The Rise of the Contract Workforce in U.S. Manufacturing and its Implications for Worker Skills Measures

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Abstract

Research and policy analysis on labor market issues often relies on employment measures that only capture employees of firms. Although prior studies have pointed to high and growing levels of contract labor in some segments of the economy, lack of data has hampered research into the size of this workforce and its broader implications for labor market analyses. This paper examines such implications in a study of U.S. manufacturers' use of contract workers and its effects on measures of skills growth. Using a new research data set developed at the Bureau of Labor Statistics, we exploit granular information on establishments' location and employment by occupation from 2000 to 2019 to impute staffing services workers in core manufacturing occupations to manufacturing industries and other sectors. We find that the share of contract workers in the manufacturing sector's core occupations rose 45 percent from 6.9 percent in 2000 to 10.0 percent in 2019. This growth in contract use coincided with sharp declines in manufacturing employment, explaining 8 percent of the decline in manufacturing direct-hire employment in its core occupations. Notably, industries experiencing steeper overall employment declines outsourced a higher share of their core workforce on average. We estimate that the replacement of direct-hire workers with contract workers, who are concentrated in low-skilled occupations, explains 19 percent of the skills growth among workers in core occupations and 17 percent of the growth in skills among manufacturing workers in all occupations.

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INTRODUCTION

Research and policy analysis on labor market issues often rely on employment measures derived from administrative data or employer surveys. With rare exceptions, however, these employment measures only capture employees of firms. Studies conducted at the firm or industry level typically miss contract workers who are hired from other firms or as independent contractors; even studies using aggregated data for the economy may miss workers hired as independent contractors. If the contract workforce used by firms is large or changing over time, their omission from labor input measures could substantially bias findings of studies on a variety of issues, such as firms' adjustment to demand shocks, productivity levels and growth, and worker and skills demand. Whether, and the circumstances in which, biases are substantively important is an empirical question. In this paper, we seek to illustrate the potential effects of contracting out on labor market analyses in a study of the use of contract workers by U.S. manufacturers and its implications for measures of skills demand.

Although prior studies—many based on case studies—have pointed to high and growing levels of contract labor in various segments of the economy,[1] the dearth of data has stymied research into the size of the contract workforce and its broader implications for labor markets. The challenge is that in administrative filings and employer surveys, firms generally report employment for only their W-2 employees. In cases where firms use workers from contract companies (e.g., cleaning companies, food services companies, or temporary help agencies), the workers are employees of the contract companies and are recorded in those industries, even when they work at the client's worksite. Although the Census Bureau collects information on firms' expenditures to track input use, there are large gaps and poor detail in the data collected for purchased services, which includes most purchases for contract labor.

Using a variety of methods, several studies have sought to overcome data obstacles and impute contract workers to user industries, primarily in manufacturing. An early paper by Segal and Sullivan (1997) employed CPS data to impute workers in the staffing services industry to manufacturers and showed the dramatic growth of these contract workers in manufacturing in the 1990s. Dey, Houseman, and Polivka (2012, 2017) used data from the Contingent Worker Supplement to the CPS, the Occupational Employment and Statistics program, and the Current Employment Statistics program to impute staffing services workers to the manufacturing sector, showing that the use of staffing services led to substantial underestimates of manufacturing labor productivity growth during recessions and overestimates during recoveries. In a study based on the evolution of the input-output structure of the U.S. economy, Berlingieri (2014) estimates that the growth of outsourcing to professional and business services accounts for 35 percent of the rise in service sector employment and 25 percent of the decline in manufacturing employment over the 1948-2002 period. More recently, Atencio-de-Leon (2022) exploits newly collected Census data on manufacturers' expenditures for staffing services and finds that growth in its use since 2007 can explain a substantial share of the measured decline in job reallocations in manufacturing reported in recent studies (e.g., Decker et al. 2020).[2]

[1] See Bernhardt (2017) et al. for a review of the research evidence on the size and growth of contract work.

[2] A recent line of research has used 1099 filings in tax data to study independent contracting and online platform workers, who are usually independent contractors (Jackson et al. 2017; Collins et al. 2019; Lim et al. 2019; Garin,

In the absence of direct information on firms' use of workers from other companies, researchers must identify the set of industries using contract workers and the industries supplying workers to these industries (Dey, Houseman, and Polivka 2010). In this study, we focus on estimating contract workers in production and material moving occupations hired through staffing services companies. Production and material moving occupations constitute the core occupations in the manufacturing sector, accounting for about 60 percent of all direct-hire employment in the sector. Further, as we document in this paper, the staffing (or employment) services industry[3] is the only identifiable industry supplying substantial numbers of contract workers in these occupations. Using a new research data set developed at the Bureau of Labor Statistics, we exploit granular information on establishments' location and employment by occupation to generate improved estimates of the contract workforce in manufacturing industries' core occupations. With these data, we estimate the size and growth of the contract workforce by occupation, industry, and region from 2000 to 2019 and examine its implications for measures of skills growth in manufacturing.

We estimate that by 2019 contract workers accounted 10.0 percent of the workforce in production and material moving occupations, a 3.1 percentage point increase over 2000 levels. This expansion of contract workers occurred during a period of tremendous contraction of the manufacturing workforce. Direct-hire manufacturing employees in production and material mover occupations dropped by 29.6 percent from 2000 to 2019. We estimate that outsourcing to staffing services accounted for 8 percent of the decline, and for some industries the shift to contract workers accounts for a considerably higher share of the decline in direct-hire employment. Interestingly, we find that industries experiencing steeper overall employment declines outsourced a higher share of their core workforce on average. This finding is consistent with the hypothesis that firms with larger losses faced greater pressure to lower costs and that outsourcing was a mechanism to lower labor costs.

Our measure of skills, based on the 2000 average national wage for each detailed occupation, shows modest growth for all direct-hire manufacturing workers and for direct-hires in production and material moving occupations; for both, the change represented only a 0.06 standard deviation increase over our base year skills measure. This finding reflects the fact that despite huge employment losses during the period, the occupational composition of the manufacturing workforce remained relatively stable. The growth in the contract share of total employment can explain 19 percent of the skills growth among production and material moving occupations and 17 percent of the growth in skills among manufacturing workers in all occupations.

In the remainder of the paper, we begin by describing our data and methodology for imputing contract workers to manufacturers by occupation (6-digit SOC), industry (6-digit NAICS), and area (state-county). We next present our findings on the size and growth of the contract workforce in these core occupations and on the implications for measures of skills

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Jackson, and Koustas 2021). These data potentially can be used to link companies to their use of independent contractors.

[3] We use staffing services and employment services interchangeably in this paper.

growth from 2000 to 2019. We close with a discussion of future research and the broader implications of our findings.

DATA AND METHODS

Creation of wage and employment outcomes for the population of U.S. employers

The occupation data come from the Occupational Employment and Wage Statistics (OEWS) survey conducted by the Bureau of Labor Statistics (BLS). The OEWS program fields a semi-annual mail survey that samples approximately 200,000 establishments in May and another 200,000 in November of each year.[4] The survey covers all workers, both full-time and part-time, in private non-agricultural industries.

The survey instrument asks establishments to provide what amounts to a complete payroll record for the pay period that includes the 12th of the sample month. Respondents report employment and wage information for each occupation by recording the number of employees in each of 12 wage intervals.[5]

The OEWS survey uses the Office of Management and Budget's (OMB) occupational classification system, the Standard Occupational Classification (SOC), to categorize workers into around 800 detailed occupations.[6] The SOC system provides much more occupational detail than most other surveys that include information about occupation.

The OEWS sampling and weighting methods guarantee that total weighted employment equals the BLS frame – the Quarterly Census of Employment and Wages (QCEW) – employment at the metropolitan statistical area (MSA) level for urban areas and balance of state (BOS) areas for rural areas but there is nothing in the methods to guarantee that estimated employment at the state-county level equals frame employment. Therefore, any analysis that attempts to measure county-specific effects will have to address this feature of the OEWS weighting scheme. As an alternative to reweighting the data, we use a research dataset that was created using a modified version of the imputation approach developed and detailed in Dey, Piccone, and Miller (DPM, 2019).

The DPM method imputes OEWS outcomes for the entire QCEW. For each reference year, they use the same dating convention as is used for the official OEWS release (that is, May

[4] Prior to November 2002, the program surveyed approximately 400,000 establishment in November of each year. For our purposes, starting with March 2003, we combine November and May panels to create a pseudo-annual sample and assign it the May year value. Our final time series includes estimates from November 2000-2002 and May 2003-2019.

[5] Wages for the OEWS survey represent straight-time, gross pay, exclusive of premium pay. Base rate, cost-of-living allowances, guaranteed pay, hazardous-duty pay, incentive pay including commissions and production bonuses, tips, and on-call pay are included while back pay, jury duty pay, overtime pay, severance pay, shift differentials, non-production bonuses, employer cost for supplementary benefits, and tuition reimbursements are excluded from the reported wage.

