HOW DIFFICULT IS IT TO FILL MANUFACTURING POSITIONS? A CROSS-SECTIONAL ASSESSMENT OF SURVEY RESULTS

Murat Arik, Middle Tennessee State University
Kristie Abston, Middle Tennessee State University
Sam Zaza, Middle Tennessee State University

ABSTRACT

For many communities, the manufacturing sector is still an important source of employment and economic vitality. However, the traditional manufacturing sector, where many of the jobs were low-skilled but high-paying, has been replaced by the advanced manufacturing operations, which create occupations that require a mix of experience and education. National and local surveys suggest that many human resource managers have difficulty filling open positions that require a blend of education, skill, and expertise. This study explores the relationship between the difficulty of filling certain manufacturing positions and the position, company, and location characteristics using survey data from human resource managers representing about 300 manufacturing organizations in the Southeast. A comprehensive survey was conducted in 2019, targeting nearly 1,300 manufacturing operations. The findings can help organizations and human resource managers prioritize their resources by focusing on the areas of concerns in filling the targeted jobs.

INTRODUCTION

A simple description of the manufacturing sector is that it "takes the raw or in-process materials and creates a new product from them" (U.S. Bureau of Economic Analysis (BEA.gov), 2020). According to the latest data (3rd quarter of 2019), the manufacturing sector accounts for a little over 11 percent of the U.S. gross domestic product (GDP) (BEA.gov, 2020). This sector has experienced dramatic ups and downs, as the U.S. economy has transformed itself over the years. For example, the manufacturing sector lost 5.832 million jobs between February 2000 and February 2010. Between February 2010 and February 2020, it gradually added nearly 1.5 million jobs in the U.S. (U.S. Bureau of Labor Statistics (BLS.gov), 2020).

As the manufacturing sector has started adding jobs, many companies experienced the difficulty of finding qualified individuals to fill the positions. For example, a survey conducted by the Society for Human Resource Management (SHRM) in 2016 shows that 68 percent of human resource managers report difficulty recruiting for full-time positions (SHRM, 2016). A recent survey in Minnesota indicates that 62 percent of the job vacancies in skilled production jobs in the manufacturing sector were difficult to fill (Leibert, 2019). Similarly, a Utah survey highlights major challenges employers face in filling some of the skilled occupations (Knold, 2015).

Empirical evidence suggests that the difficulty of filling positions is a real challenge for human resource managers. When the unemployment rate is record low across communities, finding a qualified person for certain jobs may be a challenge for businesses because of the intense competition for the labor. The low unemployment rate alone changes the nature of the difficulty of recruiting, especially in rural communities. What are the reasons for the difficulty? Why do some managers or companies have a difficult time filling certain positions?

The motivation for this study comes from our efforts to understand the workforce dynamics in the manufacturing sector and to help communities address workforce challenges they may be facing. This study is an empirical investigation of difficulties the human resource managers are confronting in recruiting for full-time positions in the manufacturing sector. By shedding light on the factors affecting the difficulty in recruitment, this empirical work contributes to the scholarly conversation on not only the narrow topic of difficulty in recruitment but also broader workforce supply and demand issues as well as both the spatial and sectoral skill-mismatch.

LITERATURE SUPPORT

Manufacturing is likely to continue to be one of the critical legs of the U.S. economy. Any recruiting difficulty in this sector may have significant implications for the economic development across the regions. There have been many scholarly works on different aspects of the supply and demand of workers and their associated issues (e.g., Barnow, Trutko, and Piatak, 2013). However, recent empirical works focus more on the difficulty of recruitment and its causes rather than broader supply and demand issues (SHRM, 2016).

The review of recent empirical studies suggests three broader reasons for the difficulty of recruitment: job-related factors, company-related factors, and regional/location-related factors (Knold, 2015; SHRM, 2016; Liebert, 2019). This research builds on those findings and further explores the relationship between the difficulty of filling positions and occupational-, wage-, company-, and location-specific factors.

Occupational characteristics. As the U.S. manufacturing industry continues to grow, the search for skilled talent is becoming the number one driver for manufacturing companies. According to Craft and Schake (2019), about 48 percent of manufacturers said that attracting and retaining a qualified applicant is on top of the two challenges manufacturing companies are currently facing. These recruitment challenges were associated with multiple compounding issues, including the awareness gap of vacant positions, difficulty of acquiring interested workers, low unemployment levels nationwide and industrywide, negative perception of the manufacturing industry among younger generations, lack of STEM skills among the workforce, and lack of technical education programs in K12 schools. The relationship between the difficulty of recruiting and the manufacturing job characteristics may be related to the applicant's skill to fulfill the job requirements. Generally, the more the job requires higher professional skills of the job seeker, the harder it is for the employer to recruit for the position.

The U.S. Manufacturing Institute, in cooperation with Deloitte Consulting, launched a survey in 2011. It found that while hiring skilled or highly skilled production positions, nearly 70 percent of manufacturing companies faced a "moderate to severe shortage" of qualified workers and showed that 600,000 U.S. manufacturing jobs were waiting to be filled (Lowe, 2015). According to Giffi (2015), executives determined that a majority of manufacturing employees are lacking the necessary knowledge, including computer skills (70%), problem-solving skills (69%), basic training (67%), and math skills (60%). Further, 14 percent of hiring difficulties are affected by skill mismatch, and 28 percent of them are caused by a lower work ethic or a passion for a manufacturing career. Another factor for having difficulty attracting skilled workers to production positions is the lack of interest in the manufacturing career track. Van Ours and Ridder (1993) found that vacancy duration is higher if that position requires a high education and experience level. These requirements would slow worker response time to adjust and meet the needs of the position. Barnow, Trutko and Piatak (2013) suggested that training time is the most significant factor in slowing worker response time. It takes four years to produce new engineers, and the lag might be more extended if the mathematics course load needs to be adjusted in high school. They also found that many occupations, requiring less than a college education, still need several years of training, and the interested job seeker would have a significant lag before qualifying for the occupation. Institutional barriers of some occupations could be another factor causing the difficulty of recruiting. Institutional barriers, such as occupational entry, licensing and certification requirements, and restrictions on immigration, could slow down the adjustment process of job seekers (Barnow et al., 2013).

Wage rate and benefits. In many cases, the wage rate and employee benefits package are considered as some of the primary reasons for the difficulty of recruiting. Barnow, Trutko, and Piatak (2013) believed that increasing wages is an obvious way to increase the number of laborers who are willing to work in a particular occupation based on the supply and demand curve of labor. Monk (2007) suggested that teachers' salaries are one of the most critical features of rural schools, directly affecting the recruitment of teachers. Today's regenerated interest in the role of skill improvement in the economic recovery has caused similarly powerful counterclaims that the reason for those unfilled jobs in manufacturing is not the skill mismatch, but rather the wages that are below the market level (Boston Consulting Group 2012; Cappelli 2011, 2012). Employment benefits are another vital part of the overall reward structure that may be used to attract applicants. Landry, Schweyer, and Whillans (2017) reported that employers across industries who included more benefits and details about them in the job advertisements gained more significant job applicants. In a study involving accounting majors' perceptions of sustainability reporting priorities, James (2017) found that employee benefits were the most crucial labor-related sustainability factor followed by work-related injuries, compensation/wages, and working conditions/training. It's plausible that reporting transparency regarding compensation was rated lower than benefits because pay secrecy and confidentiality regarding wage rates are still prevalent values in the United States.

