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Worker Hard and Soft Skills and Labor Market Outcomes: A Lens through the Temporary Help Industry over the Business Cycle

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Abstract

Utilizing detailed order data between 2007 and 2011 from a large, nationally representative staffing company, we provide insights into the characteristics of temporary help work, employers' use of staffing agencies to screen workers for permanent positions, worker soft and hard skills and job performance, and employment outcomes and labor market adjustment over the business cycle. We find that temporary help workers are terminated for performance problems at strikingly high rates, particularly in manual, low-paying occupations, and primarily for "soft skill" deficiencies. Soft skill performance problems dominate hard skill deficits in their consequences for job length and subsequent offers of employment. There are also penalties in terms of wages on subsequent assignments (when offered) for both hard and soft skills deficits cited on prior assignments, with larger decrements for those terminated due to hard skills deficiencies. During the recession, the share of temporary help workers dismissed for performance problems related to soft skills fell sharply in nonprofessional occupations, and firms lengthened temporary help assignments and reduced permanent hiring from their pool of temps, likely in response to economic uncertainty.

Introduction

Amidst the recent job growth and low unemployment rate in the United States, concerns persist that insufficient numbers of working-age adults are acquiring the “hard” and “soft” skills needed to succeed in the labor market. Although the prime-age labor force participation rate has recently rebounded from a decades-long decline, it is still below the level of labor force participation in 2007, before the deep recession’s onset (Breitwieser et al., 2018). While policy attention to improving the effectiveness of the post-secondary education sector in increasing degree completion and certifying “hard skills” is growing (Autor and Dorn, 2013; Holzer, 2013), there is considerably less consensus about the role of “soft skills” deficits in labor pipeline problems, and what types of policies might address them among both younger and more mature workers (Deming, 2015). Indeed, the research community continues to debate how to measure “soft skills” and account for the fact that publicly accessible data on observed worker skills and job performance is rarely available in conjunction with data on worker labor market outcomes (Heckman and Rubinstein, 2001; Bowles et al., 2001; Carneiro and Heckman, 2003; Heckman and Kautz, 2012; Balcar, 2014; Fan et al., 2017).

In this regard, the temporary help industry, associated with shorter job assignments and intensive monitoring of performance on those assignments by both the client firm and temporary agency, provides a valuable lens through which to examine the role of worker hard and soft skills in labor markets. . Although it fairly steadily accounts for about 2 percent of average daily employment in the U.S. economy,[1] the temporary help industry plays an outsized role in workforce adjustment during recessions and recoveries, as well as in particular industries that are more vulnerable to global economic demand shifts, such as manufacturing (Dey, Houseman, and Polivka, 2012, 2017). During the last recession, the largest since the Great Depression, employment in the temporary help industry contracted by 30 percent and accounted for 11 percent of net employment losses economy-wide. Correspondingly, the temporary help industry accounted for over 13 percent of net employment gains following the official end of the recession in June 2009.

The large role that this small industry plays in the macro economy reflects the fact that, over the past two decades, employers increasingly have relied on temporary help agencies to provide greater flexibility in meeting their staffing needs (Dey, Houseman, and Polivka 2012). During this time, the industry has also expanded the types of workers it supplies to companies. While primarily providing female clerical workers to companies in the industry's early years, temporary help agencies now supply large numbers of workers in production and other manual occupations and in a wide variety of professional and technical occupations to client companies. In addition to using temporary help agencies for flexible staffing, employers commonly screen potential hires through temporary help agencies, and temporary help jobs are widely viewed as an important port of entry to permanent employment.

In this paper, we investigate worker hard and soft skills in the temporary help industry, drawing on exceptionally detailed data on temporary help orders and worker performance on assignments from a large, nationally representative staffing company over the years 2007 and 2011 (a time period that spans the year prior to the start of the recession through the initial years of recovery). The analysis of these data presents a unique opportunity to examine the role of worker skills (and skills deficits) in employment outcomes, including how patterns in these outcomes (and labor market adjustment) play out over the business cycle. Our data yield a number of insights into the characteristics of temporary help work, including the distribution of wages and assignment lengths, the number of assignments individuals hold, the likelihood of securing a permanent job with the client company, the incidence of and reasons for termination prior to assignment completion, and the implications (descriptively) of hard and soft skills performance deficiencies for individual labor market outcomes.

Notably, our analysis of these data highlights the role of long- (and shorter) duration assignments in the temporary help industry and the high share of workers who complete their assignments unsatisfactorily, largely because of soft skills deficiencies. Although organizations often use temporary help agencies to screen workers for permanent positions, only 7 percent of assignments in our sample ended in a hire by the client employer, and the duration of those assignments was correspondingly longer. Even among contracts where the client was explicitly screening temporary help workers for permanent positions, the hire rate was just 28 percent, consistent with hypotheses that screening through an intermediary may enable firms to be more selective in hiring. Workers with drug or alcohol problems identified while on the job had their assignments terminated at the swiftest rate, and they were also least likely to be hired on second or third job assignments. In fact, each of the various soft skills performance problems (identified on a previous assignment) was more likely to reduce the probability of subsequent job assignments than the incidence of hard skills deficits on a prior assignment. We also find that workers whose first assignments were terminated because of hard or soft skills deficits had smaller increases (or larger decrements) in wages on subsequent assignments (relative to those whose assignments ended for non-performance related reasons), with the largest pay decrements for those terminated for hard skills deficits. In addition, workers terminated from assignments for hard skills performance problems were the most likely to transition to another occupation on a subsequent assignment.

Because the data we analyze span periods of economic recession and recovery, we are also able to provide insight into the dynamics of temporary help employment over the business cycle, including the adjustment of temporary help assignment length, conversion of temporary help workers to direct-hire status, and the share of hires and separations accounted for by the temporary help industry over the period. Employers' reliance on temporary help staff is most apparent during recessions when many firms simultaneously experience adverse demand conditions and terminate temporary help contracts to quickly reduce staffing levels. During the recession and initial recovery when many are uncertain about future economic conditions, employers also may disproportionately rely on temporary help staff to expand their workforce. Indeed, although the temporary help industry experienced robust growth following the official end of the recession in 2009, employment growth in the economy overall was weak until 2012. A leading hypothesis for the weak aggregate employment growth during the period is that companies were uncertain about the strength of the recovery and were reluctant to take on permanent employees (International Monetary Fund 2012). Controlling for likely improvements in the quality of temporary help workers during the recession, we find that companies reduced hiring out of the pool of temporary workers and lengthened the duration of temporary assignments during the recession and initial recovery period.

Background on the Temporary Help Industry and Measurement of Hard and Soft Skills

Nature of and Trends in Temporary Help Employment

Temporary help agencies place workers on job assignments with client organizations, typically for a fixed term. During assignments, temporary help workers are legally the employees of temporary help agencies, which cover their wages and any benefits, withhold taxes, track their performance, and pay the employer contribution to Social Security, unemployment insurance taxes, and workers' compensation. Temporary help employees work at the client's worksite, typically under the supervision of the client, although in some cases, temporary help agencies and clients have "joint employer status." For example, temporary help agencies and client organizations have joint legal responsibility for compliance with occupational safety and health regulations. Furthermore, performance information is frequently shared between the client organization and temporary help agency.

The temporary help industry's share of nonfarm payroll employment almost doubled during the 1990s, from about 1 percent at the start of the decade to 2 percent by its end, accounting for 10 percent of net new jobs during a decade characterized by extraordinary employment growth. Underlying much of the industry's rapid expansion was the supply of temporary help labor to U.S. manufacturing firms. In 1990, the share of staffing services employment in office and administrative support occupations was 42 percent, compared to 28 percent in blue-collar occupations.[2] By 2000, the relative importance of clerical and blue-collar occupations had reversed, with 47 percent of the staffing industry's employment in blue-collar jobs and just 28 percent in office and administrative jobs (Dey, Houseman, and Polivka 2012).

Temporary help employment was slow to recover from the 2001 recession, reflecting in part the sharp decline in U.S. manufacturing, although the share of manufacturing work performed by temporary help workers has continued to grow. In recent years, the industry has expanded into professional and technical occupations, which now account for about 16 percent of temporary help employment (Dey, Houseman, and Polivka 2012). In 2014, the share of nonfarm payroll employment in temporary help jobs rose to 2.1 percent, exceeding the previous peak of 2.0 percent reached in 2000.

In various special surveys and case studies, employers report that they often screen workers for permanent jobs through temporary help agencies (see, for example, Abraham [1990]; Houseman [2001]; Kalleberg, Reynolds, and Marsden [2003]; Houseman, Kalleberg, and Erickcek [2003]; and Ono and Sullivan [2006]). Additionally, in some circumstances, employers may hire workers through third-party intermediaries in order to lower benefits or other nonwage labor costs.[3] Evidence from employer surveys, however, indicates that the most important reason for using temporary help agencies is to increase workforce flexibility. Employers typically use temporary help workers because they have a short-term need for labor or because, in an uncertain economic environment, they want to be able to quickly flex up or down their workforce to accommodate fluctuations in demand. Katz and Krueger (1999) suggest that temporary help firms play an important role in increasing the efficiency of the labor market by facilitating better firm-worker matches through screening, and thus reducing firm hiring and adjustment costs (and exerting downward pressure on wages) in times of changing labor demand. In fact, some have argued that many employers have come to view regular employees as "costly sources of rigidity" (DeLong 2009). According to Kelly Services' former CEO Karl Camden, "Companies' use of temporaries used to be a gap measure. Now the largest corporations have a specific model of how much of their workforce is going to be temporary. It's a critical path for companies to fill their talent needs" (quoted in Rothschild 2012).

Employers' use of temporary help to increase workforce flexibility is most visible during recessionary periods, when many businesses are simultaneously affected by large demand shocks. Largely reflecting the temporary help industry's growth in supplying labor to manufacturers, temporary help has evidenced much greater cyclical sensitivity since 2000. During the 2007-2009 deep recession, average annual payroll employment fell by 4.9 percent while temporary help employment dropped by 29.8 percent, accounting for 11.4 percent of net employment declines during this period. Alternatively, BLS Current Employment Statistics data show that temporary help employment accounted for 89 percent of average annual net job gains from 2009 to 2011, and between the trough of the business cycle in June 2007 and December 2014, the temporary help industry accounted for 13.1 percent of net employment growth.

Defining and Measuring Worker Hard and Soft Skills

The role and repercussions of workers' hard and soft skills in firm productivity and employee labor market outcomes has received growing attention in recent years, particularly in light of research suggesting the importance of soft skills in understanding variation in individual wages and a range of life outcomes (Cappelli, 1995; Heckman and Rubinstein, 2001; Carneiro and Heckman, 2003; Bowles et al., 2001; Heckman and Kautz, 2012; Balcar, 2014; Deming, 2015; Fan et al., 2017). The (general) distinction between "hard" and "soft" skills in the literature belies a fairly wide range of conceptual and empirical definitions, particularly in how soft skills are measured. As Heckman and Rubinstein (2001) noted, the early academic literature relating skills and skill formation to labor market earnings and other life-time outcomes focused almost entirely on cognitive ability (or hard skills), reflecting a dearth of reliable measures or consensus on what should be characterized as "noncognitive." They described their own work as being in "the spirit of 'dark matter' research in astrophysics" (p. 149), given how little was known at that time about the distinctive effects of diverse traits identified as "noncognitive" and their lack of an empirical measure of any specific soft skill.

In more recent work, Heckman and Kautz (2012: 4, 10) conceptualized soft skills (with psychological origins) as "personality traits"—"thoughts, feelings, and behaviors" that are "not captured by measures of abstract reasoning power"—and instead have to be "inferred from measures of performance on tasks." Many soft skills measures drawn from psychology—such as locus of control, conscientiousness, agreeableness, etc.—are constructed from self-reported survey responses, in part because inferring them from behaviors and distinguishing them from other traits (in contexts with varying incentives) is so challenging. For example, Flossman et al. (2007) examined the relationship between noncognitive skills and wages in Germany using self-reported measures (on a four-point scale) of life control (i.e., "locus of control") from a longitudinal survey, which they used to create a standardized noncognitive skill index. They found, controlling for education, experience and other socio-economic factors, that these soft skills accounted for about a quarter of differences in wage levels (for both men and women). Borghans et al. (2008) similarly conceptualized soft skills as interpersonal interactions or behaviors (based in psychology) and drew on measures of interpersonal skills and (self-assessed) job task measures from the British Skills Survey and longitudinal data from Germany to estimate the relationships between "sociability," occupational choice and wages. Their findings, in cross-sectional and panel data (fixed effects) regressions, of significant relationships between interpersonal skills and wages also demonstrate the importance of accounting for differences in returns to different types of interpersonal skills across jobs and the assignment of people to jobs.

An alternative approach used to overcome the challenges of observing soft skills in the employment context is to classify jobs as requiring hard skills, soft skills or both using detailed occupational codes and a comprehensive database of worker attributes and job characteristics to derive occupational information (including job tasks, knowledge, skills, abilities, work activities, work context and more) (Fan et al., 2017). Balcar (2014) suggests that the impetus for this approach comes from the growing focus in human resources management on competencies or particular skills of workers (Cappelli, 1995), more so than IQ and educational attainment in hiring processes, as well as growth in the number of employees performing job tasks requiring soft skills or a combination of cognitive and soft skills (Weinberger, 2014) and the recognition that interpersonal interactions are connected to individuals' cognitive skills (Deming, 2015). Following Autor, Levy, and Murnane's (2003) early work using Occupational Information Network (O*NET) data to construct measures of the skill content of different occupations, Fan et al. (2017) identified a core set of descriptors in the O*NET skills and work activities categories that they used in classifying occupations into hard- and/or soft-skills jobs through k-mean cluster analysis. In regressions predicting log hourly wage rates, they included measures of hard skills (the commonly used Armed Forces Qualification Test scores) and three self-reported soft skills measures (of internal control, self-esteem and sociability) and estimated both pooled regressions and separate regressions for jobs classified as primarily hard-skill, soft-skill or both. Their results suggest that individuals select into jobs based on their comparative advantages in hard or soft skill sets, and consistent with the emerging empirical literature, soft (and hard) skills were positively and significantly associated with individual earnings.

In this study, we have measures of soft and hard skills observed in the employment context, specifically, measures indicating why an (assignment) order was closed, including detailed classifications of performance-related issues. For example, the data identify if a job assignment ended because of issues associated with the productivity or quality of the work performed (i.e., an individual's ability to perform the job tasks), which we identify as a "hard skill" issue, whereas there are more than a dozen different "soft skill" reasons, ranging from fighting or intoxication on the job to attendance, insubordination and other behavioral issues.[4] We further grouped the soft-skill related assignment termination reasons into four broader categories: attendance problems (i.e., excessive absences or tardiness, no-shows/no call-in); substance abuse (i.e., drug use, intoxication on the job); behavioral problems (e.g., fighting on assignment, property removed/destroyed, unacceptable behavior, insubordination, etc.), and policy non-compliance (including violations of policies of the client firm and the temporary help agency). In cases where the temporary worker left before completing an assignment, we distinguished whether the worker left because of dissatisfaction with the job (i.e., with duties, pay, benefits, or hours) or because of personal reasons (e.g., family needs, school conflict). We also identified cases where a worker was terminated from an assignment because of unfavorable background screening or drug test results. Like Fan et al. (2017), we have detailed data on the occupations of each worker assignment, as well as other characteristics of the job order, worker and labor market, which we describe in greater detail below.

Because we are measuring worker performance problems as they relate to assignment terminations, the length of worker assignments is an important employment outcome of interest in this research. At the same time, some temporary help assignments are specified to end on particular dates, and a subsequent assignment with the same employer might follow, including in the same role or type of work. We are therefore also interested in the number of assignments a given worker receives, as well as the wage paid at each assignment (and whether it increases from one assignment to the next), which might also reflect on worker job performance. In addition, we also examine whether workers transition to a different occupation on a subsequent assignment, and whether this is more likely to occur when a worker is terminated for hard skill performance deficits. And, of course, we are also interested in whether worker assignments convert to permanent jobs (i.e., job orders that end in a hire by the client), for planned "temp-to-hire" assignments and other work assignments. Below, we describe in greater detail these outcome measures: the duration of temporary help job assignments, the likelihood of receiving subsequent job assignments, changes in wages offered on assignments over time and within occupations, changes in occupation of assignments, and permanent job hires and employee quits (self-termination) from assignments.

Study Data

We use detailed data from a large, multinational staffing firm on its U.S. operations from 2007 through 2011. These data include information on all orders (temporary work assignments) with private and public sector organizations over the five-year period that spans the year prior to the start of the recession, through the recession, to the initial years of recovery. These order-level data include information on more than 800 job classifications organized into 13 broader occupational categories, the start and end date of each order, pay and hours for each calendar year in which an individual worked on the order, individual identification number and birth date, location (city, county, state or province, country) of the branch placing each order, and detailed classification of outcomes of the order (including information on employee performance). Orders are classified as temporary help or temp-to-hire. In the latter type, which accounts for about 4 percent of orders in our sample, the client is explicitly evaluating the temporary agency worker for a permanent position in its organization. The data set used in the analyses we report in this paper includes more than 1.8 million job orders.[5]

Characteristics of Temporary Help Jobs

Figure 1 shows the distribution of temporary help hours by broad occupational category over the five-year period covered by our data. The occupational categories are ones used by the temporary help firm and do not correspond strictly to categories used by the statistical agencies. In some cases (e.g. electronic assembly or light industry), broad occupational categories appear to correspond to manual occupations in a particular industry or group of industries. The largest occupational category, by far, is light industry, which accounts for 44.5 percent of hours worked in our data, followed by office occupations (24.7 percent), contact center (8.1 percent), and electronic assembly (6.5 percent). Over two-thirds of the hours are worked in light industry and office occupations, while over 80 percent of hours are worked in the top four categories.

The occupational distribution of hours in our company data is closely comparable to that of employment in the temporary help industry more generally (during the time period of our investigation), according to data collected in Bureau of Labor Statistics' Occupational Employment Statistics (OES) program. In 2006, blue-collar occupations made up 49 percent of employment in temporary help services in the OES data (Dey, Houseman, and Polivka 2012). By comparison, in 2007 light industry and electronic assembly, which together compose manual occupations in our company data, accounted for 48 percent of hours in our sample. Office and administrative support occupations accounted for 25 percent of temporary help employment in the OES data in 2006 and for 25 percent of temporary help hours in our data in 2007.[6] Also, similar to the national data, a small but sizable share of work is in professional and technical occupations. Science, engineering, information technology (IT), accounting and finance, legal, health care, and other professional occupations accounted for 13 percent of temporary help hours in 2007 in our data, compared to 16 percent of temporary help employment in the OES data in 2006.

The temporary help industry in the United States is heterogeneous, and we do not claim that these company data are representative of all firms in the industry. To the extent that they describe a typical, large national temporary-help-service firm, however, they allow us to uncover a number of interesting insights about the temporary help sector not possible with published government statistics and administrative data previously analyzed by researchers, including the role of worker hard and soft skills in their employment outcomes across job orders and over the business cycle. Below, we begin by examining assignment length, the incidence of multiple temporary job holding, and outcomes of temporary help assignments.

Assignment Length and Number of Assignments

Temporary help assignments are, in principal, short-term. Nevertheless, case studies and media reports point to instances in which workers are on assignment for extended periods of time—often more than a year—as temporary help workers (Eisenberg 1999). Our data include start and end dates for each assignment an individual works, permitting us to directly examine the incidence of long-term assignments.

