CONTRACTING OUT LABOR MARKET DYNAMISM
DOMESTIC OUTSOURCING, FIRMS' RECRUITING BEHAVIOR, AND DEVELOPMENT

BY

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DISSERTATION

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Abstract

This dissertation shows that domestic outsourcing challenges our understanding of labor market dynamism and firms' recruiting behavior —its measurement, definition, and dynamics. The first two chapters define and quantify the role of domestic outsourcing on the decline in labor market dynamism the U.S. has experienced since at least the 1990s. They tackle this issue from the worker and business perspectives, quantifying to what extent the increase in domestic outsourcing accounts for the decline in both worker and job reallocations. My results suggest that at least part of the decline reflects a transformation of the labor market towards the use of intermediaries in the matching process rather than a decline in underlying dynamism. Through the third chapter, this dissertation also provides new evidence on the matching process in a developing economy's labor market and its differences from that of a developed economy. This evidence informs frictional labor market models and reconciles higher turnover rates with lower productivity: two defining characteristics of labor markets in developing economies.

The first chapter connects the increasing use of domestic outsourcing with the decline in labor market dynamism, defining the *omitted reallocation* problem and showing that it is pervasive across labor market fluidity indicators. The empirical analysis focuses on aggregate worker reallocations, quantifying the magnitude of the omitted reallocations problem on this labor market fluidity indicator. Domestic outsourcing happens when firms contract with other firms or individuals in the U.S. to provide goods and services previously performed in-house. On the other hand, outsourced employees are workers whose employer of record (the staffing agency) is not the firm where they perform their job tasks (the client). While remaining on their staffing agency's payroll, outsourced employees reallocate across client firms. In fact, they do so at a higher pace than payroll employees, but their reallocations are omitted in the datasets used to measure labor fluidity. Therefore, the measured pace of reallocation is underestimated. To quantify this channel, I provide a decomposition of the worker reallocation rate that illustrates a relationship between the decline in reallocations and an increase in outsourced employees' job tenure. I successfully test this implication in microdata from the Job Tenure Supplement of the Current Population Survey. I find that between 1996 and 2018, outsourced employees average tenure increased by 18 months, while the average tenure of payroll employees increased

by less than 8 months. The tenure estimates translate into an increasing proportion of omitted reallocations between 1994 and 2018, accounting for over one-fifth of the observed decline in the worker reallocation rate.

The second chapter assesses how domestic outsourcing affects plant-level labor responses to revenue productivity shocks and biases the measurement of aggregate job reallocations. I develop a methodology to transform reported expenses on temporary and leased workers into plant-level outsourced employment using comprehensive administrative data on the U.S. manufacturing sector. I show that plant-level outsourced employment is twice as responsive as payroll employment to revenue productivity growth deviations and adjusts more quickly. The evidence indicates that domestic outsourcing is an important margin of adjustment that plants use to modify their workforce while they learn about the permanency of the shock. These micro implications have significant macroeconomic measurement consequences. I show that the measured pace at which jobs reallocate across workplaces is underestimated. On average, every year, we omit the equivalent to 15% of payroll reallocations. The extent of mismeasurement varies with the business cycle, falling in downturns and increasing in upturns. My findings suggest that the increasing use of labor market intermediaries accounts for a substantial portion of the measured decline in labor market dynamism and further reflects structural adjustments in the choice set of firms when facing shocks.

In the third chapter, together with Munseob Lee and Claudia Macaluso, we investigate how workers and jobs match in the context of a developing economy's labor market and what differences arise with respect to a developed one. To that end, we design a survey of employers' recruiting behavior and implement it in Peru and the Southeastern U.S. We provide three novel facts: (1) Vacancy duration is substantially shorter in Peru than in the U.S. (2) There is little difference in how employers recruit candidates for their open jobs. Referrals from employees or family recommendations, together with job posting, are the most popular methods in both countries. (3) In Peru, over-qualification is common in filled jobs. Furthermore, on average, jobs in Peru tend to be less specialized than similar ones in the U.S. To show this, we provide the first data on detailed occupational skill usage across occupations in a developing economy and find that, with respect to the same U.S. occupational title, Peruvian jobs display higher dispersion in the importance of a variety of skill dimensions. These facts inform models of frictional labor markets and shed light on the contribution of such frictions to stunted firm growth and productivity deficits in developing economies.

Para mi Abuelita. Tu tenacidad y lucha siempre estuvieron conmigo.
Somos tu legado. Te amaré por siempre.
Para Agustín. Tus pataditas me impulsaron a alcanzar la meta. Te amo hijo.