Company characteristics. The company's industry is one of the vital parts of the recruitment process. Manufacturing jobs face a higher level of safety risks compared to other industries. Thus, while in the recruitment process, applicants need to know the safety rules and procedures used by organizations. As James (2017) reported, work-related injuries and working conditions/training were rated as 1 or 2 on a 5-point scale, with 1 being most important, by 63%

and 56% of respondents, respectively, when considering labor-related sustainability reporting requirements. Injury rates and safety training could impact an organization's image among stakeholders. Likewise, reputation could be one of the company characteristics to influence the attractiveness of vacancies to job seekers. Studies in the U.S. have shown that it is hard for companies with a low reputation to attract applicants (Fombrun & Shanley, 1990; Gatewood et al., 1993). Consequently, during the recruitment process, HR managers organize a tour around the manufacturing facility to help applicants understand the position requirements, the risk associated with the job, and safety procedures in manufacturing plants. The size of the company may also affect the recruitment process. The survey results of Monk's (2007) indicated that the smallest schools face the most significant recruiting challenges as the share of inexperienced teachers is high in the smallest schools. Additionally, in Chapman, Uggerslev, Carroll, Piasentin, and Jones's (2005) study, work environment, and organizational image were the strongest predictors of job-organization attraction among the organizational characteristics predictor category. Behling, Labovitz, and Gainer (1968) also mentioned that the characteristics of the company were significant determinants of hiring results.

Location-specific. As shown by Goffette-Nagot and Schmitt (1999), jobs are more separated in rural places than in urban areas, which increases the cost of the job search process and reduces the possibility of job opportunities acceptable to rural workers. The population density of the area affects recruitment. According to the results of a survey conducted in the French Midi-Pyrénées region, Blanc, Cahuzac, and Tahar (2008) found that in the case of comparable size and departments, companies in low-density areas will encounter more difficulties in the recruitment process because they are usually far away from large city clusters, which leads to less attractive to potential job seekers. Additionally, their research findings proposed four reasons for recruiting difficulties that companies located in low-density local labor markets put forward more frequently: lack of appropriate qualification on the labor markets, the candidates' lack of motivation, area's lack of attractiveness, and wage problems. They also found that small manufacturing companies with less than ten employees are more frequent in the low-density market.

In contrast, companies in the service sectors have a large proportion of high-density areas (Blanc et al., 2008). In the process of recruitment, being located in a low-density place would have two opposite effects for companies looking for employees: on the one hand, it increases the recruiting difficulties because of a mismatch between job requirements and job seekers' skills; on the other hand, it reduces the challenges of the competition between companies on the local labor market (Blanc et al., 2008). The place where the manufacturing plant located has inadequately skilled graduates generated by local colleges also would be a factor for the difficulty in recruitment. Looker and Dwyer (1998) suggested that compared to urban teenagers, the transition from school to work for rural teenagers are different both in the process of decision-making and the cost involved. Research has indicated that educational, occupational, and social chances for rural teenagers tend to be more restricted than their urban counterparts (Wallace et al., 1990; Pavis et al., 2000, 2001; Glendinning et al., 2003). Additionally, in rural areas, the size of the social networks of the company can affect the process of recruitment. The research finding shows that rural companies in Cumbria rely almost entirely on local formal and informal networks to recruit local labor (Canny, 2004).

Another location-specific element is the impact of turnover rates for manufacturers located in rural versus urban areas. If the recruitment is more challenging in rural areas, then turnover in those areas would have a more severe impact on companies. Abston, Arik, and Graves (2019) found that rurality was positively correlated with the problem of turnover and proposed that this result could be related to institutional differences in rural versus urban manufacturers or due to worker dissatisfaction with commuting distances associated with rural living.

RESEARCH QUESTIONS

The first wave of major wage and benefits study was conducted in 2017. The second wave started in May 2019 and was completed in December 2019, with over 300 manufacturing companies participating. The broader survey includes a general segment on the benefits that the company offers to employees and an occupation-specific questionnaire allowing companies to profile as many occupations as they have. The survey itself takes nearly 90 minutes to complete. This part of the questionnaire was designed to get answers to the following four research questions:

RQ1: What is the relationship between the difficulty of recruiting and job characteristics?
RQ2: Is the wage rate the primary reason for the difficulty of recruiting?
RQ3: Do the company characteristics make a difference in the recruitment process?
RQ4: Is the location of the manufacturing plant a factor for the difficulty in recruitment?

We address these research questions by first reviewing the data and methodology. Under the method, we will introduce a conceptual framework informed by the empirical research conducted by the Society of Human Resource Management (SHRM, 2016), among others. We will then discuss the study findings.

DATA AND METHODOLOGY

Data

There are two sources of data used in this empirical research: the first source of data is the 2019 Wage and Benefits Survey, conducted by the Business and Economic Research Center at Middle Tennessee State University in partnership with the Middle Tennessee Industrial Development Association. This is the second annual survey of its kind for Middle Tennessee manufacturing. As a survey platform, we used Survey Monkey software. As discussed in the previous section, the survey included two sections: (1) company demographics and pay practices, and (2) job-specific questions. We contacted a little over 1,300 human resource managers, resulting in about 300 useable surveys. The second source of the data includes O*Net online (https://www.onetonline.org/) and BLS.gov.

The paper uses both demographic and job-related indicators, as well as spatial indicators. The dependent variable is "difficulty of filling" an occupation. We asked human resource managers to rate each occupation they introduce between 1 and 10; 1 being "easy to fill" and 10 being "extremely difficult to fill." A total of a little over 130 occupations were rated by about 300 human resource managers resulting in 2,209 ratings.

Although the survey asked the companies to report educational requirements, licensing, and other job qualities, we decided to use O*NET's "job zone" conceptual framework for each occupation (Table 2). The "job zone" framework classifies each occupational titles into one of five major categories, each of which represents a unique mix of "education," "experience," "skill set," and "license requirement." Table 1 below shows the variables of interest and sources of the indicators and a short description of each indicator.

Table 1: Variables, Sources, and Definitions

ID	Description	Source	Cluster
DIFF19	***Difficulty of Filling***	***Survey***	***Dependent Variable***
JZONE	Job Zone (Rated from 1 to 5) 1= Less Sophisticated 5= Highly Sophisticated (Education + Experience)	Onetonline.org	Independent Variable/ Occupation-Related
BENEF19	Benefits as percent of total compensation	Survey	Independent Variable/ Company-Related
POS2019	Number of Positions in a Given Occupations	Survey	Independent Variable/ Occupation-Related
AWAGE19	Average Wage for a Given Occupation	Survey	Independent Variable/ Occupation-Related
UNEMP19	Unemployment Rate	BLS.Gov	Independent Variable/ Region-Related
LFORCE19	Labor Force - County (Available Workers)	BLS.Gov	Independent Variable/ Region-Related
GROWTH19	Employment Growth - County	BLS.Gov	Independent Variable/ Region-Related
EMPSIZE19	Company Employees (Size - 2019)	Survey	Independent Variable/ Company-Related
SALES2019	Company Sales (Size - 2019)	Survey	Independent Variable/ Company-Related

Job Training	A few days to months	A few months to one year	one to two years of training	Several years of work-related experience	May need some on-the-job training
SVP Range*	Below 4.0	4.0 to < 6.0	6.0 to < 7.0	7.0 to < 8.0	8.0 and above

* SVP = Specific Vocational Preparation

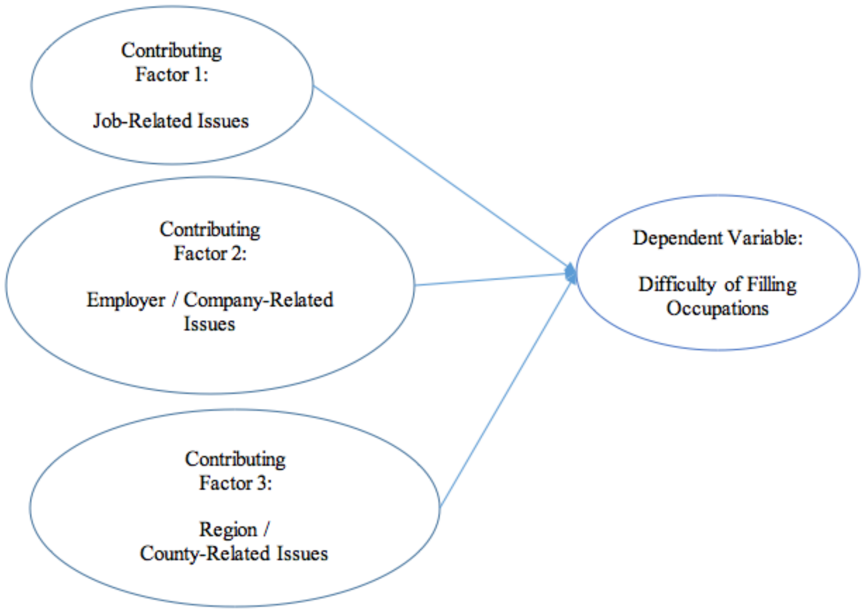
Source: O*NET (NETONLINE.ORG) & the Authors

Note: The complete list of surveyed occupations with the job zone classification is included in the appendix.

Conceptual Framework

A review of empirical research (Knold, 2015; SHRM, 2016; and Leibert, 2019) suggests several factors play critical roles in hiring difficulties. The top six reasons are (in the order of importance): (1) lack of applicants, (2) local market not producing enough, (3) competition from other employers, (4) lack of skill-set, work experience, and training, (5) soft skill, (6) low wages. Based on these findings, Chart 1 outlines the basic conceptual framework for the study. Chart 1 summarizes the empirical findings under the three major clusters of factors accounting for the difficulty of filling the positions: (1) job-specific factors, (2) employer/company-specific factors, and (3) spatial factors.

Chart 1: A Conceptual Framework of Factors Affecting the Difficulty of Filling Occupations



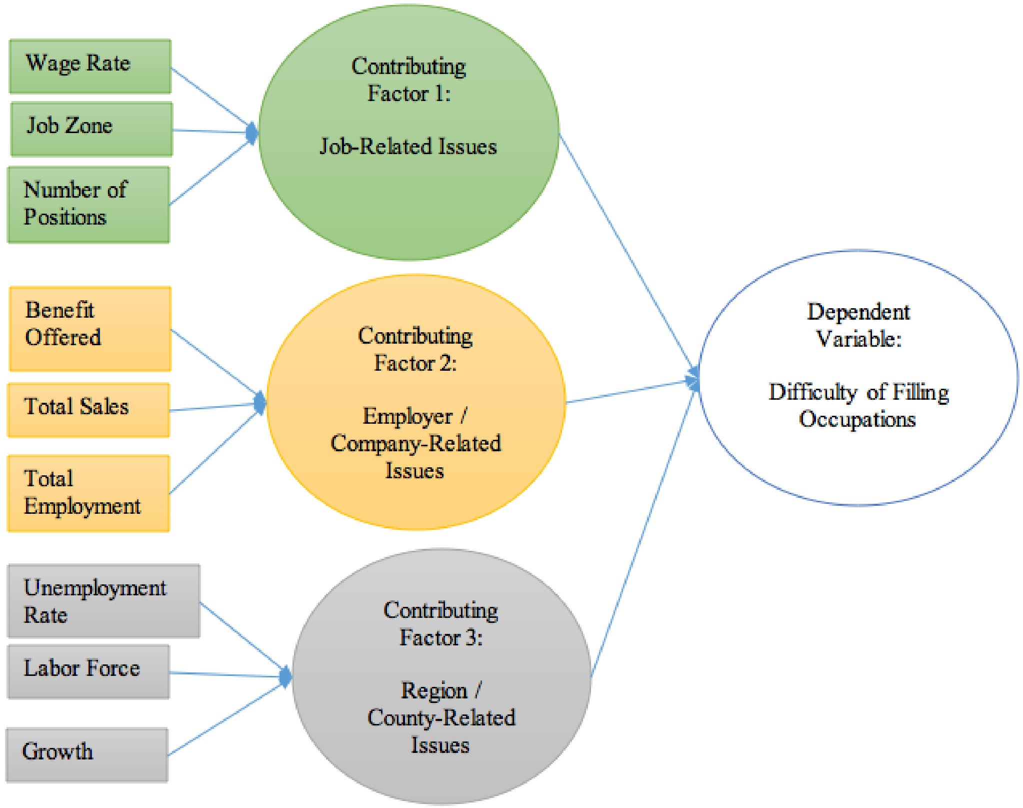
Source: Authors

The second step in the process is operationalizing these three major factors by identifying available proxy indicators to accurately measure the major cluster of factors identified in Chart 1. Chart 2 clearly identifies three indicators for each cluster of factors that will be used in the regression analysis. For the job-related issues, we used the average wage rate reported by the companies for that given occupation, job zone classification showing the complexity of the tasks to be completed, and the number of positions in that given occupation at the company to show the competitive nature of the position.

For the employer/company-related issues, we identified several survey-based indicators including (1) benefits as a percent of the total compensation, (2) total company sales to measure the size of the company, and (3) total employment as a measure of the size and labor-intensive nature of the companies. Since the companies we surveyed were in the manufacturing sector (96 percent of them), we did not introduce the sectoral control variable.

Finally, for the spatial variables, we used three indicators to measure the level of economic activity in the county where the companies are located: (1) unemployment rate – measuring the number of people currently looking for job, (2) labor force – measuring the size of the labor market, and (3) growth – measuring the employment growth from the previous year to show the vibrancy of the local economies.

