# SKILL DEMANDS AND MISMATCH IN U.S. MANUFACTURING

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Recent economic events have sparked debates over the degree of structural mismatch in the U.S. economy. One of the most frequent claims is that workers lack the skills that employers demand. The existing literature, however, analyzes this potential mismatch at a high level of aggregation with abstract indices and noisy proxies that obscure the underlying mechanisms. The authors address these issues by presenting and analyzing results from a survey of U.S. manufacturing establishments. The survey is the first, to their knowledge, to directly measure concrete employer skill demands and hiring experiences in a nationally representative survey at the industry level. The findings indicate that demand for higher-level skills is generally modest, and that three-quarters of manufacturing establishments do not show signs of hiring difficulties. Among the remainder, demands for higher-level math and reading skills are significant predictors of long-term vacancies, but demands for computer skills and other critical-thinking/problem-solving skills are not. Of particular interest, high-tech plants do not experience greater levels of hiring challenges. When the authors examine the potential mechanisms that could contribute to hiring difficulties, they find that neither external regional supply conditions nor internal firm practices are predictive of hiring problems. Rather, the data show that establishments that are members of clusters or that demand highly specialized skills have the greatest probability of incurring long-term vacancies. The authors interpret these results as a sign that it is important to think about factors that complicate the interaction of supply and demand—such as disaggregation and communication/coordination failures—rather than simply focusing on inadequate labor supply.

Matching skilled workers to appropriate jobs is one of the most critical processes in a modern economy. Firms depend on the timely supply of skills to grow and thrive, and workers depend on access to quality employment opportunities to achieve financial security and professional fulfillment. All parties have a vested stake in how supply and demand for skills

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equilibrate in the labor market. Over the past few decades, recurring debates have taken place over whether mismatch exists in this process (Berg 1970; Handel 2003; Kalleberg 2007; Cappelli 2014). Researchers have posited that structural factors, such as geographic immobility or shifting industry demands, have driven a wedge between supply and demand, thus generating economic inefficiency and, in some cases, structural unemployment. One of the most frequent assertions is that workers lack the skills that employers demand, resulting in an economically damaging skill gap (Carnevale, Smith, and Strohl 2010; Manyika et al. 2011).

These arguments intensified in the wake of the Great Recession of 2007–2009. While some analysts concluded that cyclical factors were responsible for the subsequent high unemployment levels (Lazear and Spletzer 2012; Rothstein 2012), others continued to assert the importance of structural factors in generating mismatch (Mulligan 2009, 2011a,b; Charles, Hurst, and Notowidigdo 2013). Although the balance of the evidence tends to point to the centrality of cyclical factors (Neumark and Valletta 2012), a number of researchers who acknowledge the importance of cyclicality nevertheless find nontrivial levels of structural mismatch (Estevau and Tsounta 2011; Rothwell 2012; Canon, Chen, and Marifian 2013; Sahin, Song, Topa, and Violante 2014).

One of the challenges in sorting through these claims is that the debates frequently take place at high levels of abstraction with imprecisely measured proxy variables. Most prior research does not measure either the skills employers demand or the degree to which employers have difficulty in securing these skills (Kalleberg 2007; Handel 2010). Furthermore, much of the existing evidence on this topic takes place at the inter-industry level (Canon et al. 2013; Sahin et al. 2014). While this approach is informative, it ignores mismatch that may occur within industries, and it obscures the mechanisms that underlie labor market frictions. In particular, mismatch indices typically cannot pinpoint the degree to which a shortfall in particular workforce skills is associated with signs of mismatch. Addressing this gap in the research is important because skill mismatches are a nearly constant source of public debate and carry substantial public policy implications.

We seek to add to the knowledge about skill mismatch by examining employer-level data within a broad industry sector to gauge the incidence of the potential problem and to uncover which mechanisms are at work. Specifically, we explore mismatches related to worker skills ("skill gaps") by examining detailed evidence on employer skill demands and hiring experiences in the manufacturing sector. We pose the following questions: What skills do manufacturers demand for production workers? What is the incidence of hiring difficulties (potential skill gaps) among manufacturers? What factors, including skill demands, predict these hiring difficulties? Which stories about skills and skill gaps are consistent with the observed patterns? To address these issues, we designed and administered a nationally representative survey of manufacturing establishments that, to our knowledge, provides data on skills and hiring that are unavailable from any other source.

## The Debate over Skill Gaps and Mismatch

The smooth functioning of the labor market depends on the equilibration of the supply and demand for skills, which in turn depends on matching workers to job openings. To the extent that mismatch or a gap exists between supply and demand, economic growth will suffer and workers with ill-matched skills will experience reduced economic opportunities or unemployment. Unlike mismatch due to cyclical causes, structural mismatch will, by definition, persist even as general economic conditions improve, thus making it an issue that must be dealt with through some combination of structural reforms, policy interventions, and behavioral changes among workers.

Researchers have attempted to quantify the level of structural mismatch in the economy, often employing quite diverse approaches to the topic. Mulligan (2009) used a Cobb-Douglas production function to decompose labor market changes into shifts in productivity and shifts in labor supply. He concluded that negative shifts in labor supply were behind the spiking unemployment in the Great Recession. In subsequent work, he asserted that comparison of the incidence of government benefit programs with unemployment patterns implies that the labor market disincentives associated with government programs were to blame (Mulligan 2011a,b).

A number of researchers have composed mismatch indices to measure whether imbalances exist that imply structural unemployment. These indices typically employ one of two broad methodologies. The first consists of calculating the ratio of unemployment to vacancies and interpreting the variation in this measure across industries as a sign of structural mismatch. This methodology is conceptually similar to a Beveridge curve approach to mismatch. The second methodology consists of estimating industry demand for various skills, subtracting estimated regional supply of these skills, and labeling the difference a measure of mismatch.

Utilizing the first, Beveridge-style methodology, Sahin et al. (2014) found that labor market mismatch may be responsible for up to a third of the increase in unemployment from the Great Recession.[1] Canon et al. (2013) calculated several alternative indices of this sort and concluded that mismatch could explain up to 51% of the unemployment increase. Estevau and Tsounta (2011) employed a version of the supply/demand index methodology to find that mismatch may account for 20 to 30% of the rise in

[1]Sahin et al. (2014) emphasized that they see cyclical factors as the primary force behind the spike in unemployment. Nevertheless, as noted above, their results imply a nontrivial role for structural factors.

unemployment. Other researchers, using variations of this latter methodology, also found a significant role for structural mismatch (Carnevale, Smith, and Strohl 2010; Manyika et al. 2011; Rothwell 2012).

The foregoing research has pushed the debate forward in constructive ways, but significant limitations remain. Mismatch indices rely on highly aggregated data and are unable to identify underlying mechanisms. Industry unemployment/vacancy ratios could diverge because of a skills gap, geographic immobility, or a host of other factors. Even granting the relevance of general mismatch measures that obscure underlying causes, many of the indices are highly sensitive to cyclicality, thus calling into question the structural nature of the results (see Canon et al. 2013 and Lazear and Spletzer 2012 for indications of cyclicality). Furthermore, as Rothstein (2012) noted, the Beveridge curve does not necessarily measure labor market tightness (and hence mismatch), because changes in firm strategy regarding recruitment intensity and wages can shift the curve independent of structural factors such as matching efficiency or the deficient skills of the workforce.

Supply/demand indices seem to pinpoint the source of the mismatch as skill-related, but in actuality they suffer from flaws of equal magnitude. Because of data limitations, none of these supply/demand indices directly measure either the demand for or the supply of skills. Rather, they utilize education as a proxy for skill. Although understandable given constraints, this assumption is very problematic. On the demand side, changing educational composition does not necessarily measure skill demands. For example, if a college-educated individual takes a job at a coffee shop, it would be misleading to conclude that skill demands for baristas have risen (Harrington and Sum 2010). On the supply side, educational proxies obscure variation in skill levels within educational categories. Such intra-category variation is a large and important source of skill variation (Lemieux 2006), as many employers do not choose between filling a vacancy with a high school graduate or a college-educated worker, but rather choose between workers of different skill levels within a given educational category.

One way to make progress in the debate over structural mismatch is to generate better data that focus on within-industry variation, that directly measure skill demands and hiring outcomes, and that measure key variables that allow us to test for the mechanisms behind any observed mismatch. This article seeks to achieve these objectives by presenting original survey data on manufacturing skills and skill mismatch. We believe that building up detailed industry-level results is a necessary complement to the more abstract aggregate methodologies. Although such detailed data are cross-sectional, they can speak to the longitudinal debate over labor market trends by testing whether specific skills and mechanisms are correlated with particular hiring outcomes. Including these mechanisms, which we describe below, allows us to connect the skill mismatch debate with more concrete labor market phenomena, such as technical change, employer strategies, and adjustment to growth. To our knowledge, our survey is the first to directly measure both concrete skill demands and skill mismatch in an industry context.