[6] From 2000 to 2019, the SOC structure has undergone two updates, one in 2010 and one in 2018. We make various aggregations to keep occupations consistent over the entire length of our time series. There are 765 time-consistent detailed occupations. Details are available upon request.

of the reference year combined with the five previous panels). For each observation in the QCEW that is not in the OEWS (including non-sampled units or non-responding sample units), they identify five to ten OEWS sample unit donors based on the characteristics of the establishments. The characteristics include employment, industry (6-digit NAICS), ownership, geography (either MSA or BOS area), and the amount of time between reference periods of the observations. Donor establishments are evaluated on each attribute and weights are assigned based on the closeness to the frame recipient on that attribute. The weights of the donor establishments are rescaled so that they sum to one. Estimated occupational employment at the recipient is a weighted average of the occupational employment of the donor establishments. Wages are similarly estimated but are also adjusted for differences in wage levels by area and wage growth by area and industry.[7]

Beginning with May 2021 OEWS estimates, the DPM approach is used to generate official occupational employment and wage estimates. The main advantage of this approach is that every establishment in the QCEW is represented and has an establishment weight of one. The disadvantage, from our perspective, is that the staffing pattern for an establishment is an average of similar establishments. This makes sense for constructing aggregate estimates, but not for our purpose of assigning employment services jobs to the locations where the work is actually performed. The research dataset that our analysis is based on incorporates two key modifications to this methodology.

The primary modification to this methodology is that occupation employment and wage data at the establishment-level are imputed from a single donor. The imputation process involves two stages, a matching stage where potential donors are identified and a selection stage where the best donor is selected. The process is hierarchical, where the conditions for finding acceptable matches are sequentially relaxed. At the most detailed level of the hierarchy, a donor and frame unit will match on industry (6-digit NAICS), ownership (private or type of government), state, and county and will have very similar employment levels. As the process continues through the hierarchy, geography is relaxed first and then ownership. It is not until very late in the process, after most of the frame units have already found an acceptable donor, where industry and employment proximity are relaxed. The matching stage often results in multiple potential donors. To allow variation in OEWS outcomes across observationally equivalent frame units, the selection of a particular donor from the set of acceptable matches is random. As above, wages are adjusted to account for differences by MSA and industry.

As we will discuss in detail below, our approach for assigning employment services sector jobs to the industries where the work is performed depends on the occupational staffing pattern of the employment services sector and all other sectors at the county level. It is our assumption that employment services firms provide workers to local businesses and therefore our assignment model will only be as good as our ability to accurately estimate the staffing pattern of the employment services sector and other sectors at the county level. While one might think borrowing industry specific staffing patterns across counties is fine for most industries, that is

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[7] These adjustments are not controls for industry and location. Rather, they are designed to convert the wages of the donor observations so that they more-closely approximate the recipient establishment's actual wages.

less likely the case for the employment services establishments. The client base may vary across staffing firms (e.g., some primarily supply industrial occupations, while others specialize in medical staffing) and staffing firms primarily cater to employers in their local area. Ideally, if we do not have a direct match or match within the staffing firm, we would only borrow donors from the same county but the set of OEWS responders does not always support this. The table below shows the employment level and percent of total employment matched at various levels of the hierarchy for establishments in the temporary help industry, which accounts for most of the contract workers imputed to manufacturing in production and material moving occupations. In 2000, nearly 85% of employment is assigned either directly, at the firm level, or at a very close geographic level. In 2019, this improves to slightly more than 92% of employment.

Imputation Details for Temporary Help Establishments

Hierarchy level	2000 Level	2000 Percent of total	2019 Level	2019 Percent of total
Establishment	462,521	18.42	653,592	25.21
Firm	622,069	24.77	685,547	26.44
County	869,614	34.63	886,293	34.19
State-MSA	167,117	6.66	149,296	5.76
MSA	9,644	0.38	11,592	0.45
All other	379,992	15.13	206,168	7.95

Note: All matches above "All other" must match on six-digit industry. Firm matches can be located in different geographies but must be of similar size. Matches found at the county, state-MSA, and MSA level must be of similar size.

The second modification takes advantage of the fact that this is a research series and not a production series, and thus the timeliness of the estimates is not a concern. As such, we are able to center the panels of OEWS data used to generate estimates on the reference month of the QCEW instead of using the current and previous five panels. For example, under the modified approach, the estimates for May 2019 are constructed using OEWS data collected from the November 2017, May 2018, November 2017, May 2019, November 2019, and May 2020 samples. This results in a nationally representative sample roughly centered on May 2019.

Methods for imputing contract workers to manufacturing industries

Employment, occupation, and wage information in the OEWS is reported only for W2 employees. Prior research has established that since the 1990s, however, manufacturers have made heavy use of staffing agencies to supply workers in core manufacturing occupations (Segal and Sullivan 1997; Dey, Houseman, and Polivka 2012, 2017). The empirical work in this paper focuses on workers in production and material mover occupations, which comprise 120 time-consistent six-digit SOC codes. Production and material moving occupations are the core occupations in factories, accounting for about 60 percent of direct-hire employment in the manufacturing sector during the period covered by this study.[8] In 2019, the employment services industry employed 6.3 percent of workers in production occupations and 12.7 percent of workers in material moving occupations—accounting for more production workers than any major sector outside of manufacturing (which employed 72.3 percent of production workers) and employing almost as many workers in material moving occupations as the entire manufacturing sector.[9] No industry outside of employment services systematically contracts out workers in production and material moving occupations to clients. Our empirical strategy, therefore, focuses on imputing contract workers from the employment services sector to user industries, which should capture most contract workers in these core manufacturing occupations.

To impute contract workers in production and material moving (PMM) occupations to manufacturers, we exploit the granular data in the OEWS on geography, industry, and occupational composition of U.S. establishments, including manufacturing and staffing industry establishments. Staffing agency workers assigned to a manufacturing client work at the client's factory alongside direct-hire employees, and consequently staffing agencies are located in close geographic proximity to their clients.

The staffing industry is composed of two relevant subindustries: temporary help agencies and professional employer organizations (PEOs). Temporary help agencies place workers with client organizations for a fixed term. Professional employer organizations take over some or all of the human resources functions for a portion or all of a client's workforce.[10] Although clients and staffing agencies legally have joint employer responsibilities, the staffing agency is the employer of record and workers' employment and wages are reported under the temporary agency's or PEO's employer identification number.

Let $p_{k|jgt}$ denote the share of employment services workers in occupation j, geography g, year t assigned to industry k. Denote employment in occupation j, geography g, industry k, year t as E_{jgkt} and denote contractor employment in occupation j, geography g, year t as C_{jgt}.

Contractor-adjusted employment can be written as

[8] For the analysis reported in this paper, we delete manufacturing establishments that do not include any workers in production or material moving occupations on the grounds that the complete absence of these workers implies that the establishment does not manufacture products and is likely miscoded. In both 2000 and 2019, 3.4 percent of employees in establishments with manufacturing NAICS codes had no workers in these core occupations. The most striking example is electronic computer manufacturing (NAICS 334111), where between 2000 and 2019 industry employment dropped by 75 percent to about 35,000 and the share of employees in "factoryless" establishments grew from 13 to 66 percent.

[9] According to OEWS data, in 2019, manufacturing employed 14.6 percent of workers in material moving occupations. Other sectors with large concentrations of these workers are wholesale and retail trade and transportation and warehouse.

[10] The third subindustry in employment services is employment placement agencies, which help businesses find employees. A small number of workers in PMM occupations are employed in establishments coded as employment placement agencies, which likely means that these establishments also operate a temporary help or PEO business. For employment placement agencies, we impute workers in PMM occupations to client businesses using the method used for imputing temporary help workers, described below.

$$E_{jgkt}^{*} = E_{jgkt} + p_{k|jgt}C_{jgt}$$

Let

$$\theta_{jgt} = \frac{E_{jgt}}{E_{jgt} + C_{jgt}}$$

which measures the penetration of contract workers in a given occupation and geography. The higher the value of θ_{jgt} the lower the importance of contract workers in the local labor market. Within a local labor market define industry employment in occupations that do not have substantial numbers of contract workers as

$$\tilde{E}_{gkt} = \sum_{j} E_{jgkt} \times I\left(\theta_{jgt} \geq \theta^{*}\right)$$

where θ^{*} is a fixed value. The idea is to focus on the occupations that are not commonly contracted out to provide an estimate of industry demand at the local level. The higher the value of θ^{*}, the more restrictive the set of occupations used to measure local demand. Because there are many production and material moving occupations that are rarely supplied by the staffing services sector, we choose a rather high value of $\theta^{*} = 0.95$. The results are not sensitive to the particular value of θ^{*} once it exceeds 0.10.

In order to estimate the demand for workers in occupation j, geography g, industry k, year t, we multiply non-contract industry size by contractor-adjusted occupational employment shares of national industry employment such that

$$\tilde{E}_{jgkt} = \tilde{p}_{j|kt}\tilde{E}_{gkt}$$

where

$$\tilde{p}_{j|kt} = \frac{E_{jk,t-1}^{*}}{E_{k,t-1}^{*}} \; \forall t > 2000$$

and

$$\tilde{p}_{j|kt} = \frac{E_{jkt}}{E_{kt}}, t = 2000$$

The employment level we use to determine the industry assignment of contract employees is still local since we are using local industry employment totals, after netting out occupations that are frequently contracted out within the geography.