The left panel of Table 1 shows the distribution of assignment length by broad occupational category. To better observe the assignment length distribution in the upper tail, we limit the sample in Table 1 to those assignments commencing in the years 2007, 2008, and 2009; assignments that are still open at the end of 2011 will have lasted for two or more years. Most assignments in our temporary help firm are short; about 58 percent last under a month, while under 3 percent last between one and two years and only about 1 percent exceed two years in length. The distribution of assignment length varies considerably across occupations, however. At one extreme, more than half of marketing assignments last just one day (e.g., working in a booth at a special event), and the duration for 95 percent of them is under a month. In light industry and office, the two largest occupational categories, more than half of assignments last less than a month, while under 5 percent exceed one year. In contrast, assignments in professional and technical occupations tend to be considerably longer. In the two largest professional occupations, science and engineering, more than 85 percent last more than one month and assignments of over a year are not uncommon; the duration is over two years for 6.1 and 9.5 percent of assignments in science and engineering occupations, respectively.

Such figures on assignment length can be somewhat misleading, however, because, particularly in nonprofessional occupations, the data are skewed by the high fraction of workers who quit their assignment or are fired for performance problems before the assignment is complete. Moreover, by definition, long assignments account for a larger share of the total hours worked than do short assignments. The right panel of Table 1 shows the share of all hours worked from 2007 through 2009 that were in assignments of varying durations: under one month, from one to three months, from three to six months, from six to 12 months, from one to two years, and over two years. Long assignments account for a substantial share of temporary help work overall and in all broad occupational groups. While only 2.7 percent of temporary help assignments during the period lasted between one and two years, these assignments accounted for 18.3 percent of hours worked; similarly, while 1.2 percent of assignments during this period lasted more than two years, they accounted for 13.6 percent of hours worked. In light industrial occupations, more than a quarter of hours worked were in assignments lasting over one year, and almost 10 percent were accounted for by assignments lasting over two years. In engineering occupations, about two-thirds of hours worked occurred in assignments with over one-year durations, and more than 40 percent were in assignments exceeding two years.

The total amount of time an individual works for a temporary help agency is determined by the number of assignments as well as their average length. Among all individuals in our data, the median number of assignments with this staffing company is two, whereas the mean is 10, reflecting that a substantial number (primarily in marketing) hold many assignments. There is a clear inverse relationship between the length of assignments and the number of assignments an individual holds. At one extreme, the median individual working in marketing holds 13 assignments, and the mean number of assignments is 49. In contrast, in occupations characterized by very long assignment lengths, such as science, engineering, (information technology) IT, and accounting and finance, the median individual holds only one assignment with the staffing company over the five-year period; in all but IT, the mean number of assignments is less than two.[7]

Assignment outcomes

As described above, the data include detailed coding on why an order closed that provide insights into the problems temporary help agencies have in matching workers and firms and the extent to which client organizations use temporary help agencies to screen workers for permanent jobs. The top panel of Table 2 shows the distribution of reasons an order was closed by broad occupation for assignments commencing between 2007 and 2010.[8] Among the most striking findings in the table is the high rate at which temporary help workers were terminated for performance problems, particularly in the manual, low-paying occupations. In light industry and electronic assembly, about one in four orders ended in termination for a performance problem. Moreover, about two-thirds of terminations for performance problems were the result of soft skills deficiencies. Table 3 presents additional details on the types of soft skills deficits observed on assignments by occupation. While soft skills performance problems, primarily attendance and tardiness issues, dominate hard skill performance problems in blue-collar occupations, hard skill deficits were more common (relative to soft skills problems) in the professional occupations (i.e., scientific, legal, engineering and information technology). Behavioral and drug and alcohol problems occurring at the workplace—e.g., intoxication on the job—were rarely cited and were likewise more prevalent in blue-collar vs. professional occupations. These would be relatively extreme examples of substance abuse interfering with work; for example, it is possible that attendance or behavioral problems could also reflect employee issues with substance use, but they would not be identified as drug or alcohol problems while on assignment.

These findings indicate that soft, not hard, skills may be the most critical barriers to employment for low-paid, low-skilled workers, which is consistent with research suggesting that the importance of soft skills has been undervalued in labor market policy (Heckman and Kautz 2012). In addition, about 14 percent of orders ended because the worker quit before the assignment was completed, with personal reasons rather than work-related dissatisfaction with assignments dominating these quits. Temporary help workers quit assignments before completing them in 15 percent or more of assignments in light industry, electronic assembly, contact center, scientific, engineering, and accounting and finance occupations.

Together, these data point to a significant challenge that temporary help agencies have in finding good matches between workers and organizations. Overall, more than 30 percent of assignments ended either because the temporary worker quit or was fired, and that figure topped 40 percent in three out of the four largest occupational groupings—light industry, contact center, and electronic assembly, which also constitute the lowest-paying occupations. It is possible that the difficulty of recruiting and retaining workers in these positions helps explain companies' extensive reliance on temporary help agencies to fill them. With our data, however, we are unable to determine whether companies could recruit temporary workers on their own in a more effective and less costly manner.

An outcome of particular interest is the incidence of orders ending in a hire by the client. A majority of temporary help workers desire regular employment, and companies often cite the ability to screen workers for hire as a rationale for using temporary help agencies. Case study evidence suggests that managers may feel they can be more selective in their hiring when they work through temporary help agencies because they do not personally have to engage in the unpleasant task of firing the worker on probation (Houseman, Kalleberg, and Erickcek 2003). Managers may also feel that screening through temporary help agencies lowers the odds of being sued by a disgruntled worker who is fired following a probationary period.

Across all orders in our company data, a small share, 7 percent, ended in a hire by the client company. The extent to which organizations recruit permanent staff from temporary help agencies, however, varies considerably across occupations. In the nonprofessional occupations, assignments in contact centers and electronic assembly are most likely to end in a hire by the client (12-13 percent). In professional occupations, which are associated with longer assignments, a comparatively high share of temporary orders end in hires: most notably, 22 percent in science, 20 percent in accounting and finance, and 16 percent in engineering. Among professional occupations, legal is an outlier, with only 4 percent of orders resulting in hires by the client.

Because individuals may hold multiple assignments, the probability of ever obtaining a direct-hire job with a client is higher. Over the five-year period studied, almost 14 percent of individuals taking temporary help or temp-to-hire assignments obtained a job with a client. That share was 11.6 percent for those in light industry occupations and 17-19 percent for those in office, contact center, and electronic assembly occupations; those in science occupations had the highest hire rate with clients, 30 percent. The interpretation of the hire rate data in the top panel of Table 2 is complicated by the fact that a sizable, but unknown, share of temporary help workers may not want permanent employment with the client organization.

Temp-to-hire outcomes. Temp-to-hire contracts, which account for 4 percent of the orders in our sample, are not subject to this interpretation problem. In these cases, the client company is explicitly trying out a worker for hire, and the worker understands that he or she is auditioning for the job. The bottom panel of Table 2 shows the distribution of outcomes of temp-to-hire orders by broad occupation. While the share obtaining jobs with the client is considerably higher in temp-to-hire contracts than in regular temporary contracts, a minority of these assignments ended in a hire.[9] Overall, 27.5 percent of temp-to-hire contracts resulted in a hire, and within all occupations, the share was 50 percent or less. In fact, the share of temp-to-hire orders ending in termination for performance problems (29 percent) was greater than the share resulting in a hire and exceeded the share terminated for performance problems in regular temporary help contracts. In light industry, 24 percent of orders were terminated because of a performance problem related to soft skills, more than double the 11 percent terminated owing to hard skills deficits. The data also show that a sizable minority of temp-to-hire workers (19.1 percent overall) quit before the assignment ended, either because of dissatisfaction with the job (6 percent) or for personal reasons (13 percent). In addition, 13 percent of temp-to-hire assignments overall appeared to be satisfactorily completed but did not end in a hire.

Although a minority of those in temp-to-hire contracts obtained a job with the client company, it is important to note that turnover among newly hired employees is generally high in the U.S. economy. Temporary help workers spend their probationary period—which often runs 3 months or longer—on the payroll with the temporary help company, and the distribution of tenure with the client company (including the tenure on the payroll of the temporary help company) may not differ substantially from that of new direct-hire employees. To provide a benchmark for the outcomes among workers in temp-to-hire contracts reported in Table 2, we utilize Census Bureau Quarterly Workforce Indicators (QWI), which are derived from the Longitudinal Employer-Household Dynamics (LEHD) linked employer-employee microdata. Published QWI statistics permit the construction of a couple of measures of job stability: 1) the share of workers hired at some point during the quarter who still have earnings from that employer in the following quarter, and 2) the share of newly hired employees who receive earnings from a particular employer for at least one full quarter.[10] We use these definitions to construct comparable measures for workers in temp-to-hire contracts in our company data. In instances where the individual ends the assignment but is hired by the client company, we assume the employment relationship continues. Because some individuals hired by the client will subsequently quit within one or two quarters, our measures will somewhat overstate the stability of jobs in our temporary help sample.

In the national data between 2007 and 2011, 66 percent of newly hired employees had some earnings in the quarter following the quarter of hire and only 44 percent of newly hired employees remained with their employer for at least a full quarter. In our sample of workers in temp-to-hire contracts, the comparable figures are 61 percent and 38 percent, respectively, or 5 to 6 percentage points below the national average during this period. Measures of job stability, however, differ greatly across occupations in our sample. Among those in light industry occupations, for example, 53 percent of those in temp-to-hire contracts were still with the client company in the quarter following the start of their assignment and 30 percent were employed with the client organization for at least a full quarter. These job retention figures are 15 to 25 percentage points below comparable figures for new direct-hires in manufacturing, wholesale trade, and transportation and warehousing—industries where those in light industry occupations are generally placed.[11] Although not definitive, together these data suggest client organizations are being quite selective about whom they hire from the ranks of temporary help workers.

The Role of Hard and Soft Skill Performance Problems in Individual Employment Outcomes

In this analysis, we examine the relative importance of hard and soft skills performance issues in the duration of temporary help job assignments, the likelihood of receiving subsequent job assignments, changes in wages offered on assignments over time and within occupations, and occupation transitions across assignments. We estimate Cox proportional hazard models of the (log) of assignment length (in days)—where a “failure” is defined as the end of an assignment prior to satisfactory completion—to examine the role of hard and soft skills performance problems in the time to an assignment's end, controlling for the year of the order start, economic conditions, temp-to-hire contracts and other reasons for assignment closure (where assignments terminated for reasons unrelated to performance are the reference category).[12] In separate models, we also include interactions between measures of hard and soft skills performance problems and the occupation indicators, and we alternatively estimate the hazard models separately for each broad occupational category.

In probit regression models, we estimate the probability of receiving a second (and third) job assignment after completing a first (and second) assignment, conditional on performance (on hard and soft skills dimensions) on the first (and second) assignment and including the other controls mentioned above. About half of the workers in our sample had more than one job assignment over the period we observe them; 18 percent had two job assignments, 9 percent had three assignments, and a little over 20 percent had four or more assignments.[13] We also estimate regression models to examine how wages changed from a first to a subsequent job assignment and how they relate to hard and soft skills performance on the prior assignment. Correspondingly, we examine whether workers transition to a different occupation on a subsequent assignment, and whether this is more likely to occur when a worker is terminated for hard (vs. soft) skill performance deficits. We see these analyses as primarily descriptive. Where the unit of analysis is a job order (assignment), we calculate robust standard errors clustered on the individual employee.

Job Assignment Length

In this particular analysis, we focus on completed temporary help assignments, using data that specify the reason for assignment closure, including details on performance problems when a job assignment did not close satisfactorily. This eliminates issues of censoring and allows for estimation of a simple Cox proportional hazard model (via maximum likelihood) of the log of assignment length, using the Breslow method for handling tied failures in calculating the log partial likelihood. In a Cox proportional hazards model (Cox, 1972), the hazard function is not directly estimated,

$$h(t) = h_0(t)\exp(\beta_1 x_1 + \ldots + \beta_k x_k)$$

but the model provides estimates of $\beta_1 x_1$ to $\beta_k x_k$ and their variance. The failure rate of an assignment ending depends in part (in our model) on whether performance problems arose, and specifically, the types of (soft and hard skill) performance issues that led to its closing, which potentially affect the relative risk of failure (assignment termination). We also estimate the hazard ratios for workers who remove themselves from assignments (separately for work or personal reasons) and for those whose assignments end due to information obtained in a background or drug screening or that close because they are hired into a permanent job by the client firm. Controls for worker age (and age-squared), occupation, county unemployment rates, state and the year that the assignment began are also included in the hazard models.

The hazard model results for the key variables of interest are summarized in Table 4 (presented as hazard ratios) for the overall sample (Panel A), and the results for the same hazard model estimated by occupation (i.e., without occupation controls) are also shown (Panel B). The findings indicate that both hard and soft skills performance issues factor importantly into job assignment length, and there is a fairly clear "hierarchy" in the relative importance of various soft skills across different occupations. Workers whose performance was hampered by drug or alcohol-related issues on the job had the highest hazard of experiencing the termination of their job assignment; across all occupations the hazard rate was 125 percent higher than those whose assignments ended for non-performance related reasons. Workers who removed themselves from job assignments due to work-related issues such as dissatisfaction with duties, pay or hours (or their timing), etc. had the next highest hazard rate (114 percent higher), followed by those identified as having hard skill performance problems (92 percent higher hazard rate of termination). If background pre-screening or drug test results flagged problems, the hazard rate was 86 percent higher (relative to those whose assignments ended for non-performance related reasons). Workers with attendance or tardiness issues had 66 percent higher hazard rates of termination, and the hazard rates for behavioral problems and policy noncompliance on job assignments were similar (27% and 29% higher hazard rates, respectively). Workers whose job assignments ended in a permanent hire had the longest assignment lengths; their hazard rate of assignment termination was 24 percent lower than those whose assignments ended for non-performance related reasons.

In the hazard models in which we interacted the indicators for performance problems with the occupation of assignment, the hierarchy of relative importance of the different soft and hard skills was maintained in the main effects (of performance problems)—that is, workers terminated for drug or alcohol-related issues on the job and those who removed themselves for work-related issues had the highest hazard rates. In examining the interaction terms, there were only a few notable divergences from the overall pattern (main effects) of how performance problems affected the length of assignments. Specifically, in the electronic assembly occupations and other professional services, workers with policy non-compliance issues had the highest hazard rates of termination, and in electronic assembly work, this was followed closely by hard skills performance problems.[14]

In the Cox proportional hazard models that we estimated separately by broad occupation (see Table 4, Panel B), we also included a control for the expected assignment length to account for the considerable differences in typical assignment length by broad occupation (as shown in Table 1).[15] The results presented in Panel B show that information technology, contact center, legal/finance, other professional service and engineering/scientific occupations had noticeably higher hazard rates (and presumably less tolerance) for drug and alcohol abuse problems at the work site. The hazard of experiencing termination of a job assignment for substance abuse problems at work was highest (369 percent higher) in information technology occupations and was 175-311 percent higher in the other four occupations noted above (relative to the reference category of assignments terminated for non-performance related reasons). Contact center and electronic assembly workers also had their job assignments more rapidly terminated (551 and 361 percent higher hazard rates, respectively) for problems identified in background screening and drug testing. In general, employee pre-screening was significantly more likely to result in assignment terminations in the blue-collar occupations. In all broad occupations, the soft skills performance problems dominated hard skills issues in assignment terminations.

Subsequent job offers. The results of probit regressions estimating the probability of a second (and third) job assignment conditional on prior assignment performance are shown in Table 5 and suggest some similarities, as well as differences, in the relative importance of performance problems to subsequent job offers. Performance problems associated with drug or alcohol abuse again loomed large; the probability of getting work on a second assignment was 33 percent lower if there was a history of these problems on a first assignment. And if background screening or drug test results flagged concerns, a worker had a 31 percent lower probability of securing a second assignment. The probability of getting a third job assignment was even lower (44 percent) if there was drug or alcohol abuse on a second assignment (or a negative screening result, 43 percent lower), and performance problems on the first assignment also factored into the likelihood of getting a third assignment, so that drug or alcohol problems on both previous assignments reduced the probability of a third job assignment by 58 percent.

Attendance and tardiness problems, on the other hand, factored more critically into the likelihood of receiving subsequent job assignments than they did (relatively) in assignment length. The probability of a second assignment was reduced by 31 percent if a worker had attendance problems on a first assignment, and again, the penalty was even stiffer when it came to a third assignment (32% lower probability if attendance or tardiness was an issue on the second assignment, and an additional 6% lower if this was a problem on the first assignment as well). In fact, the results in Table 5 show that the identification of any of the soft skills performance problems on a prior assignment was more likely to reduce the probability of a second (or third) job assignment than performance problems related to hard skills deficits.

Wage progression across assignments. In the temporary help industry, each assignment represents a new job on which a new wage is set, and for each job order, we have data on payments and hours by calendar year. For this analysis, we have calculated the average hourly wage on the job assignment as total payments divided by hours worked (in the first calendar year of the order), and we also deflate hourly wages by the appropriate metropolitan-level Consumer Price Index published by BLS.[16] Keeping in mind that workers with soft skill performance problems were significantly less likely to be offered subsequent job assignments, it might not be surprising to see that workers' wages on second job assignments were hit harder (reduced more relative to wages on their first assignment) when hard skill (vs. soft skill) deficiencies were identified on their first assignment (see Table 6), relative to workers whose first assignments ended due to non-performance related reasons. Workers whose first assignment ended due to hard skill performance deficits were paid on average $0.49 less per hour on their second (vs. first) assignment than those without any performance problems; this compares to decrements in hourly wages ranging from $-0.16 to $-0.46 for previously observed soft skill deficiencies (although the estimate for workers with prior substance abuse issues on assignment was not statistically significant). Interestingly, the largest reduction in hourly wages on second assignments was experienced by workers whose background screening or drug test results on a prior assignment were unfavorable; the average hourly wage for these workers on a second assignment was $2.67 lower than the average hourly wage on their previous assignment (relative to those whose first assignments ended due to non-performance related reasons). These results might imply that "second chances" come at a high price (i.e., a cost in the form of substantially reduced hourly wages on subsequent job assignments).

We were also particularly interested in understanding whether workers transitioned to a different occupation on a subsequent job assignment, and if they were more likely to change occupations if the prior assignment terminated because of a hard skills performance concern. Overall, 80 percent of the subsequent job assignments were in the same broad occupation, implying that only a fifth of the next assignments represented a transition to a new occupation. Among workers who were previously terminated for a hard skills performance issue, however, more than one-fourth transitioned to a different occupation on the next assignment. We also estimated a probit regression with a dependent variable constructed to indicate whether the next work assignment was in a different occupation, controlling for the year of the order start, economic conditions, temp-to-hire contracts and other reasons for assignment closure. We similarly found that the probability of transferring to a different occupation on a subsequent job assignment was highest for workers who were terminated for a hard skill problem on the prior work assignment (about 18.5 percent greater than when the assignment ended without a performance issue). Workers who had removed themselves from the prior work assignment due to work-related issues (e.g., dissatisfaction with duties, pay or hours) had a similarly high probability of transitioning to another occupation. The next highest probability of transferring to a different occupation was observed when the prior work assignment was terminated for a policy non-compliance problem (about 16.3 percent higher relative to assignments ending without performance issues).[17] In effect, following termination for a hard skill performance deficit, temporary help workers were more likely to transition to another occupation and earn a lower wage on the next job assignment. We also more generally confirmed that workers who transitioned to a different occupation on a subsequent job assignment were significantly more likely to experience a pay decrement.

Temporary Help Employment and Worker Performance in Recession and Recovery

The temporary help industry has played an increasingly important role in labor market adjustment during recessions and recoveries, in part because of its rapid expansion into the cyclically sensitive manufacturing sector in the 1980s and 1990s (Dey, Houseman, and Polivka 2012). Consistent with this fact, our data show the largest cyclical variations in hours worked occurred in light industrial and electronic assembly occupations, which primarily serve manufacturing clients. We use our company data to gain an understanding of the role the temporary help industry plays in gross job flows in the economy. BLS estimates gross hires and separations for payroll employment for the economy overall and by aggregate industry using data from the Job Openings and Labor Turnover Survey (JOLTS). According to BLS data, the professional and business services industry, to which temporary help services belong, accounted for between 17 and 21 percent of gross hires and separations in the economy between 2007 and 2011, although only 12 to 13 percent of workers were employed in this sector.

Our detailed company-level data, with information on the start and end dates of each order held by an individual from 2007 through 2011, allow us to estimate hire and separation rates. In order to generalize our findings to the temporary help industry overall, we must assume that hire and separation rates in our company are generally representative of the industry. The size and national reach of the company, along with the similarity of its occupational distribution to that of the temporary help industry as a whole, suggest this assumption is reasonable. In addition, we must make assumptions about what constitutes hires and separations in the temporary help firm. A temporary help firm may not consider an individual who starts a new assignment a hire if that individual recently was on another assignment for the agency. Similarly, the firm may not count an individual who ends an assignment as separating from the firm if that individual will receive a new assignment within a short time. The questionnaire used for temporary help firms in the JOLTS survey leaves the respondent with considerable discretion in classifying hires and separations.[18]

We first compute monthly hires and separations for the firm using conservative assumptions: hires are individuals who commence a new assignment during the month and have not been on another assignment within the previous 30 days; similarly, separations are individuals who terminate an assignment and are not placed into a new assignment during the subsequent 30 days. The hire and separation rates are then computed as the number of hires or separations divided by the number of unique individuals on assignment in the firm during the middle week of the month. The top panel of Table 7 displays the average monthly hire and separation rates computed using this first assumption (labeled "low"), along with average monthly hire and separation rates for all payroll employment from the JOLTS data. In our data, hire and separation rates in the temporary help firm are on the order of seven to eight times higher than those for the economy overall. If our company is representative of the temporary help industry, our data imply that this industry accounted for 11 to 14 percent of gross hires and 10 to 15 percent of gross separations during the period, as shown in the bottom panel of Table 7.

Arguably, hire and separation rates computed in this way do not fully capture the importance of the temporary help industry in filling jobs in the economy. For temporary help workers, the temporary agency is the employer of record, and, consistent with the concept of hires and separations used in the JOLTS survey, we compute hire and separation rates between the temporary help employee and the agency. However, each order commenced and terminated represents a hire and separation with a client company. In the top panel of Table 7, we also display estimates in which we compute hire and separation rates as the number of new orders commenced or terminated during the month divided by the number of unique individuals on assignment during the middle week of the month. These estimates (labeled "high") suggest monthly hire and separation rates on the order of 11 to 12 times higher in the temporary help industry than in the economy overall. Assuming our data are representative of the temporary help industry and adjusting national statistics for the "undercount" of hires and separations in temporary help, we find that the temporary help industry accounts for somewhere on the order of 17 to 21 percent of gross hires and 15 to 21 percent of gross separations during the period.[19]

Industry dynamics in recession and recovery

Macro forecasters and analysts pay careful attention to trends in the temporary help industry, because employment gains in temporary help, after a short lag, usually translate into broader gains in the private sector. Although the recession officially ended in June 2009 and the temporary help industry began registering solid employment gains by the end of the year, aggregate employment continued to fall until early 2010, and employment growth for the most part was weak thereafter, particularly in mid-2011 and early 2012. Weak employment growth during the period is widely interpreted as being a result of companies' uncertainty over the strength of the recovery and their reluctance to take on permanent employees (International Monetary Fund 2012).

Our data provide evidence of these dynamics over the business cycle. Among the most striking patterns in our data is that the share of temporary help workers dismissed for performance problems related to "soft" skills (e.g., tardiness, absenteeism) fell quite sharply in nonprofessional occupations in 2008 and 2009, during the depth of the recession, and ticked up in 2010, the initial year of recovery. Similarly, during the recession years, workers in all occupations were generally less likely to quit their assignment before completing it. These patterns likely reflect the fact that a better pool of workers is available for temporary help assignments when unemployment is high. The decline in performance problems and quit rates may also reflect a change in worker behavior; temporary help workers may be more conscientious about their performance on the job when alternative opportunities are scarce, as the "penalty" associated with termination increases in a recession (Yellen 1984). The improvement in the quality of workers in temporary help positions, by itself, would be expected to increase the rate at which these workers were offered permanent positions with the client. However, in the recession years of 2008 and 2009, the incidence of hiring by clients fell in most occupations, and together with the decline in the incidence of performance problems and quit rates, the share of assignments that were satisfactorily completed without a hire rose.[20]

Given evidence pointing to better-quality job candidates when unemployment is high, one might expect that the incidence of hiring in temp-to-hire contracts would increase during recession years. Instead, our data show that the rate at which temp-to-hire contracts were converted to permanent jobs with client organizations was lower in 2008 and 2009 than in 2007.[21] Although possible, it is doubtful that the rate at which workers turned down job offers from client firms increased during the recession years. Instead, given economic conditions and widespread uncertainty about the future, the economic outlook for some of these firms may have declined during the course of the probationary period, making them less inclined to take on permanent staff. Alternatively, given high unemployment, employers may have become more selective about whom they hired during the recession. This explanation has been offered for the broader phenomenon of high vacancy rates during the recovery (Cappelli 2012).

While hiring rates and total hours worked fell in 2008 and 2009 in all occupations, the median length of assignments rose in most occupations during the recession. An increase in assignment length could be further evidence that firms were responding to the uncertain economic environment—and fears of a double dip recession—with greater reliance on temporary help. However, descriptive statistics on assignment length conflate firm demand for temporary workers with the changing composition of the workforce; the fact that fewer temporary help workers were dismissed for performance problems or quit without completing the assignment would in and of itself lead to a rise in assignment length (as also suggested by our hazard model findings). In addition, changes over time in the composition of jobs within these broad occupational categories could be affecting assignment length.

To control for the effects of worker and job composition on assignment length, we model assignment length as a function of the year in which the assignment started, along with a set of order-level and person-level controls:

$$L_{oi} = \beta_1 X_{oi} + \beta_2 X_{o} + \beta_3 Y_{ot} + \beta_5 S_{o} + \mu_{o}\,,$$

where L_{0i} is the logarithm of assignment length for order *o* held by individual *i*, X_i is a vector of individual characteristics that include age and its square and total temporary assignments worked by individual *i* the during the five-year period and the square of total temporary assignments; X_o is a vector of order-level controls that include the starting hourly wage, order type (temporary versus temp-to-perm), and indicator variables for detailed occupation of the job being filled; Y_t is a vector of indicator variables for the year in which the assignment started; and S_o is a vector of state indicator variables.[22] We cluster the standard errors on the individual.

For orders starting in the years 2007, 2008, and 2009, our data include information not only on actual end date of the assignment but also on the expected end date at the time the order was placed. Actual assignment length may be less than expected, typically because the individual assigned to the order quits or is fired prior to its completion. On the other hand, actual assignment length may exceed the expected length if the employer extends the order after placing it. In the models reported in Table 8, we limit the sample to the years 2007–2009 and estimate models in which the dependent variable is alternately the log of actual or expected assignment length. Limiting the sample to orders commencing in these three years facilitates comparison of the determinants of actual and expected job length and minimizes problems of censored spells. In less than 1 percent of the cases, no assignment close date had been recorded as of the end of 2011. In these instances, we top-code assignment length at 720 days, although deleting these orders from our sample has no substantive effect on our estimates.[23]

The top panel of Table 8 reports the coefficient estimates on the start year indicator variables from OLS models, which are estimated separately for the four largest occupational categories: light industry, office, contact center, and electronic assembly. The coefficient estimates in the OLS models suggest that, controlling for order and individual level covariates, actual assignment durations were significantly longer in 2008 and 2009 compared to 2007 in all occupational categories. Estimates for expected assignment length display the same time patterns, except in light industry. In that occupational group, estimates show that expected assignment length was about 2.3 log points lower in 2008 and 12.1

log points lower in 2009 relative to 2007. The discrepancy in the time pattern of estimates for expected versus realized assignment lengths for light industry, which also displayed the greatest decline in total hours during those recession years, suggests that employers extended temporary assignments in lieu of hiring permanent employees in the face of uncertainty and a weak recovery.

One might be concerned, however, that in spite of the detailed controls included in these models, they inadequately capture changes in the composition of the temporary help workforce over the business cycle. To address this concern, we estimate the effects of start year on assignment length using multilevel models that control for both individual random and fixed effects. In the models we estimate, L_{ti} is the outcome (e.g., assignment length) at measurement occasion t (a temporary work assignment, $t = 1, \ldots,$ T_i) for individual i ($i = 1, \ldots, n$), where time is measured by the start date of a new work assignment. In other words, the number of observations for a given individual in our sample is equal to the number of temporary work assignments (orders) he or she had between 2007 and 2009. This modeling approach allows both the number of measurement occasions and their timing to vary across individuals (i.e., they do not need to be balanced in the sample).

At level one of the multilevel model, we model assignment length over time, across changes in the economy that are captured with time indicators (i.e., dummies for years linked to the order start date). We also add other order/time-varying covariates, as described above (e.g., detailed job information, starting wage, order type):

$$L_{ti} = \pi_{0i} + \pi_{1i}X_{1ti} + \pi_{2i}X_{0ti} + \pi_3 Y_{0t\,t} + \pi_{4i}S_0 + r_{ti}\,.$$

At level two, the intercept from the level-one model is specified as random and a function of individual worker characteristics that do not vary by order or time (e.g., total number of assignments with temp agency, state of residence):

$$\pi_{0i} = \beta_{00} + \beta_{01}X_{i(1)} + u_{0i}\,.$$

These level-one and level-two models are estimated simultaneously with unstructured errors. (See Singer and Willett [2003] and Gordon and Heinrich [2004] for a more thorough discussion of multilevel models and their interpretation.)

The coefficient estimates on the year start variables in our multilevel models, reported in the bottom panel of Table 8, are generally somewhat lower in magnitude compared to those from regression models that do not control for individual fixed and random effects, but in most cases the two sets of estimates display similar time patterns. In particular, multilevel models indicate that relative to 2007, actual assignment length in light industry fell slightly in 2008 (a 1.7 log point drop) and was somewhat higher (1.3 log points) in 2009 relative to 2007. Especially notable is the fact that the estimates for actual assignment length do not display the strong negative time patterns of those for expected assignment length in light industry occupations, suggesting that, particularly in 2009, manufacturing employers responded to the very weak and uncertain economic conditions by extending contracts for temporary agency workers.[24]

We also estimated comparable OLS and multilevel models showing the effects of start year on realized assignment length on a larger sample that included orders commencing between 2007 and 2010. In these models, assignment length for orders that had not ended as of 2011 were top-coded at 360 days. Coefficient estimates on the indicator for 2010 are positive and statistically significant in OLS and multilevel models for all four occupational categories. Coefficient estimates on the indicator variables for the other years are similar to those reported in Table 8.[25] Taken together, the results from these models suggest that, controlling for workforce and assignment composition, temporary work assignment durations significantly increased during the recession, or increased relative to the planned durations, in the four largest occupational categories.

Conclusion

Drawing on unique data from a nationally representative temporary help firm, this study generated insights into the characteristics of temporary help jobs, the implications of worker hard and soft skills (deficiencies) for employment outcomes, and the role that temporary help employment played during the recent tumultuous economic period. Nearly a third of job assignments in our data ended prematurely because the worker was terminated for performance problems or quit before completing the assignment. That figure exceeded 40 percent in three of the four largest occupational categories: light industry, contact center, and electronic assembly. Terminations for tardiness, unexcused absences, and other soft skill problems were especially high among temps in non-professional, low-paid occupations. And although their prevalence was considerably lower, the repercussions for workers who exhibited problems with substance abuse (e.g., intoxication) on the job were severe; they were the most swiftly terminated from their job assignments and were least likely to be offered a subsequent assignment. Following substance abuse problems, hard skills deficits were generally the second performance concern most likely to contribute to the quicker end to a job assignment, along with individuals removing themselves from assignments for work-related reasons (e.g., dissatisfaction with job duties, pay, hours, benefits, work conditions, etc.). Overall, in all occupations, soft skills performance problems dominated hard skills issues in their implications for continuing employment, but hard skills deficits had slightly larger repercussions for subsequent wage offers (and occupational transitions).

In about 7 percent of the assignments we observed, temporary help workers were hired by the client, while hire rates were 20 percent or more in science and finance and accounting occupations. More striking, however, were the low hire rates of workers in *temp-to-hire* contracts. Only about a quarter of workers in those contracts transitioned to a permanent job with the client, and looking within occupations, the hire rate was 50 percent or less in professional and technical occupations. Our analysis suggests that employers may use the screening process offered through temporary agencies to be highly selective in hiring, and the large share of workers going through this process do *not* make the cut.

Despite its relatively small size, the temporary help industry plays an important role in adjusting labor during recession and recovery. To the extent that our data represent the industry fairly well, they suggest that the temporary help industry accounted for a sizable share of gross hires and separations during the downturn and initial recovery years. In addition, our data reveal significant changes in the composition of the temporary help workforce and in employer behavior over the time period studied. As the economy entered a deep recession, the quality of the temporary workforce improved, as evidenced by a decline in terminations for performance problems and quits in all occupations. At the same time, employers generally lengthened assignments and reduced hiring from the pool of temporary workers, in spite of an improvement in the quality of workers and even in cases where the employer was explicitly using temporary help agencies to screen workers for permanent jobs. These findings may indicate that, given high unemployment and a weak and uncertain recovery, employers were wary of hiring employees and became especially selective in making job offers to temporary help workers. Lastly, in combination with research showing that recessions and the lack of work that comes with them can increase the risk of substance abuse (Compton et al., 2014), our findings above on the severely negative associations of drug and alcohol abuse with temporary help job outcomes (continuing employment, wages) and the prevalence of other soft skills problems (that could be related to substance abuse and mental health problems), suggest that these labor market challenges could be enduring (and compounding in their effects) long after the recession's end.

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Table 1: Distribution of Assignment Length by Broad Occupation (percent)

	Orders commencing 2007–2010 by job length						Share of hours worked 2007–2010 by job length					
	< 1 month	1–3 months	3–6 months	6–12 months	1–2 years	> 2 years	< 1 month	1–3 months	3–6 months	6–12 months	1–2 years	> 2 years
Nonprofessional occupations												
Light industrial	59.9	20.8	11.2	5.4	2.1	0.7	8.6	18.6	24.3	22.8	16.1	9.6
Office	53.3	21.6	13.4	7.2	3.2	1.3	5.7	15.1	21.7	22.8	19.0	15.7
Contact center	35.8	28.1	22.2	10.3	3.0	0.6	4.5	16.5	31.1	27.5	14.9	5.4
Marketing	94.9	3.6	0.9	0.4	0.2	0.1	40.1	23.0	11.5	9.3	6.9	9.1
Professional & technical occupations												
Scientific	13.3	20.1	24.6	22.8	13.2	6.1	0.9	5.5	15.6	27.5	27.2	23.3
Engineering	12.2	19.7	21.7	22.4	14.7	9.4	0.6	3.8	9.8	20.0	25.2	40.6
Information technology	28.3	20.0	19.1	17.0	10.1	5.6	1.6	6.1	13.3	23.1	24.9	31.0
Accounting/finance	23.2	27.4	26.2	15.1	6.4	1.7	2.3	12.3	25.0	27.4	21.6	11.4
Legal	35.9	27.9	14.7	10.6	8.4	2.6	4.5	13.5	15.5	19.4	21.4	25.8
Health care	45.2	23.3	16.8	9.8	3.5	1.4	4.7	14.5	24.5	28.6	15.5	12.2
Creative services	38.4	25.2	16.4	9.8	6.4	3.8	3.8	11.5	16.8	20.4	23.8	23.6
Professional (other)	55.5	33.0	7.8	2.2	1.0	0.5	17.6	26.6	17.6	14.6	12.7	10.8
Total	57.79	20.39	11.86	6.29	2.66	1.01	6.7	15.7	22.3	23.4	18.3	13.6

SOURCE: Authors' calculations.

Table 2: Distribution of Assignment Outcomes by Broad Occupation

Panel A:				Performance problem		Quit			
All job assignments		Hired	Completed assignment	Hard Skills	Soft Skills	Work-related reason	Personal reason	Back-ground/ drug screen	Not performance-related
Non-professional occupations									
Light Industrial	N	56,271	353,579	62,688	157,960	37,117	105,603	9,270	115,102
	%	6.27	39.39	6.98	17.6	4.14	11.77	1.03	12.82
Office	N	32,768	237,028	21,905	25,084	10,960	37,642	1,154	44,007
	%	7.98	57.73	5.34	6.11	2.67	9.17	0.28	10.72
Contact Center	N	14,370	28,133	10,854	18,621	5,828	17,824	1,068	15,972
	%	12.75	24.97	9.63	16.53	5.17	15.82	0.95	14.18
Electronic Assembly	N	7,106	13,044	4,480	9,932	2,401	9,301	348	12,314
	%	12.06	22.14	7.6	16.86	4.07	15.78	0.59	20.9
Marketing	N	654	157,534	1,070	2,037	960	2,386	107	2,807
	%	0.39	94.02	0.64	1.22	0.57	1.42	0.06	1.68
Professional and technical occupations									
Scientific	N	5,244	5,687	1,238	1,235	619	3,954	53	6,301
	%	21.55	23.37	5.09	5.08	2.54	16.25	0.22	25.9
Accounting/Finance	N	2,999	5,084	1,200	789	449	2,002	39	2,545
	%	19.85	33.65	7.94	5.22	2.97	13.25	0.26	16.85
Engineering	N	2,847	5,167	791	714	292	2,277	43	5,245
	%	16.38	29.74	4.55	4.11	1.68	13.1	0.25	30.19
Information Technology	N	1,678	6,145	778	739	459	1,690	52	3,554
	%	11.12	40.71	5.15	4.9	3.04	11.2	0.34	23.54
Professional (Other)	N	1,597	48,107	1,945	1,063	563	3,267	17	14,978
	%	2.23	67.25	2.72	1.49	0.79	4.57	0.02	20.94
Healthcare	N	1,193	6,887	688	880	378	1,231	56	1,520
	%	9.3	53.67	5.36	6.86	2.95	9.59	0.44	11.84
Legal	N	508	9,127	402	241	100	1,202	7	1,127
	%	4	71.79	3.16	1.9	0.79	9.45	0.06	8.86
Creative Services	N	241	1,255	113	74	48	199	2	511
	%	9.86	51.37	4.63	3.03	1.96	8.15	0.08	20.92

NOTE: The sample includes orders commencing from 2007 through 2010.
SOURCE: Authors' calculations.

Table 2 (continued)

Panel B:				Performance problem		Quit			
Temp-to-hire assignments		Hired	Completed assignment	Hard Skills	Soft Skills	Work-related reason	Personal reason	Back-ground/ drug screen	Not performance-related
Non-professional occupations									
Light Industrial	N	8,684	4,391	4,248	9,737	2,610	5,324	520	4,330
	%	21.8	11.02	10.66	24.44	6.55	13.36	1.31	10.87
Office	N	5,305	3,115	1,569	1,452	867	1,769	75	1,566
	%	33.75	19.82	9.98	9.24	5.52	11.25	0.48	9.96
Contact Center	N	2,838	839	1,098	2,038	652	1,628	102	853
	%	28.24	8.35	10.93	20.28	6.49	16.2	1.02	8.49
Electronic Assembly	N	738	366	240	397	117	318	11	445
	%	28.04	13.91	9.12	15.08	4.45	12.08	0.42	16.91
Marketing	N	114	52	41	49	28	42	4	38
	%	30.98	14.13	11.14	13.32	7.61	11.41	1.09	10.33
Professional and technical occupations									
Scientific	N	1,335	248	175	161	119	361	7	282
	%	49.67	9.23	6.51	5.99	4.43	13.43	0.26	10.49
Accounting/Finance	N	586	250	135	93	70	142	1	150
	%	41.07	17.52	9.46	6.52	4.91	9.95	0.07	10.51
Engineering	N	301	106	69	49	23	82	1	118
	%	40.19	14.15	9.21	6.54	3.07	10.95	0.13	15.75
Information Technology	N	324	96	69	84	34	107	4	76
	%	40.81	12.09	8.69	10.58	4.28	13.48	0.5	9.57
Professional (Other)	N	287	95	45	31	25	46	1	53
	%	49.23	16.3	7.72	5.32	4.29	7.89	0.17	9.09
Healthcare	N	146	121	60	70	22	84	8	57
	%	25.7	21.3	10.56	12.32	3.87	14.79	1.41	10.04
Legal	N	99	40	14	7	8	26	0	18
	%	46.7	18.87	6.6	3.3	3.77	12.26	0	8.49
Creative Services	N	19	10	4	5	4	4	0	7
	%	35.85	18.87	7.55	9.43	7.55	7.55	0	13.21

NOTE: The sample includes orders commencing from 2007 through 2010.
SOURCE: Authors' calculations.

Table 3: Distribution of Soft and Hard Skill Performance Problems by Broad Occupation

Job assignments ended with performance problems		Attendance	Substance abuse on assignment	Behavioral	Policy non-compliance	Hard skills
Non-professional occupations						
Light Industrial	N	126,103	5,703	13,645	11,479	62,688
	%	14.21	0.64	1.54	1.29	7.06
Office	N	18,336	512	3,676	2,454	21,905
	%	4.48	0.13	0.9	0.6	5.35
Contact Center	N	14,273	345	2,034	1,902	10,854
	%	12.8	0.31	1.82	1.71	9.73
Electronic Assembly	N	7,754	210	1,123	777	4,480
	%	13.25	0.36	1.92	1.33	7.66
Marketing	N	1,508	50	288	173	1,070
	%	0.9	0.03	0.17	0.1	0.64
Professional and technical occupations						
Scientific	N	690	48	294	191	1,238
	%	2.84	0.2	1.21	0.79	5.1
Accounting/Finance	N	496	19	178	89	1,200
	%	3.29	0.13	1.18	0.59	7.97
Engineering	N	363	37	176	126	791
	%	2.1	0.21	1.02	0.73	4.57
Information Technology	N	443	27	164	95	778
	%	2.95	0.18	1.09	0.63	5.18
Professional (Other)	N	801	11	129	116	1,945
	%	1.12	0.02	0.18	0.16	2.72
Healthcare	N	551	14	166	140	688
	%	4.32	0.11	1.3	1.1	5.39
Legal	N	110	9	79	39	402
	%	0.87	0.07	0.62	0.31	3.16
Creative Services	N	46	2	19	7	113
	%	1.88	0.08	0.78	0.29	4.63

NOTE: The sample includes orders commencing from 2007 through 2010.
SOURCE: Authors' calculations.

Table 4: Results of Hazard Models Predicting the Time to Job Assignment End

Panel A:	**All Completed Assignments (N=1,516,287)**			
Performance-related factors predicting risk of assignment termination (log assignment length)	Hazard Ratio	Std. Error	95% Confidence Interval	
Attendance	1.656	0.006	1.645	1.668
Substance abuse on assignment	2.247	0.039	2.173	2.325
Behavioral	1.272	0.009	1.254	1.290
Policy non-compliance	1.287	0.010	1.266	1.307
Hard skills	1.924	0.008	1.909	1.940
Quit, work-related	2.144	0.012	2.120	2.168
Quit, personal	1.321	0.004	1.312	1.329
Background/drug screening	1.864	0.181	1.542	2.254
Completed assignment	1.831	0.005	1.820	1.841
Hired	0.755	0.002	0.751	0.759

NOTES: **Log of job assignment length is the predicted variable.** Other control variables not shown include worker age (and age-squared), broad occupation, county unemployment rate, state and year that the assignment began. Standard errors adjusted for 855,499 clusters (in employee ID).

Panel B:

Performance-related factors predicting risk of assignment termination (log assignment length)	Light Indus.	Office	Contact Center	Elec. Assemb.	Eng./ Scientific	Acct./ Finance, Legal	Info. Tech.	Prof. Other	Other Services
Attendance	1.508	1.393	1.410	1.550	1.951	1.574	1.747	1.597	1.282
Substance abuse on assignment	1.903	2.370	4.105	2.015	2.752	3.841	4.686	2.925	2.471
Behavioral	1.224	1.304	1.542	1.222	1.491	1.098	1.914	1.248	1.263
Policy non-compliance	1.292	1.328	1.355	1.350	1.650	1.346	1.561	1.351	1.329
Hard skills	1.631	1.650	1.686	1.819	2.080	1.763	2.194	1.968	1.773
Quit, work-related	1.953	1.522	2.061	2.135	1.876	1.607	1.611	1.674	1.442
Quit, personal	1.329	1.172	1.303	1.326	1.158	1.108	1.274	1.265	1.047
Background/drug screening	1.699	1.516	6.512	4.611	1.347	n.a. †	n.a.	n.a.	n.a.
Completed assignment	1.388	1.158	0.937	1.168	0.998	0.940	1.175	0.898	1.112
Hired	0.669	0.693	0.648	0.702	0.868	0.707	0.832	0.587	0.698

†As seen in Table 2, there were too few observations to estimate these coefficients.

Table 5: Results of Probit Models Predicting the Probability of a Subsequent Job Assignment

Panel A: (N=905,506)				
Performance-related factors predicting the probability of a subsequent (2nd) job assignment	Coefficient	Std. Error	95% Confidence Interval	
Attendance	-0.306	0.001	-0.308	-0.303
Substance abuse on assignment	-0.332	0.001	-0.334	-0.330
Behavioral	-0.262	0.002	-0.266	-0.258
Policy non-compliance	-0.228	0.003	-0.233	-0.223
Hard skills	-0.179	0.002	-0.182	-0.176
Quit, work-related	-0.203	0.002	-0.207	-0.200
Quit, personal	-0.260	0.001	-0.263	-0.258
Background/drug screening	-0.309	0.013	-0.336	-0.283
Completed assignment	0.026	0.002	0.022	0.029
Hired	-0.343	0.001	-0.345	-0.341
Panel B: (N=330,008)				
Performance-related factors predicting the probability of a subsequent (3rd) job assignment	Coefficient	Std. Error	95% Confidence Interval	
Attendance (1st assign.)	-0.058	0.004	-0.066	-0.050
Substance abuse on 1st assignment	-0.139	0.035	-0.207	-0.071
Behavioral (1st assign.)	-0.066	0.010	-0.087	-0.046
Policy non-compliance (1st assign.)	-0.048	0.010	-0.068	-0.028
Hard skills (1st assign.)	-0.037	0.004	-0.045	-0.030
Attendance (2nd assign.)	-0.316	0.003	-0.322	-0.311
Substance abuse on 2nd assignment	-0.440	0.005	-0.449	-0.431
Behavioral (2nd assign.)	-0.273	0.006	-0.285	-0.261
Policy non-compliance (2nd assign.)	-0.234	0.007	-0.249	-0.219
Hard skills (2nd assign.)	-0.126	0.004	-0.134	-0.118
Quit, work-related (2nd assign.)	-0.137	0.005	-0.147	-0.127
Quit, personal (2nd assign.)	-0.239	0.003	-0.245	-0.233
Background/drug screening (2nd assign.)	-0.425	0.044	-0.511	-0.338
Completed assignment (2nd assign.)	0.100	0.003	0.094	0.105
Hired (2nd assign.)	-0.407	0.002	-0.412	-0.403

NOTES: Worker had a second (or third) job assignment is the predicted (binary) dependent variable. Other control variables not shown include worker age (and age-squared), industry, county unemployment rate, state and year that the assignment began.

Table 6: Results of a Regression Predicting Changes in Hourly Wages from a First to Second Job Assignment

Performance-related factors predicting wages on a 2nd job assignment (N=331,618)	Coefficient	Std. Error	95% Confidence Interval	
Attendance	-0.230	0.018	-0.265	-0.195
Substance abuse on assignment	-0.165	0.145	-0.448	0.119
Behavioral	-0.464	0.043	-0.547	-0.380
Policy non-compliance	-0.417	0.042	-0.499	-0.334
Hard skills	-0.494	0.017	-0.528	-0.461
Quit, work-related	-0.044	0.022	-0.087	-0.002
Quit, personal	-0.038	0.015	-0.068	-0.008
Background/drug screening	-2.673	0.793	-4.227	-1.120
Completed assignment	-0.053	0.010	-0.072	-0.034
Hired	-0.320	0.025	-0.369	-0.271

NOTES: Dependent variable is the change in wages from a first to second job assignment, conditional on a second job assignment being offered. Other control variables not shown include worker age (and age-squared), industry, county unemployment rate, state and year that the assignment began. In a separate regression, we also controlled for job family (90 unique indicators), and the results generally differed by less than 0.01 for each coefficient estimate above (although the pseudo R-squared value doubled). Observations with average changes in hourly wages greater than $30 or less than -$30 were excluded (n=338).