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Chapter 1

Contracting out Worker Reallocations

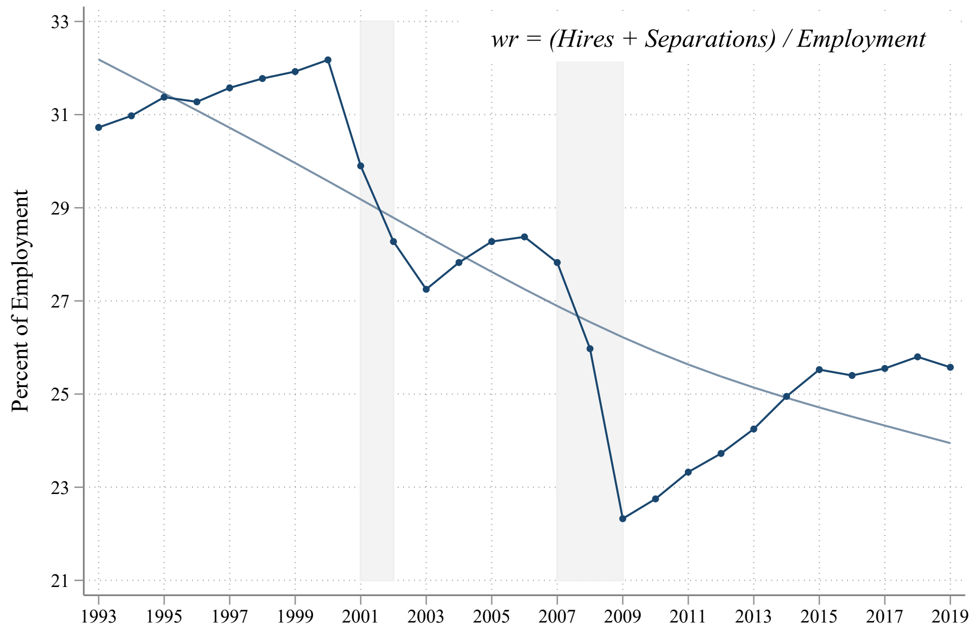
1.1 Introduction

The U.S. has seen a decline in the pace at which jobs and workers move across businesses since at least the 1990s: a lower worker reallocation rate is cause for concern since it negatively affects real wages and employment rates, especially for young workers and the less educated (Davis & Haltiwanger, 2014). At the same time, publicly available datasets suggest a sharp increase in the employment share of outsourced workers. This paper connects the two phenomena defining the *omitted reallocations* problem and shows that it is pervasive across labor market fluidity indicators. I quantify the magnitude of the omitted reallocations problem on aggregate worker reallocations and, in doing so, I document that the average tenure of outsourced workers at staffing agencies is increasing over time both unconditionally and relative to payroll employees.

Domestic outsourcing happens when firms contract with other firms or individuals in the U.S. to provide goods and services previously performed in-house. To investigate the relationship between domestic outsourcing and labor market fluidity, I develop the concept of *omitted reallocations*. When a business outsources tasks that were previously performed in-house (client business), the employer of record for the employees performing these tasks (outsourced workers) changes to the contracting firm (staffing agency). The staffing agency reallocates its employees from client to client while acting as their legal employer throughout. As a result, the reallocations of outsourced workers across client businesses are omitted in the datasets used to measure labor fluidity, generating the *omitted reallocations* problem.

Accurately measuring labor flows is important; and the omitted reallocations problem leads to an

Figure 1.1. The worker reallocation rate fell by more than a quarter between 2000 and 2010.



Note: The figure displays yearly averages of the quarterly worker reallocation rate. Source: Author's calculations based on Quarterly Workforce Indicators, seasonally adjusted.

underestimation of the measured pace of job and worker reallocations across businesses and the number of vacancies in the economy. Both gross labor flows and vacancies are key parameters in most search models and, thus, central to their calibration. Moreover, the use of intermediaries, such as staffing agencies, in the search process for job candidates destroys the equivalency between a job change and an employer change in the data, masking both the behavior of firms and the behavior of a certain type of job seeker in the search process. Researchers have not yet documented the consequences that domestic outsourcing imposes when measuring and defining labor flows, let alone the magnitude of the omitted reallocations problem. This paper addresses these issues. Specifically, this paper answers how domestic outsourcing affects the measurement and behavior of worker reallocations, which, in turn, affects our understanding of this labor flow: its definition and relationship with wage, productivity, and economic growth.

I proceed in two steps. First, I define the omitted reallocations problem and show that it arises in the data used to track labor market activity. Datasets relying on the Unemployment Insurance (UI) system define a job as a worker-employer pair in which the employer is the entity in charge of reporting to the UI. This is the case of the Longitudinal Employer-Household Dynamics (LEHD) and the Business Employment Dynamics (BED). The reallocation of outsourced workers and jobs across client businesses are then omitted in these datasets because outsourced workers' employer of record is the staffing agency. In datasets that do not rely on the UI system, such as the Job Openings and Labor Turnover Survey (JOLTS), positions filled by outsourced workers are explicitly excluded from the count generating the same problem. Therefore, official data sources omit both the reallocation of workers and jobs across client businesses and the vacancies they fill. The undercount affects aggregate labor flows, vacancies, and labor market activity composition across sectors. The services sector is "stealing" the labor market dynamism of its client industries.