The final industry k assignment share of contract workers in occupation j, geography g, year t is given by

$$\tilde{p}_{k|jgt} = \frac{\tilde{E}_{jgkt}}{\tilde{E}_{jgt}}$$

and the contract-adjusted employment level is given by

$$E^*_{jgkt} = E_{jgkt} + \tilde{p}_{k|jgt} C_{jgt}$$

Imputations for PEO workers are complicated by the fact that during the period of our study, the BLS was working with states to reclassify workers in PEO establishments to the industry of the client organization (see Dey, Houseman, and Polivka 2010). As a result, the number of PEO workers in production and material mover occupations steadily dropped from 2000 to 2019 and by 2019 was nearly 80 percent lower than at the start. Although in reassigning PEO workers to user industries the BLS's goal, like the goal of this paper, is to better understand the industries where workers are working, the reassignment process has been incomplete and has been phased in over many years. Additionally, PEO workers are not reassigned to user industries in Census data, which often are used in research and policy analysis. To make the treatment of PEO workers more consistent over time in the OEWS data and more consistent with their treatment in Census data, we use PEO employer identification numbers to flag workers who have been reassigned to manufacturing industries and classify them as contract workers.[11] For PEO workers in production and material mover occupations who have not been assigned to a user industry, we apply the same method used to impute temporary help workers to client industries.

Trends in Contract Employment in U.S. Manufacturing Plants

Our imputation methods yield annual estimates of contract employment from 2000 to 2019 used by U.S. manufacturing establishments in production and material moving occupations. These estimates are generated at the state-county, 6-digit NAICS industry, and 6-digit SOC occupation level.

Figure 1 provides a high-level picture for the manufacturing sector of the share of contract employment in PMM occupations over the period. In 2000, 6.0 percent of PMM manufacturing workers were contractors. That share rose by 45 percent to 10.0 percent in 2019. Our period includes two recessions, and consistent with earlier research, we estimate strong cyclical patterns in the share of contract employment. From 2000 to 2001, a mild recession, the contract share dropped by 0.9 percentage points from 6.9 to 6.0 percent. The so-called Great Recession in 2008 and 2009 was much deeper, and from 2007 to 2009, contract employment's share of PMM occupations fell from 8.9 to 6.4 percent. Following the Great Recession, the contract share of PMM occupations rose steadily until 2015, when it peaked at 10.8 percent. During the next 4 years, the contract share declined slightly and leveled off at 10.0 percent. The

[11] Our method flags an establishment as reclassified if it shares the same EIN as an establishment classified as a PEO. This method may miss many cases of reassignment because often a firm uses multiple EINs. In future work, we plan to identify all EINs belonging to PEO firms.

tailing off of contract use by manufacturers at the end of our period may reflect the very tight labor markets prevailing at the time and the difficulty staffing agencies experienced attracting workers.[12]

The growth in contract use was not concentrated in a few industries. Figure 2 plots the contract share of PMM workers in 2000 against that share in 2019 for the 360 six-digit manufacturing NAICS industries. The 45-degree line shown in red divides industries into those whose contract share rose (above the line) and those whose contract share declined (below the line). As is evident from the graph, the contract share rose in a large majority of manufacturing industries (89 percent).

Contract use by industry

The growth in contract use by manufacturers comes against the backdrop of sharp declines in direct-hire employment. The first two panels of Table 1 show total employment in PMM occupations (defined as the sum of direct-hire and contract employment) and the share of contract employment in 2000 and 2019 by broad manufacturing industry (3-digit NAICS) and for the sector. The third panel of Table 1 shows from 2000 to 2019 the percent change in total employment, the percentage point change in the contract share, the percent change in direct-hire employment and the percent of the direct-hire employment change explained by the change in contract employment. Employment in all but two of the 21 3-digit NAICS industries (food and beverage and tobacco products manufacturing) dropped over the period. Among declining industries, the employment drops exceeded 10 percent in all but two industries (petroleum and coal and chemicals industries). Employment declines were especially steep in textiles (70.8%), apparel (79.1%), leather (57.9%), and computer and electronic products (53.7%).

The contract share of PMM employment grew in all industries except beverage and tobacco, and thus, outside this industry, the decline (growth) in an industry's direct-hire employment is greater than its actual use of PMM workers. Between 2000 and 2019, direct-hire PMM employees in the manufacturing sector declined by 29.6 percent, but with the inclusion of contract workers, total PMM employment declined by 27.1 percent, meaning that the shift to contract workers can explain 8.3 percent of the aggregate employment decline. As shown in the last column of Table 1, among the 19 industries experiencing employment declines, there is considerable variation in the share of the direct-hire employment decline explained by the shift to contract employment. That share is negatively associated with the magnitude of the decline. For instance, although textile mills, textile product mills, and apparel manufacturing had larger than average growth in contract employment, contract employment can explain only a small share of the large relative declines in direct-hire employment (50.4 to 80.0 percent) in these industries. Conversely, the growth in contract employment explains a large share of the decline in direct-

[12] The temporary help industry supplies a majority of the contract workers used by manufacturers, and because temporary help workers generally are seeking permanent jobs, agencies may have experienced a particularly difficult time attracting workers in the late 2010's.

hire employment in industries experiencing relatively small employment declines, such as petroleum and coal (26.8%) and chemicals (51.7%).

More interesting are industries falling between these extremes. For example, in plastics and rubber, primary metals, fabricated metals, and miscellaneous manufacturing, which all experienced a 20 to 28 percent decline in direct-hire employment, we estimate that the growth of contract employment can explain 11 to 13 percent of the employment decline. In transportation manufacturing, the growth of contract employment can explain 18.5 percent of the 14.3 percent decline in direct-hire PMM employment.

As evidenced by the sharp decline in their employment share during recessions, contract workers bear a disproportionate share of employment contractions associated with business cycle downturns. Notably, however, the contract share of PMM employment grew by 3.1 percentage points between 2000 and 2019, while overall employment declined by nearly 30 percent. Additionally, in Table 1, the correlation between the percent change in total employment declines and growth in contract share is -0.54, implying that industries that experienced larger proportionate employment declines shifted employment more into contract workers. We more formally test this association using data for the 360 detailed manufacturing industries, estimating the following linear regression:

$$S_{19,i} = \beta_0 + \beta_1 E_{19-00,i} + g_i + \beta_2 g \times E_{19-00,i} + \beta_3 S_{00,i}$$

The dependent variable, S_{19}, is the contract share of PMM employment in 2019 in industry *i.* E_{19-00} is the proportionate change in total PMM employment between 2000 and 2019, g is an indicator variable equal to one if total employment grew over the period, and S_{00} is the contract share of PMM employment in 2000. The inclusion of g in the model allows for a different relationship between the share in contract employment and employment change for growing and declining industries. The coefficient of interest is β_1, which captures the association between the change in the contract share and the change in employment for declining industries. The sum of β_1 and β_2 captures this association for growing industries.

Table 2 reports the results of this model. The coefficient estimate on employment change, -0.0224, is negative and statistically significant at the 0.01 level. The average industry growth in the contract share was 0.03. The model implies that for declining industries, conditional on contract share in 2000, an additional ten percentage point decline in employment is associated with a 0.0024 increase in the contract share. Although we cannot definitively say why the size of the contract share growth is associated with larger employment declines, assuming the size of the employment drop is an indicator of the competitive pressure an industry's manufacturers face to lower costs, this finding is consistent with the hypothesis that contract employment is a mechanism for reducing labor costs. Among industries whose employment expanded over the period, there is no significant association between employment change and contract use.[13]

Contract use by region

Employment losses and contract use in manufacturing also vary considerably by geography. The first panel of Table 3 shows total employment levels (direct-hire and contract) in PMM manufacturing in 2000 and 2019 and the percent change in PMM employment over the period by broad geographic region in the United States. Although the largest absolute declines in PMM manufacturing employment were in the Southeast followed by the Great Lakes region, the regions experiencing the largest relative (percentage) declines were the Mideast and New England. Manufacturing employment in the Rocky Mountain region is relatively low and experienced a small employment decline.

The middle panel of Table 3 compares the actual decline in total PMM employment between 2000 and 2019, the predicted decline based on the region's industry composition in 2000, and the ratio of actual to predicted employment. Initial industry composition is an accurate predictor of employment decline in many regions. The Far West, Great Lakes, and Plains regions performed as expected given their initial industry composition; the Mideast and New England regions underperformed, experiencing employment losses that were 20 to 25 percent greater than projected. Employment losses in the Southeast and Southwest, were 13 and 17 percent less, respectively, than projected. The Southeast, which experienced the largest absolute losses in employment due to high concentrations of textile, apparel, and furniture manufacturing in the region, benefited from the growth in other industries such as transportation. Projected employment losses based on industry composition in the starting period in the Rocky Mountain region were more than triple realized losses, but the region's manufacturing employment base is relatively small.

The third panel of Table 3 shows the estimated contract share of PMM manufacturing employment in 2000 and 2019. By 2019, relative contract use was highest in the Southeast and Southwest, followed by the Great Lakes region, according to our estimates. Interestingly, industry composition in the initial and ending years do little to explain geographic variation in contract employment or contract growth, and the apparent regional differences in contracting warrant further exploration.

Contract use by occupation

The use of contract workers by manufacturers varies considerably across production and material moving occupations as well. Table 4 displays the distribution of employment for direct-hire and contract workers by broad (3-digit SOC) occupation in 2000 and 2019. Both direct-hire and contract employment are concentrated in four occupations—assemblers and fabricators, metal and plastics workers, other production workers (which includes helpers), and material

[13] The sum of the coefficients on employment change and the interaction of employment change with growth (-0.0026) captures the association for growing industries and is insignificant.

moving occupations. In 2000, 75.8 percent of direct-hire employees and 93.8 percent of contract workers were hired in one of these four broad occupations. By 2019, those shares had increased somewhat to 78.3 percent and 94.2 percent for direct-hires and contract workers, respectively, though patterns varied across the four occupations. The shares of direct-hire workers in assembler and fabricator and other production worker occupations rose, while the shares in metal worker and material mover occupations fell slightly. As with direct hires, the share of contract workers who were assemblers and fabricators increased over time and the share of metal and plastic fell. Otherwise the patterns differed, with the contract share in other production worker occupations falling and the contract share in material mover occupations rising, and for total employment (direct-hire and contract combined), the share of manufacturing employment in each occupation was little changed.

THE EFFECT OF CONTRACTING OUT ON MEASURES OF SKILLS CHANGES

Given the widespread and increased use of contract workers in manufacturing, measures of worker skills that omit contract workers will be biased if the levels of or changes in contract workers' skills, on average, differ from those of direct-hire workers. We explore the effects of contracting out on skills measures in this section.

As discussed above, we measure relative skills at the 6-digit SOC level, which includes 120 detailed occupations that were consistently defined between 2000 and 2019. We define skill for each detailed occupation as its mean national wage in 2000.[14,15] Higher aggregates (e.g., by 3-digit SOC or industry) are weighted averages of these skills measures where the weights are the occupations' employment shares. Table 5 displays, by broad occupation, total employment levels, percent contract, and mean skill for direct-hire and contract workers in 2000 and 2019 along with changes in skills over this period for direct-hires and contract workers. The largest occupations, which account for over 75 percent of direct-hire employment and over 90 percent of contract employment in both years, are bolded in the table.

The contract share increased for three out of the four major occupations, with particularly large increases observed for assemblers and fabricators (6.2 to 12.7 percent) and material movers (14.8 to 24.0 percent). The contract share for other production occupations fell, but by less than a percentage point. Notably, the mean skill level for contract workers is lower in both years within each of these four broad occupations, reflecting the fact that contract workers are more concentrated in low-skilled occupations within these broad occupational categories.[16] For example, within the assembler and fabricator category, contract workers are concentrated in team assemblers, within the other production worker category they are concentrated in production

[14] Acemoglu and Autor (2011) and Autor and Dorn (2013) similarly define occupational skill according to the national mean wage in a base year.
[15] OEWS employment data is collected in wage intervals with establishments reporting the number of workers they employ in each occupation and wage interval. Calculating an occupation mean wage requires either a distributional assumption or simply assuming a single wage for the interval. In keeping with previous OEWS methods, we use a within interval mean wage derived from National Compensation Survey data.
[16] By 2019, however, the difference in mean skill between direct-hire and contract workers in metal and plastic worker occupations had narrowed to just 0.01.

worker helpers, and within the material mover category they are concentrated in hand material mover and packer and picker occupations.

The last two columns of Table 5 show skill change by occupation for direct-hire and contract workers between 2000 and 2019. Within the four major occupational categories, skill levels of direct-hire workers increased for two (assemblers and fabricators and other production workers) and fell for two (metal and plastic workers and material movers), reflecting the changes in the composition of detailed occupations over time. In contrast, for contract workers within occupation skills measures increased for each of the four major categories. Moreover, the growth in skills was the same or greater than that for direct-hire workers for each of the four broad occupations, leading to a narrowing of the skills gap over time between direct-hire and contract workers, as can be seen in the last row of Table 5, which summarizes the overall changes in skills for the direct-hire and contract workers.

We formally examine changes in skills and the contribution of contracting out to measured skills growth next. Table 6 reports the average skill of workers in PMM occupations and of all manufacturing workers—in each case first excluding and then including contract workers in PMM occupations—along with the change in our skills measure and the percent of the skills growth explained by contracting. Our skills measure is a weighted average of the applicable detailed occupations' 2000 national average hourly wage, where the weights are the occupational employment in manufacturing establishments in 2000 or 2019. To provide some context for the skills changes observed over time, we also report the change in terms of standard deviations, defined as the standard deviation of the skill measure for all PMM workers or for all workers in occupations used by manufacturers in 2000.

Our measures suggest that skills growth in manufacturing over the period was modest: 0.18 and 0.13 among direct-hire and direct-hire and contract workers in PMM occupations, respectively, and 0.53 and 0.44 among direct-hire and direct-hire and contract workers in all manufacturing occupations. These skills growth estimates translate into between a 0.046 and 0.064 standard deviation increase in skills. As expected, the growth in measured skills between 2000 and 2019 is lower when the calculations include contract workers. Our estimates of the growth of contracting in PMM occupations can explain 19 percent of the growth in measured skills among PMM manufacturing workers and about 17 percent for workers in all manufacturing occupations. A caveat to these findings is that our measures of contract workers may miss some contracting, particularly for non-PMM occupations, which only capture some contracting out to PEOs.[17] Non-PMM occupations include, for example, office and administrative, building and maintenance, repair, and professional and technical occupations, all of which likely experienced some growth in outsourcing by manufacturers.

To better understand the effects of contract workers on the skills growth reported in Table 6, we report a detailed decomposition of skill changes, showing the contribution to skill changes of each employment type: direct-hire PMM workers, contract PMM workers, and, when all

[17] For both PMM and non-PMM occupations, we remove PEO workers who have been reassigned by BLS to manufacturing and count them as contract workers. Otherwise, we do not impute any staffing industry workers to non-PMM occupations.

manufacturing occupations are included in the analysis, non-PMM workers. Let s_{kt}^x denote the average skill of x type jobs (i.e., direct hire PMM jobs, contracted PMM jobs, and non-PMM jobs,) in industry k and year t. Similarly, let e_{kt}^x denote the employment level of x type jobs in industry k and year t.

Define the average skill of x type jobs in year t as

$$s_t^x = \sum_k s_{kt}^x \times \frac{e_{kt}^x}{e_t^x}$$

where e_t^x is total employment of x type jobs in year t.

Define the average skill in year t as the weighted average of the average skill of x type jobs in year t such that

$$s_t = \sum_x s_t^x \times \frac{e_t^x}{e_t}$$

where e_t is total employment in year t. We are decomposing the change in average skills from 2000 to 2019, $s_{19} - s_{00}$, which can be written as

$$s_{19} - s_{00} = \sum_x s_{19}^x \times \frac{e_{19}^x}{e_{19}} - s_{00}^x \times \frac{e_{00}^x}{e_{00}} \pm s_{19}^x \times \frac{e_{00}^x}{e_{00}} = \sum_x s_{19}^x \left(\frac{e_{19}^x}{e_{19}} - \frac{e_{00}^x}{e_{00}}\right) + \frac{e_{00}^x}{e_{00}} (s_{19}^x - s_{00}^x)$$

This equation shows that the change in average skills can be decomposed into the part due to the change in the shares of the x type jobs from 2000 to 2019 (holding average skill fixed for each job type at 2019 levels) and the part due to the change in the average skill of the x type jobs (holding job type employment shares fixed at 2000 levels). The change in the average skill for all workers is the sum of the contributions of each job type.

As we detail in the appendix to this paper, the change in average skills due to the change in the employment shares of each job type x, $\left(\frac{e_{19}^x}{e_{19}} - \frac{e_{00}^x}{e_{00}}\right)$, may be further decomposed into the part due to the change in the industry composition of the manufacturing sector and the part due to the change in job type shares within industries. Similarly, the change in the average skill of each job type x, $s_{19}^x - s_{00}^x$, may be decomposed into the part due to the change in skills within industries and the part due to the change in industry composition (holding each job type's share constant at 2019 levels).

Panels a and b of Table 7 show the decompositions for PMM occupations in manufacturing without and with contract workers. For the Panel a decomposition — PMM occupations, direct-hire workers only — there is only one job type, and thus the first set of terms pertaining to changes in job type shares is not relevant. This decomposition shows that the increase in skills was due to both an increase in the occupational skill composition within industries (0.079) and a shift toward more skill intensive industries (0.097), with the contribution of the latter being somewhat larger the former. Panel b shows the decomposition with the inclusion of direct-hire and contract PMM workers. The first set of terms shows the effect of the shift in employment shares from direct-hire to contract workers, holding the average skill level of each job type fixed. The negative total contribution (-0.045) captures the fact that contract workers, on average, are lower skilled than direct-hire workers. Interestingly, for the second set of terms, which captures changes in job type average skills holding job type shares constant, including contract workers increases the overall contribution to total skills growth relative to that found when the decomposition was limited to direct-hire workers (0.176 in Panel a v. 0.187 in Panel b). The decomposition shows that this finding comes from the within industry skill changes (0.093 in Panel b v. 0.079 in Panel a). Consistent with the results presented in Table 5, this finding implies that the growth in within industry skills was somewhat higher among contract workers than direct hires, leading to a narrowing of the skills gap.

Panels c and d show the decompositions for all occupations without and with contract workers. The first set of figures in Panel c displays the effects of the decline in the share of PMM relative to non-PMM direct-hire workers. The net positive effect on total average skills reflects the higher average skill level of non-PMM workers. The second set of terms in Panel c, which captures the contribution of skills changes for each job type, shows increases in average within industry skills for both non-PMM and PMM direct hires. Notably, however, the shift in industry composition had the effect of reducing average skills for non-PMM workers while increasing it for direct-hire PMM workers. Panel d shows that adding PMM contract workers lowers the total average skills increase from 0.539 to 0.440, as reported in Table 6. Comparing the decompositions in Panels c and d, this effect comes entirely from the shift in job type shares from higher skilled direct-hire workers to lower skilled contract workers (holding skills constant for each job type); the overall contribution of the change in skills is about the same (negligibly higher—0.262 v. 0.258) with the inclusion of contract workers.