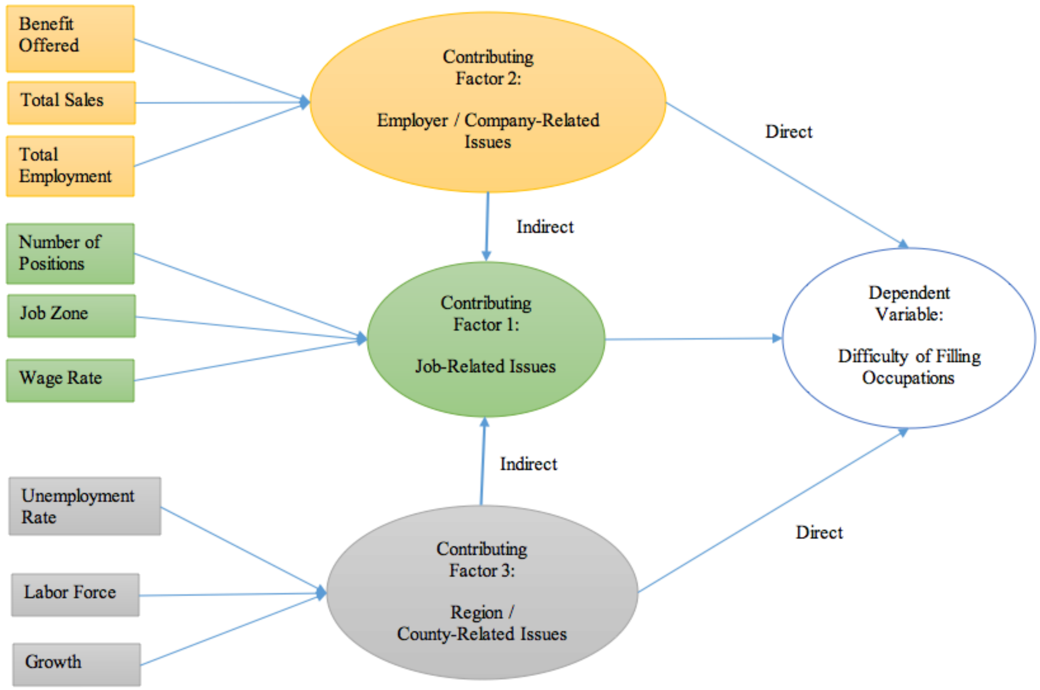
Chart 2: Operationalizing the Factors Affecting the Difficulty of Filling Occupations



Source: Authors

As a final step in the conceptualization process, Chart 3 shows a full model that introduces company-related and spatial factors as the control factors. According to Chart 3, the difficulty of filling a position is primarily related to the job-specific factors. However, both the company-specific indicators and spatial factors, directly and indirectly, affect the outcome.

Chart 3: Direct and Intervening Variables Affecting the Difficulty of Filling Occupations



Source: Authors

Methods

In this paper, we used a simple OLS regression analysis, using standard econometric software to test the following models:

Model 1: Job-related factors: the difficulty of filling positions is a function of the job-related issues:

$$Diff19 = a_1 + \beta_1 AWage19 + \beta_2 JZone + \beta_3 POS2019 + \varepsilon_i \tag{1}$$

Model 2: Employer / company-related factors: the difficulty of filling positions is a function of the employer / company-related issues:

$$Diff19 = a_1 + \beta_1 BENEF19 + \beta_2 EMPSIZE19 + \beta_3 SALES2019 + \varepsilon_i \tag{2}$$

Model 3: Spatial factors: the difficulty of filling positions is a function of the location (county) where the company/position is located:

$$Diff19 = a_1 + \beta_1 UNEMP19 + \beta_2 Growth19 + \beta_3 LFORCE19 + \varepsilon_i \tag{3}$$

Model 4: Combined model: job-related factors controlled by the company and spatial factors account for the difficulty of filling positions:

$$Diff19 = a_1 + \beta X_i + \varepsilon_i \quad (4)$$

where $\boldsymbol{X_i}$ represents the independent variables, including indicators for job-related issues, company / employer-related issues, and spatial factors as control variables.

Multicollinearity and Outliers

Some of the independent variables are likely strongly correlated with each other. To control multicollinearity, we first check the Pearson correlation tables to exclude any indicator that may strongly correlate with other indicators. As a rule of thumb, we excluded one of the indicators with a correlation ratio over 0.8.

Furthermore, regional labor force, company employment, and company sales data include both small and large indicators suggesting that some of the observations may have an outsized impact on the regression results. For example, Davidson County has a labor force of more than 400,000. At the other end of the spectrum, Moore County's labor force is 3,753. To control the impact of those indicators on the regression results, we transformed those indicators into the natural logarithmic form. Table 3 summarizes the indicators by model.

Table 3: Models and Indicators Used

ID	Description	Model 1	Model 2	Model 3	Model 4
DIFF19	***Difficulty of Filling***	***Dependent Variable***			
JZONE	Job Zone (Rated from 1 to 5) 1= Less Sophisticated 5= Highly Sophisticated (Education + Experience)	Yes			Yes
BENEF19	Benefits as percent of total compensation		Yes		Yes
POS2019	Number of Positions in a Given Occupations	Yes			Yes
AWAGE19	Average Wage for a Given Occupation	Yes			Yes
UNEMP19	Unemployment Rate			Yes	Yes
LFORCE19	Labor Force - County (Available Workers) (ln)			Yes	Yes
GROWTH19	Employment Growth - County (%)			Yes	Yes
EMPSIZE19	Company Employees (Size - 2019) (ln)		Yes		Yes
SALES2019	Company Sales (Size - 2019) (ln)		Yes		Yes

RESULTS AND DISCUSSION

Job-Related Factors

For research questions 1 and 2, we explored the relationships between job-related factors and the difficulty of filling a position. Table 4 presents the Pearson correlation matrix among the indicators, and Table 5 shows the results of the Ordinary Least Square (OLS) regression. Table 4 suggests that none of the indicators have any significant correlations with each other.

Table 4: Descriptive Statistics of Model Variables and Correlation Matrix

Variables	Means	SD	DIFF19	JZONE	AWAGE19	POS2019
DIFF19	5.7338	2.2691	1			
JZONE	3.2553	0.98221	0.2204	1		
AWAGE19	30.9	17.92	0.21542	0.56231	1	
POS2019	10.657	64.094	-0.03168	-0.12339	-0.08478	1

Table 5 presents the regression results in equation form and the table format with basic diagnostic information. The total number of observations was 2,201. After 367 observations dropped because of the missing values, 1,833 observations were used in the model. Table 5 suggests that the model is significant (F), and t-values (Heteroscedasticity-corrected robust t-values(HACSE)) for Job Zone and Wage Rate are statistically significant, suggesting that job-related factors have important implications for the difficulty of filling certain occupations. The findings indicate that the availability of similar job positions (POS2019) has no impact on the difficulty of filling.

Table 5: Model 1: Job Equation: OLS Regression Results

DIFF19 = +4.122 + 0.337*JZONE + 0.0167*AWAGE19 – 9.23E-05*POS2019 (SE) (0.181) (0.0643) (0.00365) (0.000808)					
	Coefficient	HACSE	t-HACSE	t-prob	Part.R^2
Constant	4.1233	0.2695	15.3	0.0000	0.1134
JZONE	0.33663	0.08789	3.83	0.0001	0.0080
AWAGE19	0.016737	0.004835	3.46	0.0005	0.0065
POS2019	-9.2258e-05	0.0005787	-0.159	0.8734	0.0000
sigma	2.20201	RSS 8868.52			
R^2	0.059	F(3,1833) = 38.09 [0.000]**			
Adj . R^2	0.057	log-likelihood -4045.83			
no. of observations	1833	no. of parameters 4			
mean(DIFF19)	5.73322	se(DIFF19) 2.26789			
When the log-likelihood constant is NOT included:					
AIC	1.558092	SC 1.59295			
HQ	1.58536	FPE 4.85942			
When the log-likelihood constant is included:					
AIC	4.41880	SC 4.43083			
HQ	4.42323	FPE 82.9963			

Company / Employer-Related Factors

Our third research question was about the role of company characteristics in recruiting for certain occupations. To test the impact of company-related factors, we use three different measures: benefits as a percent of total compensation (BENE19), company sales (SALES2019), and company employment size (EMPSIZE19). As Table 6 indicates, instead of log form, we used non-transformed indicators in the equation. None of the regressors have strong correlations with each other. The direction of correlations suggests that the difficulty of hiring is negatively associated with the benefits and company size. The sign of correlation suggests that large companies do not have a problem with finding people.

Table 6: Descriptive Statistics of Model Variables and Correlation Matrix
Model 2: Company Characteristics

Variables	Mean	SD	DIFF19	BENEF19	EMPSIZE19	SALES2019
DIFF19	5.7793	2.314	1			
BENEF19	0.3131	0.18618	-0.0344	1		
EMPSIZE19	327.59	561.46	-0.1071	0.01336	1	
SALES2019	2.13E+08	7.94E+08	-0.2068	0.00933	0.22818	1

Table 7 further clarifies several issues regarding company characteristics and hiring difficulty. As Table 7 shows, 630 observations were dropped because of the missing values. Overall, F-value suggests the model is significant. Table 7 shows that, contrary to some survey data, benefits are not a statistically significant predictor of the hiring difficulty. The company size does matter, especially the sales volume. Table 7 suggests (Heteroscedasticity-corrected robust t-values (HACSE)) that large companies do not have a problem finding a skilled workforce, as the relationship between the sales volume and hiring difficulty is negative.

Table 7: Model 2: Company / Employer Equation: OLS Regression Results

DIFF19 = + 6.117 – 0.3947*BENEF19 – 0.000259*EMPSIZE19 – 5.602e-10*SALES2019 (SE) (0.116) (0.306) (0.000104) (7.38e-11)					
The estimation sample is: 1...2202					
Dropped 630 observation(s) with missing values form the sample					
	Coefficient	HACSE	t-HACSE	t-prob	Part.R^2
Constant	6.11736	0.2116	28.9	0.0000	0.3478
BENEF19	-0.394721	0.6146	-0.642	0.5208	0.0003
EMPSIZE19	-0.000259016	0.0001143	-2.27	0.0235	0.0033
SALES2019	-5.60241e-10	8.800e-11	-6.37	0.0000	0.0252
sigma	2.2605	RSS		8012.24903	
R^2	0.0475672	F(3,1568) =		26.1 [0.000]**	
Adj. R^2	0.045745	log-likelihood		-3510.67	
no. of observations	1572	no. of parameters		4	
mean(DIFF19)	5.77926	se(DIFF19)		2.31405	
When the log-likelihood constant is NOT included:					
AIC	1.63371	SC		1.64735	
HQ	1.63878	FPE		5.12285	
When the log-likelihood constant is NOT included:					
AIC	4.47159	SC		4.48523	
HQ	4.47666	FPE		87.4956	

Spatial Factors

Our fourth research question was about the impact of locations on the difficulty of hiring. To measure the impact of location, we used three indicators: unemployment rate (UNEMP19), the labor force (LNFORCE19) in the logarithmic form, and employment growth (GROWTH19). Tables 8 and 9 present the regression results. Table 8 shows the correlation matrix and descriptive statistics for the spatial factors model. Table 8 shows that the labor force and unemployment rate has a strong negative correlation, suggesting that the regions with a large labor force have a low unemployment rate.

Table 8: Descriptive Statistics of Model Variables and Correlation Matrix
Model 3: Spatial Characteristics

Variables	Mean	SD	DIFF19	UNEMP19	GROWTH 19	LNLFOR CE19
DIFF19	5.7071	2.3009	1			
UNEMP19	3.174	0.53371	-0.0355	1		
GROWTH 19	3.3776	1.263	0.00764	-0.4234	1	
LNLFOR CE19	10.575	1.1047	0.05511	-0.6593	0.30287	1

Table 9 presents the findings for Model 3, which shows that the model itself is not a significant model to predict the difficulty of hiring. Both Model 3 as a general and t-values (Heteroscedasticity-corrected robust t-values (HACSE)) for regressors are not statistically significant.

Table 9: Model 3: Spatial Factors Equation: OLS Regression Results

DIFF19 = + 4.562 – 0.01141*UNEMP19 – 0.01935*GROWTH19 + 0.1178*LNLFORCE19 (SE) (0.959) (0.128) (0.0428) (0.0589)					
The estimation sample is: 1...2209					
	Coefficient	HACSE	t-HACSE	t-prob	Part.R^2
Constant	4.56247	2.139	2.13	0.0330	0.0021
UNEMP19	-0.0114102	0.2581	-0.0442	0.9647	0.0000
GROWTH19	-0.0193475	0.08568	-0.226	0.8214	0.0000
LNLFORCE19	0.117842	0.1333	0.884	0.3768	0.0004
sigma	2.29886	RSS		11652.9022	
R^2	0.00313069	F(3,2205) =		2.308 [0.075]	
Adj.R^2	0.00177441	log-likelihood		-4971.24	
no. of observations	2209	no. of parameters		4	
mean(DIFF19)	5.70711	se(DIFF19)		2.3009	
When the log-likelihood constant is NOT included:					
AIC	1.66664	SC		1.67696	
HQ	1.67041	FPE		5.29433	
When the log-likelihood constant is included:					
AIC	4.50451	SC		4.51484	
HQ	4.50828	FPE		90.42444	

Combined Model

Model 4: Job-related factors controlled by the company and spatial factors

The combined model (Model 4) tests the impact of job characteristics on the difficulty of filling, controlled by factors associated with the company and spatial characteristics. Table 10 shows the regression results for Model 4. The combined model does not include the growth indicator as it was dropped by the model to improve the regression fit. Table 10 shows a very robust model (F-value) with several indicators that are statistically (t-values (Heteroscedasticity-corrected robust t-values (HACSE))) significant.

When we look at the job-related indicators controlled by the company, and spatial characteristics, the impact of wage rate and job zone classification is significant. This finding confirms empirical surveys that suggest the wage rate is a factor. However, the sign of wage rate is positive, suggesting that most of the difficulty of hiring is occurring at the high-wage level occupations.

Table 10: Model 4: Combined Model: OLS Regression Results

$$
\begin{aligned}
\text{DIFF19} = &+ \underset{(1.21)}{10.7} - \underset{(0.307)}{0.504}*\text{BENEF19} + \underset{(0.00444)}{0.0264}*\text{AWAGE19} - \underset{(0.0017)}{0.000401}*\text{POS2019} \\
&+ \underset{(0.0731)}{0.262}*\text{JZONE} - \underset{(0.146)}{0.677}*\text{UNEMP19} - \underset{(8.64e-11)}{8.92e-10}*\text{SALES2019} \\
&- \underset{(0.000108)}{0.000282}*\text{EMPSIZE19} - \underset{(0.0785)}{0.37}*\text{LNLFORCE19}
\end{aligned}
$$

(SE)

The estimation sample is: 2...2201

Dropped 868 observation(s) with missing values from the sample

	Coefficient	HACSE	t-HACSE	t-prob	Part.R^2
Constant	10.7334	2.153	4.98	0.0000	0.0184
BENEF19	-0.503733	0.6316	-0.798	0.4253	0.0005
AWAGE19	0.02640	0.006492	4.07	0.0001	0.0123
POS2019	-0.0004012	0.001865	-0.215	0.8297	0.0000
JZONE	0.261730	0.09778	2.68	0.0075	0.0054
UNEMP19	-0.67739	0.2660	-2.55	0.0110	0.0049
SALES2019	-8.92259e-10	1.074e-10	-8.31	0.0000	0.0496
EMPSIZE19	-0.000281573	0.0001426	-1.97	0.0486	0.0029
LNLFORCE19	-0.370405	0.1345	-2.75	0.0060	0.0057

sigma	2.1212	RSS	5952.79602
R^2	0.146512	F(8,1326) =	28.39 [0.000]**
Adj.R^2	0.141351	log-likelihood	-2887.15
no. of observations	1332	no. of parameters	9
mean(DIFF19)	5.81757	se(DIFF19)	2.28914
When the log-likelihood constant is NOT included:			
AIC	1.51069	SC	1.54579
HQ	1.52385	FPE	4.52987
When the log-likelihood constant is included:			
AIC	4.34857	SC	4.38367
HQ	4.36172	FPE	77.3678

Job zone classification also shows a similar type of relationship: those occupations that are difficult to fill are also the ones that require a sophisticated mixed skill set of education and experience. This finding confirms the human resource managers' view on improving the pipeline through education and training.

Another finding that deserves close attention is that sales volume and employment size account for the difficulty of hiring. However, this problem seems relegated to the smaller firms rather than large ones as the strong statistically significant relations between sales volume and difficulty of hiring suggests.

In terms of the spatial effect, both labor force and unemployment indicators are statistically significant, suggesting that, controlled by other factors, they do have a substantial impact on the difficulty of hiring. The negative relationship between the labor force and the difficulty of hiring suggests that large labor markets do not have a problem in finding people, whereas small areas have difficulties in finding people. In Model 4, the unemployment rate becomes statistically significant, and its sign is negative, suggesting that when the labor market is tight, the recruiters have a difficult time finding the right people.

CONCLUSIONS, IMPLICATIONS, AND FUTURE RESEARCH

Strategic recruitment and staffing are always high on the priority list for human resource managers. Yet, finding the right people for jobs that require complex skill sets is an important emerging problem for human resource managers. The findings from our study suggest that some occupations, especially those occupations that pay high wages and require a sophisticated combination of education and experience, are not getting enough hits from the labor market. The spatial features and company characteristics are further affecting the outcome as smaller labor markets, and smaller companies are impacted more than larger markets and larger companies.

One critical implication of this study is that human resource managers in smaller companies need to be even more creative in their efforts to source and recruit applicants with the desired combination of education and experience. For example, smaller companies must drill into the metrics that identify which sources have produced the best, long-term employees and explore how to maximize those sources. Smaller companies typically cannot afford to offer the same array of benefits as larger companies; however, our findings indicate that benefit as a percent of the compensation is not a significant incentive for candidates to consider a job. Therefore, smaller companies may see more significant gains in their recruitment efforts by focusing on the company culture and investing in the education and training pipeline. The difficulty of hiring does not seem to be a pressing problem for larger companies.

For future research, the third wave of the survey may include a battery of questions informed by the literature to get more precise details on the difficulty of hiring from the human resource managers' perspective in the manufacturing sector. Additional information regarding turnover by positions and total rewards strategies might bolster this research and explain more about the difficulties of hiring in the manufacturing sector.

LIMITATIONS AND FUTURE RESEARCH

This study has several limitations that can be addressed in future studies. First, this study focuses on the manufacturing sector. Thus, these results may not generalize to other sectors, even though most types of organizations would be impacted by the factors studied here. Second, spatial units included in the sample are limited to Middle Tennessee, including 40 counties. These findings may not be generalizable to other geographic areas. Expanding geographical coverage may have an impact on the magnitude and directions of spatial indicators. Third, the authors acknowledge that there may be a reverse causality between the difficulty of hiring and the average hourly wage in the study. To test the reverse causality assumptions, we need to get additional survey data from the third wave of the study and test for the direction of causality. Finally, future research can use the findings as a benchmark to evaluate the impact of the pandemic on employees' recruiting.

REFERENCES

Abston, K. A., Arik, M., & Graves, B. C. (2019). WORKFORCE TURNOVER AND ABSENTEEISM IN THE MANUFACTURING SECTOR. *Global Journal of Business Disciplines*, *3*(1), 57-79.

Adams, J., Greig, M., & McQuaid, R. W. (2000). Mismatch unemployment and local labour-market efficiency: the role of employer and vacancy characteristics. *Environment & Planning A*, *10*, 1841.

Barnow, B. S., Trutko, J., & Piatak, J. S. (2013). Conceptual Basis for Identifying and Measuring Occupational Labor Shortages.

Barnow, B. S., Trutko, J., & Piatak, J. S. (2013, January). Occupational Labor Shortages: Concepts, Causes, Consequences, and Cures. Kalamazoo, MI: Upjohn Institute for Employment Research, 2013. ISBN: 9780880994125.

Behling, O., Labovitz, G., & Gainer, M. (1968). College recruiting: A theoretical basis. Personnel Journal, 47, 13–19.

Blanc, M., Cahuzac, E., & Tahar, G. (2008). Hiring Difficulties and Manpower Flows: Does Labour Market Density Matter? *Environment and Planning A: Economy and Space*, *40*(5), 1090–1108. https://doi.org/10.1068/a3939

Boston Consulting Group. 2012. *Skills gap in U.S. manufacturing is less pervasive than many believe*. Boston: Boston Consulting Group.

Bureau of Economic Analysis. U.S Department of Commerce. https://www.bea.gov/

Canny, A. (2004). What employers want and what employers do: Cumbrian employers' recruitment, assessment and provision of education/learning opportunities for their young workers. *Journal of Education and Work*, *17*(4), 495-513.

Cappelli, P. 2011. Why companies aren't getting the employees they need. *The Wall Street Journal*, October 24.

Cappelli, P. 2012. *Why good people can't get jobs*. Philadelphia: Wharton Digital Press.

Chapman, D. S., Uggerslev, K. L., Carroll, S. A., Piasentin, K. A., & Jones, D. A. (2005). Applicant attraction to organizations and job choice: a meta-analytic review of the correlates of recruiting outcomes. *Journal of applied psychology*, *90*(5), 928.

Craft, J., & Schake, S. (2019). Job Applicants as the New Customer: Strategies for Successful Recruiting in Midwest Manufacturers. *International Journal of Managerial Studies and Research (IJMSR)*. Volume 7, Issue 4, April 2019, PP 1-14.