Table 7: Hire and Separations, Economy-Wide and in the Temporary Help Industry

	A: National and Estimated Temporary Help Industry Hire and Separation Rates				
	2007	2008	2009	2010	2011
			Average Monthly Hire Rates		
National	3.8	3.3	2.9	3.1	3.2
Temporary help—low	28.5	25.3	23.8	25.1	23.3
Temporary help—high	45.2	40.4	37.0	37.9	34.7
			Average Monthly Separation Rates		
National	3.7	3.5	3.2	3.1	3.0
Temporary help—low	28.3	27.2	24.2	23.8	23.4
Temporary help—high	45.0	42.3	37.4	36.5	34.7
	B: Estimated Share of Hires and Separations Accounted for by Temporary Help Industry				
			Hires		
Low estimate	0.14	0.13	0.11	0.13	0.13
High estimate	0.21	0.19	0.17	0.18	0.18
			Separations		
Low estimate	0.15	0.13	0.10	0.13	0.14
High estimate	0.21	0.19	0.15	0.18	0.19

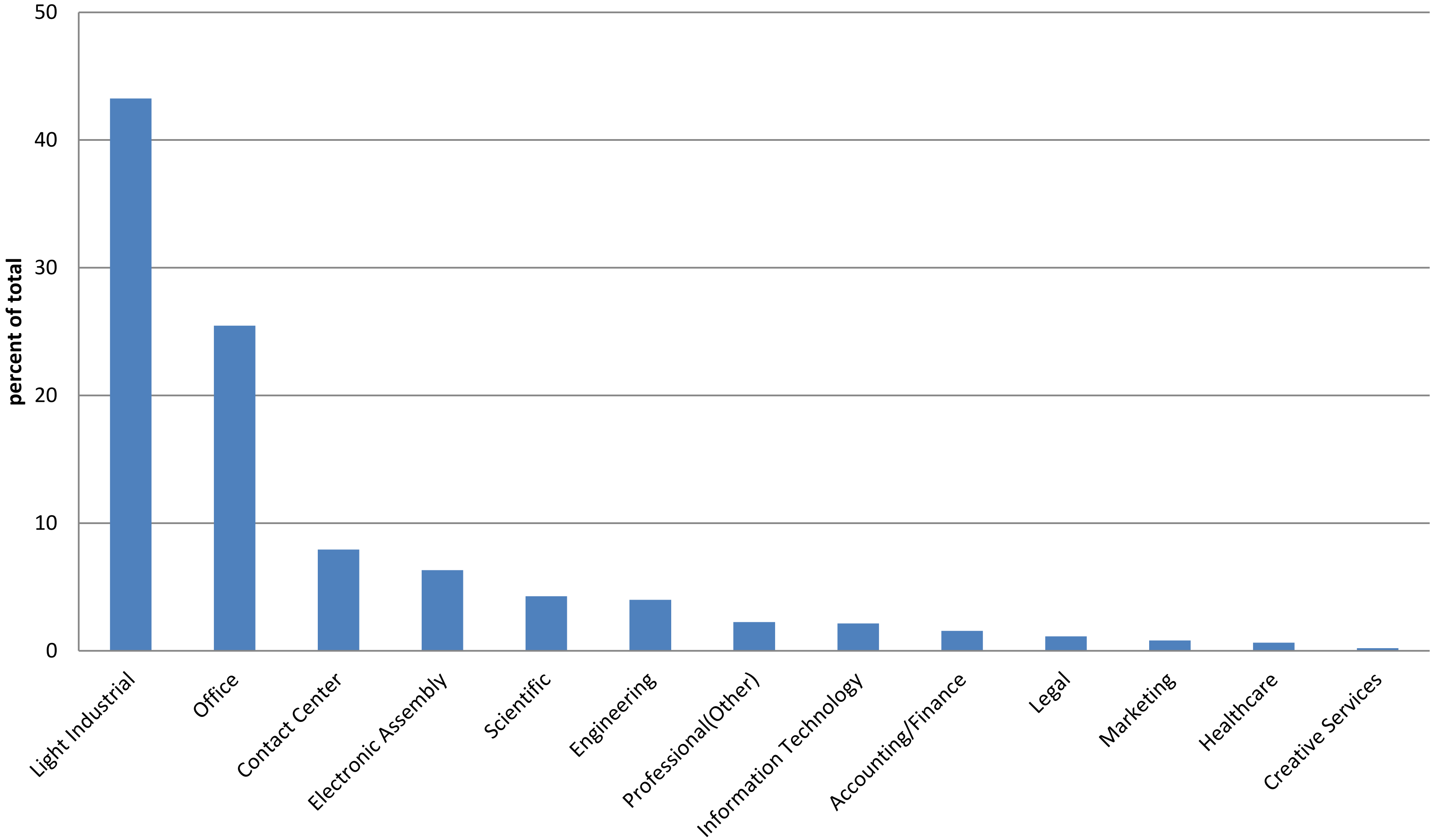
SOURCE: Authors' calculations from temporary help firm data and the Job Openings and Labor Turnover Survey, BLS

Table 8 The Effect of Start Year on Assignment Length

	Dependent variable: ln(actual assignment length)				Dependent variable: ln(expected assignment length)			
	Light industrial	Office	Contact center	Electronic assembly	Light industrial	Office	Contact center	Electronic assembly
Order start year								
				OLS models				
2008	0.0206***	0.0861***	0.0592***	0.0463*	−0.0229***	0.0814***	0.0030	0.0869***
	(0.0060)	(0.0079)	(0.0121)	(0.0214)	(0.0066)	(0.0084)	(0.0094)	(0.0176)
2009	0.0537***	0.1180***	0.1605***	0.2208***	−0.1209***	0.0624***	0.0543***	0.1457***
	(0.0073)	(0.0100)	(0.0146)	(0.0258)	(0.0084)	(0.0108)	(0.0124)	(0.0221)
				Multilevel models				
2008	-0.0166**	0.0616***	0.0450***	0.0427*	−0.0389***	0.0684***	−0.0116	0.0835***
	(0.0053)	(0.0070)	(0.0117)	(0.0210)	(0.0052)	(0.0069)	(0.0082)	(0.0166)
2009	0.0125*	0.0722***	0.1404***	0.1966***	−0.1228***	0.0358***	0.0405***	0.1267***
	(0.0061)	(0.0083)	(0.0137)	(0.0245)	(0.0059)	(0.0083)	(0.0097)	(0.0194)
N	534,133	285,189	72,611	28,488	534,133	285,189	72,611	28,488

NOTE: Coefficient estimates on start year dummy variables from OLS regression or multilevel models that include individual and order level controls (see text). The sample includes orders commencing in the years 2007, 2008 and 2009. Standard errors are reported in parentheses, and are clustered on individuals in OLS models. * signifies significance at the 0.05 level, ** at the 0.01 level, and *** at the 0.001 level.

Figure 1 Distribution of Hours by Broad Occupations (percent)



[1] BLS Monthly Employment Data, December 2019, https://americanstaffing.net/staffing-research-data/asa-data-dashboard/bls-employment-situation/.

[2] Temporary help services make up about three fourths of the employment in the staffing services industry in government statistics. Occupational statistics broken out for the temporary help component of staffing services are not available prior to 2000.

[3] Because the temporary help agency is the employer of record, employers may circumvent ERISA and IRS nondiscrimination rules requiring that retirement and health insurance benefits broadly benefit their employees by hiring workers through temporary help agencies.

[4] In all, the data include more than 100 unique reasons for why an order was closed, although a couple of dozen are identified in over 90 percent of cases.

[5] We drop from our sample orders in educational occupations, which are primarily substitute teachers and account for a very small share of hours worked in the firm. Use of substitute teachers varies little over the business cycle.

[6] For any sample of workers, the hours and employment distributions by occupation generally will be very similar. The two will differ only to the extent that average hours vary across occupations. The OES data provide point-in-time employment figures, whereas our company data show hours worked over the course of a year.

[7] Our data only cover assignments in one company, and it is possible that individuals take assignments with other temporary help agencies.

[8] We omit assignments commencing in 2011 because a high share are still open at the end of the year and so the reason the assignment ended is missing.

[9] In regular temporary help contracts, 6.0 percent of orders result in hires. Although the probability of hire is considerably lower than in temp-to-hire contracts, a majority of temporary help workers hired by client organizations come from regular temporary help contracts.

[10] Specifically, the first measure of stability includes individuals with no earnings from a particular employer in quarter $t\text{-}1$, but with earnings from that employer in quarters t and $t+1$. The second measure includes individuals with no earnings from a particular employer in quarter t-1, but with earnings from that employer in quarters t, $t+1$ and $t+2$.

[11]Note that in some cases those who appear in the LEHD data as new direct-hires will have already been screened through a temporary help agency.

[12] The reference category—job assignments closing for reasons unrelated to performance—includes closed reason codes such as contract lost with client firm, need no longer exists, plant shutdown or strike (at client firm), and other administrative-related reasons.

[13] The marketing, office and other professional industries account for the lion's share of temporary help workers with more than four job assignments in our sample (more than half of workers in marketing and 20-25% in office and other professional industries had more than four job assignments).

[14] The results from the hazard models with interaction terms between industry and worker performance problems are available from the authors upon request.

[15] In including the control for expected assignment length, about 24 percent of the observations (from the last two years of the study period) were lost from the estimation sample (still leaving more than 1.15 million observations).

[16] BLS does not publish CPIs for all metropolitan areas, but it does publish regional measures by size of city. In cases where a metropolitan measure was not published, we used a regional measure according to the size of the city in which the branch was located.

[17] The detailed results from probit regressions predicting transitions to a different industry from the first assignment to the next are available from the authors upon request.

[18] For respondents from temporary help firms, the JOLTS survey defines a hire as an addition to the payroll, who "may be a new hire or previously separated rehire, may be permanent, short-term, or seasonal, or may be a recall from layoff." Separations are defined as quits; layoffs, discharges, and terminations of permanent, short-term or seasonal employees; and retirements, transfers to another location, employee disability, and deaths.

[19] We adjusted the national hire and separation numbers by adding in the difference between high and low estimates of hires and separations for the temporary help industry. In other words, we assume that the conservative (low) estimates represent what is reported in the JOLTS data, and we add the difference between high and low estimates to both the numerator (temporary help industry hires/separations) and denominator (national hires/separations) when estimating the share of hires/separations accounted for by the temporary help industry.

[20] These results are available from the authors (Reference Table A).
[21] These results are available from the authors (Reference Table B).
[22] We also experimented with including indicator variables for county in lieu of state, but these had little effect on our estimates, and inclusion of county-level dummies complicated the running of multilevel models, discussed below.
[23]We do not report estimates for these models for professional and technical occupations because incomplete assignments are a significant problem.
[24] This interpretation is consistent with underlying data for light industry showing that the 7.4 percentage decline in the share of assignments between 2007 and 2009 that ended before the expected stop date was accompanied by a 5.3 percentage point increase in those lasting longer than expected, with most of the increase in actual versus expected occurring between 2008 and 2009. Of the 5.3 percentage point increase, 3.8 percentage points were in assignments lasting at least a week longer than planned.
[25] These results are available from the authors (Reference Table C). We also experimented with including detailed assignment outcome measures (e.g., terminated for tardiness, completed assignment, hired, etc.) as controls. Adding these controls had no substantive effect on multilevel model estimates.