Second, I quantify the magnitude of the omitted reallocations problem on aggregate worker reallocations. The biggest challenge to investigating outsourced worker reallocations reflects the very nature of the problem at hand: *omitted* reallocations. I overcome this challenge by providing a decomposition of the worker reallocation rate with testable implications in the data and combining several data sources to test such implications and estimate the number of outsourced worker reallocations. The decomposition illustrates that the number of omitted reallocations depends on both the share of outsourced workers in the economy and the tenure of these workers at staffing agencies. Consequently, the number of omitted reallocations can increase over time either due to a growing share of outsourced workers or by these workers spending longer spells with one staffing agency while being assigned to different clients throughout.

I successfully test the longer tenure prediction in microdata from the Job Tenure Supplement of the Current Population Survey (CPS-JT). Consistent with an increasing number of omitted reallocations, my baseline estimates show that outsourced workers are indeed spending longer spells at staffing agencies. Between 1996 and 2018, the average tenure of outsourced workers increased by 18 months. Moreover, outsourced workers' tenure is increasing even relative to payroll employees' tenure. For the same period, payroll employees' tenure increased by less than 8 months. The fact that the "tenure gap" between outsourced and payroll employees is important because it supports domestic outsourcing as one of the underlying causes of the decline in worker reallocations over an overall tenure increase: the longer a worker stays at an employer, the fewer reallocations she makes.

I estimate the number of omitted reallocations leveraging information on tenure at staffing agencies, the average length of an individual assignment in a client business, and aggregate outsourced employment. I document three facts. First, the worker reallocation rate is underestimated. Average yearly gross worker flows would be 14% higher if we accounted for the hires and separations of outsourced workers. Second, the number of omitted reallocations increased sharply after the Great Recession. Third, in 2018, the worker reallocation rate would have been

21% higher if outsourced workers' reallocations were considered. That is, over one-fifth of the drop in payroll worker reallocations between 1996 and 2018 is accounted for by domestic outsourcing.

CONTRIBUTION TO THE LITERATURE. This paper makes explicit the challenges imposed by the changing nature of employer-employee relationships when measuring and defining labor flows. Just to mention a few of these challenges, not accounting for the reallocations of outsourced workers across client businesses and the vacancies they fill hinders our understanding of job ladders by making invisible in the data the rungs filled by outsourced workers. It also biases industries' labor demand estimates, masks labor market frictions in the hiring process, impedes an accurate assessment of the industries and workers absorbing negative shocks and, in general, the behavior of firms when facing unexpected conditions. In sum, the omitted reallocations problem underscores the fact that domestic outsourcing poses a new dimension to our understanding of labor markets and their dynamics.

In the domestic outsourcing body of work, this paper adds the observed decline in labor fluidity as one of the aggregate consequences of domestic outsourcing—adding labor fluidity indicators to the list of measurement issues that arise for not accounting for outsourced workers.

In addition to contributing separately to the domestic outsourcing and labor market fluidity bodies of work, the omitted reallocations hypothesis establishes a bridge between them. In particular, considering omitted reallocations allows complementing previous findings on the causes of the decline in labor market fluidity with results from the domestic outsourcing literature. For example, the literature on domestic outsourcing has shown that the need to adjust for workload fluctuations is the most commonly cited reason by firms for using staffing arrangements (Houseman, 2001). Through the lens of omitted reallocations, this result now complements the finding that the decreased dynamism can be explained by a more sluggish responsiveness of businesses to idiosyncratic productivity shocks (Decker, Haltiwanger, Jarmin, & Miranda, 2020). Businesses use temporary employees as a margin of adjustment when facing shocks; therefore, Decker et al. (2020)'s result might be reflecting changes in the dynamics of employment growth relative to this margin—omitted in responsiveness measures based on the volatility of firm-level employment growth. This paper argues that allowing a broader definition of firms' responsiveness to include domestic outsourcing enriches our understanding of firm-level adjustments to shocks —I investigate this hypothesis in the second chapter of the dissertation.

Other previously studied causes for the observed decline in labor market dynamism include increasing costs for employment adjustment. Higher firing costs affect labor market fluidity negatively by reducing incentives to separate employees from the firm. Match-specific human capital, on-the-job training costs, and exceptions to the employment-at-will doctrine lead to a lessen labor market dynamism through this mechanism (Cairo & Cajner, 2017; Davis & Haltiwanger, 2014; Fujita, 2018). These findings are consistent with firms outsourcing to reduce payroll-related costs (Abraham & