors	282	6,500	8.6%	1 : 23	$48,370
15	Operating Engineers & Other Construction Equipment Operators	124	27,920	8.7%	1 : 225	$48,226

[1] Source: HWOL, Quarter 4, 2010; N=131,248; Green jobs comprised 22.1 percent of all posted occupations.

[2] Source: BLS/OES data

[3] Source: Projections came from each state's Workforce agency for years 2008-2018.

[4] Source: IBRC using HWOL and BLS/OES data

[5] Source: BLS. Note that the mean wage is weighted by each state's employment for the occupation.

"Of the top 15 green and growing occupations, only two are considered part of the auto industry (industrial engineers and computer-controlled machine tool operators, metal and plastic)."

Table 9: Indiana's Top 15 Green and Growing Occupations Projected to 2018

Rank	Description	HWOL Postings[1]	Total Employment 2009[2]	10-Year Expected Growth[3]	Postings-to-Employment Ratio[4]	Mean Wage[5]
1	Truck Drivers, Heavy and Tractor-Trailer	4,371	52,830	15.4%	1 : 12	$38,880
2	Sales Representatives, Wholesale and Manufacturing, Except Technical and Scientific Products	1,056	7,110	6.7%	1 : 7	$79,890
3	Marketing Managers	863	2,260	11.0%	1 : 3	$100,880
4	Engineering Managers	401	3,400	3.2%	1 : 8	$99,490
5	Training and Development Specialists	314	4,480	23.0%	1 : 14	$50,260
6	Public Relations Specialists	292	4,590	21.6%	1 : 16	$45,800
7	Electricians	215	12,680	9.4%	1 : 59	$52,450
8	Computer Software Engineers, Systems Software	203	3,340	21.1%	1 : 16	$77,910
9	Financial Analysts	157	2,240	15.5%	1 : 14	$68,690
10	Civil Engineers	136	2,910	22.6%	1 : 21	$70,660
11	Construction Laborers	128	15,570	23.5%	1 : 122	$37,500
12	Environmental Engineers	124	510	32.9%	1 : 4	$79,590
13	Construction Managers	120	4,050	23.9%	1 : 34	$84,920
14	Industrial Safety and Health Engineers	110	620	9.1%	1 : 6	$68,660
15	Personal Financial Advisors	86	1,790	18.8%	1 : 21	$96,980

[1] Source: HWOL, Quarter 4, 2010; N=24,595; N=43,921; Green jobs comprised 22.3 percent of all posted occupations in Indiana.

[2] Source: BLS/OES data

[3] Source: Projections came from the Indiana Department of Workforce Development.

[4] Source: IBRC using HWOL and BLS/OES data

[5] Source: BLS/OES data

Table 9 shows Indiana's top 15 green and growing occupations. Two-thirds of the occupations listed are reflected in **Table 8**, but Indiana does have five unique green and growing occupations, of which most are in high demand (sales representatives, engineering managers; electricians; environmental engineers; and industrial safety and health engineers). Interestingly, Indiana is the only state to list environmental engineers as a top green and growing occupation. The average wage for these top 15 occupations was $70,171 and the average expected growth was 17.2 percent.

Table 10 portrays Michigan's top 15 green and growing occupations, of which all occupations match the tri-state list. The average wage ($63,900) and average growth (13.9 percent) of the top 15 list is slightly higher in Michigan than the tri-state area. In addition to the Michigan top 15 mirroring the tri-state region, based on its ratio of postings to jobs, Michigan also has slightly stronger demand for these occupations.

Ohio, like Indiana, has several occupations in its top 15 of green and growing that are not reflected in the tri-state's top 15 (see **Table 11**). One-third of the state's top green and growing occupations are auto related, reflecting the dominance of the industry in the state. The average wage of Ohio's top green and growing occupations was $66,500 and average expected growth was 6.2 percent.

Table 10: Michigan's Top 15 Green and Growing Occupations Projected to 2018

Rank	Description	HWOL Postings[1]	Total Employment 2009[2]	10-Year Expected Growth[3]	Postings-to-Employment Ratio[4]	Mean Wage[5]
1	Industrial Engineers	4,920	20,000	13.2%	1 : 4	$79,260
2	Truck Drivers, Heavy and Tractor-Trailer	4,557	46,140	11.1%	1 : 10	$39,560
3	Marketing Managers	1,864	3,560	7.7%	1 : 2	$101,070
4	Computer-Controlled Machine Tool Operators, Metal/Plastic	640	8,680	5.8%	1 : 14	$36,570
5	Comp. Software Engineers, Systems Software	638	6,740	23.9%	1 : 11	$82,170
6	Training and Development Specialists	603	4,610	19.9%	1 : 8	$54,930
7	Public Relations Specialists	582	6,330	17.3%	1 : 11	$55,030
8	Construction Laborers	414	19,060	9.9%	1 : 46	$34,850
9	Financial Analysts	398	4,920	15.4%	1 : 12	$77,680
10	Civil Engineers	290	5,720	20.0%	1 : 20	$72,070
11	Personal Financial Advisors	279	3,170	29.9%	1 : 11	$90,330
12	Industrial Engineering Technicians	272	5,690	8.9%	1 : 21	$47,290
13	Construction Managers	191	4,310	9.5%	1 : 23	$92,280
14	Construction and Building Inspectors	118	2,120	10.8%	1 : 18	$50,580
15	Operating Engineers and Other Construction Equipment Operators	45	7,520	5.7%	1 : 167	$45,240

[1] Source: HWOL, Quarter 4, 2010; N=43,921; Green jobs comprised 22.2 percent of all posted occupations in Michigan.

[2] Source: BLS/OES data

[3] Source: Projections came from the Michigan Department of Energy, Labor and Economic Growth—Bureau of Labor Market Information and Strategic Initiatives.

[4] Source: IBRC using HWOL and BLS/OES data

[5] Source: BLS/OES data

"The average wage ($63,900) and average growth (13.9 percent) of the top 15 list is slightly higher in Michigan than the tri-state area."

Table 11: Ohio's Top 15 Green and Growing Occupations Projected to 2018

Rank	Description	HWOL Postings[1]	Total Employment 2009[2]	10-Year Expected Growth[3]	Postings-to-Employment Ratio[4]	Mean Wage[5]
1	Truck Drivers, Heavy and Tractor-Trailer	7,415	65,800	10.7%	1 : 9	$39,180
2	Industrial Engineers	3,820	11,910	2.8%	1 : 3	$71,680
3	Marketing Managers	3,192	3,710	4.8%	1 : 1	$113,980
4	Maintenance and Repair Workers, General	2,548	54,460	3.5%	1 : 21	$36,150
5	Sales Representatives, Wholesale and Manufacturing, Except Technical and Scientific Products	2,512	19,160	7.7%	1 : 8	$77,730
6	Mechanical Engineers	2,250	12,340	-1.6%	1 : 5	$70,510
7	First Line Supervisors/Managers of Mechanics/Installers/Repairers	1,311	16,480	-3.8%	1 : 13	$59,410
8	Public Relations Specialists	952	6,390	14.1%	1 : 7	$52,450
9	Computer-Controlled Machine Tool Operators, Metals/Plastics	917	11,850	-4.3%	1 : 13	$35,660
10	Training and Development Specialists	877	8,960	15.7%	1 : 10	$53,480
11	Financial Analysts	729	6,890	11.7%	1 : 9	$73,200
12	Engineering Managers	704	5,840	-2.8%	1 : 8	$109,250
13	Electricians	572	22,800	1.4%	1 : 40	$48,180
14	Civil Engineers	544	6,480	13.7%	1 : 12	$73,080
15	Computer Software Engineers, Systems Software	536	9,700	19.6%	1 : 18	$83,140

[1] Source: HWOL, Quarter 4, 2010; N=62,732; Green jobs comprised 21.8 percent of all posted occupations in Ohio.

[2] Source: BLS/OES data

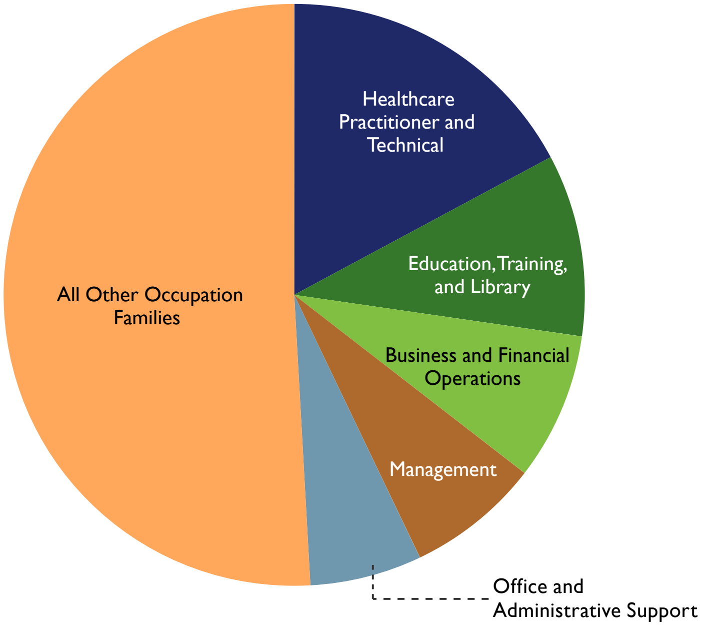
[3] Source: Projections came from the Ohio Department of Jobs and Family Services—Labor Market Information Bureau

[4] Source: IBRC using HWOL and BLS/OES data

[5] Source: BLS/OES data

"One-third of Ohio's top green and growing occupations are auto related, reflecting the dominance of the industry in the state."

Figure 6: Distribution of Tri-State Non-Green and Growing Occupations by Job Family§



§ O*NET groups occupations based upon work performed, skills, education, training and credentials into "job families."

Source: Indiana, Michigan and Ohio Labor Market Information offices

3.3 Other Growing Occupations

While the green economy is an important organizing theme for this research, roughly 83 percent of the growing occupations in each of the states were non-green. **Figure 6** shows the distribution of the non-green and growing job families for the tri-state region. As expected, healthcare practitioners and technical occupations topped the list, with education, training, and library as the second most dominant job family among growing occupations. The healthcare and technical occupations also have the highest mean wages in the tri-state region, indicating appealing fields to enter.

Help Wanted Online (HWOL) provides a "real-time" gauge of the demand for labor. Based on HWOL postings, one-third of the top 15 non-green occupations in the tri-state region are in the healthcare practitioner and technical occupations, followed by computer and mathematical science occupations (see **Table 12**). These occupations are in high demand, with ratios ranging from one posting per job to one posting per 21 jobs. Moreover, the top 15 are expected to grow 15.2 percent through 2018. The average wage for the top 15 occupations was $64,100.

Michigan's non-green and growing occupations are a virtual copy of the tri-state listing (see **Table 13**). The only exception is the occupation of sales representatives. The ratio of postings to jobs for Michigan's occupations is also similar to the tri-state region. Of the top 15 occupations, the average wage was $65,500 and the average expected growth was 14.7 percent.

Indiana's top 15 non-green and growing occupations had three occupations that differed from the tri-state listing—two for sales representatives and one for occupational therapist assistants (see **Table 14**). Similar to the tri-state listing, healthcare practitioners dominate the list. Within Indiana, these occupations are in high demand and have a very strong expected growth forecasted. The average wage in Indiana for these top non-green growing occupations (about $59,300) was not as high as in Michigan, but Department of Labor projections suggest that Indiana's average expected growth for these jobs will be higher (17.2 percent).

Table 15 shows Ohio's top non-green and growing occupations, based on the HWOL job postings in the fourth quarter of 2010. The state had three occupations that were not in the tri-state list: first-line supervisors/managers of non-retail sales workers, sales representatives and occupational therapist assistants. Occupational therapists had a very high ratio of postings to jobs (2.3 postings per job), indicating that the state has a high demand for these skilled workers. Overall, the average Ohio wage of the top 15 non-green and growing occupations was the highest in the tri-state region, $68,000, and expected to grow by an average of 12 percent through 2018.

3.4 The Geographic Dimensions of Labor Demand

The purpose of a workforce development agency publishing a list of growing occupations is to provide job seekers with guidance about the expected wages and demand for prospective occupations. That said, the aggregated data on a statewide level might be misleading if the jobs are highly clustered in one part of the state and non-existent in another. This section highlights some of the differences in labor

Table 12: Tri-State Top 15 Non-Green and Growing Occupations Projected to 2018

Rank	Description	HWOL Postings[1]	Total Employment 2009[2]	10-Year Expected Growth[3]	Postings-to-Employment Ratio[4]	Mean Wage[5]
1	Registered Nurses	23,415	260,370	19.5%	1 : 11	$60,750
2	Occupational Therapists	14,728	10,820	23.9%	1 : 1	$68,962
3	Physical Therapists	12,620	17,820	26.3%	1 : 1	$73,557
4	Computer Systems Analysts	10,422	38,060	15.0%	1 : 4	$77,109
5	Executive Secretaries and Administrative Assistants	9,971	101,740	7.6%	1 : 10	$41,237
6	Medical and Health Services Managers	7,796	28,290	14.0%	1 : 4	$82,542
7	Computer Support Specialists	7,740	46,030	10.2%	1 : 6	$42,408
8	First-Line Sup/Mgrs of Office and Administrative Support	7,662	98,500	6.5%	1 : 13	$48,399
9	Speech-Language Pathologists	7,352	9,640	15.4%	1 : 1	$72,655
10	Computer Software Engineers, Applications	5,759	36,380	29.5%	1 : 6	$78,684
11	Sales Managers	5,587	26,530	10.0%	1 : 5	$104,688
12	Network and Computer Systems Administrators	4,708	30,040	15.9%	1 : 6	$62,740
13	Insurance Sales Agents	4,467	29,110	8.7%	1 : 7	$59,556
14	Licensed Practical and Licensed Vocational Nurses	3,854	80,190	18.8%	1 : 21	$40,013
15	Bookkeeping, Accounting, and Auditing Clerks	3,703	148,640	6.0%	1 : 40	$33,345

[1] Source: HWOL, Quarter 4, 2010; N=463,988; Non-green jobs comprised 77.9 percent of all HWOL postings.

[2] Source: BLS/OES data

[3] Source: Projections came from each state's respective Bureau of Labor agency for the years 2008-2018.

[4] Source: IBRC using HWOL and BLS/OES data

[5] Source: BLS/OES data

"Based on HWOL postings, one-third of the top 15 non-green occupations in the tri-state region are in the healthcare practitioner and technical occupations, followed by computer and mathematical science occupations."

Table 13: Michigan's Top 15 Non-Green and Growing Occupations Projected to 2018

Rank	Description	HWOL Postings[1]	Total Employment 2009[2]	10-Year Expected Growth[3]	Postings-to-Employment Ratio[4]	Mean Wage[5]
1	Registered Nurses	8,614	84,620	20.2%	1 : 10	$64,100
2	Executive Secretaries and Administrative Assistants	3,479	34,690	7.4%	1 : 10	$42,640
3	Computer Systems Analysts	3,165	12,820	15.6%	1 : 4	$80,180
4	Physical Therapists	3,026	6,550	26.8%	1 : 2	$74,310
5	Medical and Health Services Managers	2,818	9,590	13.6%	1 : 3	$84,920
6	Computer Software Engineers, Applications	2,584	9,600	24.8%	1 : 4	$77,220
7	Computer Support Specialists	2,568	15,420	7.6%	1 : 6	$44,350
8	First-Line Sup/Mgrs of Office and Administrative Support	2,441	28,180	5.9%	1 : 12	$49,990
9	Sales Representatives, Services, All Other	1,935	15,480	6.9%	1 : 8	$54,950
10	Sales Managers	1,847	9,740	10.8%	1 : 5	$104,670
11	Occupational Therapists	1,845	4,370	23.3%	1 : 2	$64,290
12	Speech-Language Pathologists	1,676	2,740	10.8%	1 : 2	$70,270
13	Insurance Sales Agents	1,606	8,630	11.9%	1 : 5	$61,170
14	Network and Computer Systems Administrators	1,584	8,240	17.1%	1 : 5	$66,520
15	Licensed Practical and Licensed Vocational Nurses	1,288	18,720	17.7%	1 : 15	$42,540

[1] Source: HWOL, Quarter 4, 2010; N=153,492; Non-green jobs comprised 77.8 percent of all Michigan postings.

[2] Source: BLS/OES data

Source: Projections came from the Michigan Department of Energy, Labor and Economic Growth—Bureau of Labor Market Information and Strategic Initiatives for 2008-2018.

[4] Source: IBRC using HWOL and BLS/OES data

[5] Source: BLS/OES data

> *"Of the top 15 non-green and growing occupations in Michigan, the average wage was $65,500 and the average expected growth was 14.7 percent."*

Table 14: Indiana's Top 15 Non-Green and Growing Occupations Projected to 2018

Rank	Description	HWOL Postings[1]	Total Employment 2009[2]	10-Year Expected Growth[3]	Postings-to-Employment Ratio[4]	Mean Wage[5]
1	Occupational Therapists	3,681	2,390	30.9%	1 : 1	$67,980
2	Registered Nurses	2,966	57,880	22.3%	1 : 20	$57,910
3	Speech-Language Pathologists	2,710	2,070	22.5%	1 : 1	$65,160
4	Physical Therapists	2,315	4,170	30.6%	1 : 2	$69,340
5	Executive Secretaries and Administrative Assistants	1,920	21,830	11.2%	1 : 11	$38,670
6	First-Line Supervisors/Managers of Office and Administrative Support	1,657	24,910	9.3%	1 : 15	$47,270
7	Medical and Health Services Managers	1,537	6,960	15.9%	1 : 5	$78,290
8	Sales Representatives, Wholesale and Manufacturing, Except Technical and Scientific Products	1,516	31,160	4.0%	1 : 21	$57,880
9	Computer Systems Analysts	1,433	7,380	17.2%	1 : 5	$70,030
10	Computer Support Specialists	1,427	8,740	7.7%	1 : 6	$40,630
11	Sales Managers	1,138	5,800	11.4%	1 : 5	$93,780
12	Sales Representatives, Services, All Other	1,110	10,290	13.2%	1 : 9	$52,400
13	Occupational Therapist Assistants	1,085	790	30.3%	1 : 1	$49,430
14	Insurance Sales Agents	981	6,550	9.0%	1 : 7	$62,440
15	Licensed Practical and Licensed Vocational Nurses	920	20,610	22.8%	1 : 22	$37,920

[1] Source: HWOL, Quarter 4, 2010; N=85,918; Non-green jobs comprised 77.7 percent of all Indiana postings.

[2] Source: BLS/OES data

[3] Source: Projections came from the Indiana Department of Workforce Development for years 2008-2018.

[4] Source: IBRC using HWOL and BLS/OES data

[5] Source: BLS/OES data

> *"Similar to the tri-state listing, healthcare practitioners dominate the list. Within Indiana, these occupations are in high demand and have a very strong expected growth forecasted."*

Table 15: Ohio's Top 15 Non-Green and Growing Occupations Projected to 2018

Rank	Description	HWOL Postings[1]	Total Employment 2009[2]	10-Year Expected Growth[3]	Postings-to-Employment Ratio[4]	Mean Wage[5]
1	Registered Nurses	11,835	117,870	15.0%	1 : 10	$59,740
2	Occupational Therapists	9,202	4,060	16.8%	2.3 : 1	$74,570
3	Physical Therapists	7,279	7,100	19.0%	1 : 1	$75,340
4	Computer Systems Analysts	5,824	17,860	12.1%	1 : 3	$77,830
5	Executive Secretaries & Administrative Assistants	4,572	45,220	5.5%	1 : 10	$41,400
6	Sales Representatives, Wholesale and Manufacturing, Except Technical and Scientific Products	3,898	61,020	1.7%	1 : 16	$58,850
7	Computer Support Specialists	3,745	21,870	11.5%	1 : 6	$41,750
8	First-Line Sup/Mgrs of Office & Admin. Support	3,564	45,410	5.2%	1 : 13	$48,030
9	Medical and Health Services Managers	3,441	11,740	11.6%	1 : 3	$83,120
10	Speech-Language Pathologists	2,966	4,830	13.1%	1 : 2	$77,220
11	Sales Managers	2,602	10,990	7.8%	1 : 4	$110,460
12	Computer Software Engineers, Applications	2,356	20,690	23.7%	1 : 9	$81,480
13	Network and Computer Systems Administrators	2,323	15,510	12.8%	1 : 7	$62,310
14	Occupational Therapist Assistants	1,971	2,400	23.1%	1 : 1	$51,290
15	First-Line Sup./Mgrs of Non-Retail Sales Workers	1,965	10,650	0.9%	1 : 5	$75,880

[1] Source: HWOL, Quarter 4, 2010; N=224,578; Non-green jobs comprised 78.2 percent of all Ohio postings.

[2] Source: BLS/OES data

[3] Source: Projections came from the Ohio Department of Jobs and Family Services—Labor Market Information Bureau for years 2008-2018.

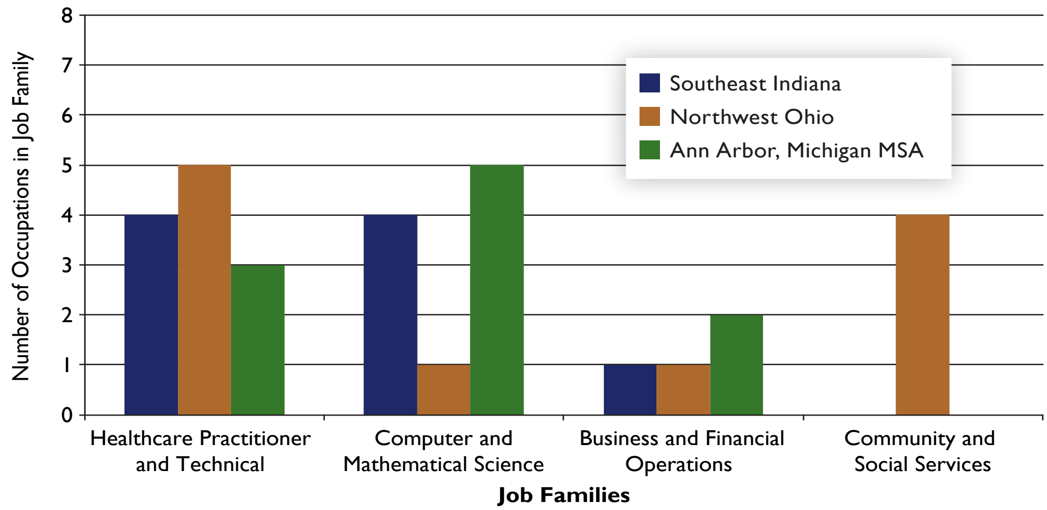
[4] Source: IBRC using HWOL and BLS/OES data

[5] Source: BLS/OES data

> *"Overall, the average Ohio wage of the top 15 non-green and growing occupations was the highest in the tri-state region, $68,000, and expected to grow by an average of 12 percent through 2018."*

demand and wages in three sub-state regions, namely, the Ann Arbor MSA region, Economic Development Region (EDR) 2 in Northwest Ohio and Economic Growth Region (EGR) 9 in Southeast Indiana. In order for this comparison across sub-state regions to have merit, the data needed to be on the same temporal basis given the tremendous shifts in the composition of the labor force due to the recession. While it would have been desirable to use 2008-2018 projections like those used above, these were not yet available at the sub-state level at the time of this writing. That said, the 2006-2016 employment projections still reveal that regional labor markets are distinct.[9]

Figure 7: Different Regions–Different Job Needs: The Distribution of Selected Growing Job Families in Three Sub-State Regions§



§ O*NET groups occupations based upon work performed, skills, education, training and credentials into "job families."

Source: Indiana, Michigan and Ohio Labor Market Information offices

Figure 7 presents a high-level view of how the demand for certain occupations can differ across regions. **Figure 1** presents the number of growing occupation titles within selected job families in the three sub-state regions.[10] As with the tri-state region as a whole, the job family with the most growing occupations is healthcare and technical occupations. Except for healthcare occupations, the regions diverge with respect to the occupations in greater demand. In Northwest Ohio, for example, the demand for computer and mathematical science occupations appears to be significantly less than in the Indiana and Michigan regions. In contrast, the need for community and social services occupations appears to be substantially greater in Northwest Ohio compared to the regions in Indiana and Michigan.

The difference between the sub-state regions is even more obvious with the detailed occupation data. In the Ann Arbor region, for example, there is not a great deal of overlap with occupations in demand in the rest of the state. Only five of Michigan's top 15 occupations were also in Ann Arbor's top 15. The differences go beyond the volume of demand (or head count). Of those five occupations, only computer systems analysts had a higher mean wage in the Ann Arbor region than in the state as a whole.

Michigan (as shown in **Table 13**), in contrast to the Ann Arbor region in **Table 16**, has a stronger demand for healthcare practitioners and technical occupations, while the computer and mathematical sciences occupations dominate the sub-state region. The column that presents the percentage of Michigan jobs for a particular occupation in the Ann Arbor region also highlights the regional differences in the labor market. For example, nearly a quarter of Michigan's interior designers are employed in the Ann Arbor region while the region has only about 6 percent of the state's dental hygienists.

Table 17 highlights the top 15 growing occupations for EGR 9 in Southeast Indiana. This region has several different growing occupations than the statewide projections. Only three occupations are in both the statewide and the EGR 9 top 15 lists.

The column that presents the percentage of Indiana jobs for a particular occupation in EGR 9 also

[9] In order to make the data more current, 2006 base employment figures were extrapolated to 2009 using the expected average annual growth rate from 2006 to 2016.

[10] This is not the number of jobs; it is the number of occupations.

Table 16: Top 15 Growing Occupations for Ann Arbor, Michigan Projected to 2016

Rank	Description	Projected 2009 Employment[1]	10-Year Expected Growth[2]	Percentage of Total MI Jobs in Region[3]	Ratio of Statewide Postings to Jobs[4]	Mean Wage (2009)[5]
1	Network Systems and Data Communications Analysts	561	44.4%	10.2%	1 : 15	$71,232
2	Computer Software Engineers-Applications	1,140	35.4%	11.9%	1 : 4	$76,902
3	Interior Designers	259	34.0%	24.7%	1 : 13	$51,072
4	Personal Financial Advisors*	286	32.7%	9.0%	1 : 11	$73,311
5	Medical Assistants	1,442	30.7%	7.2%	1 : 17	$32,466
6	Dental Hygienists	534	29.6%	5.9%	1 : 102	$62,790
7	Customer Service Representatives*	6,406	28.3%	11.2%	1 : 15	$32,697
8	Dental Assistants	640	28.0%	6.8%	1 : 24	$38,808
9	Computer Systems Analysts	1,099	27.6%	8.6%	1 : 4	$75,789
10	Computer Software Engineers-Systems Software*	650	27.5%	9.6%	1 : 11	$77,721
11	Veterinarians	217	27.5%	12.8%	1 : 106	$94,017
12	Logisticians	448	26.5%	8.9%	1 : 30	$65,394
13	Veterinary Technologists and Technicians	189	25.7%	12.7%	1 : 21	$37,128
14	Network and Computer Systems Administrators	673	25.6%	8.2%	1 : 5	$76,755
15	Market Research Analysts	430	25.0%	7.2%	1 : 6	$58,758

* According to O*NET, this occupation is green.

1 Source: Michigan Department of Energy, Labor and Economic Growth—Bureau of Labor Market Information and Strategic Initiatives—for 2006 employment and projections to 2016. The 2009 figure is a synthetic projection—not the actual 2009 estimates or a published projection for 2009—using the average annual growth rate from 2006.

2 Source: Michigan Department of Energy, Labor and Economic Growth—Bureau of Labor Market Information and Strategic Initiatives for 2006-2016.

3 Source: BLS/OES data for Michigan. Divided synthetic 2009 employment figure for Ann Arbor region by statewide employment OES estimates.

4 Source: IBRC using HWOL and BLS/OES data. Statewide ratio of postings to jobs. Regional data are unavailable.

5 Michigan Department of Energy, Labor and Economic Growth—Bureau of Labor Market Information and Strategic Initiatives, published 2009 OES values.

> *"Nearly a quarter of Michigan's interior designers are employed in the Ann Arbor region while the region has only about 6 percent of the state's dental hygienists."*

Table 17: Top 15 Growing Occupations for EGR 9 in Indiana Projected to 2016

Rank	Description	Projected 2009 Employment[1]	10-Year Expected Growth[2]	Percentage of Total IN Jobs in Region[3]	Ratio of Statewide Postings to Jobs[4]	Mean Wage (2007)[5]
1	Gaming Supervisors	229	49.7%	28.2%	1 : 58	$49,692
2	Computer Software Engineers, Systems Software*	116	48.5%	3.5%	1 : 16	$66,393
3	Network Systems and Data Communications Analysts	74	47.7%	2.2%	1 : 18	$60,134
4	Veterinarians	63	45.5%	6.0%	1 : 62	$60,851
5	Dental Hygienists	178	33.3%	4.5%	1 : 102	$59,560
6	Dental Assistants	246	33.0%	4.3%	1 : 37	$28,878
7	Compliance Officers, except Agriculture, Construction, Health & Safety, and Transportation	109	32.3%	3.4%	1 : 646	$42,522
8	Registered Nurses	1,993	31.3%	3.4%	1 : 20	$53,793
9	Physical Therapists	145	28.4%	3.5%	1 : 2	$67,622
10	Team Assemblers*	5,807	28.3%	10.3%	1 : 1257	$28,505
11	Postsecondary Teachers	732	27.7%	5.2%	1 : 17	$54,385
12	Paralegals and Legal Assistants	251	26.7%	7.1%	1 : 19	$35,347
13	Chemists*	135	25.6%	5.4%	1 : 35	$48,659
14	Network and Computer Systems Administrators	209	24.6%	3.3%	1 : 8	$57,254
15	Computer Software Engineers, Applications	173	22.8%	2.8%	1 : 7	$69,890

*According to O*NET, this occupation is green.

1 Source: Indiana Department of Workforce Development for 2006 employment and projections to 2016. The 2009 figure is a synthetic projection—not the actual 2009 estimates or a published projection for 2009—using the average annual growth rate from 2006.

2 Source: Indiana Department of Workforce Development for 2006-2016.

3 Source: BLS/OES data for Indiana. Divided synthetic 2009 employment figure for EGR 9 by statewide employment (OES) estimates.

4 Source: IBRC using HWOL and BLS/OES data. Statewide ratio of postings to jobs. Regional data are unavailable.

5 Indiana Department of Workforce Development, published 2007 OES values.

“Over a quarter of Indiana’s gaming supervisors are employed in EGR9 while the region has just over 3 percent of the state’s registered nurses.”

Table 18: Top 15 Growing Occupations for EDR 2 in Ohio Projected to 2016

Rank	Description	Projected 2009 Employment[1]	10-Year Expected Growth[2]	Percentage of Total OH Jobs in Region[3]	Ratio of Statewide Postings to Jobs[4]	Mean Wage (2008)[5]
1	Financial Analysts*	362	43.8%	5.3%	1 : 9	$ 73,437
2	Mental Health Counselors	316	42.9%	14.1%	1 : 32	$ 43,386
3	Substance Abuse and Behavioral Disease Counselors	392	40.0%	10.0%	1 : 34	$ 43,407
4	Network Systems and Data Comm. Analysts	290	38.5%	3.0%	1 : 16	$ 75,054
5	Physical Therapist Assistants	736	32.8%	15.5%	1 : 3	$ 49,539
6	Mental Health and Substance Abuse Social Workers	406	32.4%	8.3%	1 : 8	$ 37,107
7	Dental Hygienists	740	29.4%	10.4%	1 : 72	$ 64,407
8	Physical Therapists	790	27.4%	11.1%	1 : 1	$ 85,197
9	Respiratory Therapists	891	20.2%	16.7%	1 : 25	$ 50,799
10	Securities/Commodities/ Financial Services Sales Agents	795	20.0%	7.3%	1 : 1095	$ 70,077
11	Registered Nurses*	11,052	19.5%	9.4%	1 : 10	$ 57,414
12	Pharmacists	928	18.2%	7.9%	1 : 19	$ 100,695
13	Industrial Engineers*	1,220	17.2%	10.2%	1 : 3	$ 74,088
14	Medical and Public Health Social Workers	441	16.7%	7.0%	1 : 6	$ 46,788
15	Advertising Sales Agents	451	16.3%	8.7%	1 : 5	$ 45,444

*According to O*NET, this occupation is green.

[1] Source: Ohio Department of Jobs and Family Services, Labor Market Information Bureau, for 2006 employment and projections to 2016. The 2009 figure is a synthetic projection—not the actual 2009 estimates or a published projection for 2009—using the average annual growth rate from 2006.

[2] Source: Ohio Department of Jobs and Family Services—Labor Market Information Bureau for 2006-2016.

[3] Source: BLS/OES data for Ohio. Divided synthetic 2009 employment figure for EDR 2 by statewide employment OES estimates.

[4] Source: IBRC using HWOL and BLS/OES data. Statewide ratio of postings to jobs. Regional data are unavailable.

[5] Source: Ohio Department of Jobs and Family Services—Labor Market Information Bureau, published 2008 OES values.

highlights the regional differences in the labor market. For example, over a quarter of Indiana's gaming supervisors are employed in EGR 9 while the region has just over 3 percent of the state's registered nurses.

Of particular interest is the difference in HWOL postings. While several EGR 9 occupations have low ratios of statewide HWOL postings to jobs, high growth is expected in the region for those occupations over the next 10 years. The presence of a new casino in the region brings bright prospects for gaming supervisors. While there is a lot of competition for team assembler jobs in the state, with one posting for every 1,257 jobs, the projected demand in the region is pretty good due in large part to an auto assembly plant in Greensburg.

Except for financial analysts at the top of the list, healthcare practitioners and community and social services occupations occupy most of the top 15 jobs in Ohio's EDR 2 in the northwestern section of the state (see **Table 18**).

There are four occupations that are shared by both the region's and the state's top 15 lists. While the region appears to need many workers in the community and social services occupations in the coming years, these types of jobs have lower demand in the state as a whole.

The column that presents the percentage of Ohio jobs for a particular occupation in EDR 2 also highlights the differences between the regional and statewide labor market. The region employs about 16 percent of the state's respiratory therapists but only 3 percent of Ohio's network systems analysts.

3.5 Conclusion

This chapter has focused on where the jobs are. While many opportunities may exist for displaced workers, not all the growing occupations will be a good fit for the skill sets and worker traits of those looking for work.

Even as the auto industry continues to hire, the hiring will not be sufficient to re-absorb all the displaced autoworkers. Of the occupations that are expected to grow in the tri-state region, few are auto-related. Most green auto sector jobs are specialized in nature, requiring not just a bachelor's degree in an engineering discipline, but additional formal training to gain expertise in several technical fields.

Given that the green jobs that are expected to grow represent a small share of current openings, most displaced auto workers will likely migrate not only to other industries, but also to occupations that are not green. This chapter presented examples of occupations that have the brightest prospects in the tri-state region. The next chapter presents how a displaced worker may determine which occupation would make the best fit with her or his knowledge, skills, traits and values.

4. Career Pathway Clusters

The previous chapter presented the occupations that are in demand today and that have the brightest prospects for the future. Organized around the themes of jobs in the automobile sector, the green economy and other growing occupations, the chapter identified possible career options for displaced workers or others entering the job market.

"Within a pathway cluster, one should be able to transition from one occupation to another with relative ease."

The question then becomes, how does one transition to the occupations with the brightest prospects? The displaced autoworker has a certain skill set based upon her or his occupation. Does that skill set match the needs of the growing occupations? How can one make that assessment? What additional skills or training does one need to transition to those occupations that are green, expected to grow or both?

The career pathways resources presented in this chapter, and the skills gap resource presented in the following chapter, address these questions. This chapter first describes how the pathway clusters work and how they may be used. Second, the chapter presents the methodology for developing occupation clusters based on broad similarities between occupations. Third, the results of the cluster formation are presented, complete with several examples of occupations within pathway clusters. Finally, the missing dimension for making a career transition within a pathway cluster is discussed, thus providing a segue to Chapter 5.

4.1 Pathway Clusters—A Description

How a pathway cluster is constructed and defined is driven by how a displaced worker would use such a resource. The operating principle for the pathway cluster is that a worker will seek, and be most productive in, occupations that are most similar to his or her current or former job. This operating principle is like that for the TORQ system for finding occupations that best match one's knowledge, skills and abilities.[11] While the TORQ system pulls in many of the elements, requirements and characteristics of an occupation to determine whether a new occupation is a good match with a past occupation, the pathway cluster approach distills occupation and worker requirements into fewer, more user-friendly categories.

Within a pathway cluster, one should be able to transition from one occupation to another with relative ease. Because pathway clusters are constructed based on occupational similarities, transitions from one pathway cluster to a different cluster would be relatively more difficult. The advantage that pathway clusters have over other career transition resources is that the user is provided a set of many possible target occupations, rather than a series of one-at-a-time matches. Combined with the features of the skill-gap analysis, a worker in transition will also know the time required for the education or training needed to move from one occupation to another.

4.2 Pathway Cluster Methodology

4.2.1 Data

In order to create pathway clusters, the research team analyzed the multitude of dimensions and characteristics for each occupation as published by O*NET.[12] In total, O*NET uses nearly 700 job or worker characteristics to describe and define an occupation. The research team compressed many of these characteristics data into three realigned

[11] TORQ is a powerful tool that provides a compatibility score for comparing one occupation with another. See www.torqworks.com/products for more information.

[12] Data for this analysis come from the Occupational Information Network (O*NET) which is supported by the U.S. Department of Labor's Employment and Training Administration. More information is available at www.onetcenter.org/overview.html. This analysis does not use the new 2010 SOC system because, at the time of the analysis, O*NET data were still based on the 2000 SOC system.

O*NET categories to develop pathway clusters. Below are the three broad categories with the O*NET-type occupational identifiers:[13]

1. ***Requirements of the worker (R):*** Worker requirements that can be gained by the worker through study or training

    - *Knowledge:* Sets of principles and facts in a subject area (aka knowledge requirement)
    - *Cross-Functional Skills:* The capacity to perform the activities across different jobs

2. ***Traits of the worker (T):*** The internal or personal traits of workers who are drawn to—or perform well in—the occupation

    - *Interests:* Preferences for the type of work and work environment based on personality types
    - *Work Values:* Work duties, outcomes and environment that are personally satisfying
    - *Work Styles:* Personal characteristics that influence performance

3. ***Occupational requirements (O):*** The requirements for the job, such as work activities like lifting heavy objects or gathering data

    - *Generalized Work Activities:* Type and intensity of personal interactions and mental processes like problem solving and information gathering
    - *Work Context:* Physical activities and social factors that influence the nature of work

[13] Not all terms were directly taken from O*NET; many O*NET terms were translated to appeal to a general audience. Occupational interests, for example, are based on the system developed by John L. Holland for matching vocational roles with personality types. For complete information, see John. L. Holland, *Making Vocational Choices: A Theory of Vocational Personalities and Work Environments* (Odessa, FL: Psychological Assessment Resources, 1997).

Compressing the data, removing characteristics with significant overlap and realigning the remaining occupation characteristics means that there will not be a one-to-one correspondence with O*NET definitions and categories, but the general thrust of the O*NET method remains intact. The relative simplicity of the pathway cluster resource should compensate for any loss of adherence to strict O*NET definitions.

4.2.2 Methods

The research team used the following procedures in compressing the O*NET occupation characteristics to create a small number of intuitive and meaningful occupation pathway clusters that can best differentiate occupations: correlation, spread and skew.

Variables that were highly correlated with others were removed or combined. For example, several skill areas had a great deal of overlap and were combined into a single skill variable. The research team also removed variables for which the range of scores was narrow and did not differ substantially across occupations, as well as variables for which very low or very high scores were overabundant.

The research team then analyzed the remaining occupation variables for 731 jobs, comparing the scores of the variables that describe the characteristics of occupations by their level of similarity (or dissimilarity) to determine the patterns they form. For example, a high knowledge variable score for transportation typically occurs among occupations that also have high scores in public safety and security, but low scores in the fine arts occupations. The goal is to have the minimum number of characteristics that logically complement intuitively related occupations (e.g., engineering and physics) and characteristics that differentiate those jobs that are not.

Creating pathway clusters is both a science and an art. The cluster formation, which depends heavily on statistics and mathematical analysis, reflects the science. The research team then moved to the "art" of the analysis—examining the clusters to see if they each had well-balanced combinations of occupations that made logical and intuitive sense.

Through an iterative process, multiple sets of clusters were formed and then improved to account for seemingly unusual combinations of factors or clusters of occupations. The final set of clusters represents the best attempt to sort all occupations into groupings that account for their similarities in worker requirements such as knowledge and skills, as well as worker traits and occupational requirements.

For a more detailed and technical explanation of the methodology, please see Appendix A.

Table 19: Summary of Career Pathway Clusters

Cluster Name[§]	Number of Occupations	Number of Auto[*]	Number of Green[¤]
Information and Investigation	62	0	12
Health, Social and Personal Services	90	0	0
Production, Construction and Engineering	217	44	55
Engineering and Applied Technology	75	20	26
Construction and Extraction, Equipment Operation, and Repair	69	2	15
Design and Production	73	20	14
Liberal Arts, Education and Human Relations	86	0	7
Business, Sales and Administration	105	2	15
Transportation and Public Services	97	0	20
Environmental Sciences and Food Service	74	1	15

[§] Clusters are ordered based on their relative strength, or how "tight" the clusters are. Information and investigation was the strongest cluster. The environmental sciences and food service cluster, in contrast, had the weakest similarity scores. The number of occupations in a cluster does not speak to the cluster's relative strength or importance.

[*] Based on the CAR definition of auto-related occupations. It does not include two residual occupation categories "all other" for which there are no job specific data.

[¤] Based on the six-digit SOC definitions of the 2009 vintage of O*NET. The 2010 eight-digit O*NET/SOC definitions have considerably more jobs classified as green.

Source: IDWD and IBRC

4.3 Pathway Cluster Results

The research produced seven career pathway clusters. **Table 19** shows how the 731 occupations are distributed among these groupings. While the occupations were fairly well divided among the clusters, the production, construction and engineering cluster had a disproportionate share of occupations, so it was divided into three sub-clusters: 1) engineering and applied technology; 2) construction and extraction, equipment operation, and repair; and 3) design and production.

The clusters in **Table 19** are ordered based on the relative similarity of occupations within each. Information and investigation was the strongest cluster, with the greatest similarity scores. The environmental sciences and food service cluster had the weakest similarity scores and, therefore, required the most "artful" adjustments by the research team.

It is not surprising that the concentration of auto occupations in the production, construction and engineering cluster is high. For autoworkers looking for work within their cluster, it should be encouraging to know that they have options outside of the auto sector; 80 percent of the occupations in that cluster are not unique to auto manufacturing.

As **Table 19** shows, green occupations are fairly well distributed across clusters, with the exception of the health, social and personal services cluster. Any worker, automotive or otherwise, interested in making a transition to a green occupation would likely have several green target occupations within their cluster for which they have a relatively similar skill set and worker traits.

Below is a brief summary of each of the pathway clusters that highlights some key worker requirements (***R***), worker traits (***T***) and occupational requirements (***O***) that define each cluster. For illustration, these summaries also describe a diverse group of sample occupations within each cluster. While at first glance many of these occupations may not seem to have obvious similarities, the pattern of high scores among the key characteristics that define each particular cluster helps to explain their fit within each group.

Table 20: Information and Investigation Cluster: Key Occupation Factors

Category	Variable Type	Detailed Variable
R	Knowledge	Computers and Electronics
R	Knowledge	Mathematics
R	Skills	Systems/Programming
T	Interests	Investigative
T	Work Styles	Independence and Detail*
O	Work Activities	Information*

*This measure represents a combination of several O*NET variables
Source: IDWD and IBRC, using O*NET data

Sample Occupations

- Computer and Information Scientists, Research
- Astronomers
- Physicists
- Engineering Teachers, Postsecondary
- Atmospheric, Earth, Marine, and Space Sciences Teachers, Postsecondary
- Library Science Teachers, Postsecondary

Table 21: Health, Social and Personal Services Cluster: Key Occupation Factors

Category	Variable Type	Detailed Variable
R	Knowledge	Medicine and Dentistry
R	Knowledge	Psychology
R	Knowledge	Therapy and Counseling
T	Interests	Social*
T	Work Styles	Social
T	Work Values	Relationships
O	Work Activities	Assisting and Caring for Others
O	Work Contexts	Dealing with Conflict or Aggressive People*

*This measure represents a combination of several O*NET variables
Source: IDWD and IBRC, using O*NET data

Sample Occupations

- Marriage and Family Therapists
- Nursing Instructors and Teachers, Postsecondary
- Family and General Practitioners
- Internists, General
- Psychiatrists
- Surgeons

The first three clusters are described in somewhat greater detail, especially the production, construction and engineering cluster because it has the preponderance of automotive occupations.

4.3.1 Information and Investigation

Despite cutting across several worker or occupation requirements and many different types of professions, the occupations in this cluster share strong similarities (see **Table 20**). Across a range of subject areas, these occupations are oriented toward collecting and analyzing data. Some common knowledge areas required for these occupations include knowledge in computers, electronics and mathematics. Workers also need elevated skills in systems and programming. These workers share several personal characteristics, such as working independently and having great attention to detail. Workers drawn to these occupations are personally interested in working with ideas, searching for facts and solving problems.

As a group, the occupations in this cluster require identifying, collecting and processing information. This cluster contains a particularly broad array of occupations ranging from physicists and astronomers, to postsecondary teachers in atmospheric sciences and engineering, to computer and information scientists.

4.3.2 Health, Social and Personal Services

This might be called the "helping cluster." Two key occupational requirements define this cluster: assisting and caring for others, and dealing with unpleasant, angry or physically aggressive people (see **Table 21**). Workers need knowledge in medicine and dentistry, psychology, as well as therapy and counseling. Workers are also characterized by prefering higher levels of social interaction at work

Table 22: Production, Construction and Engineering Cluster: Key Occupation Factors

Category	Variable Type	Detailed Variable
R	Knowledge	Building and Construction
R	Knowledge	Design
R	Knowledge	Engineering and Technology
R	Knowledge	Mechanical
R	Knowledge	Physics
R	Knowledge	Production and Processing
R	Skills	Monitoring/Design*
T	Interests	Physical Objects/Hands-On
O	Work Activities	Equipment*

*This measure represents a combination of several O*NET variables
Source: IDWD and IBRC, using O*NET data

and having concern for others and self-control. Workers also value building relationships and tend to be drawn to vocations in teaching, networking and communicating. Occupations such as medical doctors, therapists and nursing instructors fit this cluster, despite a wide range of major occupational groups (as defined by BLS and O*NET). The range of helping cluster occupations include: health care practitioners and technical workers; community and social services; and education, training and library occupations.

4.3.3 Production, Construction and Engineering

This "super cluster" covers a wide range of worker and job characteristics. It is also the cluster with the greatest number of manufacturing and auto sector occupations. The strength of similarity of the occupations within this cluster is relatively strong compared to the other pathway clusters. This super cluster is dominated by occupations with high scores in six knowledge groups: mechanical; engineering and technology; design; physics; building and construction; and production and processing (see **Table 22**). Because these factors dominate the super cluster, they are a common thread through the sub-clusters.

Worker requirements include skill sets in selecting and operating equipment, managing material resources, and monitoring the performance of processes and equipment. This cluster also features hands-on, practical occupations requiring problem solving and working with machinery. In addition, occupations in these clusters work with a wide spectrum of materials, often outdoors. Finally, an important occupational requirement is work activity related to inspecting, handling and maintaining large or sophisticated pieces of equipment.

Because this cluster is so large, the research team subdivided this super-cluster into three sub-clusters using the same iterative exploratory methodology:

4.3.4 Engineering and Applied Technology

This sub-cluster is marked by occupations that focus on skills in equipment monitoring and design, as well as systems and programming (see **Table 23**). Workers with knowledge in engineering and technology dominate this cluster. While this cluster includes workers that need a knowledge foundation in physics, it also includes the "-cians" like technicians and electricians with knowledge in specialized areas. Examples of occupations in this cluster include a wide range of engineers, technicians and mechanics. Three major occupational groups dominate this

Table 23: Engineering and Applied Technology Sub-Cluster: Key Occupation Factors

Category	Variable Type	Detailed Variable
R	Knowledge	Engineering and Technology
R	Knowledge	Mechanical
R	Knowledge	Physics
R	Skills	Monitoring/Design*
R	Skills	Systems/Programming*

*This measure represents a combination of several O*NET variables
Source: IDWD and IBRC, using O*NET data

Sample Occupations

- Electrical Engineers
- Electronics Engineers, Except Computer
- Mechanical Engineers
- Elevator Installers and Repairers
- Radio Mechanics
- Power Distributors and Dispatchers

Table 24: Construction and Extraction, Equipment Operation and Repair Sub-Cluster: Key Occupation Factors

Category	Variable Type	Detailed Variable
R	Knowledge	Building and Construction
R	Knowledge	Chemistry
R	Knowledge	Public Safety and Security
R	Knowledge	Transportation
O	Work Activities	Equipment*

*This measure represents a combination of several O*NET variables
Source: IDWD and IBRC, using O*NET data

Sample Occupations

- First-Line Supervisors and Managers of Construction and Extraction Workers
- Operating Engineers and Other Construction Equipment Operators
- Roustabouts, Oil and Gas
- Manufactured Building and Mobile Home Installers
- Extruding and Drawing Machine Setters, Operators, and Tenders, Metal and Plastic
- Water and Liquid Waste Treatment Plant and System Operators

Table 25: Design and Production Sub-Cluster: Key Occupation Factors

Category	Variable Type	Detailed Variable
R	Knowledge	Design
R	Knowledge	Engineering and Technology
R	Knowledge	Production and Processing

Source: IDWD and IBRC, using O*NET data

Sample Occupations

- Commercial and Industrial Designers
- Construction Carpenters
- Stone Cutters and Carvers, Manufacturing
- Machine Feeders and Offbearers

Table 26: Liberal Arts, Education and Human Relations Cluster: Key Occupation Factors

Category	Variable Type	Detailed Variable
R	Knowledge	Communications and Media
R	Knowledge	Fine Arts
R	Knowledge	History and Archeology
R	Knowledge	Philosphy and Theology
R	Knowledge	Sociology and Anthropology
T	Interests	Artistic

Source: IDWD and IBRC, using O*NET data

Sample Occupations

- Anthropologists
- Architecture Teachers, Postsecondary
- Area, Ethnic, and Cultural Studies Teachers, Postsecondary
- Art, Drama, and Music Teachers, Postsecondary
- Foreign Language and Literature Teachers, Postsecondary
- Choreographers
- Music Directors

cluster: architecture and engineering; installation, maintenance and repair; and production.

4.3.5 Construction and Extraction, Equipment Operation and Repair

In order to build structures or extract minerals, one needs to operate equipment, so it is of little surprise that equipment operators are clustered with construction workers. Knowledge in transportation, public safety and security, and building and construction are also key among occupations in this cluster. Many types of repairers and installers are among the occupations within this cluster in addition to production occupations.

4.3.6 Design and Production

The third sub-cluster is differentiated from the other two by knowledge in production and processing and design. While this cluster is similar to the first sub-cluster in the strength of engineering and technology, the artistic elements of design tend to dominate this cluster. Occupations range from artisans such as jewelers and tailors to design-oriented production jobs such as industrial engineering technicians and photographic process

Table 27: Business, Sales and Administration Cluster: Key Occupation Factors

Category	Variable Type	Detailed Variable
R	Knowledge	Administration and Management
R	Knowledge	Customer and Personal Service
R	Knowledge	Economics and Accounting
R	Knowledge	Personnel and Human Resources
R	Knowledge	Sales and Marketing
C	Interests	Enterprising

Source: IDWD and IBRC, using O*NET data

Sample Occupations

- Public Relations Managers
- Medical and Health Services Managers
- Chief Executives
- General and Operations Managers
- Loan Counselors
- First-Line Supervisors/Managers of Non-Retail Sales Workers

Table 28: Transportation and Public Services Cluster: Key Occupation Factors

Category	Variable Type	Detailed Variable
R	Knowledge	Geography
R	Knowledge	Law and Government
R	Knowledge	Public Safety and Security
R	Knowledge	Transportation

Source: IDWD and IBRC, using O*NET data

Sample Occupations

- Transportation Managers
- Urban and Regional Planners
- First-Line Supervisors/Managers of Police and Detectives
- Forest Fire Inspectors and Prevention Specialists
- Police Detectives
- Aviation Inspectors

workers. Like the other sub-clusters, the major occupation groups are diverse: arts and design; production; and transportation and material moving.

4.3.7 Liberal Arts, Education and Human Relations

Worker knowledge requirements dominate all the most important factors for this cluster—particularly knowledge of fine arts, history and archeology, philosophy and theology, sociology and anthropology, and communications and media (see **Table 26**). Workers in this cluster also tend to have personal artistic interests. The cluster is dominated by education occupations such as postsecondary art and music teachers, music directors and some social science occupations.

4.3.8 Business, Sales and Administration

Like many of the clusters, knowledge requirements also dominate the business, sales and administration cluster. Workers are required to have knowledge in one of the following areas: sales and marketing, economics and accounting, administration and management, personnel and human resources or customer and personal service (see **Table 27**). Those attracted to occupations in this cluster have personal interests in starting up and carrying out projects, leading people and making decisions, and often have an appetite for taking risks. Sample occupations in this cluster span management, business and financial operations, and sales and related occupations.

4.3.9 Transportation and Public Services

Knowledge areas of public safety, transportation, law and travel services were the primary drivers that formed this cluster. Key occupations within this cluster range from aviation inspectors to police detectives and urban and regional planners (see **Table 28**). The major occupational category of transportation and material moving dominated the cluster, followed closely by the two major categories of law, public safety and security and life, physical and social science.

4.3.10 Environmental Sciences and Food Service

This cluster, the weakest of the seven, is largely defined by high scores in the worker requirements of knowledge in food production, biology and chemistry. This pathway cluster is composed of an extensive array of occupations including scientists

Table 29: Environmental Sciences and Food Service Cluster: Key Occupation Factors

Category	Variable Type	Detailed Variable
R	Knowledge	Biology
R	Knowledge	Chemistry
R	Knowledge	Food Production

Source: IDWD and IBRC, using O*NET data

Sample Occupations

- Commercial and Industrial Designers
- Construction Carpenters
- Stone Cutters and Carvers, Manufacturing
- Machine Feeders and Offbearers

in the natural science and environmental disciplines as well as agriculture (see **Table 29**). This is also the "food cluster" that includes dietitians and food service workers. It may not be intuitively obvious how the occupations in this cluster are comparable, but based on O*NET surveys, incumbent workers in these occupations share relatively high scores in biology and chemistry, as well as food production.

4.4 Finding and Closing the Skills Gap[14]

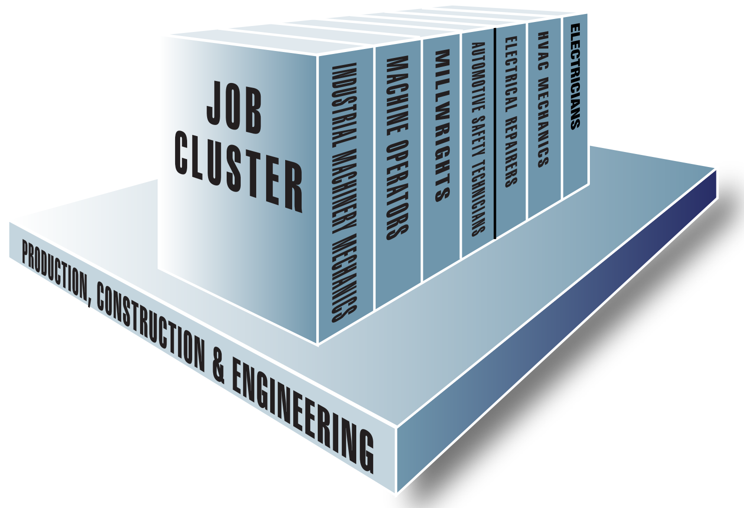
The pathway cluster analysis groups occupations based on the similarities and differences of hundreds of job and worker characteristics. Given the goal of the project is to help a displaced worker transition from one occupation to another, it would be natural to respond with: "Great. So now what?"

The occupations within a pathway cluster provide a set—albeit a large set—of potential target occupations. The number of potential targets can be winnowed down further based on whether the occupation is in the same job zone, an O*NET classification scheme based on the level of skill required for a job. As one ascends the job zone levels, there are additional education and training requirements for the job. The highest job zone levels may require thousands of hours of education and on-the-job training to achieve the skill level required for work such as advanced surgical procedures or astrophysics. For example, it would be very difficult, and time-intensive, for a radiological technician—job zone 3 requiring an associate degree—to transition to a nuclear medicine physician—job zone 5 requiring extensive graduate education—even though both jobs deal with radiation equipment and medicine. The skills gap is enormous.

The next step for the pathway cluster work, then, is to provide meaningful, user-friendly instruments to measure the skills gap between occupations and to assess the relative ease or difficulty of moving from one occupation to another.

The skills gap therefore, is primarily a knowledge or human capital gap. Closing the knowledge gap can take months or years in the classroom earning credits and degrees, just as closing many types of skills gaps requires many months or even years as an apprentice. The next chapter explores a method and a measure for determining the size of that skills gap and the relative ease of moving from one occupation to another: the number of hours of education and training.

Figure 8: Selected Occupations in the Production, Construction and Engineering Cluster



Source: Indiana Business Research Center

[14] The gap, or difficulty to make a transition, between any two occupations involves more than O*NET-type skills; it may reflect differences in knowledge, abilities, physical strength and educational attainment, as well as skills. However, to be consistent with common usage, this report uses the term "skills gap" to refer to gaps between occupations in *any* of the relevant O*NET occupation description characteristics.

The pathway cluster analysis groups occupations based on the similarities and differences of over 500 job and worker characteristics. The occupations within a pathway cluster provide a set of potential target occupations for a displaced worker. **Figure 8** is a picture of this first step, namely, organizing occupations into groups based on their similarities across a wide range of job and worker requirements. Thus, the Driving Change project has not only identified the displaced workers and the green and growing occupations of promise, but the research team has developed a resource that can identify occupations that are relatively similar to the original occupation of the displaced worker. The next step for the pathway cluster work then, is to provide meaningful, user-friendly instruments to measure the skills gap between occupations and to assess the relative ease or difficulty of moving from one occupation to another.

5. Closing the Skills Gap

As described in the previous chapter, pathway clusters offer displaced workers a resource to identify target occupations that are generally similar to their former occupations.

This chapter addresses the questions of how long and how difficult the transition will be from an originating occupation to a destination occupation. Like the selected occupations from the production cluster presented in **Figure 9**, there is a distance between them. One cannot simply jump from one job to another. So what will it take to get from one occupation to the next?

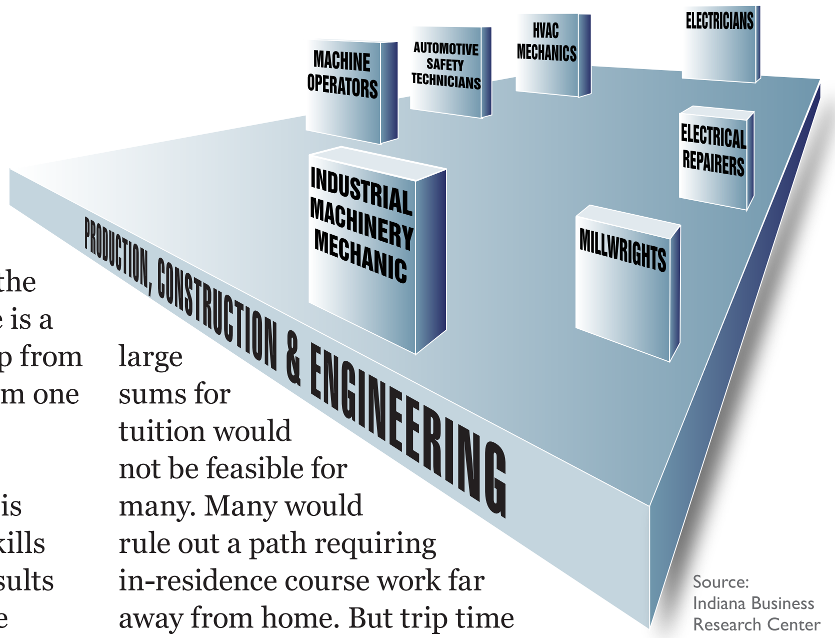
First, the chapter describes the skills gap analysis and presents the method used to measure the skills gap. The second section presents some of the results of the skills gap analysis, demonstrating that the pathway cluster analysis indeed groups occupations in a fashion that, on average, reduces the time and level of effort required to move to an occupation in a cluster rather than a different pathway cluster. Finally, more detailed results of the skills gap analysis are discussed, together with examples of how the resource can be used for a couple of auto sector occupations that have been particularly hard hit in the recent recession.

5.1 What Are "Skills Gaps"?

The goal of the research team was to boil down the complex components of a worker's skills, an occupation's needs and the mechanisms needed to move from one occupation to another into one dimension. That dimension is time. The research team developed a time to transition measure—"trip time"—that could inform a worker's decision about which pathway to follow.

In short, time is the dimension on which to measure a skills gap, the length of a journey to move from occupation A to occupation B. There are many other considerations, of course. A path that means paying large sums for tuition would not be feasible for many. Many would rule out a path requiring in-residence course work far away from home. But trip time can represent the difference between working in one occupation and migrating to another.

Figure 9: Selected Occupations in the Same Cluster as an Industrial Machinery Mechanic



Source: Indiana Business Research Center

The research team followed other models that also use time as the primary gap-closing measure. O*NET, for example, surveys incumbent workers to determine, among many things, the level of proficiency necessary for a wide range of worker and job characteristics and the educational and training time it would take for an individual to become proficient at a particular job. O*NET rates each proficiency level on a 0 to 7 scale and the research team estimated the extent to which each level requires more *time* in terms of education and training. A key finding is that as one moved through the levels, the estimated time required to complete each increased substantially. The difference in training to move from level 1 to level 2, for example, was approximately 26 hours on average, notably less than that the gap between a level 5 and a level 6, an average of 278 hours. The O*NET scale, therefore, was not linear.

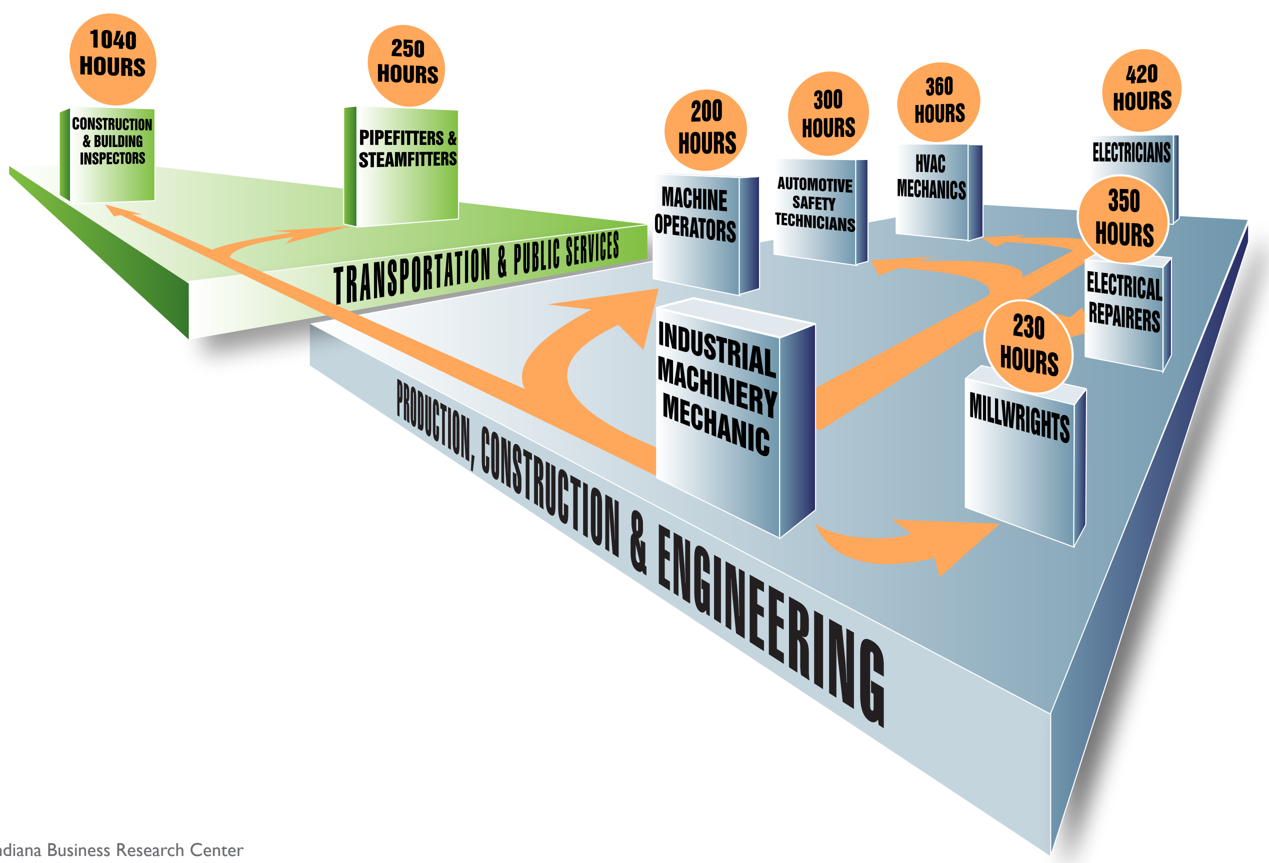
The research team sought to improve and simplify the methodology. First, the estimated hours required for education and training were made consistent across different formats—academic, vocational or apprenticeships. An hour in a college classroom is different from an hour in a vocational training laboratory, but both represent a time investment by the worker and are expressed in hours in the trip-time calculation. While the "time to completion" may be dependent on when courses start or if they are on a compressed time schedule, the goal of the pathway time measure is to measure relative ease or difficulty and the length of time, all things being equal.

The research team also adjusted the O*NET time dimension based on the fact that gaining skills and training in one knowledge area enhances one's skills in another knowledge area. One might call this "overlap" in educational pursuit. Students often gain knowledge and skills in tandem; not all knowledge is gained sequentially. For example, as one pursues education in physics, one also develops knowledge in the highly correlated knowledge area of mathematics as well. As one learns to operate specialized machines, she is also gaining experience in instruments and monitoring production processes. In other words, the body of coursework or training is not necessarily sequential or additive.

The research team first estimated the longest training gap among the important knowledge and skills for all 650,000 combinations of possible starting occupation and destination occupation. Then, using this principal knowledge or skill as the dominant gap, analysts added only the non-overlapping portions of additional training time to the dominant gap to derive the trip time—the total skills gap measure in hours.

If the pathway clusters are how occupations are grouped based on their similar characteristics, then **Figure 10** shows how trip time, or preparation time, adds an additional dimension—time—to measure

Figure 10: Trip Times to Transition from an Industrial Machinery Mechanic to Selected Occupations



Source: Indiana Business Research Center the distance between occupations.

5.2 Measuring Occupation Transitions

Using the O*NET job zone framework, the research team then applied the trip-time methodology to the pathway cluster analysis described in Chapter 4. O*NET groups occupations into job zones based on their required levels of formal education, experience and on-the-job training. In all, there are five zones, with zone one occupations requiring little or no preparation and zone five occupations needing extensive preparation. As **Figure 11** shows, the pathway clusters have different proportions of occupations within each of the five job zones. Some pathway clusters have a disproportionate share of high-requirement occupations—the information and investigation cluster for example—and other pathway clusters have a relatively larger share of occupations with lower preparation requirements.

Table 30: Average Job Zones for Occupations within Each Pathway Cluster

	Pathway Cluster	Job Zone Average
1	Information and Investigation	12
2	Health, Social and Personal Services	0
3	Production, Construction and Engineering	55
3a	*Engineering and Applied Technology*	26
3b	*Construction and Extraction, Equipment Operation, and Repair*	15
3c	*Design and Production*	14
4	Liberal Arts, Education and Human Relations	7
5	Business, Sales and Administration	15
6	Transportation and Public Services	20
7	Environmental Sciences and Food Service	15
All Clusters		**3.0**

Source: IDWD/IBRC, using O*NET data

These differences can greatly affect the trip times to transition within a pathway cluster and between clusters. **Table 30** presents the job zone average for each cluster. Generally speaking, the higher the average job zone, the longer the trip time to move within that pathway cluster.

Therefore, while the pathway cluster method used to group occupations might suggest that all intra-cluster trip times are less than trip times between clusters, this is not always true. There are several reasons for this. One, occupations were grouped into pathway clusters according to many criteria including personal traits of the worker (such as highly social) and work activities (such as handling heavy objects), not just knowledge and skill levels. Two, some types of subject areas are highly specialized and require many years to become an expert. The trip time to move from being an atmospheric scientist to being an operations research analyst would be considerable, even though both are in Cluster 1. Three, stepping down the job zone ladder is easier than stepping up or moving within. The trip time for the atmospheric scientist—job zone 4—to move into being

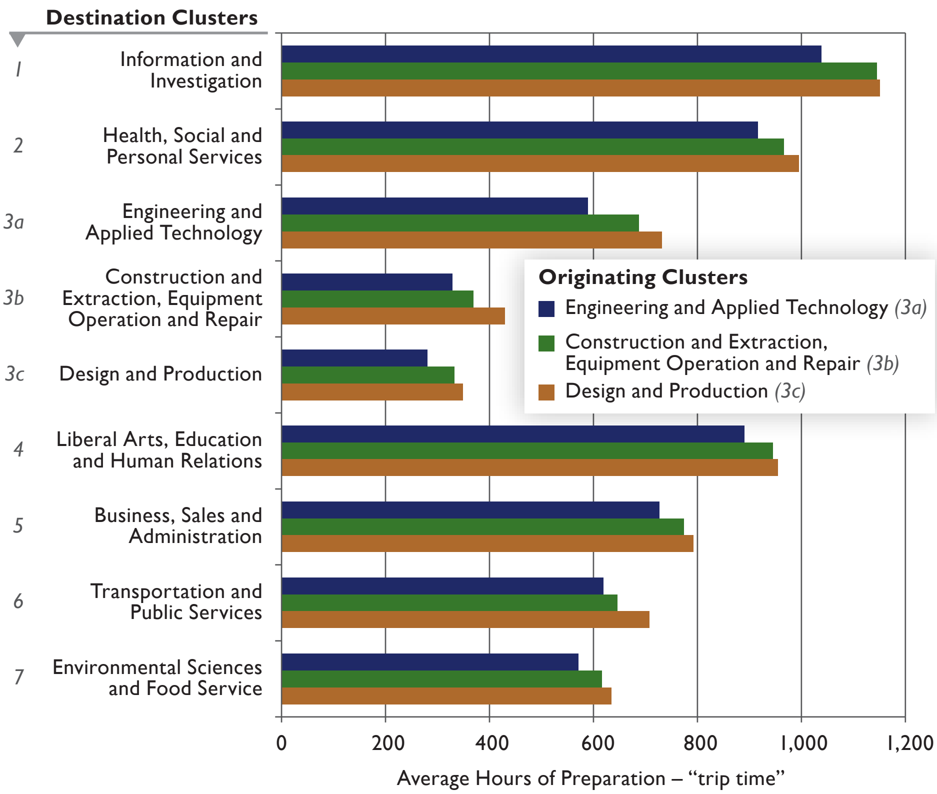
Figure 11: Percentage of Occupations in Each Job Zone, Selected Clusters

Source: IDWD/IBRC, using O*NET data

a billing, cost and rate clerk—job zone 2—would be minimal.

The O*NET job zone framework, therefore, not only provides data on the amount of preparation needed for an occupation, but also provides an explanation for why transitions within a pathway cluster might exceed the trip time to another cluster. The job zones help explain why it may be more challenging to change occupations within Cluster 1 than within other pathway clusters. Cluster 1 has a high average zone largely because it does not have any occupations in zone one and few in zone two. While trip times from one occupation to another are generally lower if the transition occurs within a pathway cluster than between clusters, differences in average job zones matter. For example, moving from a Cluster 1 occupation to a Cluster 3c occupation, the average trip time is smaller (314 hours) than if one were to move within cluster 1 (850 hours). This is because Cluster 3c has, on average, more occupations that require minimal preparation.

Figure 12: Average Trip Time from Production, Construction and Engineering Clusters to All Destination Clusters



Source: IDWD and IBRC, using O*NET data

That said, as a rule, it is easier to move within clusters. **Figure 12** presents this case graphically. **Figure 12** shows the average trip time to transition from the three production, construction and engineering sub-clusters (originating clusters) to the other clusters. To transition from engineering and applied technology (Cluster 3a) to any other cluster requires more trip time than within that sub-cluster, with the exception of the other two production sub-clusters (3b and 3c). Those two sub-clusters have a greater proportion of occupations in job zones 1 and 2, thus making it relatively easier, on average, to make the transition to occupations in Cluster 3a.

The production, construction and engineering clusters have a preponderance of the automobile and construction sector occupations—those sectors hardest hit by the Great Recession. Given that trip times between clusters are typically greater than trip times within clusters, and given that the clusters are based on the similarities and differences of worker requirements, worker traits and job demands, a displaced worker would be well served to consider occupation options within her or his cluster first.

5.3 Trip Times for Automotive Occupations

This section puts the pathway cluster and trip-time research into practice. While the section focuses primarily on automotive originating occupations, the Driving Change analysis and resources are applicable to all occupations.

5.3.1 From Automotive to Green, High-Wage/High-Demand

Because the green economy was another theme for the Driving Change project, the pathway cluster and trip-

Table 31: Sample Career Transitions from Automotive Occupations to Green, High-Wage/High-Demand Occupations

Auto Sector Occupation		Destination Occupation		
Occupation	Pathway Cluster	Occupation	Pathway Cluster	Skill Gap Transition Time
Team Assemblers	3c	Hazardous Materials Removal Workers	3b	300
		Insulation Workers, Floor, Ceiling, and Wall	7	250
Helpers—Production Workers	3a	Construction Laborers	3b	370
		Truck Drivers, Heavy and Tractor-Trailer	6	370
First-Line Supervisors/Managers of Production and Operating Workers	5	First-Line Supervisors/Managers of Farming, Fishing, and Forestry Workers	5	360
		Computer-Controlled Machine Tool Operators, Metal and Plastic	3a	300
Maintenance and Repair Workers, General	3b	Roofers	3b	215
		Insulation Workers, Floor, Ceiling and Wall	7	5

Note: High-wage/high-demand jobs are Indiana occupations that are expected to grow in demand and earn a wage rate greater than the state average.

Source: IDWD and IBRC

time analysis will present a sample of green and high-wage/high-demand occupations to which automotive workers can transition, as shown in **Table 31**. Given that a displaced worker would likely entertain several options before committing to an educational or retraining program, the table provides two transition options for representative automotive occupations, one within the originating cluster and one outside. These examples also have relatively short trip times. Some workers may prefer transitions with the shortest trip time in order to adopt new career opportunities as quickly as possible. However, transitions within the same pathway cluster allow workers to move to an occupation that is much more similar to their previous occupation in terms of worker requirements, worker traits and job requirements.

The most common job among automotive workers is team assembler. As Chapter 2 showed, almost 33,000 team assemblers lost their jobs in the last few years in the tri-state region. While there may be declining job opportunities within the automotive industry, there are several opportunities for these workers both within their pathway cluster 3 (production, construction and engineering) and outside of their cluster. If a team assembler wants a green job that is considered high-wage/high-demand, he or she can transition to a hazardous materials removal worker with 300 hours of training time. Outside of the pathway cluster, he or she can transition to an insulation worker in the environmental sciences and food service cluster with only 250 hours of training time.

Production helper is another declining auto sector occupation. On average, these workers can make relatively fast transitions to construction laborers, both in job zone one that requires relatively little job preparation. Outside of their cluster, production helpers can transition to truck drivers with 370 hours of trip time.

Production supervisors, from the business, sales and administration cluster, are able to make a relatively fast transition (360 hours) to supervisors of farming, fishing, and forestry workers—an occupation that O*NET places in the “green increased demand” category. By changing to the engineering and applied technology pathway cluster, a production supervisor can readily become a computer-controlled machine tool operator in 300 hours.

Finally, maintenance and repair workers can stay within their cluster and migrate to a green occupation: becoming a roofer would require 215 hours of trip time. But with almost no additional training,

Table 32: Career Transitions from Automotive Occupations to Non-Green, High-Wage/ High-Demand Occupations

Auto Sector Occupation		Destination Occupation		
Occupation	**Pathway Cluster**	**Occupation**	**Pathway Cluster**	**Skill Gap Transition Time**
Team Assemblers	3c	Extruding, Forming, Pressing, and Compacting Machine Setters, Operators, and Tenders	3c	130
		Pipelayers	3b	170
		Coin, Vending, and Amusement Machine Servicers and Repairers	6	300
Helpers—Production Workers	3a	Excavating and Loading Machine and Dragline Operators	3b	200
		Extruding, Forming, Pressing, and Compacting Machine Setters, Operators, and Tenders	3c	200
		Coin, Vending, and Amusement Machine Servicers and Repairers	6	330
First-Line Supervisors/Managers of Production and Operating Workers	5	Food Service Managers	5	280
		First-Line Supervisors/Managers of Housekeeping and Janitorial Workers	6	135
		Surgical Technologists	2	240
Maintenance and Repair Workers, General	3b	Earth Drillers, Except Oil and Gas	3b	0
		Paving, Surfacing, and Tamping Equipment Operators	3b	25
		Cargo and Freight Agents	6	340

Source: IDWD and IBRC

these workers can go green and transition into the insulation worker occupation.

5.3.2 From Automotive to Non-Green, High-Wage/High-Demand Occupations

Placing the requirement of transitioning from an auto sector occupation to a green occupation, as defined by O*NET, greatly reduces a displaced worker's options. As Chapter 3 showed, non-green jobs comprised almost 82 percent of all HWOL postings in Indiana during the fourth quarter of 2010.

As a result, a displaced worker may also want to consider options that are not green. **Table 32** presents a sampling of career transition alternatives for displaced autoworkers into high-wage/high-demand occupations that are not currently considered green. A quick look at **Table 32** shows that several potential non-green opportunities also have reduced trip times.

This chapter presented three new concepts to help workers in their search for new occupations. The first major element in the process is defining the relative distance between occupations, that is, defining the skills gap. The skills gap is the education, training or apprenticeship time required to transition from one occupation to another. Second, as an example of the skills gap analysis, the leading destination occupation trip times were presented for auto sector jobs with the largest losses. Third, the chapter showed that trip-time reports can be a powerful resource for workers plotting their transition to an alternative occupation.

The trip-time method is groundbreaking because it compresses all the differences between occupations into a common numéraire, namely the preparation or retraining time it would take to change jobs. The skills gap is primarily a knowledge or human capital gap. The trip-time method measures the distance of a skills gap and the relative ease of moving from one occupation to another. Because up-skilling entails increasing the level, or mix, of a worker's human capital, the following section briefly discusses an online resource to match training and education programs with green and growing occupations.

6. Finding Work—Resources to Target Opportunities

One of the Driving Change project goals was to develop a resource to help displaced workers plot a path, in some cases a green path, to a new future. Thus, the Driving Change website provides a web-based resource—the Tri-State Training Program Database—where one can look up educational, training and vocational programs for green and/or growing occupations. Based on their targeted occupations, users can find all the relevant postsecondary schools offering programs for that occupation within their selected geographic boundary.

For the dislocated worker, the question of how to move from old job A to new job B is far from academic.

Not only workers seeking change, but also education and workforce development policymakers may find this site useful because the data present the relative concentration or scarcity of educational programs at a highly granular geographic level. For economic development practitioners who may be trying to cultivate the growth of firms or attract new investment, it may expose a region's training weak spots. If a region does not have a specially trained workforce, what educational programs are nearby to fill the gap?

For the dislocated worker, the question of how to move from old job A to new job B is far from academic. Training dollars are of little use in workforce development efforts if they fail to move an individual closer to re-employment in a career with a future. The Tri-State Training Program Database—combined with the new pathway cluster analysis developed for the Driving Change project and the estimated time to transition to a new occupation—can help dislocated workers make decisions about which new occupations make the most sense for them.

These resources, tools and analysis are online and free of charge, helping today's displaced workers in the tri-state region find suitable employment, but also serving as a foundation for expanding the workforce development toolkit in the future.

The Tri-State Training Program Database is available at www.drivingworkforcechange.org/database.asp.

7. Conclusion

Given restructuring in the auto industry, many displaced workers need help to find suitable alternative jobs. The two-step pathway cluster and skills gap analyses presented in this report offers valuable guidance to displaced workers charting pathways to new career opportunities.

The technique used to group occupations into pathway clusters is groundbreaking. Pathway clusters are based not upon industries or functions, but upon the similarities and differences of worker and job characteristics. Not only are occupations in a given pathway cluster considered similar to one another in terms of their knowledge and skill requirements, the pathway cluster analysis also measures the degree to which worker traits such as "highly social" or "attentive to detail" make occupations more or less similar. Job transitions within a given cluster, therefore, are typically easier than moving from one cluster to another.

There are seven pathway clusters. Auto industry occupations are concentrated in the production, construction and engineering cluster, but there are dozens of green or high-wage/high-demand jobs in the same cluster that may make good target occupations for a displaced worker. Except for the health, social and personal services cluster, green occupations are well distributed throughout the seven pathway clusters.

Knowing the alternative occupations that are most similar to one's current occupation—those in the same pathway cluster—is a good first step. A worker still needs to know the relative difficulty or ease in closing the skills gap between two occupations. The uniform measure, or common denominator, to gauge the difficulty or ease of making the transition from one occupation to another is the amount of time required to prepare for the new occupation.

The skills gap is the education, training or apprenticeship time required to transition from one occupation to another. The skills gap analysis then measures the "trip time" required to change from any one occupation to another based on the aggregate size of the gaps between the old and new jobs. While the trip-time measure is not perfect, it is a great advance over many previous career pathway tools because it provides users an understandable measure of a worker's skills gap.

Finally, this project produced a tri-state training program database for green and growing occupations as a resource to complement the trip time results. After a displaced worker generates a set of suitable alternative occupations, he or she can match those occupations with postsecondary educational, technical and vocational programs in the region. The skills gap and training program databases, together with all the Driving Change analysis and research results, are freely available on the web at www.drivingworkforcechange.org.

This report highlighted and summarized two of the Driving Change project goals:

- Examine job opportunities now and in the future as alternative career pathways for displaced workers

- Identify the skills gap and the required educational and technical training needed for dislocated workers to transition into new occupations

The Driving Change website provides access to separate reports covering each of the project's goals in more depth. In addition, the site provides access to multiple tools stemming from this project, including the training database that matches green and growing occupations to training programs available in the tri-state region.

Future Directions

The new career pathway resources developed by the Driving Change research complement the financial support available through such channels as Trade Adjustment Assistance, Rapid Response Services for workers or employers, and the National Emergency Grant On-the-Job Training Program. The Driving Change resources can make these efforts more effective, helping job seekers and workforce development staff members identify feasible career and training alternatives.

As with any pioneering research, the results can be refined and improved. For example, the time needed in educational programs to close knowledge gaps is fairly well established. However, the trip times for vocational education, apprenticeships or on-the-job-training programs for many skilled labor occupations are not as robust. In addition, the amount of information and data that O*NET has for newer occupations is not as complete as for more established occupations, making the skills gap and trip-time assessments more difficult. Therefore, before any widespread adoption or deployment, it is recommended that the skills gap and trip-time assessments be recalibrated.

In a similar fashion, the training database needs to be augmented to ensure that all types of training programs, not just the ones present in the Integrated Postsecondary Education Data System (IPEDS), are included. There are many vocational and technical institutions and programs that are not currently in the IPEDS database.

Finally, pathway cluster and trip-time data would be even more powerful if integrated with "real time" labor market information (LMI) data. This real-time LMI data could not only include information about current labor market demand for occupations through such sources as HWOL or Burning Glass, as well as projections for future employment, but head count and enrollment data for relevant education and training programs in the region. The latter would ensure that a hot job today is not a cold job tomorrow. By providing an estimate for current labor demand together with a headcount of the number of people in the current training pipeline, workforce development workers and officers can assess the degree to which the labor market will be in relative balance. It would be a shortsighted to generate an oversupply of a skilled labor type in two years in order to fill a shortage today.

The pathway cluster and trip-time analysis and results can provide displaced workers as well as staff in workforce development and career placement an additional set of tools to complement such resources as O*NET, TORQ, CareerConnect and CareerOneStop. It is the sincere hope of the entire Driving Change team that these tools will help displaced workers transition to gainful employment.

Appendix A: Career Pathway Cluster Methodology

The goal in creating career pathway clusters is to group occupations that are most similar. This principle is similar to the TORQ system which provides a compatibility score for comparing one occupation with another also using job requirements and worker characteristics information that O*NET has collected.[15] While TORQ incorporates all data for O*NET's knowledge, skills and abilities (KSA) categories, it does not use all of the O*NET categories that describe occupations. The pathway cluster approach avails itself of all O*NET occupation data and then, based on statistical analysis, carefully selects a subset of variables that have the greatest descriptive power to define and differentiate occupations.

Data Selection

The research team analyzed 518 characteristics about occupations and their incumbent workers published by O*NET—the Occupational Information Network—which is supported by the U.S. Department of Labor's Employment and Training Administration.[16] Specifically, this analysis uses detailed information from the O*NET 14.0 Production Database (released in 2009) about occupations classified through a system highly compatible with the 2000 Standard Occupational Classification (SOC).[17] While O*NET provides data for over 1,100 occupations, data were only used for 741 occupations because some occupations had incomplete data. In addition, there were cases where multiple O*NET occupations belong to the same SOC grouping.

While several hundred O*NET variables were available for the development of the career clusters, it was crucial to select or develop a much narrower subset of variables to create a small set of coherent and meaningful occupational groupings. For each variable across 741 occupations with available data, analysts typically reviewed level scores which indicate the proficiency expected for incumbent workers.[18] The research team used the following strategies for selecting variables that would best differentiate occupations:

- ***Spread.*** Variables were removed if their scores among occupations were not well distributed across the full range of level scores (zero through 7 or the standardized scale of zero through 100). In other words, those variables that had scores within a narrow range between occupations and, thus, did not differentiate between them. Consider the work context variable for face-to-face contact, for example, over three-quarters of occupations had high scores between 84 and 100 on the standardized scale and none had scores lower than 39.

- ***Skew.*** Even if variables had a wide range of values, variables for which the vast majority of occupations had very high or very low scores (often many values of zero on the standardized scale) were removed. For example, even though occupations varied widely for their level of frequency for working in an open vehicle or open piece of equipment, over 200 occupations had scores of zero so this variable was removed.

- ***Correlation.*** Variables were removed or combined if they were highly correlated with others (typically, a correlation above 0.5). By

[15] More information about TORQ by Workforce Associates is available at www.torqworks.com/products.

[16] More information is available at www.onetcenter.org/overview.html.

[17] These analyses do not use the new 2010 SOC system because O*NET data is still based on the 2000 SOC system.

[18] For many variables, two kinds of scores were available: level scores that indicate proficiency and importance scores that indicate how crucial the particular characteristic is for the job. The research team decided to use level scores for this analysis since proficiency in terms of training was considered key for this research; coincidentally, rarely are high level scores not also associated with high importance. While level scores ranged from 1 to 7, they were standardized to range from 0 to 100, following O*NET guidelines.

avoiding excessive correlation, researchers ensured that each variable provides a unique contribution to the comparisons between occupations. For example, researchers removed the skill "judgment and decision making" since it was highly correlated with over 60 other variables, including two key knowledge areas "administration and management" and "personnel and human resources." Overall, knowledge variables were the least correlated among the different types of variables. As a result, knowledge was given priority and never removed or combined.

- ***Factor Analysis.*** Although factor analysis determined the eventual pathway clusters, initial rounds of factor analysis provided the researchers information to combine variables with similar patterns of high and low scores across occupations.

Eventually variables representing seven types of information about incumbent workers and their occupations were chosen in the following categories:[19]

1. ***Requirements of the worker (R):*** Worker requirements that can be gained by the worker through study or training
    - ***Knowledge:*** Sets of principles and facts in a subject area (i.e., knowledge requirement)
    - ***Cross-Functional Skills:*** The capacity to perform the activities across different jobs
2. ***Traits of the worker (T):*** The internal or personal traits of workers who are drawn to—or perform well in—the occupation
    - ***Interests:*** Preferences for the type of work and work environment based on personality types. Occupational Interest Profiles are compatible with Holland's model of personality types and work environments.[20] Here workers fit six broad types of interests as adapted from the O*NET website:[21]
        - **Realistic** (includes practical, hands-on problems and solutions)
        - **Investigative** (involves working with ideas and requires an extensive amount of thinking)
        - **Artistic** (involves working with forms, designs and patterns)
        - **Social** (involves working with, communicating with and teaching people)
        - **Enterprising** (involves starting up and carrying out projects, leading people and making many decisions)
        - **Conventional** (involves following set procedures and routines)
    - ***Work Values:*** Work duties, outcomes and environment that are personally satisfying
    - ***Work Styles:*** Personal characteristics that influence performance
3. ***Occupational requirements (O):*** The requirements for the job, such as work activities (e.g., lifting heavy objects or gathering data)

[19] Not all terms are directly taken from O*NET; many have been translated to appeal to a general audience.

[20] For complete information, see John. L. Holland, *Making Vocational Choices: A Theory of Vocational Personalities and Work Environments* (Odessa, FL: Psychological Assessment Resources, 1997).

[21] Please see the O*NET content modules online for more information: www.onetcenter.org/content.html.

- ***Generalized Work Activities:*** Type and intensity of personal interactions and mental processes like problem solving and information gathering

- ***Work Context:*** Physical activities and social factors that influence the nature of work

After removing the variables that didn't provide much descriptive information, had a lot of overlap with other variables or could be combined with several variables, the number of occupational characteristics numbered 53. All original O*NET knowledge area variables were retained, but many other O*NET variables that were similar in nature—for example the social context at a job—were combined before conducting the factor analysis. The final 53 variables used for the career pathway clusters are summarized in **Table 33**.

Factor Analysis

The research team used the method that the Indiana Department of Workforce Development (IDWD) developed in 2006 as a springboard to create the pathway clusters.[22] More specifically, the research team used exploratory factor analysis techniques (following the principle components method) to group occupations based on patterns of similarity among their O*NET scores. For example, analysis among the knowledge variables may reveal that high scores for transportation typically occur among occupations that also have high scores in public safety and security but low scores in the fine arts.

Factors can be thought of as patterns of similarity or dissimilarity, and the technique of exploratory factor analysis was used by the research team to recognize patterns of similarity among occupations' O*NET scores in the set of 53 occupation characteristics, without any prior assumptions. Using statistical software, factors (or "patterns") were estimated that gave priority to each of the variables in turn as a weighted sum of scores for all 53 variables. Such a process can be summarized according to the following formula:[23]

$$F_i = W_{i1} X_1 + W_{i2} X_2 + \ldots + W_{i53}\ X_{53}$$

where X_1 through X_{53} represent each of the 53 variables

F_i represents each of the 53 factors denoted by i

W_{i1} through W_{i53} represent the weighting for each variable by factor denoted by i

Once estimated, factors were rotated using the promax oblique method, not only to simplify and clarify the data structure but to allow the factors themselves to correlate—an important consideration in the social science research.[24] This allowed the research team to use the Kaiser rule to determine which patterns of weightings that occurred frequently and consistently enough across the variables to form a factor that had an eigenvalue greater than 1.[25]

The Cattrell Scree test was also used to visually map the point at which the gradient between factors noticeably levels off or seems to plateau.[26] For each retained factor, coefficients ranging from 1 (high association) to -1 (low association) were calculated for every variable to indicate how well it fit the particular pattern. Job characteristics that seem to logically complement each other (e.g., engineering and physics) should have high coefficients in the same factor, but characteristics that differ (clerical and food

[22] Please see the methodology section of this article for more information: Allison Leeuw, "The Butcher, the Baker and the Candlestick-Maker Revisited: Indiana's New Skills-Based Career Clusters," *InContext,* December 2006, www.incontext.indiana.edu/2006/december/6.asp.

[23] This formula was adapted from tutorial materials by Karl L. Wuensch of East Carolina University, Department of Psychology. More information is available at http://core.ecu.edu/psyc/wuenschk/StatsLessons.htm.

[24] For more information, see Anna B. Costello and Jason W. Osborne, "Best Practices in Exploratory Factor Analysis: Four Recommendations for Getting the Most from Your Analysis," *Practical Assessment, Research & Evaluation* 10, no. 7 (2005).

[25] The eigenvalue here is essentially the amount of variance in all the variables which is accounted for by a particular factor and a value of 1 means that the pattern explains at least as much variance as one of the variables. Please see more detailed explanations posted by G. David Garson (North Carolina State University) at http://faculty.chass.ncsu.edu/garson/PA765/factor.htm.

[26] For more information on factor selection, see the factor analysis guidelines posted by Richard B. Darlington (Cornell University, Department of Psychology) at www.psych.cornell.edu/darlington/factor.htm.

Table 33: Final Set of Variables Used for Creation of Career Pathway Clusters

Category	Type	Variable
R	Knowledge	Administration and Management
R	Knowledge	Clerical
R	Knowledge	Economics and Accounting
R	Knowledge	Sales and Marketing
R	Knowledge	Customer and Personal Service
R	Knowledge	Personnel and Human Resources
R	Knowledge	Production and Processing
R	Knowledge	Food Production
R	Knowledge	Computers and Electronics
R	Knowledge	Engineering and Technology
R	Knowledge	Design
R	Knowledge	Building and Construction
R	Knowledge	Mechanical
R	Knowledge	Mathematics
R	Knowledge	Physics
R	Knowledge	Chemistry
R	Knowledge	Biology
R	Knowledge	Psychology
R	Knowledge	Sociology and Anthropology
R	Knowledge	Geography
R	Knowledge	Medicine and Dentistry
R	Knowledge	Therapy and Counseling
R	Knowledge	Education and Training
R	Knowledge	English Language
R	Knowledge	Foreign Language
R	Knowledge	Fine Arts
R	Knowledge	History and Archeology
R	Knowledge	Philosophy and Theology
R	Knowledge	Public Safety and Security
R	Knowledge	Law and Government
R	Knowledge	Telecommunications
R	Knowledge	Communications and Media
R	Knowledge	Transportation
R	Cross-Functional Skills	COMBINED Social Skills
R	Cross-Functional Skills	COMBINED Systems/Programming
R	Cross-Functional Skills	COMBINED Monitoring/Design
T	Interests	Realistic
T	Interests	Investigative
T	Interests	Artistic
T	Interests	Social
T	Interests	Enterprising
T	Interests	Conventional

Category	Type	Variable
T	Work Values	Relationships
T	Work Styles	COMBINED Social
T	Work Styles	COMBINED Independence and Detail
O	Generalized Work Activities	COMBINED Information
O	Generalized Work Activities	COMBINED Leadership
O	Generalized Work Activities	COMBINED Communication
O	Generalized Work Activities	COMBINED Equipment
O	Generalized Work Activities	Assisting and Caring for Others
O	Work Contexts	COMBINED Decision Making/Competition
O	Work Contexts	COMBINED Team Work and Responsibility
O	Work Contexts	COMBINED Conflict/Unpleasant/Aggressive People

Source: IDWD and IBRC

production) would have high coefficients in different factors.

The final step in assigning occupations to pathway clusters based on the retained factors involved both art and science. Factor loading scores (the extent to which each variable fits each retained pattern) were determined through statistical regression and then applied to each occupation to see whether or not its combination of scores across all variables made it a good "fit" into a pathway cluster. The research team then examined each pathway cluster to see if they were well balanced in their representation of occupations (ideally at least 10 percent in each cluster, assuming there are fewer than 10), and whether the combination of occupations within each cluster made sense given workers' job roles.

Through an iterative process, multiple sets of pathway clusters were formed and then improved to account for seemingly unusual combinations of factors or clusters of occupations. Each time the exploratory factor analysis process was repeated from the beginning by making some key adjustments:

- ***Modifying variables.*** Typically the modification process involved combining variables that were in the same cluster previously into fewer simplified variables. For example, the variables for the skills social perceptiveness, coordination, persuasion, negotiation, instructing and service orientation all fit the same cluster on earlier attempts at factor formation so were combined into a single "social skills" variable.
- ***Creating subsets of higher skilled occupations for factor development.*** Another strategy during this process was to select only occupations that had at least one high score among knowledge or skill variables for use in the development of the factors and then use these factors to assign clusters to the complete set of occupations.
- ***Reducing the number of retained factors.*** Instead of allowing as many factors as had eigenvalues above 1.0, attempts were made to retain one or two fewer factors in cases where there may have been a noticeable break between the intervals between the eignenvalues of the last two or three factors or between the proportion of the variance accounted for by the final few factors.

The research team settled on a final set of seven pathway clusters based on a final set of seven retained factors. **Table 34** summarizes the fact that the pattern of similarity among variables in the first pattern were easily the most distinctive as illustrated by its high eigenvalue (15.5) and the large proportion of the overall variation in variable scores it explains (almost 30 percent). Alternatively, factor 7 was the weakest of the retained factors with the least distinctive pattern of high and low scores among variables.

Table 34: Eigenvalues and Variance Explained by Each Factor Used to Derive Pathway Clusters

Factor	Eigenvalue	Variance Explained	Pathway Cluster Derived by This Factor
1	15.488	0.292	Information and Investigation
2	8.752	0.165	Health, Social and Personal Services
3	4.282	0.081	Production, Construction and Engineering
4	3.562	0.067	Liberal Arts, Education and Human Relations
5	2.375	0.045	Business, Sales and Administration
6	1.919	0.036	Transportation and Public Services
7	1.840	0.035	Environmental Sciences and Food Service

Source: IDWD and IBRC

To name each pathway cluster and to appropriately assign occupations, the research team relied on the actual factor loading scores for each variable within each pattern. **Table 35** shows that while several key variables had factor loading scores above 0.7 for factor 1 (e.g., computer knowledge, investigative interests, systems and programming skills and information-related work activities), only one variable had such high factor-loading scores for factor 7 (food production knowledge).

Each occupation was assigned a regression-based coefficient score for how well its pattern of scores for all variables fit. However, the research team had to reassign occupations with ambiguous patterns of scores that made them appear to fit several potential clusters. This was particularly the case for several low-skilled occupations that were originally assigned to the seventh and weakest cluster but did not fit the

Table 35: Factor Weightings by Variable for Each Factor Used to Derive Pathway Clusters

Variable	1	2	3	4	5	6	7
Computers and Electronics	0.913	-0.151	-0.030	-0.008	0.060	-0.027	-0.189
Engineering and Technology	0.389	-0.209	0.785	0.010	-0.001	0.117	0.013
Design	0.185	-0.301	0.783	0.307	0.120	0.080	-0.070
Building and Construction	-0.168	-0.158	0.690	0.095	0.133	0.410	0.102
Mechanical	-0.068	-0.060	0.879	-0.063	-0.069	0.178	0.019
Mathematics	0.735	-0.196	0.229	-0.145	0.306	-0.030	0.163
Physics	0.417	0.034	0.714	-0.052	-0.124	0.132	0.174
Chemistry	0.179	0.319	0.613	-0.137	0.011	-0.036	0.488
Biology	0.291	0.508	0.189	-0.080	0.040	-0.067	0.620
Psychology	0.070	0.727	-0.072	0.184	0.074	0.099	0.087
Sociology and Anthropology	0.161	0.407	-0.198	0.506	-0.018	0.085	0.122
Geography	0.358	-0.225	-0.008	0.374	-0.055	0.568	0.172
Medicine and Dentistry	0.051	0.913	0.083	-0.205	-0.032	-0.194	0.334
Therapy and Counseling	0.012	0.844	-0.083	0.136	-0.059	0.001	0.124
Education and Training	0.346	0.337	0.186	0.353	0.074	0.087	0.136
English Language	0.657	0.077	-0.197	0.265	0.087	0.035	0.036
Foreign Language	0.059	0.217	-0.120	0.424	0.004	0.151	0.258
Fine Arts	-0.255	-0.047	0.124	0.929	0.102	-0.136	-0.209
History and Archeology	0.220	-0.043	-0.129	0.708	-0.112	0.238	0.133

Variable	1	2	3	4	5	6	7
Philosophy and Theology	0.096	0.405	-0.189	0.566	-0.111	0.137	0.074
Public Safety and Security	-0.042	0.296	0.428	-0.180	-0.110	0.735	0.010
Law and Government	0.414	0.101	-0.094	-0.066	0.202	0.456	0.116
Telecommunications	0.497	-0.094	0.236	0.009	-0.136	0.418	-0.310
Communications and Media	0.457	-0.016	-0.137	0.474	0.075	0.126	-0.118
Transportation	-0.198	-0.093	0.383	0.022	0.037	0.778	-0.062
COMBINED Social Skills	0.371	0.339	0.076	0.278	0.179	-0.029	-0.129
COMBINED Systems/Programming	0.673	-0.108	0.431	-0.069	0.019	-0.051	-0.093
COMBINED Monitoring/Design	0.217	-0.081	0.779	0.031	-0.048	-0.109	-0.150
Realistic	-0.320	-0.041	0.635	-0.177	-0.273	0.131	0.106
Investigative	0.873	0.084	0.180	-0.047	-0.229	-0.177	0.193
Artistic	0.050	-0.056	0.046	0.895	-0.004	-0.281	-0.166
Social	0.020	0.638	-0.384	0.235	-0.026	-0.087	0.063
Enterprising	-0.173	-0.038	-0.350	-0.076	0.678	0.165	-0.165
Conventional	0.348	-0.352	-0.476	-0.651	0.147	0.116	-0.130
Relationships	-0.108	0.684	-0.263	0.073	0.114	-0.004	-0.069
COMBINED Social	-0.061	0.704	-0.158	0.067	0.128	0.051	-0.199
COMBINED Independence and Detail	0.472	0.202	-0.018	0.116	0.106	-0.309	-0.226
COMBINED Information	0.781	0.217	0.118	0.016	0.019	-0.002	-0.081
COMBINED Leadership	0.269	0.347	0.200	0.231	0.292	0.102	-0.026
COMBINED Communication	0.144	0.288	-0.125	0.189	0.425	0.056	-0.078
COMBINED Equipment	-0.264	0.101	0.804	-0.075	-0.245	0.197	-0.058
Assisting and Caring for Others	-0.142	0.960	-0.014	-0.086	-0.101	-0.006	0.027
COMBINED Decision Making/Competition	0.205	0.373	0.287	-0.209	0.154	0.014	-0.361
COMBINED Team Work and Responsibility	0.157	0.294	0.416	-0.008	0.207	0.168	-0.196
COMBINED Conflict/Unpleasant/Aggressive People	-0.179	0.585	-0.168	-0.237	-0.030	0.362	-0.238

Source: IDWD and IBRC

theme of the cluster. For example, the initial "best fit" of helpers/production workers (SOC: 51-9198) into Cluster 7 was so weak that this occupation was reassigned to the pathway cluster associated with factor 3 (production, construction and engineering).

Finally, due to the large number of occupations (217) assigned to the production, construction and engineering cluster, the research team repeated the factor analysis procedures outlined above for this group of occupations. This produced the three sub-clusters: engineering and applied technology; construction and extraction, equipment operation and repair; and design and production.

Appendix B: Skills Gap Methodology

Data

The research team used the Occupational Information Network (O*NET)[27] data to derive a meaningful, albeit imprecise, measure for the relative training gaps between a particular occupation and a target occupation—the training "trip time." Specifically, the research relies on the scores that O*NET assigns to job requirements based on surveys of incumbent workers. The research team evaluated 808 occupations, classifying 161 occupational attributes into five categories:

- ***Knowledge:*** Distinct sets of principles and facts in 33 subject areas
- ***Cross Functional Skills:*** 25 capacity areas needed to perform the activities across different jobs
- ***Basic Skills:*** 10 developed capacities that enhance learning or the more rapid acquisition of knowledge
- ***Abilities:*** 52 worker attributes that influence performance
- ***Work Activities:*** 41 general types of behaviors that occur on multiple jobs

Based on incumbent worker surveys, O*NET reports score for both the level—a general measure of proficiency—and importance for each of the 161 variables (or job attributes). The trip-time analysis focuses primarily on the level scores that range from 0 to 7. These proficiency scores were the foundation for estimating training times.[28]

That said, importance scores did influence estimating the skills gap. For any particular occupation pairing—original occupation to a destination occupation—a variable needed a moderate level of importance—3.5 on a scale of 1 to 5—to be included in calculating the skills gap.

The research team also used O*NET's job zone. A job zone is another O*NET category that provides an approximate measure of the degree of preparation for a particular occupation. Job zones range from 1 to 5. Zone 1 jobs can usually be filled with unskilled labor with little or no preparation. Zone 5 jobs need extensive preparation.

Methods

Developing a Measure of Preparation Time Based on O*NET Surveys of Incumbent Workers

As mentioned above, O*NET surveys individuals in occupations to collect information about job and worker attributes. For the purposes of determining the amount of preparation needed for a particular occupation, O*NET asks incumbents about the level of training needed across several different categories,

Table 36: Example of Analysts' Raw Initial Estimates for Number of Hours of Training Needed for Levels of Science Knowledge

Level	O*NET Scale Level Anchor Statement	Analyst 1 Hour Estimate	Analyst 2 Hour Estimate
2	Conduct standard tests to determine soil quality	1	7
4	Conduct product tests to ensure safety standards are met, following written instructions	180	180
6	Conduct analyses of aerodynamic systems to determine the practicality of an aircraft design	1,460	2,190

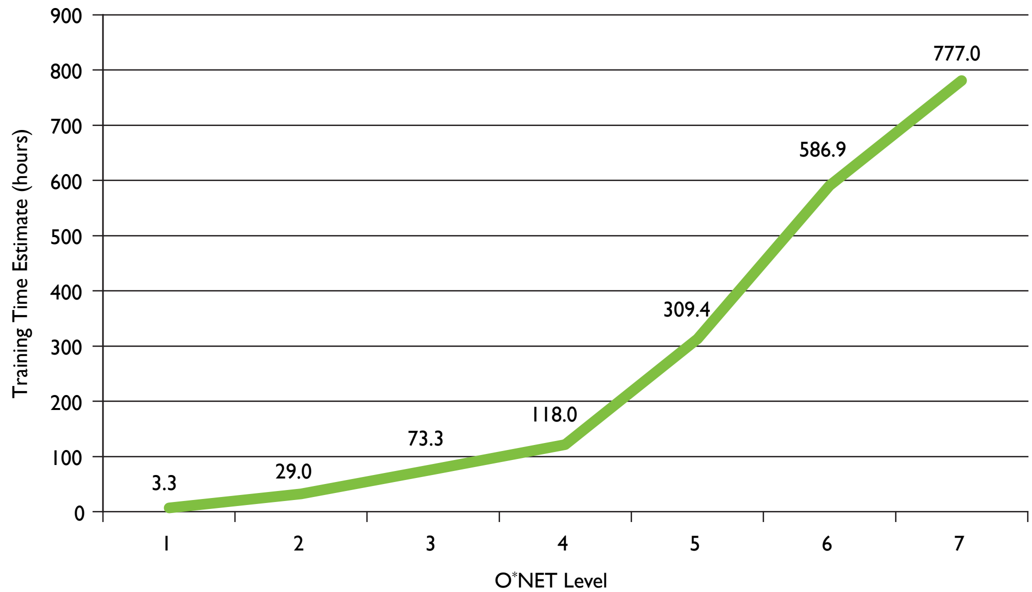
Source: IDWD and IBRC

[27] The Occupational Information Network (O*NET) is supported by the U.S. Department of Labor's Employment and Training Administration. More information is available at www.onetcenter.org/overview.html.

[28] This scale can also be standardized from 0 to 100. For more information, see www.onetonline.org/help/online/scales.

e.g., knowledge or skills. The concept or term "scale anchor" is a reference point for incumbents to self-assess the level of preparation or training needed for a particular job component.

Figure 13: Training Time Scale by O*NET Level



Source: IBRC and DWD

For the 161 variables in the five categories mentioned above, several research analysts independently scrutinized each of the statements O*NET uses in the incumbent surveys as reference points—scale anchors—for the level of preparation. These statements help incumbent workers rate the level needed for a particular competency area in their occupation. (Examples of three O*NET scale levels are presented in **Table 36)**. Analysts then re-scored each statement from its simple 0 to 7 scale to an approximate hour of preparation scale. The hourly statements were based on the education and training time it would take for an individual to become proficient for the level that matched a particular statement.

The range did not appear to be evenly distributed across the scale in terms of complexity. As one moved through the 0-7 scale, the suggested time required to move to the next higher level increased significantly. The difference in training to move from level 2 to level 4, for example, was far less than that the gap between a level 4 and a level 6.

Table 36 shows a rough example of two analysts' estimates for the Science knowledge area. Note that while each analyst has a subjective view of the number of hours of training needed for a particular level of training, for both analysts, the number of hours to move from one level to another increased at a roughly geometric rate.

Once analysts completed estimates for all knowledge areas, the hours of preparation time estimates were harmonized and averaged so that the ranges among analysts would be uniform. The uniform value then became a new measure that reflects an approximate training time. Analysts estimated training times based on years. Each year was translated as the equivalent of contact time in a student's major field of study of an academic program—roughly 540 hours or 30 credit hours. The same procedure was repeated by harmonizing estimates for all variables of the remaining attribute categories reflecting cross-functional skills, basic skills, abilities and work activities. Then the results of all five occupational categories were averaged to produce a new continuous scale illustrated in **Figure 13**.

The results demonstrated that as one moved through the 0-7 scale, the estimated time required to complete each level increased significantly such that the difference in training to move from level 1 to level 2, for example, was far less than the gap between a level 5 and a level 6.

This continuous training time scale ranged from a low of 3.4 hours to a high of 777 hours. The training time scale replaced the traditional 1 to 7 O*NET scale for the 58 knowledge and cross-functional skill variables used for the time gap analysis.

Determining Time Gaps by Knowledge Area and Skills Area between Occupations

Researchers took several important steps to estimate the total training time gaps between the original and destination occupations for knowledge and cross-functional skill levels.

Researchers adjusted the length of the gaps to reduce the potential "double-counting" that may result from training overlap. For example, consider an occupation that needs knowledge in physics. If the largest hour training gap for two jobs is 120 hours in physics knowledge, the full 120 hours is the critical gap. All 120 hours of training time goes into the trip time. If the second-largest gap is 100 hours in mathematics and the two knowledge areas—physics and math—have a correlation score of 0.55, the gap in mathematics is reduced 55 percent to 45 hours. The 45 hours in math is then added to the 120 hours of physics training for a first round total of 165. Researchers would adjust every other gap in the knowledge and skill areas in the same way.

This is an iterative process for each relevant knowledge gap and skills gap. The second iteration in this example uses computer programming as the next critical gap. For the above example, the next highest training gap would be reduced by computer programming's correlation to mathematics (the highest remaining gap), from say 60 hours to 30 hours given a correlation of 0.50. The total skills (and knowledge) gap is now 195 (or 165 hours from the first iteration plus 30 hours from the second iteration).

This iterative process of adding the highest remaining training time gap and then resorting and reducing the remaining gap scores by their correlation to the highest remaining time gap continued until all gaps in the relevant knowledge and skill areas were accounted for and summed together. The sum of the knowledge gap and the sum of the skills gap were then added together in the last step into one trip time.

The process—involving each of the 652,864 pairings of originating and destination occupations—can be expressed with equations.

1) Calculating training time gaps between originating and destination occupations. Only positive gaps are estimated—negative gaps are treated as zero. The following equations represent this process for knowledge (a) and skills (b) gaps:

   a) If $K_{i,d} > K_{i,o}$, then $K_{i,do} = K_{i,d} - K_{i,o}$,

      otherwise, $K_{i,do} = 0$

   b) If $S_{j,d} > S_{i,o}$, then $S_{j,do} = S_{j,d} - S_{j,o}$,

      otherwise, $S_{j,do} = 0$

   where $K_{i,do}$ represents the gap between the training time for knowledge area K_i of the destination occupation d ($K_{i,d}$) subtracted by the training time for the same knowledge area of the occupation of origin o ($K_{i,o}$). Similarly, $S_{j,do}$ represents the gap between the training time for skill S_j of the destination occupation d ($S_{j,d}$) subtracted by the same skill of the occupation of origin o ($S_{j,o}$).

2) Calculating the correlation between every pair of knowledge ($c_{K_i.K_i}$), knowledge-to-skill ($c_{K_i.S_j}$) and skill ($c_{S_j.S_j}$) score combination—1,711 pairs and correlation coefficients. The correlation coefficients approximate the overlap between the proficiency of each knowledge area or skill with proficiency in other. These correlation coefficients ratchet-down the skill and knowledge gaps to account for the fact that many gaps can be closed at the same time.

3) The first iteration of trip time gaps are ranked from highest knowledge gap ($K^1_{r1,do}$) to lowest ($K^1_{rz,do}$) followed by the highest skill gap ($S^1_{r1,do}$) to lowest ($S^1_{rz,do}$), where *r1* is the greatest gap and *rz* is the least gap for either knowledge or skill. Gaps

of zero are removed.[29] Sorting the gaps by knowledge then skills gives priority to knowledge gaps.

$$K^1_{r1,do}, K^1_{r2,do}, K^1_{r3,do}, \dots, K^1_{rz,do}, S^1_{r1,do}, S^1_{r2,do}, S^1_{r3,do}, \dots, S^1_{rz,do}$$

4) The largest portion (G^1_{do}) of the total training gap between the originating and destination occupations can be estimated as simply the full amount of the highest training gap.

$$G^1_{do} = K^1_{r1,do}$$

To determine the next largest portion of the total training gap (G^2_{do}), the initial highest gap from the first iteration—G^1_{do}—is removed and all remaining gaps are reduced by the degree to which they are correlated with the largest gap (G^1_{do}) of the first iteration:

$$K^2_{i,do} = (1 - c_{K_{r1,do} \cdot K_{i,do}}) * K^1_{i,do}$$

$$S^2_{i,do} = (1 - c_{K_{r1,do} \cdot S_{i,do}}) * S^1_{i,do}$$

5) For the second iteration, all but the largest gap are resorted in order from highest remaining knowledge gap ($K^2_{r1,do}$) to lowest ($K^2_{rz,do}$) followed by the highest skill gap ($S^2_{r1,do}$) to lowest ($S^2_{rz,do}$):

$$K^2_{r1,do}, K^2_{r2,do}, K^2_{r3,do}, \dots, K^2_{rz,do}, S^2_{r1,do}, S^2_{r2,do}, S^2_{r3,do}, \dots, S^2_{rz,do}$$

The second-largest portion (G^2_{do}) of the total training gap is the highest remaining training gap.

$$G^2_{do} = K^2_{r1,do}$$

6) This iterative process continues for all applicable knowledge and skill gaps (for the occupation pair). The total trip time (TT_{do}) is the sum of all adjusted skills gap and knowledge gap between a particular originating and destination occupation pair.

$$TT_{do} = \sum_{m=1}^{n} G^m_{do}$$

where the superscript represents each iteration for the total of training gaps between the originating occupation and the destination occupation.

As mentioned above, the database of trip times has a total of 652,864 records, one for each origin and destination occupation pair.

Because of the automotive workforce and green themes running through the project, the research team generate a trip-time subset of transitions from automotive occupations to green and/or growing—i.e., high-wage/high-demand—occupations. Access to both the complete trip-time database, as well as specially formatted output for autoworker occupations, are available on the web at www.drivingworkforcechange.org.

[29] The superscript in this notation represents the iteration of the ranking where the first iteration uses the original knowledge and skill gaps between the originating occupation and destination occupation. The next iteration re-ranks the knowledge and skill gaps after the previous highest knowledge/skill training gap has been removed along and all remaining gaps have been reduced to the extent to which they were uncorrelated with the highest gap of the previous iteration.