## Skill Gap Mechanisms

To situate our investigation of skill gaps in the manufacturing sector, we describe more specifically the economic factors and stories that could potentially give rise to such mismatch. Defining a skill gap starts with the observation that the market for skills has both a supply side and a demand side. A skill gap implies that the quantity demanded for a particular skill exceeds the quantity supplied. One of the puzzles that arise from the skill gap claims is that wages have not risen in a manner consistent with excess demand for skills (Rothstein 2012; Osterman and Weaver 2014). To the extent that employers or analysts claim that a skill gap exists, they are asserting that the market is not clearing. We discuss several potential explanations for this skill gap phenomenon. The first three potential mechanisms imply that skill gaps are a relatively minimal or temporary problem, while the remaining three imply more serious economic frictions. Note that with the exception of the first mechanism, these potential causes are not mutually exclusive.

### No Skill Gap Exists

Employers might complain about skills to lobby for increased public training subsidies or to pursue other public policy goals, such as increasing the number of skilled immigrant worker visas. In these instances, there is no mismatch to explain, with cyclical economic factors accounting for observed labor market outcomes. A variant of this explanation would be that only a small minority of manufacturers experience hiring difficulties, but these are the loudest and most vocal employers. Such a situation would generate a disconnect between the debate in the popular media and the economic statistics. It is worth noting that this "no skill gap" outcome is consistent with two different demand stories. On the one hand, skill demands could have risen to high levels, but workers have generally kept pace in educational and skill attainment. On the other hand, skill demands might not have risen to very high levels, thus explaining why stagnating educational attainment has not generated spiking wages for skilled production workers (Beaudry, Green, and Sand 2013).

### Some Manufacturers Are Not Competitive (Due to External or Internal Factors)

Another way in which skill gaps can be illusory relates to the competitive position of manufacturers. Although the conventional narrative concerning skill gaps is that supply constraints are holding up employers whose cost structure is otherwise in line with industry standards, it may also be that some manufacturers are simply not competitive for a variety of cost, productivity, or quality reasons. From 2000 to 2011, more than 66,000 U.S. manufacturing establishments closed, and a third of all manufacturing jobs were lost (Atkinson, Stewart, Andes, and Ezell 2012). It is doubtful that even substantial improvements in America's education system could have reversed these losses. When a manufacturer can survive only by paying below-market wages, the resulting situation is not a skill gap but rather a painful transition period.

Lack of competitiveness could result from factors that are either external or internal to the establishment. External factors include globalization shocks and the rise of Chinese manufacturing. Internal factors include the organization of production, utilization of human resources, and hiring and recruitment practices. For example, it could be that manufacturing plants that have more extensive internal hiring and promotion—internal labor markets (ILMs)—are able to deal with hiring challenges more effectively, while those that choose not to rely on ILMs may struggle (Osterman 1987; Batt and Colvin 2011). Similarly, establishments that implement Total Quality Management (TQM) programs with a wider range of employees might face fewer difficulties, perhaps through reduced turnover (Shortell et al. 1995; Kaynak 2003).

### Temporary Adjustment Problems Exist

If employer demands for a particular skill escalate quickly, there will be an inevitable delay while the supply side of the market responds. For example, if a technology shock, such as hydraulic fracturing (fracking) to stimulate greater oil and gas production, were to lead to a sudden increase in demand for welders in areas where no such welders had previously been employed, it would take time for local educational institutions to change their curricula or for individuals with the requisite skills to move to the area. As long as this mismatch diminishes relatively rapidly, we would generally not think of this situation as a skill gap.

### Supply-Side Frictions Might Lead to Market Failure

Worker attitudes or low-quality educational institutions might also seriously hinder the regional production of particular skills. In such a scenario, the wage necessary to recruit workers with the required skills might be extremely high. Given that manufacturers deal in tradable goods whose prices are set in national and international markets, employers might decide to forego these skill inputs rather than incur heavy labor costs. Note that this latter scenario requires an additional assumption about employer training. It must also be the case that employers do not find the return from utilizing these skills to be high enough to justify internal training in these skills. This refusal to conduct internal training could result because the skills are quite general, and employers fear their employees will be poached by other employers (Cappelli 2012). Alternatively, the cost of producing the desired skills (whether general or specific) could be very high for a single manufacturing establishment. Smaller-sized employers might lack the economies of scale necessary to efficiently conduct training in particular skills.

### Increased Rate of Technical Change

Many analysts assert that technical change has led to increased demand for higher-level skills. Although the details of these various skill-biased technical change (SBTC) stories vary, the general idea is that new technology is a complement to the skills necessary to perform complex cognitive tasks and a substitute for more routine skills (Autor, Levy, and Murnane 2003; Brynjolfsson and McAfee 2011). In theory, the overall effect on skilled manufacturing production workers is ambiguous, with some skills becoming redundant and others seeing enhanced demand (Autor 2014). Skill gaps could arise if neither the displaced workers nor other workers in the economy are capable of performing (or being trained to perform) the tasks that see heightened demand. To the extent that skill gaps occur for higher-level skills, SBTC theories imply that technical change should be a strong predictor of these gaps. Note that SBTC by itself does not generate skill mismatch. It must be combined with another market friction or failure that explains why the supply side of the market does not respond. Nevertheless, it is important to include these technical change theories in the analysis because they imply a testable prediction about the positive correlation of technology and skill mismatch.

### Communication, Coordination, and Disaggregation

Problems of communication, coordination, and disaggregation might come between supply and demand. In this case, it is not that workers have some behavioral resistance to education, or that the school system is fundamentally flawed, but rather that systematic issues prevent supply and demand from equilibrating. It might be that employers are willing to pay more for a high-productivity set of skills, and local community colleges are willing to train in such skills, but the two sides simply do not communicate about their needs and constraints, perhaps because of an absence of appropriate labor market intermediaries (communication failure). Alternatively, it might be that the payoff to investing in a production system that utilizes higher skills depends on worker investments in human capital, while the payoff to making these human capital investments depends on employer investments. In these cases, coordination failure prevents either side from initiating the investment (Cooper and John 1988). If employers recognize that a higher-productivity equilibrium exists, they might complain about employees not making the first move. Note that these scenarios also rely on an assumption that employers cannot unilaterally solve the problem through internal training.

One of the factors that exacerbates these coordination and communication failures is the presence of many disaggregated establishments. Larger, more vertically integrated manufacturing plants have the potential to internalize more of these externalities. Over the past few decades, however, the average size of a manufacturing establishment has declined by more than 40% (Henly and Sanchez 2009). In addition, researchers have found that the disaggregated nature of modern manufacturing has created significant labor market challenges (Weaver and Osterman 2014). Although we do not have good data on corporate training, disaggregation may reduce internal training and increase reliance on external sources of skill training (such as community colleges) that are subject to these challenges.

One particular area of interest is the connection between industry clusters and disaggregation. Although a large literature exists on the positive ability of clusters to address economic issues related to communication, innovation, human resources, and a host of other key business functions (Porter 2000; Iammarino and McCann 2006), the mere presence of a cluster does not solve problems or mitigate difficulties. Clusters have the potential to lower transaction and search costs—including the acquisition of skilled or specialized labor—but such benefits are potential rather than guaranteed outcomes. If the potential benefits of a cluster are unrealized, or if an economic shock exposes a cluster's weakness, a cluster may simply behave as a disaggregated group of business establishments that each face a high baseline of communication and logistics costs relative to a single, large, vertically integrated firm (Carbonara 2005). In such a situation, latent coordination problems that a well-functioning cluster would otherwise address might come to the fore (Rodriguez-Clare 2005).[2]

## Empirical Strategy

To shed light on these issues concerning skills and skill gaps, we conduct empirical analysis of original survey data. The survey was administered to a nationally representative sample of manufacturing establishments in late 2012 and early 2013, and its questions focus on "core" production workers (defined as the workers most central to the production process). The survey

[2]These issues are ultimately connected to the skill production system that prevails in a given region or nation. It may well be that the disaggregation and coordination problems described above are more likely to occur in training and skill regimes that are characterized by low levels of coordination among firms, government, and third-party intermediaries, such as the Liberal Market Economies highlighted in the Varieties of Capitalism (VoC) literature (Hall and Soskice 2001). Because our data are from a single country, we cannot test for the effects of cross-country variation. Coordination problems are not limited to liberal skill formation regimes, however. Busemeyer (2015) extended a version of the VoC formulation to country-level skill production systems. He noted that statist systems such as Sweden's—which are characterized by a relatively heavy government role in skill formation—have experienced failures in efforts to foster employer participation in vocational training and apprenticeships (Busemeyer 2015: 12). Thus, skill-related coordination problems are not limited to liberal economies such as the United States and the United Kingdom.

asked detailed questions about skill demands, and it operationalized the concept of a skill gap by measuring the number of core production worker vacancies that an employer was unable to fill for a period of three months or more. We discuss the survey methodology and key variables in greater detail below.

To address our first research question, regarding what skills manufacturers demand, we analyze average employer demands for the detailed skills measured in our survey. To address the average level of skill gaps, we measure what proportion of manufacturers show evidence of prolonged hiring difficulties. We then explore what factors predict these difficulties by conducting a reduced form analysis in which we regress an indicator for skill gaps/hiring difficulties on a range of explanatory variables. In addition to detailed skills, these include controls for supply and demand factors, as well as establishment-level characteristics and measures of the regional and institutional environment. We organize these explanatory variables in groups that allow us to distinguish between the various economic mechanisms that could explain the skill gap phenomenon.

## Survey Methodology

We conducted this manufacturing skills survey as part of the Massachusetts Institute of Technology's Production in the Innovation Economy (PIE) project. To gather data on skills, hiring outcomes, and establishment characteristics, we developed an original survey instrument that asked manufacturers detailed questions about skill demands, hiring experiences, and plant characteristics. In developing the survey, we did not follow any one particular template but rather sought guidance from multiple sources. For the skill questions, we followed the strategy outlined in Michael Handel's STAMP survey (Handel 2010). For as many relevant skills as possible, we sought to frame the questions in objective terms that managers could easily understand (e.g., Does this job require reading any document that is longer than five pages?), as opposed to more subjective Likert scales. We did include a number of subjective ratings, but we have built our main analysis around the objective questions. For questions regarding hiring experiences and plant characteristics, we relied on prior surveys that we had developed for previous research as well as on information gathered from interviews with plant managers in a variety of manufacturing industries.

We randomly selected the sample of 2,700 manufacturing establishments on a stratified basis from Dun & Bradstreet's database to reflect the frequency of different establishment sizes based on 2010 employment data from the Census Bureau's County Business Patterns survey.[3] The survey

[3]We also trimmed the sample to exclude industry codes for the baking, quick printing, and publishing industries. We excluded these sectors because we feel the industry dynamics associated with quick printers (such as FedEx/Kinkos), small bakeries, and newspaper/book publishers differ substantially from other manufacturing establishments. The sample was limited to manufacturing plants that have at least 10 employees.

administrators called each establishment in the sample to identify the most appropriate respondent. The target respondents were either plant managers or human resources staff with knowledge of operations. We mailed the survey to the entire sample in October 2012. As an incentive, and as compensation for response time, we included a $10 bill with each survey packet. Reminder postcards were sent 10 days after the initial mailing, and we sent a second mailing of the survey to non-responders in early November. In mid-November, we made follow-up phone calls to non-responders. Excluding ineligible establishments, incorrect addresses, and unusable surveys, the total response rate was 35.7%, yielding 903 completed surveys. Responses were submitted from October 2012 to January 2013.

Because it would not be informative to ask specific questions about skills or hiring that characterize the entire manufacturing workforce (production employees, managers, clerical workers, etc.), the survey asked respondents to answer questions based on their "core" workers. These were defined as the employees who are most critical to the production process (for other examples of this approach see Ben-Ner and Urtasun 2013 and Osterman 1995). Examples of occupational titles that respondents classified as core workers include manufacturing associates, fabricators, assemblers, production technicians, and process operators. We asked respondents to base their answers on permanent employees, as opposed to temporary staff or independent contractors. On average, permanent core employees represented 63% of total employment in the survey establishments.

One question that arises with surveys such as ours is whether a single respondent can accurately provide data at the establishment level. In general, the literature contains a number of examples of single-respondent surveys that have provided well-validated results (Batt, Colvin, and Keefe 2002; Bloom and Van Reenen 2007). Following the literature, we conducted field interviews to inform our survey questions and to verify the level of knowledge of survey respondents. We targeted plant managers as primary respondents because these individuals have both operational and human resource knowledge. To more rigorously test data integrity for our survey, we conducted a data quality and bias analysis. The results of this exercise, which are contained in Appendix A, indicate that our data are representative of U.S. manufacturing workforce characteristics.

## Skill Demands

What skills do manufacturing employers actually demand? In the survey we posed a battery of concrete questions about the skills required to perform core production jobs. For example, with respect to reading skills we asked four questions: whether the job requires an employee to read basic instruction manuals, complex technical documents, any document longer than five pages, or articles in trade journals. With regard to computers and technology, we asked whether the job requires skills ranging from Internet search capabilities to computer-aided design skills to computer-numerically controlled (CNC) programming.

We categorized skills in two groups: basic and extended. Basic skills involve lower-level skill demands in each category, and extended skills involve elevated skill demands. For example, in the math category we defined basic math as addition/subtraction, multiplication/division, and fractions/decimals/percentages. Extended math consists of algebra, geometry, trigonometry, probability, statistics, calculus, and other advanced math demands. Table 1 contains the basic and extended skill results.

Demand for particular basic skills is widespread. Of the establishments surveyed, 76% require basic reading for their core production positions, while 74% require the ability to perform a bundle of basic math skills (addition/subtraction, multiplication/division, and fractions/decimals). Sixty-two percent of establishments require computer usage on at least a weekly basis, and 42% require either basic word processing or the ability to perform Internet searches for information. What is striking, however, is how modest these demands are. Only 42% of establishments require all of the basic reading, writing, and math skills.

With regard to higher-level skills, extended reading and extended computing are the most frequently demanded, with 53% and 42% of establishments requiring these for core production workers, respectively. By contrast, only 22% of establishments require extended writing. In addition to academic skills, we asked whether the establishment required a unique skill that other plants in the area do not require. About one-quarter of establishments reported such a requirement.

As with basic skill demands, the extended skill demands are notable for their modesty, particularly with regard to math. Only 38% of establishments require at least one of the extended math skills. The breakdown in math demands is even more revealing. Whereas just under a third of establishments require algebra, geometry, or trigonometry, only 7% require calculus or other similar advanced mathematics. Thus, even among some of the more demanding establishments, the math requirements for core production workers in the United States are mostly at a level that is attainable by a talented high school graduate or, without question, a community college graduate.

After reading and math, computer capabilities are the next most commonly required higher-level skills. Twenty-eight percent of establishments require core workers to be able to use computer-aided design or manufacturing (CAD/CAM) software, while a similar percentage require the use of some other type of engineering or manufacturing software. Only 19% require computer-programming skills. Overall, 42% of establishments require some type of extended computer capability.

Although the skill debate in the United States frequently focuses on "hard" science- and math-related skills, another line of thought argues that soft skills—such as the ability to work in teams—are increasingly important

Table 1. Skill Demands for Core Production Jobs

| Variable | All establishments | |
|---|---|---|
| **Basic Skills** | *% Demand* | |
| Basic reading (ability to read basic instruction manuals) | 75.6 | |
| Basic writing (ability to write short notes, memos, reports less than one page long) | 60.5 | |
| Basic math (ability to perform all of math categories below) | 74.0 | |
| Addition and subtraction | 94.4 | |
| Multiplication and division | 85.6 | |
| Fractions, decimals, or percentages | 77.9 | |
| Require basic reading, writing, and math | 42.4 | |
| Require use of computers several times per week or more frequently | 62.3 | |
| Ability to use word processing software or ability to search Internet for information | 41.7 | |
| **Extended Skills** | | |
| Extended reading | 52.6 | |
| Extended writing | 22.1 | |
| Extended math (ability to perform any of three math categories below) | 38.0 | |
| Algebra, geometry, or trigonometry | 31.7 | |
| Probability or statistics | 14.0 | |
| Calculus or other advanced mathematics | 7.3 | |
| Extended computer | 41.9 | |
| Use CAD/CAM | 28.4 | |
| Use other engineering or manufacturing software | 29.2 | |
| Ability to write computer programs (such as program a CNC machine for a new piece, etc.) | 18.6 | |
| Unique skill | 25.9 | |
| **Soft / Problem-Solving Skills** | *% Reporting "very important"* | *% Reporting "moderately or very important"* |
| Cooperation with other employees | 81.2 | 99.3 |
| Ability to evaluate quality of output | 71.0 | 95.8 |
| Ability to take appropriate action if quality is not acceptable | 76.3 | 97.7 |
| Ability to work in teams | 64.2 | 91.1 |
| Ability to learn new skills | 50.1 | 89.3 |
| Ability to independently organize time or prioritize tasks | 45.6 | 84.4 |
| Ability to solve unfamiliar problems | 38.8 | 83.0 |
| Ability to critically evaluate different options | 35.7 | 74.1 |
| Ability to initiate new tasks without guidance from management | 35.2 | 80.9 |

*Source:* MIT PIE Manufacturing Survey, 2012–2013.

to modern production systems (Osterman 1995; Gale, Wojan, and Olmstead 2002; Heckman and Kautz 2012). In this latter view, demands have risen for both interpersonal skills and skills involving worker initiative and problem solving. We asked a variety of questions to gauge the levels of demand in these areas. The bottom section of Table 1 contains the percentages of establishments that reported these various skills were "very important" as well as the combined percentages that reported either "very important" or "moderately important" for core production positions. The results contain several notable features. First, a large majority of manufacturing establishments—more than eight in ten—place high importance on cooperation with fellow employees. Just under two-thirds of respondents also selected the ability to work in teams as a critical skill for core workers. Two other skills that received high ratings were the ability to assess the quality of output and the ability to take steps to fix quality problems. Of the establishments surveyed, 71% and 76%, respectively, cited these quality-related measures as very important. Thus, interpersonal skills and quality assessment appear to be critical skills for core workers in production systems around the country.

The next notable feature about the results is the relatively low level of "very important" responses for skills that are often thought to be essential for modern, high-tech, high-productivity manufacturing. While eight out of ten establishments view solving unfamiliar problems or initiating new tasks without guidance as at least moderately important, less than 40% view these skills as very important for core production workers. Only half feel that the ability to learn new tasks is very important. The picture that these results provide of core production systems in U.S. manufacturing is one in which performing high-quality work in a cooperative fashion using existing procedures is important, but exercising creative problem solving or taking initiative is substantially less so.

These descriptive survey results point to several conclusions regarding skill demands for core production workers. First, basic academic skills and interpersonal skills are important. Demand for basic levels of math, reading, and computer skills is widespread. Requirements for extended reading and computer abilities, in particular, are common, encompassing more than half of all manufacturing establishments. Cooperation and teamwork are also skills on which large numbers of manufacturing establishments place great value. At the same time, however, a substantial percentage of establishments have relatively low skill demands. Even among the plants requiring higher skill levels, the skill demands appear modest, particularly with regard to math. With regard to skills that are generally perceived as critical for high-tech, flexible manufacturing systems, emphasis on problem solving, initiative, self-management, and other similar skills appears surprisingly muted.

### Hiring and Vacancies: Evidence on Skill Gaps

Our survey data suggest that most employers are able to hire the workers they seek within a reasonable time frame. The mean establishment in our survey required about six weeks to recruit and hire a core worker, while the median establishment required four weeks. Employers in the survey received an average of 24 applications per open position and conducted six interviews per open position. The average acceptance rate by successful applicants was 85%.

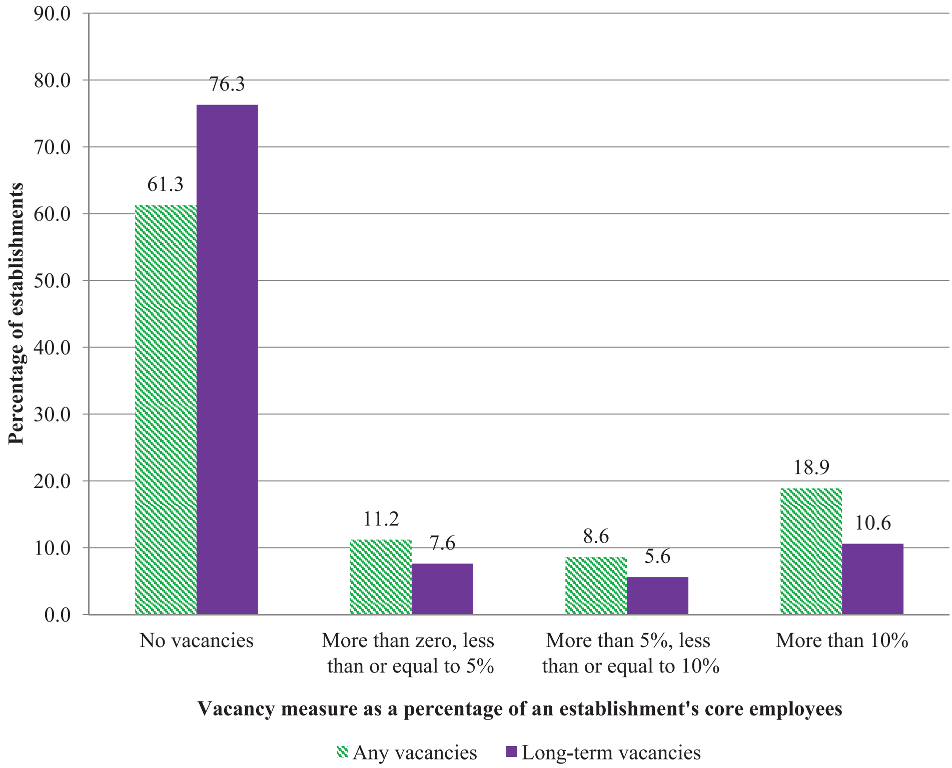
To probe skill mismatch more deeply, we focus on vacancies among core production positions. Some level of vacancies is required for the smooth operation of the labor market, and therefore the presence of a vacancy for a given position at a particular point in time is not necessarily a sign of a problematic gap between demand and supply. To address this issue, we asked establishments about the number of current core production vacancies that had persisted for three months or more. We believe that such long-term vacancies are the best concrete measure of potential skill gaps.[4] Even in the case of these extended vacancies, factors other than skill mismatch can explain the existence of such a prolonged job opening. As Cappelli (2012) noted, in the face of weak product demand, some firms may advertise an open position while waiting for a truly extraordinary candidate to come along. Indeed, Davis, Faberman, and Haltiwanger (2012) have argued that the intensity with which employers searched for workers fell during the Great Recession. Nevertheless, this long-term vacancy measure represents a substantial improvement over the use of undifferentiated vacancies. Long-term vacancies can be viewed as an upper bound on the potential amount of skill mismatch.

Figure 1 contains data on core worker vacancies and long-term core worker vacancies as a percentage of an establishment's core workforce. More than 60% of establishments do not have any core worker vacancies, and 76% do not have any long-term vacancies. Just less than 8% of establishments have long-term vacancies that amount to between 0 and 5% of the establishment's total permanent core workers. About 16% of establishments experienced long-term vacancies at a level that was greater than 5% of their core workforces.

These results contrast greatly with the opinion surveys from nonrandom samples that have shaped the public debate about manufacturing skill gaps. While the Deloitte/NAM 2011 opinion survey (which has received considerable publicity) found that 74% of manufacturers suffer from a lack of skilled production workers, our survey data indicate that at most a quarter of manufacturing establishments show signs of hiring distress with regard to production workers. Similarly, the Deloitte survey reported that the median manufacturer has vacancies equivalent to 5% of its total workforce. Although our survey focuses on core workers and not the entire manufacturing workforce, our data indicate that the median establishment has zero core worker vacancies. Given that core workers are 63% of an establishment's employment, these results call into question both the incidence and the severity of manufacturing skill gaps. We believe that our survey data

[4]No single standard defines long-term vacancies, so we relied on practical considerations, field interviews, and logic in selecting three months as the cutoff. In general, even successful hiring processes take multiple weeks, so choosing a quick deadline of one to two months would likely overstate the true level of structural difficulty in hiring. In field interviews, most plant managers and CEOs were not troubled by a hiring process that lasted four to six weeks. At the same time, we did not want to select an extremely long time period that would result in understating any potential problems. Although six-month measures are sometimes used in surveys and the literature, our feeling is that this longer period masks the real financial and operational difficulties that might result from vacancies that remain unfilled for three to five months.

*Figure 1.* Vacancies




*Source:* MIT Production in the Innovation Economy (PIE) Manufacturing survey, 2012–2013.

indicate that at most 16 to 25% of manufacturing establishments have signs of hiring distress that could potentially indicate structural mismatch.

## Predictors of Hiring Difficulties

We now turn to an analysis of what factors predict the signs of hiring difficulties that we do observe. Are the long-term vacancies in our data the result of skill demands? If so, which skills? We can also explore whether other establishment-level or regional variables are associated with hiring problems and assess which stories about the origin of skill gaps are consistent with these results.

We utilize two dependent variables in our initial analysis. The first variable is a binary indicator that equals 1 if an establishment reports any long-term vacancies among core workers. We employ logistic regression to estimate these specifications (the tables report marginal effects). The second variable is a continuous measure of long-term vacancies as a percentage of total core workers. Following the literature on fractional dependent variables, we use a generalized linear model (GLM) to estimate this

*Table 2.* Long-Term Vacancies and Skill Demands

| | (1) Any L-T vacancies | (2) L-T vacancies percentage | (3) Any L-T vacancies |
|---|---|---|---|
| Extended reading | 0.097*** | 0.012** | |
| | (0.032) | (0.005) | |
| Extended writing | −0.019 | −0.002 | |
| | (0.036) | (0.007) | |
| Extended math | 0.106*** | 0.014** | |
| | (0.037) | (0.006) | |
| Extended computer | −0.010 | 0.007 | |
| | (0.032) | (0.006) | |
| Ability to learn new skills | 0.060 | −0.002 | 0.057 |
| | (0.037) | (0.006) | (0.035) |
| Ability to solve unfamiliar problems | −0.046 | 0.008 | −0.053 |
| | (0.038) | (0.006) | (0.039) |
| Ability to work in teams | −0.002 | 0.001 | 0.003 |
| | (0.032) | (0.006) | (0.032) |
| Ability to evaluate quality of output | −0.041 | −0.001 | −0.041 |
| | (0.036) | (0.006) | (0.037) |
| Extended reading index | | | 0.133*** |
| | | | (0.044) |
| Extended math index | | | 0.120** |
| | | | (0.050) |
| Extended computer index | | | −0.092** |
| | | | (0.042) |
| Total establishment employment (100s) | 0.046*** | −0.004** | 0.048*** |
| | (0.014) | (0.002) | (0.014) |
| Observations | 832 | 832 | 832 |
| Pseudo R-squared | 0.050 | — | 0.063 |

*Source:* MIT PIE Manufacturing Survey, 2012–2013.
*Notes:* Standard errors in parentheses. All specifications also include a quadratic in establishment employment, which is measured in 100s of employees. Specifications (1) and (3) use logit analysis and report marginal effects. Specification (2) reports marginal effects for a generalized linear model (GLM) with a complementary log-log link function. Standard errors are clustered by four-digit NAICS codes.
*$p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

specification (Papke and Wooldridge 1996). To accommodate that the fractional distribution is not symmetric and contains a steep spike at zero, we have used complementary log-log link function. The two dependent variables can be thought of as measuring the incidence and severity of hiring difficulties, respectively. After our initial analysis, we focus on the binary indicator for the presence of any long-term vacancies to streamline the subsequent analysis. All data in the logit and linear analyses are unweighted. We cluster standard errors by four-digit NAICS industry codes. Descriptive statistics for all key variables are contained in Appendix B.

Our empirical strategy is to first examine the relationship between skill variables and long-term vacancies (Table 2). We then turn to an investigation of different packages of explanatory variables that are associated with differing economic explanations for the skill gap phenomenon (Table 3).

*Table 3*. Long-Term Vacancies and Skill Mismatch Mechanisms

| | *(1) Any L-T vacancies* | *(2) Any L-T vacancies* | *(3) Any L-T vacancies* | *(4) Any L-T vacancies* | *(5) Any L-T vacancies* | *(6) Any L-T vacancies* | *(7) Any L-T vacancies* | *(8) Any L-T vacancies* |
|---|---|---|---|---|---|---|---|---|
| Extended reading | 0.089*** | 0.093*** | 0.094*** | 0.119*** | 0.099*** | 0.113*** | 0.110*** | 0.120*** |
| | (0.034) | (0.031) | (0.030) | (0.034) | (0.032) | (0.037) | (0.038) | (0.036) |
| Extended writing | −0.018 | −0.002 | −0.025 | −0.026 | −0.015 | 0.000 | 0.006 | 0.020 |
| | (0.037) | (0.037) | (0.036) | (0.037) | (0.036) | (0.038) | (0.038) | (0.038) |
| Extended math | 0.099** | 0.097** | 0.097*** | 0.109*** | 0.116*** | 0.106** | 0.108** | 0.075* |
| | (0.042) | (0.040) | (0.037) | (0.040) | (0.037) | (0.043) | (0.043) | (0.043) |
| Extended computer | −0.003 | 0.007 | −0.019 | −0.003 | −0.018 | 0.004 | 0.007 | −0.006 |
| | (0.034) | (0.035) | (0.030) | (0.031) | (0.032) | (0.033) | (0.033) | (0.034) |
| Ability to learn new skills | 0.064* | 0.057 | 0.058 | 0.068* | 0.075** | 0.052 | 0.053 | 0.055 |
| | (0.035) | (0.039) | (0.037) | (0.035) | (0.036) | (0.038) | (0.037) | (0.036) |
| Ability to solve unfamiliar problems | −0.050 | −0.061 | −0.046 | −0.056 | −0.053 | −0.080** | −0.075** | −0.067** |
| | (0.040) | (0.040) | (0.038) | (0.037) | (0.037) | (0.036) | (0.037) | (0.034) |
| Ability to work in a team | −0.000 | 0.012 | −0.005 | 0.009 | −0.005 | 0.020 | 0.021 | 0.023 |
| | (0.034) | (0.030) | (0.033) | (0.033) | (0.032) | (0.031) | (0.033) | (0.033) |
| Ability to evaluate quality of output | −0.045 | −0.045 | −0.036 | −0.043 | −0.044 | −0.054 | −0.051 | −0.052 |
| | (0.036) | (0.035) | (0.035) | (0.035) | (0.034) | (0.034) | (0.035) | (0.033) |
| **Package 1: External/no skill gap** | | | | | | | | |
| Unemployment rate | −0.006 | | | | | −0.005 | −0.005 | −0.007 |
| | (0.007) | | | | | (0.007) | (0.008) | (0.008) |
| Log manufacturing wage differential | 0.037 | | | | | 0.022 | 0.013 | 0.003 |
| | (0.045) | | | | | (0.048) | (0.050) | (0.048) |
| More foreign competition | 0.023 | | | | | −0.001 | −0.009 | 0.006 |
| | (0.041) | | | | | (0.040) | (0.040) | (0.040) |
| Percentage change in core employees (2 years) | 0.032 | | | | | 0.044 | 0.059** | 0.059** |
| | (0.043) | | | | | (0.051) | (0.027) | (0.027) |
| **Package 2: Internal HR** | | | | | | | | |
| Preference for internal hiring (ILM) | | −0.037 | | | | −0.042 | −0.034 | −0.043 |
| | | (0.032) | | | | (0.037) | (0.037) | (0.037) |

*(continued)*

*Table 3*. Continued

| | (1) *Any L-T vacancies* | (2) *Any L-T vacancies* | (3) *Any L-T vacancies* | (4) *Any L-T vacancies* | (5) *Any L-T vacancies* | (6) *Any L-T vacancies* | (7) *Any L-T vacancies* | (8) *Any L-T vacancies* |
|---|---|---|---|---|---|---|---|---|
| TQM percentage | | −0.001 | | | | −0.001 | −0.001 | −0.000 |
| | | (0.001) | | | | (0.000) | (0.000) | (0.001) |
| Union | | −0.001 | | | | −0.002 | −0.001 | −0.012 |
| | | (0.039) | | | | (0.044) | (0.044) | (0.045) |
| Formal training hours | | −0.000 | | | | −0.000 | −0.000 | −0.000 |
| | | (0.000) | | | | (0.000) | (0.000) | (0.000) |
| Unique skill | | 0.083** | | | | 0.082** | 0.086*** | 0.094*** |
| | | (0.037) | | | | (0.033) | (0.033) | (0.033) |
| **Package 3: Supply/geographic frictions** | | | | | | | | |
| Total county employment (100s) | | | −0.000 | | | −0.000 | −0.000* | −0.000* |
| | | | (0.000) | | | (0.000) | (0.000) | (0.000) |
| Community college—no resources | | | 0.010 | | | 0.019 | 0.019 | 0.019 |
| | | | (0.038) | | | (0.041) | (0.042) | (0.042) |
| Community college—no help | | | −0.011 | | | −0.027 | −0.030 | −0.027 |
| | | | (0.036) | | | (0.044) | (0.046) | (0.043) |
| **Package 4: Technology** | | | | | | | | |
| High technology | | | | −0.101*** | | −0.068 | −0.056 | 0.006 |
| | | | | (0.037) | | (0.042) | (0.042) | (0.049) |
| Above average technology | | | | −0.017 | | −0.032 | −0.032 | −0.025 |
| | | | | (0.033) | | (0.031) | (0.032) | (0.033) |
| Frequent product innovation | | | | 0.020 | | 0.035 | 0.045 | 0.055 |
| | | | | (0.038) | | (0.046) | (0.042) | (0.042) |
| Frequent process innovation | | | | −0.005 | | −0.007 | −0.021 | −0.025 |
| | | | | (0.039) | | (0.048) | (0.044) | (0.046) |
| **Package 5: Disaggregation/communication/coordination** | | | | | | | | |
| Industry cluster | | | | | 0.109*** | 0.119*** | 0.124*** | 0.124*** |
| | | | | | (0.038) | (0.039) | (0.041) | (0.039) |
| Work w/industry cluster | | | | | −0.019 | −0.000 | −0.009 | −0.001 |
| | | | | | (0.044) | (0.053) | (0.051) | (0.050) |

*(continued)*

*Table 3*. Continued

| | *(1) Any L-T vacancies* | *(2) Any L-T vacancies* | *(3) Any L-T vacancies* | *(4) Any L-T vacancies* | *(5) Any L-T vacancies* | *(6) Any L-T vacancies* | *(7) Any L-T vacancies* | *(8) Any L-T vacancies* |
|---|---|---|---|---|---|---|---|---|
| Other institutions | | | | | −0.011 | −0.030 | −0.030 | −0.042 |
| | | | | | (0.032) | (0.032) | (0.033) | (0.032) |
| Total establishment employment (100s) | 0.038*** | 0.050*** | 0.042*** | 0.039*** | 0.046*** | 0.040*** | 0.039*** | 0.049*** |
| | (0.014) | (0.013) | (0.014) | (0.015) | (0.015) | (0.014) | (0.015) | (0.015) |
| **Industry cluster interactions (difference-in-difference for marginal probability)** | | | | | | | | |
| Extended reading | | | | | | | 0.008 | 0.025 |
| | | | | | | | (0.076) | (0.074) |
| Extended math | | | | | | | 0.001 | −0.021 |
| | | | | | | | (0.066) | (0.068) |
| Log manufacturing wage differential | | | | | | | 0.006 | −0.006 |
| | | | | | | | (0.090) | (0.091) |
| Unique skill | | | | | | | −0.083 | −0.087 |
| | | | | | | | (0.073) | (0.069) |
| High technology | | | | | | | 0.049 | 0.093 |
| | | | | | | | (0.075) | (0.080) |
| Percentage change in core employees (2 years) | | | | | | | 0.129** | 0.123** |
| | | | | | | | (0.053) | (0.052) |
| Community college—no resources | | | | | | | 0.106* | 0.106* |
| | | | | | | | (0.061) | (0.061) |
| Industry fixed effects | — | — | — | — | — | — | No | Yes |
| Observations | 770 | 780 | 823 | 796 | 793 | 678 | 678 | 678 |
| Pseudo R-squared | 0.049 | 0.060 | 0.058 | 0.056 | 0.065 | 0.105 | 0.121 | 0.145 |

*Source:* MIT PIE Manufacturing Survey, 2012–2013.
*Notes:* Table contains marginal effects from logit analysis. Standard errors in parentheses. All specifications include a quadratic in establishment employment. Standard errors are clustered by four-digit NAICS codes.
*p < 0.10; ** p < 0.05; *** p < 0.01.

Note that our data are cross-sectional and that instrumental variables or other techniques that clearly establish causality are generally unavailable given both the questions we explore and the nature of our data. We recognize, for example, that just as wage levels could cause hiring problems, employers might respond to hiring problems by adjusting wages. Similar endogeneity arguments can be made with regard to other variables. Our strategy is thus to use a reduced-form approach to test for consistency of the cross-sectional data with various economic stories as outlined above. Although we cannot definitively prove that a given mechanism or dynamic is taking place, we can show that the data are not consistent with some mechanisms. Furthermore, we can shift the prior probability associated with the economic stories for which we find positive evidence.

In the first two columns of Table 2, our right-hand-side variables consist of binary indicators for whether a plant demands the extended skills discussed above: extended reading, writing, math, and computer skills. We also include demand indicators for soft/critical thinking skills: ability to learn new skills, ability to solve unfamiliar problems, ability to work in teams, and ability to evaluate quality of output. In addition, as our survey was stratified by employment size, we include controls for total establishment employment and employment squared (to capture nonlinearities) with all specifications (in Tables 2 and 3).

The results from the first two columns of Table 2 indicate that not all higher-level skills have similar relationships with hiring difficulties. Only extended reading and extended math demands are significant in this regard. Demand for extended reading is associated with a 9.7 percentage point increase in the probability of an establishment experiencing a prolonged vacancy (column (1), $p < 0.01$) and a 1.2 percentage point increase in long-term vacancies as a percentage of an establishment's core workforce (column (2), $p < 0.05$). Extended math is associated with a 10.6 percentage point increase in the probability of having a prolonged vacancy ($p < 0.01$) and a 1.4 percentage point increase in the percentage measure ($p < 0.05$). In general, the soft-skill/critical-thinking marginal effects are small in magnitude and insignificant. Demands for higher-level computer and writing skills are likewise insignificant. Establishment size has a significant relationship with long-term vacancies, but the relationship is a somewhat mechanical one based on the nature of the dependent variable. In the binary specification, increasing total employment by 100 employees is associated with a significant 4.6 percentage point increase in the probability of any long-term vacancy, while in the GLM model a similar increase is associated with a significant 0.4 percentage point decrease in long-term vacancies as a proportion of the establishment's workforce. Thus, larger establishments are more likely to have a long-term vacancy—perhaps because they have more resources to tolerate unfilled positions—while smaller establishments that have vacancies experience higher percentage levels of these hiring difficulties, in part because these plants have smaller workforces. To streamline the analysis, we focus on the binary-vacancy dependent variable for the remainder of this article. This measure is arguably the most general and the most policy relevant.

The last column of Table 2 explores whether the intensity of demand for higher-level skills matters. For the skill categories in which we asked about three or more distinct higher-level skills, we construct indices for each skill category that measure how many extended skills of that type an establishment demands. For example, if an establishment demands one extended math skill, the value of the math index would be 1, while the index value would equal 3 if the establishment demands three such skills. The results indicate that greater intensity in math and reading demands is associated with significant increases in long-term vacancies. Results for the computer index, however, are perhaps surprising. Greater intensity in higher-level computer demands is associated with a significant 9.2 percentage point decrease in the probability of experiencing a long-term vacancy. This result runs counter to the idea that computer technology is raising skill demands for production workers to unobtainable levels. We will further explore the role of technology below.

Before moving on to the rest of the analysis, note the overall explanatory power of the skill variables. Although the marginal effects of math and reading skill demands are highly significant, the skill variables combined explain only 4 to 5% of the total variation in long-term vacancies.[5] Given that these skill measures are the most precise ones currently available for manufacturing establishments, this result implies that it will be important to investigate a range of other predictors of hiring difficulties in future research.

In Table 3 we expand our analysis to include variables associated with various skill gap mechanisms and explanatory stories. We employ the binary long-term vacancy indicator as our dependent variable, and we include the binary skill indicators and employment size controls in all specifications. We allow the sample size to vary based on the maximum number of available observations for each specification. Results are similar in both magnitude and significance if we limit the sample across all specifications to the most restrictive model.

Our first package of "mechanism" regressors contains external variables associated with the "no skill gap,""not competitive," and "temporary adjustment" explanations discussed above. To test for whether macroeconomic factors are driving hiring patterns, we have included the county unemployment rate from 2011.[6] We have included a variable measuring the difference between the log of an establishment's average wage for core production workers and the log of the county's average manufacturing wage

[5]Although the pseudo-$R$-squared statistics cannot be strictly interpreted as percentages of explained variation, comparable linear models yield coefficients very similar to the marginal effects from the nonlinear specifications, and the $R$-squared values from these models imply explained variation in the 4 to 5% range.

[6]Bureau of Labor Statistics (BLS) Local Area Unemployment data (http://www.bls.gov/lau/).

to measure whether noncompetitive wages are responsible for prolonged vacancies.[7] We additionally include an indicator for whether a plant reports having more foreign then domestic competition. If globalization pressures are behind hiring difficulties, we would expect the marginal effect of this variable to be positive and significant. To explore whether hiring difficulties are an adjustment problem for plants that are growing, we have added a variable measuring the percentage growth in the core production workforce over the past two years.

The results from column (1) of Table 3 do not show a significant relationship between these variables and the probability of experiencing a long-term vacancy. By contrast, extended reading and math continue to be large and significant predictors of long-term vacancies. The other skill variables generally remain small and insignificant.

Our second package of mechanism variables contains measures of internal plant practices that may indicate a link between an establishment's human resource strategy and the hiring outcomes it experiences (as opposed to external supply frictions). We include an indicator for whether an establishment reports having a preference for internal hiring to fill vacancies (thus implying an internal labor market [ILM]). As a measure of the plant's approach to quality systems, we incorporate a variable that records the percentage of a plant's core workforce that participates in a Total Quality Management (TQM) program. To directly measure training, we use a variable that contains the total hours of formal training that an establishment provides to its core workers on an annual basis. If plants have the ability to solve some of their recruiting difficulties through the adoption of high-road human resource strategies, such as ILMs, TQM systems, and internal training, then we would expect the marginal effects of these variables to be negative. We also include an indicator for union status, as unions have the potential to promote workforce investment and training. Finally, because one of the important factors an employer must deal with in securing a trained workforce is the specificity of the skills it demands, we include a binary indicator for whether a plant demands a unique or specialized skill not demanded by other area establishments. By testing whether problems exist with unique skill demands, we are testing whether establishments face hiring challenges as a result of being unable or unwilling to internalize the production of plant-specific skills.

None of the internal human resource variables show significant effects. Unique skill requirements, however, are a significant predictor of hiring difficulty. Demanding a unique skill is associated with an 8.3 percentage point increase in the probability of experiencing an extended core worker vacancy (Table 3, column (2)). The predictive power of this variable

[7]BLS Quarterly Census of Employment and Wages (QCEW), third quarter 2012 (http://www.bls.gov/cew/).

indicates that we should pay attention to the various challenges and externalities associated with obtaining workers with highly specialized skills.

Our third package of mechanism variables includes proxies for supply frictions and geographic constraints. We include total county employment to investigate whether hiring difficulties are the result of the size of the regional labor market. This variable also serves as a rough proxy for geographic mismatch from historical patterns of development. We include two measures relating to community colleges to proxy for the quality of labor supply. The first is an indicator variable that equals 1 if the establishment reported that its local community college lacked sufficient resources (financial and physical plant) to produce high-quality graduates. Respondents without a local community college were coded as lacking resources. The second measure is an indicator that equals 1 if the establishment reported that the community college had not been helpful in meeting its needs. Respondents who had no local community college or no relationship with that college were coded as not helpful.[8] Note that this second measure is somewhat ambiguous as it is not clear who is at fault for this unhelpful status. Nevertheless, if the failure of local educational systems to produce skilled production workers is a major driver of hiring difficulties, we would expect a positive correlation between both of the community college variables and long-term vacancies.

The results in column (3) of Table 3 show little effect for these various supply measures. Although these three variables provide only partial measures of the quality of regional labor supply, they do not provide significant evidence in support of pure supply-side causes for hiring problems.

Our fourth package of mechanism regressors focuses on technology variables. We include a measure of whether a plant is in a high-tech industry subsector (based on Bureau of Labor Statistics methodology; see Hecker 2005). We additionally include an indicator that equals 1 if an establishment reported that an industry expert would rate the level of the establishment's technology as above average. We incorporate two variables designed to measure innovation. The first is an indicator that equals 1 if establishments report that they introduce new or redesigned products with more-than-incremental changes at least every two years or more frequently. The second is a similar variable for process innovation in production methods.

In the results for this specification (Table 3, column (4)), product and process innovation effects have opposite signs and are not significant predictors of hiring difficulties. However, somewhat surprisingly, high-tech status is associated with a significant 10.1 percentage point *reduction* in the probability of experiencing a long-term vacancy. The sign on the above-

[8]Because fewer respondents answered these specific community college questions than some of the more general skill questions, we have not dropped missing responses for these questions from the analysis in order to preserve sample size. Rather, we have included dummy variables that flag these observations in order to control for any heterogeneity. The community college variables have the same signs and significance levels in specifications that drop the flagged observations.

average technology effect is also negative, although imprecisely estimated. At first blush, this is a counterintuitive result. Conventional stories about technology generally predict that higher levels of technology will be associated with higher skill demands and consequently greater hiring problems. This result is all the more unexpected because the high-tech plants in our data do have significantly higher skill demands than their non–high-tech counterparts (results not shown). Two points are worth keeping in mind. First, because in these specifications we have independently controlled for skill demands, it could be that high-tech status is serving as a proxy for more sophisticated or effective human resources or recruitment practices. Having said this, it is worth pointing out that when we include the high-tech indicator in specifications that do not control for other skill demands (not shown), it consistently shows a negative—albeit insignificant—relationship with long-term vacancies. These results highlight a second point: the high-tech result is consistent with the finding that computer skill demands were not associated with greater hiring problems. At a minimum, the fact that these variables are not positive and significant is a sign that the relationship between technology and skill demands may be more complex than is commonly thought.

Our fifth package of mechanism regressors explores the disaggregation/communication/coordination failure scenario discussed above. We first include a measure of whether an establishment reports being part of a geographic cluster of plants in the same industry. The expected sign of the relationship between industry cluster and hiring difficulties is ambiguous. On the one hand, clusters may imply denser labor markets with a greater availability of specialized skills, thus lowering hiring problems. On the other hand, cluster status might imply a disaggregated situation in which competition for workers is more intense or businesses have greater difficulty communicating or coordinating their needs with other firms and educational institutions. To test whether communication is an issue, we include an indicator that equals 1 if an establishment reports that it works with the other plants in its cluster on training, skills, or other employment-related issues. To test whether the cluster might suffer from inadequate labor market intermediaries or other problems of disaggregation, we include an indicator that equals 1 if an establishment reports that institutions other than the community college have been helpful in employment matters.

The results (Table 3, column (5)) show that cluster status is highly predictive of hiring difficulties. Membership in an industry cluster is associated with a 10.9 percentage point increase in the probability of incurring a long-term vacancy ($p < 0.01$). The cluster cooperation and other institution effects are both negative—possibly implying that collaboration and other institutions can address some of the challenges of disaggregation—but both are imprecisely measured. Taken together, this package of variables provides an indication that some aspect of clusters may be problematic from a labor market perspective.

In column (6) of Table 3, we include a specification that combines the skill regressors with all of the various mechanism regressors. Extended reading and math maintain their large and significant associations with hiring difficulties. Of interest, the demand for the ability to solve unfamiliar problems shows a significant negative effect in this general specification. Among other significant predictors, unique skill maintains its predictive power, implying that manufacturers struggle with the issue of externalizing training for establishment-specific skills. In this aggregate specification, high-tech loses its significance (but retains a negative sign and a reasonably large magnitude). Industry cluster retains its large and highly significant association with hiring problems. In many ways the industry cluster result is the most intriguing, as it is one of the largest and most robust effects in our data. The strength of the effect raises the possibility that geographic or industry factors may play a significant role in hiring frictions.

## Cluster Discussion and Analysis

The cluster result presents a puzzle. One might reasonably suppose that the more specialized workforce and the more sophisticated labor market institutions often associated with clusters would mitigate rather than exacerbate hiring problems. However, clusters are not an automatic solution to all economic challenges. A lack of high-quality supporting institutions or managerial leadership may result in a low-productivity cluster that survives but does not solve economic problems in a fashion that leads to growth (Sonobe, Higuchi, and Otsuka 2013). Likewise, if the cluster consists of too many similar businesses, as opposed to establishments possessing differentiated and complementary capabilities, the presence of a cluster can actually be associated with negative economic outcomes because of competition and congestion costs (Delgado, Porter, and Stern 2014). Clusters that are legacies of an older economic logic that no longer prevails can become subject to a sclerotic economic "lock-in" (Grabher 1993). Even in cases where the cluster is providing effective solutions to a set of economic or business challenges, clusters may experience difficulties in adapting to particular types of economic shocks or changing circumstances (Carbonara, Giannoccaro, and McKelvey 2010).

Because clusters consist of multiple, distinct business establishments, they have higher baseline communications and logistics costs than does a single vertically integrated firm (Carbonara 2005). If the benefits of clusters—such as reduced search costs—are unrealized or do not extend to all areas of operations, coordination problems could manifest themselves (Rodriguez-Clare 2005).

Our analysis of subnational geographic and industry effects necessarily remains tentative because of limited sample size. We have conducted some exploratory analyses related to clusters, however, that point toward interesting areas for future research. Specifically, we have added a number of interactions involving the indicator for industry cluster to the specification containing all mechanism packages from Table 3. Column (7) from Table 3 contains the results of this analysis. Each interaction at the bottom of Table 3 is the difference in marginal effects for the listed variable for cluster establishments minus non-cluster establishments. As the results from column (7) of Table 3 show, the main effects of the various explanatory variables remain largely the same in magnitude and significance to the full specification in column (6).

At first, it might seem that greater levels of hiring problems in clusters simply reflect more intense competition for a limited pool of available workers. One possibility is that clusters are competing for a pool of workers with higher-level general skills (such as math and reading), but that supply does not respond because cluster demand is too small to influence overall production of these general skills. Regardless of the skills involved, if non-cluster firms were bidding wages for similar workers out of reach of manufacturing plants, then we would expect to see more sensitivity to wage differentials in clusters than in non-clusters. However, the results from the interaction analysis contradict these hypotheses. The differences in the marginal effects on long-term vacancies of demanding higher-level reading and math skills are small and insignificant, and log wage differentials show no greater predictive power in clusters than in non-clusters. For example, the marginal effect on long-term vacancies of demanding extended reading skills is 11.54 percentage points in industry-cluster establishments compared with 10.78 percentage points in non-cluster establishments, resulting in an insignificant 0.8 percentage point difference in the probability of experiencing long-term vacancies (Table 3, column (7)).

Another possibility is that clusters imply a greater specialization of skills than do non-cluster settings. Such highly specialized skills may be a problem if a plant is unwilling or unable to conduct internal training and if local training providers also refuse to do so (perhaps because of limited economies of scale). The results of our additional analysis likewise cast doubt on this hypothesis. Demand for unique skill is a large and significant predictor of hiring difficulties for non-cluster establishments, but a much smaller and insignificant predictor for cluster establishments, resulting in a difference of 8.3 percentage points in column (7) of Table 3. Although the difference between the two marginal effects is not significant, perhaps as a result of sample size, these outcomes imply that clusters do not exacerbate the problem of hiring workers with highly specialized skills and that, in accordance with agglomeration theories, they may in fact mitigate this challenge.

If these factors do not, at least initially, appear to explain the cluster effect, what factors might contribute? One potential explanation relates to adjustment problems and the communication and coordination failures mentioned earlier. When industry sectors and establishments experience growth, it is possible that cluster and non-cluster areas respond differently to this growth. It could be that the disaggregated nature of clusters presents special communication and coordination challenges in the face of economic shocks and the changing demand for workers. Indeed, our analysis of interaction effects shows that while growth in the total core workers employed at non-cluster establishments is not predictive of hiring problems, growth in core workers employed in cluster establishments is associated with a much larger and significant increase in long-term vacancies. A doubling of the workforce is associated with a highly significant 13.3 percentage point increase in the probability of a long-term vacancy for cluster establishments as compared to an insignificant 0.3 percentage point increase for non-cluster establishments, yielding a significant difference in probabilities of 12.9 percentage points (Table 3, column (7)).

The institutional environment might be another factor that differentially affects the hiring success of clusters. It might be that cluster-based plants are more sensitive to poor institutions or inadequate resources because of their disaggregated nature. The results in Table 3 provide limited support for this hypothesis. An assessment of insufficient resources at the local community college (reported by the respondent) is associated with a 10.6 percentage point greater likelihood of a long-term vacancy for cluster establishments than non-cluster establishments (significant at the 90% level).

One question that might be asked about the cluster results is whether they are merely a proxy for industry effects. It might be that certain industries are more likely to group in clusters and that these industries experience greater hiring difficulties for economic or technological reasons that are unrelated to clusters. We tested for this possibility, with results displayed in column (8) of Table 3, by adding industry fixed effects to the specification in column (7). Our sample size is too small to accommodate narrow industry classifications, so we created indicators for five manufacturing sectors (chemicals and plastics; metal, fabrication, and machinery; computer and electrical; transportation; and other manufacturing). The reference category is other manufacturing types. Although the inclusion of fixed effects diminished the magnitude and significance of the main effects of the extended math variable—an expected result given the collinearity of math demands and industry sectors—most of the other marginal effects remain similar in magnitude and significance, including the unique skill and cluster results. The interaction effects remained largely similar, with both the employment growth and the community college resource differences retaining their magnitude and significance. Thus, the cluster effect appears to extend across industries and to have some connection with adjustment/employment growth. Ultimately, more analysis and additional data will be required to pin down the mechanisms that are underlying the cluster effect.

## Conclusion

Despite the prominence of the debate over skill mismatch, data linking precisely measured skill demands with hiring outcomes has been lacking. Our survey is the first, to our knowledge, to directly measure concrete employer skill demands and hiring experiences in a nationally representative survey of establishments at the industry level.

Overall, the results qualify our view of skill mismatch. Three-quarters of U.S. manufacturing plants show no sign of hiring difficulties. We estimate an upper bound on potential skill gaps of 16 to 25% of manufacturing establishments. This finding contrasts sharply with other, nonrandom surveys that have reported figures in excess of 60 or 70% (Deloitte 2011).

Among the minority of manufacturing establishments that do show potential signs of hiring distress, the relationship between skill demands and hiring problems is not simple or clear-cut. While higher-level math demands are predictive of hiring difficulties, higher-level computer demands are not. Extended reading skills are unexpectedly prominent as predictors of long-term vacancies. Many other skill demands, including those for soft skills and problem-solving/initiative skills, are not associated with hiring difficulties.

When we examine the mechanisms that might contribute to hiring difficulties, a mixed picture emerges. High-tech plants, often thought to be hampered by inadequate workforce skills, are not associated with significantly greater hiring difficulties. Beyond higher-level math and reading demands, the two largest and most consistently robust predictors of hiring difficulties are demand for unique skills and membership in an industry cluster. Both of these factors raise questions about the relationship between a manufacturing establishment and other regional actors, including other firms, educational institutions, and training providers. The positive relationship between unique skill demands and long-term vacancies indicates that a number of establishments are unwilling or unable to solve their skill challenges through internal training, even for skills that are highly specific to a particular plant. As the size of manufacturing plants has declined—and with it the economies of scale in internal training—the issue of how manufacturing plants obtain specialized skills from external institutions is worthy of attention.

Further examination of cluster effects indicates that hiring difficulties in clusters may be attributable to adjustment problems in the face of employment changes rather than heightened competition or specialization of cluster skill demands. We hypothesize that this effect may be related to challenges associated with disaggregated establishments, communication/coordination failures, and the manner in which disaggregated plants interact with their institutional environments. Overall, the picture that emerges is one in which what matters for the smooth operation of the labor market is the connection between the demand and supply sides of the market rather than the unilateral actions of either side. Pure regional/supply-side variables are not predictive, and neither are variables related to purely internal plant practices. Rather, factors that point to the existence of multiple disaggregated establishments or that complicate the interaction between an employer and labor-supply institutions (such as unique skill demands) emerge as the most significant predictors of hiring challenges. The mechanics of labor market disaggregation, communication, and coordination may ultimately provide a more appropriate framework for thinking about labor market challenges than conventional skill mismatch formulations.

## Appendix A
## Survey Data Quality Analysis

To test the quality of the data we took two steps: 1) a bias analysis using data available in the Dunn and Bradstreet universe on respondents and nonrespondents to determine what response biases might exist, and 2) a comparison of patterns in our survey with those in the U.S. Census Bureau's Current Population Survey (CPS) to assess external validity.

We conducted the response bias analysis by using a linear probability model to regress an indicator for completing the survey on indicators for the various establishment size categories, indicators for geographic region, and indicators for two-digit SIC codes.[9] The results indicate that the largest size categories of establishments—those with more than 100 employees—were 12 to 20% less likely to respond.[10] We employ establishment size weights in our descriptive statistics to correct for these deviations. We also control for employment size in our regression specifications. Establishments in the South were 8% less likely to respond than were their counterparts in the Northeast. Other geographic differences were insignificant. Out of the 20 two-digit industry SIC codes, five were significantly more likely to respond than the base category of food products, with increased response

*Table A.1.* Comparison of Manufacturing Survey and CPS Data

| *Variable* | *Manufacturing survey* | *CPS (2012)* |
|---|---|---|
| Hourly wage | 16.95 | 16.49* |
| Union (%) | 18.1 | 13.7* |
| Female (%) | 26.7 | 26.6 |
| Age 30 or less (%) | 20.6 | 21.3 |
| Age 31–40 (%) | 27.5 | 22.0* |
| Age 41–55 (%) | 35.8 | 38.8* |
| Age 56 plus (%) | 16.1 | 17.9* |

*Sources:* MIT PIE Manufacturing Survey (2012–2013) and Current Population Survey NBER Merged Outgoing Rotation Group (MORG) data (2012).
*Notes:* We have used employment weights for the manufacturing survey and individual earnings weights for the CPS.
*$p < 0.05$.

[9]We conducted this bias analysis with SIC rather than NAICS codes because only SIC codes were available for the nonrespondents in the sample.

[10]Results are available upon request from the authors.

probabilities in the 8 to 12% range. These sectors were rubber and miscellaneous plastic; stone, clay, glass, and concrete; fabricated metal; industrial machinery and equipment; and electronic equipment except computers. Many of these are establishments in the size category—less than 100 employees—that was most likely to respond. Our use of establishment size weights and employment controls should mitigate this issue.

To test the external validity and data quality of our survey after the application of the relevant weights, we calculated a number of statistics on the production workers covered by the survey and compared these with statistics on manufacturing production workers from the 2012 CPS merged outgoing rotation groups (as compiled by the National Bureau of Economic Research). We should note that because our survey is an establishment survey and the CPS is a household survey, we expect some deviation between the two surveys.[11] The key question is whether the broad data patterns are similar.

We can see from examination of Table A.1 that although a number of statistically significant differences occur between means in the two surveys, the magnitude of these differences is generally modest. Overall, these results imply that the manufacturing survey is faithfully capturing data on manufacturing production workers and the establishments at which they are employed.

## Appendix B
## Descriptive Statistics

*Table B.1.* Descriptive Statistics for Key Variables

| *Variable* | *Mean* | *SE* |
|---|---|---|
| Long-term vacancy (indicator) | 0.239 | 0.021 |
| Long-term vacancy (percentage of core workforce) | 0.037 | 0.006 |
| Extended reading | 0.526 | 0.025 |
| Extended writing | 0.221 | 0.021 |
| Extended math | 0.380 | 0.024 |
| Extended computer | 0.419 | 0.024 |
| Ability to learn new skills | 0.501 | 0.025 |
| Ability to solve unfamiliar problems | 0.388 | 0.024 |
| Ability to work in teams | 0.642 | 0.024 |
| Ability to evaluate quality of output | 0.710 | 0.022 |
| Total establishment employment (100s) | 0.721 | 0.020 |
| More foreign competition | 0.225 | 0.021 |
| Percentage change in core workers (past 2 years) | −0.165 | 0.050 |

*(continued)*

[11]We chose to validate our data with the CPS rather than with an establishment survey such as the Bureau of Labor Statistics' Current Employment Statistics (CES) survey because the CES includes working supervisors in its definition of production workers. As a result, wages and some other workforce characteristics are not comparable between the manufacturing survey and the CES.

*Table B.1.* Continued

| *Variable* | *Mean* | *SE* |
|---|---|---|
| Preference for internal hiring (ILM) | 0.620 | 0.024 |
| Percentage of core workers who participate in TQM | 24.707 | 1.851 |
| Union | 0.065 | 0.009 |
| Hours of formal training/year (core workers) | 14.283 | 1.500 |
| Unique skill | 0.259 | 0.022 |
| Community college—no resources | 0.242 | 0.021 |
| Community college—no help | 0.587 | 0.024 |
| High technology | 0.218 | 0.020 |
| Above average technology | 0.361 | 0.023 |
| Frequent product innovation | 0.591 | 0.025 |
| Frequent process innovation | 0.562 | 0.025 |
| Industry cluster | 0.439 | 0.025 |
| Do you work with cluster on employment? | 0.077 | 0.012 |
| Are other institutions helpful on employment? | 0.253 | 0.022 |
| County unemployment rate (BLS LAU 2011) | 8.989 | 0.093 |
| Log manufacturing wage differential (vs. QCEW 3Q 2012) | −0.478 | 0.020 |
| Total county employment (QCEW 3Q 2012; 100s) | 3,776.464 | 305.788 |

*Source:* MIT PIE Manufacturing Survey, 2012–2013.
*Notes:* The means use establishment weights that reflect the survey design. The second column of data presents the standard errors of these weighted survey mean estimates.

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