While we estimate that contracting out of PMM occupations explains 17 to 19 percent of the measured skills growth for all manufacturing workers and PMM workers, respectively, the magnitude of the skills growth itself is small. This finding seems to contradict the popular narrative that production worker jobs have been rapidly automated and that there has been a surge in the education and training requirements for the remaining manufacturing workers (see, for example, Rampell 2022). One factor contributing to our finding of modest skills growth for all manufacturing workers is that, while there was a steep decline in manufacturing employment in the 2000s, the decline in the share of workers who are in PMM occupations has been modest. Among direct-hire employees, that share has dropped by 3.0 percentage points, from 60.7 to 57.7 percent. Including PMM contract workers and PEO contract workers in non-PMM jobs, the decline in the share of workers is just 1.4 percentage points from 64.8 to 63.5 percent, although this figure is subject to the caveat that we do not capture all contract work. Under the assumption that the overall share of contract workers is higher in PMM occupations than non-PMM occupations, the 3.0 percentage point decline in the share of PMM workers represents an upper bound estimate of the drop, and if the share of contract work missing from our measures is higher among non-PMM occupations than among PMM ones, the 1.4 represents a lower bound estimate of the percentage point decline in the share of PMM workers in manufacturing.

The modest decline in the share of PMM workers in manufacturing helps explain the small contribution of the shift from PMM to non-PMM occupations to average skills growth for all manufacturing workers. It does not explain the relatively small skills growth for PMM workers. Below, we further explore skills growth in manufacturing using alternative data sources and present some preliminary findings regarding the consistency of alternative measures with the wage measure used in this paper.

Evidence of growth in skills demand from other data sources

A common proxy for worker skills is educational attainment. Data from the Current Population Survey includes information on workers' education, industry, and occupation and has been used to argue that there has been a large increase in educational attainment among manufacturing workers in the 2000s (e.g. Rampell 2022). Figures 3a to 3c report educational attainment of all manufacturing workers and separately of workers in non-PMM and PMM occupations in 2003 and 2018.[18] Not surprisingly, manufacturing workers with bachelor's degree or higher are concentrated in non-PMM occupations in both years. The data also show an increase in educational attainment among workers in both non-PMM and PMM occupations. Among workers in non-PMM occupations, the share with at least a four-year college degree rose by 10 percentage points over the 15-year period, from 40 to 50 percent, while there was little change in net in the share with an associate degree. This compares to a smaller 3-percentage-point rise among workers in PMM occupations with at least a four-year college degree from 6 to 9 percent, and nearly a 4-percentage point rise in the share with an associate degree among from about 6 to 10 percent. The share with some college, but no degree also rose by about a percentage point. These gains were matched by declines in the share with lower educational attainment, primarily among those without a high school degree, which dropped by 7.2 percentage points.

While the CPS data show that by 2018, 19 percent of PMM workers in manufacturing have an associate degree or higher, a 7-percentage point increase since 2003, the increase may reflect the increase in supply of workers with these credentials and does not necessarily imply that employers require these educational credentials to hold jobs in production and material moving occupations. To shed light on the latter, we turn to the Occupational Requirements Survey (ORS). The BLS conducts the ORS for the Social Security Administration to support the SSA's review of applications for disability insurance. This employer survey yields detailed information for occupations at the 6-digit SOC level on job requirements in the areas of education, training and experience; cognitive and mental demands; physical demands; and environmental conditions. Here we focus on the education, training and experience requirements measures of jobs in the ORS. Selected occupations are covered in the survey, with a focus on larger occupations, and employers are only asked questions deemed appropriate for the occupation. For example, employers are not asked whether they require that workers in technical and professional occupations be literate. We use 2022 ORS data, which are derived from four

[18] Because of a substantial change in the occupational coding used in the CPS in 2003, we start our analysis in this year.

samples conducted between 2018 and 2022.[19] These data include at least one measure for occupations that account for about two-thirds of PMM manufacturing workers.

Table 8 displays survey results for requirements pertaining to education, training and experience for manufacturing PMM occupations. The first two columns of the first panel show, for each of nine requirements, a weighted average of values for the occupations covered by the survey question, where the weights are direct-hire manufacturing employment in the occupation in 2000 and 2019, respectively. The next two columns report weighted averages of the values for occupations covered by the survey question using as weights the employment of all workers (direct-hire and contract workers) in the occupation. The second panel reports for each measure the difference in skills requirements for direct-hire and for all workers between 2000 and 2019. Like the measure used in our main analysis, this measure captures changes in skills requirements due to changes in the occupational composition of the workforce; it does not capture changes in skills requirements that may have occurred within detailed occupations. The last column shows the percent of PMM workers that each ORS question covers.

Overall educational requirements for workers in PMM occupations are low. The ORS asked employers about bachelor's and associate degree requirements for only one of the 120 PMM occupations, first-line supervisors of production and operating workers. For this occupation, a bachelor's degree is required for an estimated 18.8 percent and an associate degree for 6.8 percent. If one can assume that the question is not asked for other PMM occupations because a college degree is not needed or the number of employers requiring such credentials is de minimis, these numbers imply that currently an associate or bachelor's degree is required for about 1.5 percent of this workforce. At the other extreme, the figures imply that employers have no educational requirements for at least a quarter of the workforce and do not require literacy for about a fifth of the workforce. Among workers in occupations covered by the questions, the jobs typically require between 35 and 40 days of on-the-job training, and a little over half of employers require no prior work experience.

Additionally, the skills measures in the ORS generally are slightly higher for direct-hire than for contract workers and show modest increases for both groups between 2000 and 2019, with the increase usually greater for the direct-hire group.[20] These patterns are consistent with the skills measures we report based on the OEWS. While the ORS data do not cover occupations accounting for 37 percent of manufacturing workers in PMM occupations in 2019, workers in uncovered occupations are paid lower wages, on average, than workers in in covered occupations, suggesting that skills requirements generally would be lower for these occupations than for covered occupations. In future research, we plan to use O*NET data, which will permit a more complete analysis of skills requirements for detailed manufacturing occupations and how

[19] The published data are preliminary and will be updated when a fifth sample of employers is surveyed in 2023.
[20] The main exceptions are the requirement for specific vocational preparation beyond a short demonstration, which fell for both groups over time and fell more for direct-hires, and literacy requirement, which is slightly higher for all workers and fell for both groups over time.

skills requirements may have changed over time, because of both changes in the composition of occupations and changes in the skills requirements within occupations.

Conclusion

Using a new research data set with information on the location, industry, and occupational composition of all U.S. establishments from 2000 to 2019, we impute contract workers from staffing services industries to manufacturing for production and material moving occupations. These granular data enable us to estimate this manufacturing contract workforce by detailed industry, occupation, and geographic region. Over the period, we estimate that the share of contract workers in core manufacturing occupations grew by 45 percent from 6.9 percent in 2000 to 10.0 percent in 2019. Growth in contracting tended to be larger in industries experiencing larger relative declines in employment, suggesting that the shift to contract work may reflect greater pressures on establishments in severely declining industries to lower costs. We also find considerable variation in the size of contract workforce and its growth across regions that cannot be explained by industry composition and that warrants further examination.

Overall, the growth in contract workers accounts for 8 percent of the decline in direct-hire employment in production and material moving occupations over the period, and the growth in contract workers accounts for a substantially higher share of the decline in direct-hire workers in some industries. In future work, we plan to check the sensitivity of our results to different methods of imputing contract workers to manufacturing, although the fact that our sectoral level estimates for the first half of the period are similar to ones generated in earlier research using different data and methods gives us some confidence in the aggregate results (Dey, Houseman, and Polivka 2012).

We also explore biases in skills growth measures that arise from outsourcing. Our estimates indicate that the substitution away from direct-hire workers toward contract workers, who tend to be concentrated in lower-skilled occupations, accounts for a substantial share of measured skills growth – 19 percent of the apparent skills growth among workers in production and material mover occupations and 17 percent for workers in all occupations. Our findings point to the potential importance more generally of accounting for the contract workforce in studies of labor markets and their dynamics. Fruitful areas for research, for example, may include studies on the effects of outsourcing on measures of workforce adjustment in response to demand shocks and productivity measures at the firm and industry levels.

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Appendix: Decomposition of Change in Average Skills

Let s_{kt}^x denote the average skill of x type jobs (i.e, non-PMM jobs, direct hire PMM jobs, and contracted PMM jobs) in industry k and year t. Similarly, let e_{kt}^x denote the employment level of x type jobs in industry k and year t.

Define the average skill of x type jobs in year t as

$$s_t^x = \sum_k s_{kt}^x \times \frac{e_{kt}^x}{e_t^x}$$

where e_t^x is total employment of x type jobs in year t.

Define the average skill in year t as the weighted average of the average skill of x type jobs in year t such that

$$s_t = \sum_x s_t^x \times \frac{e_t^x}{e_t}$$

where e_t is total employment in year t. We are decomposing $s_{19} - s_{00}$ which can be written as

$$s_{19} - s_{00} = \sum_x s_{19}^x \times \frac{e_{19}^x}{e_{19}} - s_{00}^x \times \frac{e_{00}^x}{e_{00}} \pm s_{19}^x \times \frac{e_{00}^x}{e_{00}} = \sum_x s_{19}^x \left(\frac{e_{19}^x}{e_{19}} - \frac{e_{00}^x}{e_{00}}\right) + \frac{e_{00}^x}{e_{00}} (s_{19}^x - s_{00}^x)$$

The change in average skill can be decomposed into a change in the share of x type jobs from 2000 to 2019 (holding average skill fixed at 2019 levels) and a change in the average skill of x type jobs (holding job type shares fixed at 2000 levels).

We can further decompose the change in the shares of x type jobs from 2000 to 2019 into two components. In particular,

$$\frac{e_{19}^x}{e_{19}} - \frac{e_{00}^x}{e_{00}} = \sum_k \frac{e_{k,19}^x}{e_{k,19}} \times \frac{e_{k,19}}{e_{19}} - \frac{e_{k,00}^x}{e_{k,00}} \times \frac{e_{k,00}}{e_{00}} \pm \frac{e_{k,00}^x}{e_{k,00}} \times \frac{e_{k,19}}{e_{19}}$$

which can be rewritten as

$$\frac{e_{19}^x}{e_{19}} - \frac{e_{00}^x}{e_{00}} = \sum_k \frac{e_{k,00}^x}{e_{k,00}} \left(\frac{e_{k,19}}{e_{19}} - \frac{e_{k,00}}{e_{00}}\right) + \frac{e_{k,19}}{e_{19}} \left(\frac{e_{k,19}^x}{e_{k,19}} - \frac{e_{k,00}^x}{e_{k,00}}\right)$$

The first term measures the change in industry composition from 2000 to 2019 (holding the shares of x type jobs within industries as fixed at 2000 levels). The second term measures the within industry change in shares of x type jobs from 2000 to 2019 (holding the overall industry composition fixed at 2019 levels).

Similarly, we can decompose the change in the average skill of x type jobs into two components such that

$$s_{19}^x - s_{00}^x = \sum_k \frac{e_{k,00}^x}{e_{00}^x} \left(s_{k,19}^x - s_{k,00}^x\right) + s_{k,19}^x \left(\frac{e_{k,19}^x}{e_{19}^x} - \frac{e_{k,00}^x}{e_{00}^x}\right)$$

The first term measures the within industry change in average skill of x type jobs (holding the industry shares of x type jobs fixed at 2000 levels). The second term measures the change in industry composition of x type jobs (holding within industry skill of x type jobs fixed at 2019 levels).

Putting this altogether, we can decompose the change in average skill into four components. The first two, which hold within job type skills fixed, capture the components of average skills change arising from the shift in job types due to:

1) The change in industry composition

$$\sum_x s_{19}^x \sum_k \frac{e_{k,00}^x}{e_{k,00}} \left(\frac{e_{k,19}}{e_{19}} - \frac{e_{k,00}}{e_{00}} \right)$$

2) The change in job types within industries

$$\sum_x s_{19}^x \sum_k \frac{e_{k,19}}{e_{19}} \left(\frac{e_{k,19}^x}{e_{k,19}} - \frac{e_{k,00}^x}{e_{k,00}} \right)$$

The next two, which hold job type shares fixed, capture the components of the average skills change arising from the change in skills within job types due to:

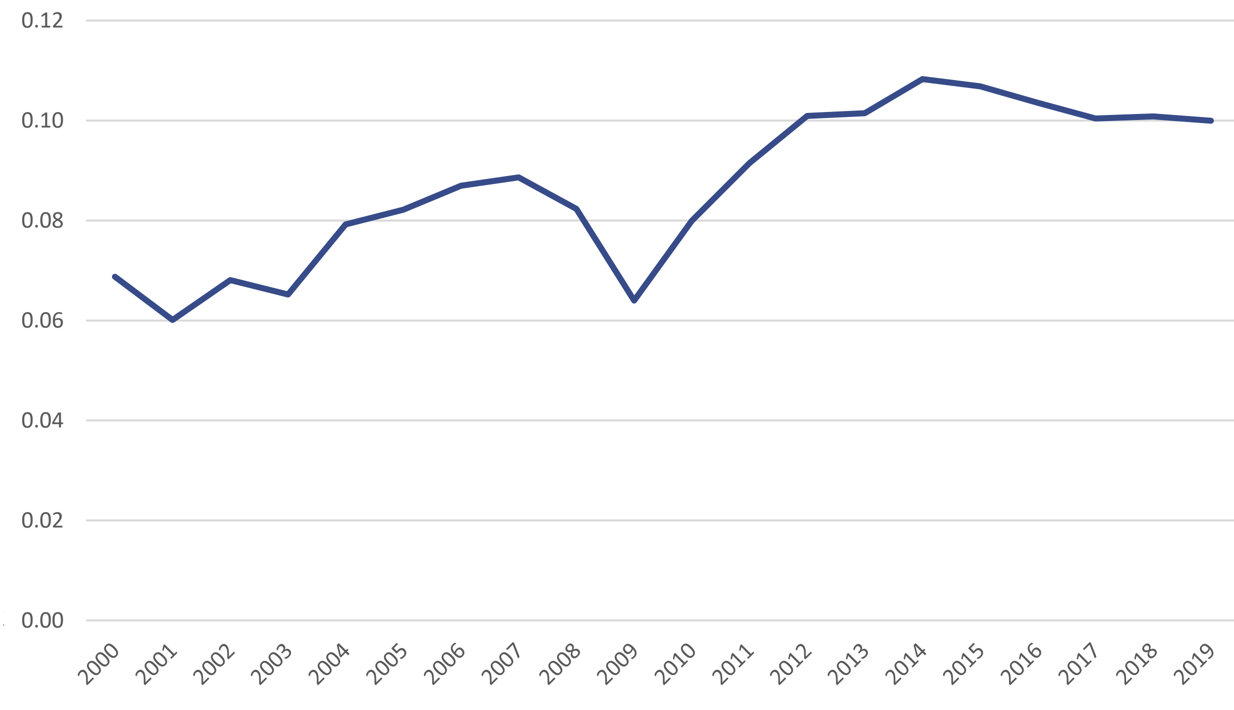
3) The change in job type skills within industries

$$\sum_x \frac{e_{00}^x}{e_{00}} \sum_k \frac{e_{k,00}^x}{e_{00}^x} \left(s_{k,19}^x - s_{k,00}^x \right)$$

4) The change in industry composition

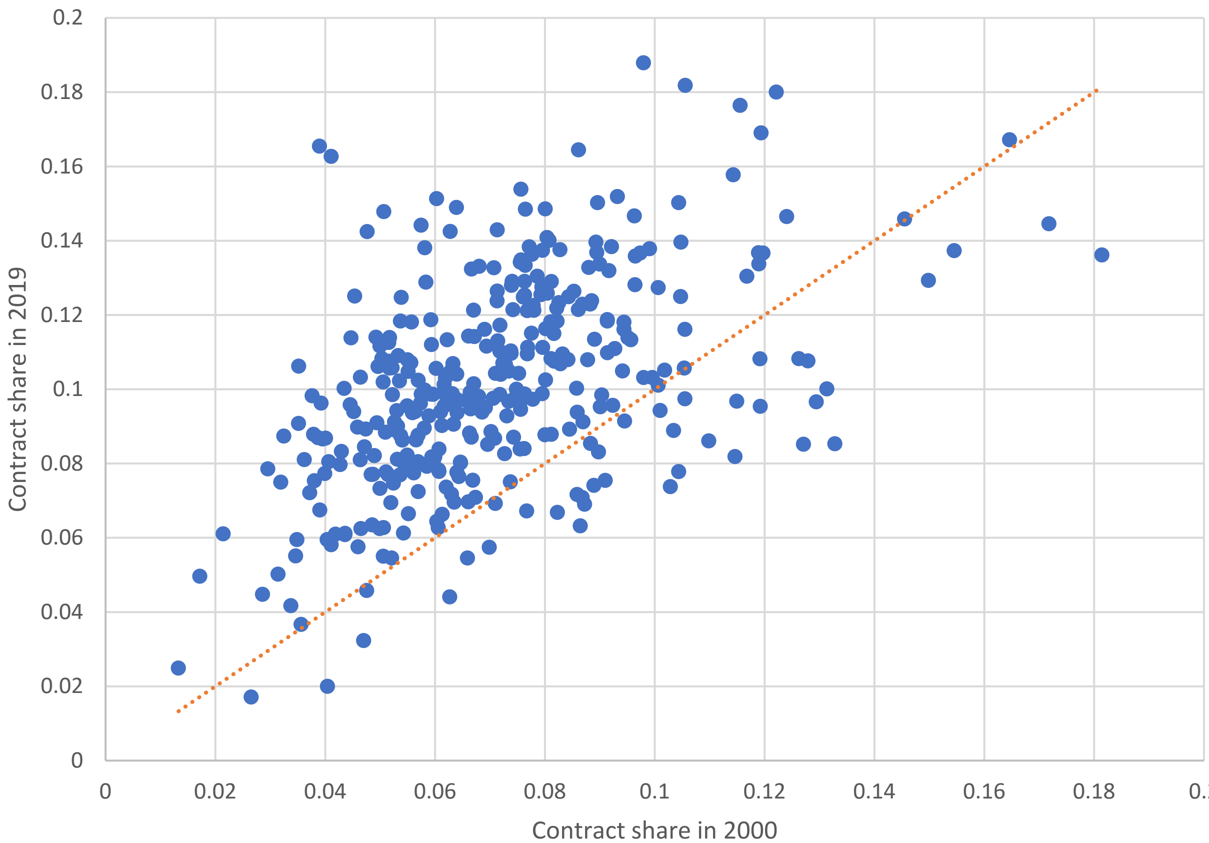
$$\sum_x \frac{e_{00}^x}{e_{00}} \sum_k s_{k,19}^x \left(\frac{e_{k,19}^x}{e_{19}^x} - \frac{e_{k,00}^x}{e_{00}^x} \right)$$

Figure 1: Contract Share of Workers in Production and Material Mover Occupations, Manufacturing, 2000-19



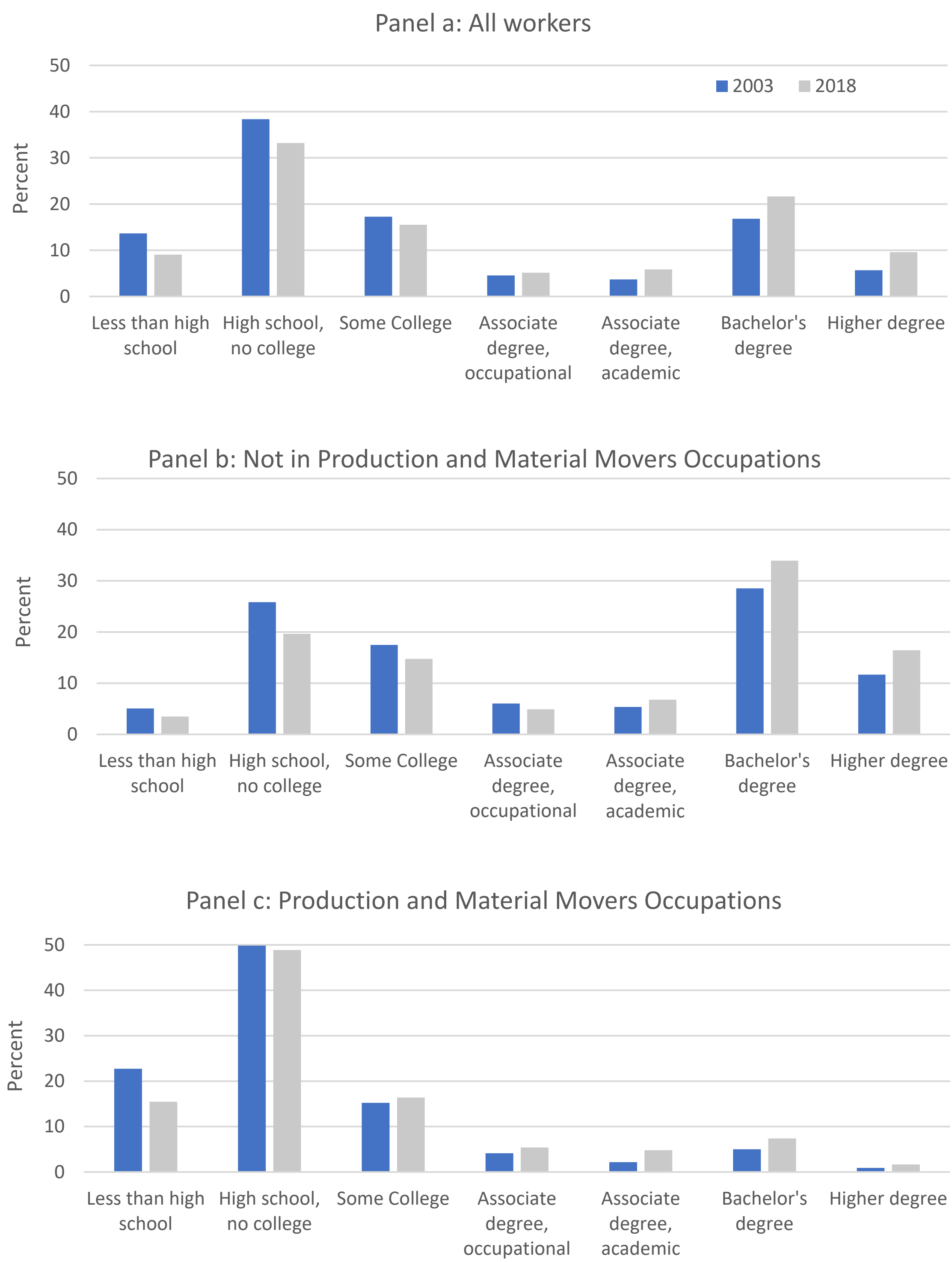
Note: Estimates based on Occupational Employment and Wage Statistics (OEWS) and Quarterly Census of Employment and Wages (QCEW) data. Staffing services workers in production and material moving occupations are assigned back to detailed industries based on their estimated relative importance as employers of these occupations at the county level.

Figure 2: Contract share by detailed industry, 2000 v. 2019



Note: Estimates based on Occupational Employment and Wage Statistics (OEWS) and Quarterly Census of Employment and Wages (QCEW) data. Staffing services workers in production and material moving occupations are assigned back to detailed industries based on their estimated relative importance as employers of these occupations at the county level.

Figure 3: Educational attainment, manufacturing workers, 2003 and 2018



Note: Authors' calculations based on Current Population Survey (CPS) data.

Table 1: Direct-Hire and Contract Employment Patterns, Production and Material Moving Occupations by Industries

	2000		2019		Change 2000-19			
Industry title	Total (Direct hire + Contract) Employment	Percent contract	Total (Direct hire + Contract) Employment	Percent contract	Percent change in total employment	Percent change in DH emp	Percentage point change in percent contract	Percent of DH emp change explained by contract growth
Food	1,114,816	7.8%	1,194,068	10.0%	7.1%	4.6%	2.2	-54.5%
Beverage and tobacco	99,326	13.8%	112,232	11.8%	13.0%	15.7%	-2.1	17.2%
Textile mills	284,966	5.1%	83,247	10.2%	-70.8%	-72.3%	5.0	2.1%
Textile product mills	169,821	6.8%	88,366	11.1%	-48.0%	-50.4%	4.3	4.8%
Apparel	387,509	5.4%	81,001	9.6%	-79.1%	-80.0%	4.3	1.2%
Leather and allied products	51,541	7.2%	21,683	7.7%	-57.9%	-58.2%	0.6	0.4%
Wood products	422,862	5.5%	291,366	8.8%	-31.1%	-33.5%	3.3	7.1%
Paper	435,038	7.7%	271,548	11.8%	-37.6%	-40.3%	4.0	6.8%
Printing	498,683	8.0%	272,646	11.4%	-45.3%	-47.4%	3.4	4.3%
Petroleum and coal	58,959	4.9%	57,513	5.8%	-2.5%	-3.4%	0.9	26.8%
Chemicals	460,899	7.7%	445,600	11.1%	-3.3%	-6.9%	3.4	51.7%
Plastics and rubber	743,970	8.0%	572,312	11.7%	-23.1%	-26.1%	3.7	11.7%
Nonmetallic minerals	317,838	8.8%	219,771	11.3%	-30.9%	-32.7%	2.5	5.7%
Primary metals	434,968	6.2%	270,554	8.2%	-37.8%	-39.2%	2.0	3.5%
Fabricated metals	1,267,038	7.0%	1,049,009	9.7%	-17.2%	-19.6%	2.7	12.2%
Machinery	876,229	5.6%	667,531	9.2%	-23.8%	-26.7%	3.6	10.8%
Computer and electronics	738,393	7.3%	341,946	10.5%	-53.7%	-55.3%	3.2	2.9%
Electrical equipment, appliances	422,832	6.8%	251,000	9.6%	-40.6%	-42.5%	2.9	4.3%
Transportation	1,269,639	5.7%	1,121,948	8.5%	-11.6%	-14.3%	2.8	18.5%
Furniture	532,023	6.2%	288,228	10.5%	-45.8%	-48.3%	4.3	5.2%
Miscellaneous manufacturing	481,798	7.0%	366,259	11.5%	-24.0%	-27.7%	4.5	13.3%
Total	11,069,150	6.9%	8,067,829	10.0%	-27.1%	-29.6%	3.1	8.3%

Note: Estimates based on Occupational Employment and Wage Statistics (OEWS) and Quarterly Census of Employment and Wages (QCEW) data. Staffing services workers in production and material moving occupations are assigned back to detailed industries based on their estimated relative importance as employers of these occupations at the county level.

Table 2: The Relationship between Share of Employment in Contract Arrangements in 2019 and Industry Growth 2000-2019

Contract share 2000	0.6128
	(0.0591)
Emp change, 2000-19	-0.0224
	(0.0077)
Employment increased	0.0036
	(0.0051)
Emp change*increased	0.0199
	(0.0099)
Intercept	0.0524
	(0.0053)

Note: The dependent variable in the regression is the contract share of detailed industry employment in 2019. The mean is 0.103. Standard errors are in parentheses. There are 360 six-digit NAICS industries.

Table 3: Manufacturing Employment and Contract Incidence by Region, Production and Material Moving Occupations

Region	2000 Total Employment	2019 Total Employment	Percent change	2000-19 Employment change: Actual	Predicted	Ratio Actual/ Predicted	Contract rate: 2000 Contract share	2019 Contract share	Change in percent contract
Far West	1,429,482	1,013,155	-29.1%	-416,327	-405,854	0.97	8.7%	9.8%	1.0
Great Lakes	2,717,803	2,050,556	-24.6%	-667,246	-658,334	0.99	6.6%	10.1%	3.4
Mideast	1,259,335	798,478	-36.6%	-460,857	-361,242	0.78	4.0%	9.7%	5.6
New England	534,320	316,578	-40.8%	-217,742	-163,377	0.75	5.4%	8.1%	2.7
Plains	914,467	738,370	-19.3%	-176,097	-171,214	0.97	5.1%	5.9%	0.8
Rocky Mountain	235,162	219,939	-6.5%	-15,223	-53,195	3.49	8.1%	9.9%	1.9
Southeast	3,087,867	2,211,783	-28.4%	-876,084	-987,931	1.13	7.5%	11.4%	3.9
Southwest	890,713	718,970	-19.3%	-171,744	-200,173	1.17	9.0%	11.2%	2.2

Note: Predicted 2019 employment equals 2000 industry-region employment times industry growth rate from 2000 to 2019. Estimates based on Occupational Employment and Wage Statistics (OEWS) and Quarterly Census of Employment and Wages (QCEW) data. Staffing services workers in production and material moving occupations are assigned back to detailed industries based on their estimated relative importance as employers of these occupations at the county level.

Table 4: Distribution of Manufacturing Employment by Occupation and Employment Type, Production and Material Mover Occupations, 2000 and 2019 (percent)

	Direct hires		Contract workers		All workers	
Occupation	2000	2019	2000	2019	2000	2019
Supervisors of production workers	5.7	6.3	0.8	0.9	5.4	5.8
Assemblers and fabricators	**18.9**	**19.7**	**17.0**	**25.8**	**18.8**	**20.3**
Food processing workers	4.0	5.9	0.5	1.9	3.7	5.5
Metal workers and plastic workers	**20.6**	**20.2**	**11.8**	**9.8**	**20.0**	**19.1**
Printing workers	3.3	2.5	2.0	0.9	3.2	2.4
Textile, apparel, and furnishings workers	6.8	3.3	2.2	1.1	6.5	3.1
Woodworkers	3.1	2.7	0.6	0.8	2.9	2.5
Plant and system operators	1.3	0.9	0.0	0.1	1.2	0.8
Other production occupations	**23.5**	**26.1**	**34.8**	**23.7**	**24.3**	**25.9**
Material moving workers	**12.9**	**12.3**	**30.2**	**34.9**	**14.0**	**14.5**
All production and material moving workers	100	100	100	100	100	100

Note: Estimates shown for minor group occupations defined by time-consistent SOC occupations. Estimates based on Occupational Employment and Wage Statistics (OEWS) and Quarterly Census of Employment and Wages (QCEW) data. Staffing services workers in production and material moving occupations are assigned back to detailed industries based on their estimated relative importance as employers of these occupations at the county level.

Table 5: Skills of Direct-Hire and Contract Workers by Production and Material Moving Occupation, 2000 and 2019

	2000				2019				Skill change, 2000-19	
			Mean skill				Mean skill			
Occupation	Employment	Percent contract	Direct hires	Contract workers	Employment	Percent contract	Direct hires	Contract workers	Direct hires	Contract workers
Supervisors of production workers	598,586	1.0	20.97	20.97	466,472	1.6	20.97	20.97	0.00	0.00
Assemblers and fabricators	**2,077,121**	**6.2**	**11.92**	**11.77**	**1,640,891**	**12.7**	**12.01**	**11.86**	**0.09**	**0.09**
Food processing workers	414,635	0.9	9.73	10.09	442,976	3.5	9.90	10.35	0.17	0.26
Metal workers and plastic workers	**2,212,799**	**4.1**	**13.78**	**13.40**	**1,544,846**	**5.1**	**13.74**	**13.73**	**-0.04**	**0.33**
Printing workers	353,639	4.4	13.68	12.23	192,212	3.9	13.65	13.37	-0.02	1.14
Textile, apparel, and furnishings workers	715,437	2.4	9.55	9.58	250,580	3.4	9.73	9.73	0.18	0.15
Woodworkers	325,987	1.4	11.07	11.15	204,102	3.1	11.00	10.99	-0.07	-0.15
Plant and system operators	129,177	0.2	20.42	19.05	67,983	1.5	20.56	19.90	0.15	0.85
Other production occupations	**2,687,496**	**9.9**	**12.31**	**10.80**	**2,086,446**	**9.2**	**12.70**	**11.60**	**0.39**	**0.79**
Material moving workers	**1,554,274**	**14.8**	**10.36**	**9.57**	**1,171,321**	**24.0**	**10.23**	**9.85**	**-0.13**	**0.28**
All production and material moving occupations	11,069,150	6.9	12.60	10.99	8,067,829	10.0	12.78	11.33	0.18	0.34

Note: Estimates shown for minor group occupations defined by time-consistent SOC occupations. Estimates based on Occupational Employment and Wage Statistics (OEWS) and Quarterly Census of Employment and Wages (QCEW) data. Staffing services workers in production and material moving occupations are assigned back to detailed industries based on their estimated relative importance as employers of these occupations at the county level. Skill is measured by the average national wage in the occupation in 2000.

Table 6: Skills Growth and Effect of Contracting on Skills Measures

		Skill (2000 mean wage)		2000-19 Change in Skill Measure in SDs (2000 mean wage)	% Skills growth explained by contracting
		2000	2019		
Production and material moving occupations	Direct hires only	12.60	12.78	0.057	19.4%
	Direct hire and contract workers	12.49	12.63	0.046	
All occupations	Direct hires only	15.84	16.37	0.064	16.9%
	Direct hire and contract workers	15.63	16.07	0.054	

Note: Estimates based on Occupational Employment and Wage Statistics (OEWS) and Quarterly Census of Employment and Wages (QCEW) data. Staffing services workers in production and material moving occupations are assigned back to detailed industries based on their estimated relative importance as employers of these occupations at the county level.

Table 7: Decomposition of Average Skill Change for Production and Material Moving Occupations and for All Occupations by Employment Type, 2000-19

		Panel a: PMM occupations, direct hire only				*Panel c: All occupations, direct hire only*			
		Non-PMM	Direct hire PMM	Contract PMM	Total	Non-PMM	Direct hire PMM	Contract PMM	Total
Change in job type employment share	Change in industry composition					0.219	-0.129		0.090
	Change in share within industry					0.464	-0.273		0.191
	Total					0.683	-0.402		0.280
Change in average skill	Change in within industry skill		0.079		0.079	0.258	0.049		0.307
	Change in industry composition		0.097		0.097	-0.110	0.061		-0.049
	Total		0.176		0.176	0.148	0.110		0.258
	Total		0.176		0.176	0.831	-0.292		0.539

		Panel b: PMM occupations, direct hire and contract workers				*Panel d: All occupations, direct hire and contract workers*			
		Non-PMM	Direct hire PMM	Contract PMM	Total	Non-PMM	Direct hire PMM	Contract PMM	Total
Change in job type employment share	Change in industry composition		-0.019	0.017	-0.002	0.192	-0.117	0.003	0.079
	Change in share within industry		-0.380	0.337	-0.043	0.304	-0.403	0.199	0.099
	Total		-0.399	0.354	-0.045	0.496	-0.520	0.202	0.178
Change in average skill	Change in within industry skill		0.073	0.020	0.093	0.246	0.047	0.013	0.306
	Change in industry composition		0.090	0.004	0.094	-0.105	0.058	0.002	-0.045
	Total		0.164	0.023	0.187	0.142	0.105	0.015	0.262
	Total		-0.235	0.377	0.142	0.638	-0.414	0.217	0.440

Note: Estimates based on Occupational Employment and Wage Statistics (OEWS) and Quarterly Census of Employment and Wages (QCEW) data. Staffing services workers in production and material moving occupations (PMM) are assigned back to detailed industries based on their estimated relative importance as employers of these occupations at the county level. Skill is the detailed occupation national average wage in 2000. Occupation skills do not vary over time.

Table 8: Skills Requirements of Workers in Production and Material Moving Occupations, Occupational Requirements Survey

	Percent requiring skill				Difference in Skills Requirements, 2000 v. 2019		
	Direct-hires, 2000	Direct-hires, 2019	All workers, 2000	All workers, 2019	Direct-hires	All workers	Percent of PMM workers covered by skill
Minimum education level is a bachelor's degree (%)	18.80	18.80	18.80	18.80	n.a.	n.a.	5.6%
Minimum education level is an associate's degree	6.80	6.80	6.80	6.80	n.a.	n.a.	5.6%
Minimum education level is a high school diploma (%)	54.39	55.06	53.75	54.13	0.67	0.38	58.8%
No minimum education requirement (%)	46.84	44.49	47.30	45.43	-2.35	-1.87	55.6%
Specific vocational preparation is beyond short demonstration, up to & including 1 month (%)	46.03	44.65	46.97	45.92	-1.38	-1.05	44.7%
Days of on-the-job training, mean	37.95	39.77	36.72	38.17	1.82	1.45	56.9%
Literacy is required (%)	38.26	37.14	38.82	38.13	-1.12	-0.69	52.8%
Prior work experience is required (%)	49.33	49.54	48.13	47.86	0.20	-0.27	50.4%
Prior work experience is not required (%)	53.29	52.09	54.82	53.89	-1.20	-0.94	53.9%

Note: Authors' calculations based on 2022 Occupational Requirements Survey (ORS). Data is unavailable for 37 percent of production and material moving workers. The ORS skills measures are weighted by estimated employment, either all workers or direct hires only and in 2000 and 2019.