Gatewood R D, Gowan M A, Lautenshlager G J, 1993, Corporate image, recruitment image, and initial job choice decisions. *Academy of Management Journal* 36, 414–427

Glendinning, A., Nuttall, M., Hendry, L., Kloep, M., & Wood, S. (2003). Rural communities and well-being: a good place to grow up? *The Sociological Review*, *51*(1), 129-156.

Goffette-Nagot, F., & Schmitt, B. (1999). Agglomeration economies and spatial configurations in rural areas. *Environment and Planning A*, *31*(7), 1239-1257.

Fabling, R., & Mare, D. C. (2016). Firm-Level Hiring Difficulties: Persistence, Business Cycle and Local Labour Market Influences. Journal of Labor Research, 37(2), 179–210. https://doiorg.ezproxy.mtsu.edu/https://link.springer.com/journal/volumesAndIssues/12122

Fombrun C., & Shanley M. (1990) What's in a name? Reputation building and corporate strategy. *Academy of Management Journal* 33, 233–258

Giffi, C., Rodriguez, M. D., & Mondal, S. (2017). How modern manufacturers can create positive perceptions with the US public. *Deloitte Insights. National Association of Manufacturers. Manufacturing Institute.*

Giffi, C.,Wellener, P., Dollar, B.,Manolian, H. A., Monck, L., & Moutray, C. (2018). Deloitte and The Manufacturing Institute skills gap and future of work study. *Deloitte Insights*

James, M. L. (2017). SUSTAINABILITY REPORTING PRIORITIES–A STUDY EXPLORING ACCOUNTING MAJORS'PERCEPTIONS. *Global Journal of Accounting and Finance Volume*, *1*(2), 48-65.

Knold, M. (2015, July). Difficult-to-Fill Jobs Study. Brief Report. *Department of Workforce Services. Economic Research and Analysis Unit.*

Landry, A. T., Schweyer, A., & Whillans, A. (2017). Winning the war for talent: Modern motivational methods for attracting and retaining employees. *Compensation & Benefits Review*, *49*(4), 230-246.

Leibert, A. (2019, September). Hiring Difficulties in Manufacturing. *Minnesota Economic Trends.*

Looker, E. D., & Dwyer, P. (1998). Education and negotiated reality: Complexities facing rural youth in the 1990s. *Journal of youth studies*, *1*(1), 5-22.

Lowe, N. J. (2015). From skill mismatch to reinterpretation: Challenges and solutions for manufacturing worker retention and recruitment. In *Handbook of manufacturing industries in the world economy*. Edward Elgar Publishing.

Meinhert, D. (2015). HR Gets Creative to Hire Manufacturing Workers. *Society for Human Resource Management (SHRM)*

Monk, D. H. (2007). Recruiting and Retaining High-Quality Teachers in Rural Areas. 17(1), 155–174. https://doi-org.ezproxy.mtsu.edu/10.1353/foc.2007.0009

Nordlof, H., Wiitavaara, B., Winblad, U., Wijk, K., & Westerling, R. (2014). Safety culture and reasons for risk-taking at a large steel-manufacturing company: Investigating the worker perspective. *Safety Science*

ONET OnLine. U.S Department of Labor. https://www.onetonline.org/

Orr, J., &Biu, O. (2017, October 10). Projecting Supply and Demand for Middle-Skill Occupations in US States and Metro Areas. *Metropolitics*.

Pavis, S., Hubbard, G., & Platt, S. (2001). Young people in rural areas: socially excluded or not? *Work, employment and society*, *15*(2), 291-309.

Pavis, S., Platt, S., & Hubbard, G. (2000). Young people in rural Scotland. *Pathways to social inclusion and exclusion. York: York Publishing Services Ltd*.

Society for Human Resource Management. The New Talent Landscape. Recruiting Difficulty and Skills Shortages (2016, June). 16-0156

U.S Bureau of Labor Statistics. U.S Department of Labor. https://www.bls.gov/

Van Ours J C., & Ridder G. (1993) Vacancy durations: search or selection? *Oxford Bulletin of Economics and Statistics* 55, 187–198

Wallace, C., Boyle, F., Cheal, B., & Dunkerley, D. (1993). The employment and training of young people in rural south west England. *British Journal of Education and Work, 6*(3), 25-44.

Appendix A: Surveyed Occupational Titles and Job Characteristics

Title of Occupations	Average Wage ($)	Difficulty of Filling (1-10)	Number of Jobs Reported	Job Complexity Zone
Chief Executives	$80.40	6.72	124	5
General and Operations Managers	$52.40	6.31	330	4
Marketing Managers	$39.25	5.97	49	4
Sales Managers	$51.75	5.94	127	4
Administrative Services Managers	$28.77	5.33	88	3
Facilities Manager	$41.16	6.33	62	3
Computer and Information Systems Managers	$39.15	5.94	45	4
Treasurers and Controllers	$44.49	6.46	98	5
Industrial Production Managers	$38.64	5.96	620	4
Purchasing Managers	$32.73	5.59	59	4
Transportation Managers	$34.67	6.06	108	4
Human Resources Managers	$39.36	5.89	88	4
Training and Development Managers	$35.71	5.86	6	4
Construction Managers	$34.59	7.75	9	4
Architectural and Engineering Managers	$49.86	6.67	37	5
Funeral Service Managers	$52.89	6.50	3	4
Regulatory Affairs Managers	$42.66	5.80	298	4
Buyers and Purchasing Agents, Farm Products	$25.20	5.41	127	4
Claims Examiners, Property and Casualty Insurance	$24.99	5.00	8	4
Environmental Compliance Inspectors	$45.07	6.00	4	4
Human Resources Specialists	$24.64	5.20	129	4
Logisticians	$29.82	5.82	85	4
Management Analysts	$28.18	3.88	82	5
Compensation, Benefits, and Job Analysis Specialists	$39.47	6.86	9	4
Training and Development Specialists	$24.13	5.67	12	4
Market Research Analysts and Marketing Specialists	$21.59	5.89	44	4
Energy Auditors	$35.14	6.50	19	3
Accountants	$29.76	5.75	121	4
Assessors	$24.81	6.00	14	4
Budget Analysts	$29.50	3.50	2	4
Financial Analysts	$33.01	5.57	46	4
Computer Systems Analysts	$28.30	5.83	38	4
Information Security Analysts	$27.00	6.50	3	4
Computer Programmers	$43.10	7.40	49	4
Software Developers, Applications	$39.93	10.00	2	4
Web Developers	$25.41	5.67	19	3
Database Administrators	$31.50	5.33	5	4
Network and Computer Systems Administrators	$30.28	6.40	23	4
Computer Network Architects	$42.83	6.00	4	4
Computer User Support Specialists	$24.71	4.92	24	3
Computer Network Support Specialists	$23.04	5.00	8	4
Software Quality Assurance Engineers and Testers	$24.74	5.44	88	4
Aerospace Engineers	$46.09	7.75	16	4
Chemical Engineers	$39.70	5.00	20	4
Civil Engineers		8.00		4
Electrical Engineers	$37.51	6.58	68	4

Appendix A (Continued)

Title of Occupations	Average Wage ($)	Difficulty of Filling (1-10)	Number of Jobs Reported	Job Complexity Zone
Industrial Safety and Health Engineers	$38.30	6.71	168	4
Mechanical Engineers	$37.17	6.72	146	4
Biochemical Engineers	$35.07	6.14	128	4
Architectural Drafters	$24.86	5.38	41	4
Aerospace Engineering and Operations Technicians	$31.04	6.13	43	3
Chemists	$38.67	6.00	66	4
Chemical Technicians	$17.95	7.00	22	3
Quality Control Analysts	$24.59	5.43	130	3
Occupational Health and Safety	$27.95	5.88	20	3
Commercial and Industrial Designers	$31.44	7.00	5	4
Graphic Designers	$22.81	5.57	47	4
Editors	$40.72	5.00	78	4
Registered Nurses	$36.66	6.67	3	3
Occupational Health and Safety Specialists	$25.72	8.67	9	4
Security Guards	$14.39	4.67	25	2
First-Line Supervisors of Housekeeping and Janitorial Workers	$18.90	5.00	22	2
First-Line Supervisors of Landscaping, Lawn Service, and Groundskeeping Workers	$27.00	3.00	3	3
Janitors and Cleaners, Except Maids and Housekeeping Cleaners	$13.63	4.11	49	2
Landscaping and Groundskeeping Workers	$17.80	3.64	34	1
First-Line Supervisors of Retail Sales Workers	$35.49	4.89	37	2
First-Line Supervisors of Non-Retail Sales Workers	$30.82	5.29	253	4
Door-To-Door Sales Workers, News and Street Vendors, and Related Workers	$31.12	6.13	105	2
First-Line Supervisors of Office and Administrative Support Workers	$23.83	5.22	137	3
Switchboard Operators, Including Answering Service	$14.46	3.44	10	2
Bill and Account Collectors	$19.31	4.78	25	2
Statement Clerks	$16.71	5.00	18	2
Bookkeeping, Accounting, and Auditing Clerks	$20.19	4.77	68	3
Payroll and Timekeeping Clerks	$21.34	4.87	19	2
Procurement Clerks	$15.91	3.14	11	3
Customer Service Representatives	$18.25	4.88	167	2
File Clerks	$17.33	3.33	5	2
Order Clerks	$17.04	2.50	12	2
Human Resources Assistants, Except Payroll and Timekeeping	$19.85	5.82	18	3
Receptionists and Information Clerks	$15.46	2.94	43	2
Cargo and Freight Agents	$20.31	3.20	6	2
Dispatchers, Except Police, Fire, and Ambulance	$23.12	4.00	7	2
Production, Planning, and Expediting Clerks	$23.83	5.57	81	3
Shipping, Receiving, and Traffic Clerks	$17.63	4.38	235	2
Executive Secretaries and Executive Administrative Assistants	$24.56	5.00	15	3
Secretaries and Administrative Assistants, Except Legal, Medical, and Executive	$17.81	4.00	79	2
Data Entry Keyers	$15.89	2.33	7	2
Office Clerks, General	$18.19	5.50	26	2
Construction Carpenters	$18.75	6.50	5	2
Construction Laborers	$19.20	2.50	164	2
Electricians	$27.49	5.78	58	3

Appendix A (Continued)

Title of Occupations	Average Wage ($)	Difficulty of Filling (1-10)	Number of Jobs Reported	Job Complexity Zone
Painters, Construction and Maintenance	$16.08	4.00	13	2
Sheet Metal Workers	$23.33	5.33	8	2
Structural Iron and Steel Workers	$18.33	7.33	72	2
First-Line Supervisors of Mechanics, Installers, and Repairers	$33.18	6.55	73	3
Computer, Automated Teller, and Office Machine Repairers	$25.96	7.29	133	3
Aircraft Mechanics and Service Technicians	$23.56	5.57	178	3
Industrial Machinery Mechanics	$25.05	7.13	494	3
Maintenance and Repair Workers, General	$22.90	6.51	613	3
First-Line Supervisors of Production and Operating Workers	$26.06	5.75	627	2
Aircraft Structure, Surfaces, Rigging, and Systems Assemblers	$15.67	4.71	3,719	2
Bakers	$13.68	6.60	447	2
Extruding and Drawing Machine Setters, Operators, and Tenders, Metal and Plastic	$17.16	4.65	535	2
Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic	$17.97	5.56	168	2
Machinists	$21.37	6.50	344	3
Metal-Refining Furnace Operators and Tenders	$18.20	6.00	10	2
Model Makers, Metal and Plastic	$19.05	7.00	71	3
Foundry Mold and Coremakers	$17.86	6.40	173	2
Multiple Machine Tool Setters, Operators, and Tenders, Metal and Plastic	$22.18	9.50	13	2
Tool and Die Makers	$26.88	8.07	121	3
Welders, Cutters, and Welder Fitters	$19.49	6.32	519	3
Sewing Machine Operators	$13.82	8.25	80	1
Extruding and Forming Machine Setters, Operators, and Tenders, Synthetic and Glass Fibers	$20.49	5.50	42	2
Upholsterers	$14.79	6.67	74	2
Woodworking Machine Setters, Operators, and Tenders, Except Sawing	$16.30	6.50	27	2
Chemical Equipment Operators and Tenders	$17.31	4.00	2	2
Crushing, Grinding, and Polishing Machine Setters, Operators, and Tenders	$16.60	5.25	115	2
Cutters and Trimmers, Hand	$16.36	6.00	107	1
Extruding, Forming, Pressing, and Compacting Machine Setters, Operators, and Tenders	$15.60	2.00	25	2
Furnace, Kiln, Oven, Drier, and Kettle Operators and Tenders	$14.13	5.00	17	2
Inspectors, Testers, Sorters, Samplers, and Weighers	$17.52	4.73	471	2
Packaging and Filling Machine Operators and Tenders	$19.05	4.67	335	2
Coating, Painting, and Spraying Machine Setters, Operators, and Tenders	$17.63	4.00	36	2
Cleaning, Washing, and Metal Pickling Equipment Operators and Tenders	$16.47	4.00	5	2
Paper Goods Machine Setters, Operators, and Tenders	$16.33	5.50	185	2
Helpers--Production Workers	$13.46	4.67	297	2
Recycling and Reclamation Workers	$16.70	4.45	3,411	2
First-Line Supervisors of Transportation and Material-Moving Machine and Vehicle Operators	$25.99	5.63	103	2
Heavy and Tractor-Trailer Truck Drivers	$21.34	4.91	133	2
Light Truck or Delivery Services Drivers	$25.00	5.00	1	2
Industrial Truck and Tractor Operators	$16.31	6.29	114	2
Laborers and Freight, Stock, and Material Movers, Hand	$15.30	4.52	1,021	2
Packers and Packagers, Hand	$15.27	4.56	135	2
Tank Car, Truck, and Ship Loaders	$15.51	2.67	45	2

Appendix B: Specific Survey Questions Associated with the Current Paper			
Q1. What is your company's annual sales (recent year)?			
Q2. How many people does your company employ (recent year)?			
Q3. Please calculate total employee benefits as percent of total wages.			
Q4. For each occupation below, please input (a) average hourly wage, (b) total employees, and (c) difficulty of filling:			
Occupation title	Average Hourly Wage ($)	Difficulty of Filling (1= easy; 10= difficult)	Number of employees
Occupation 1			
Occupation 2			
...			
Occupation 200			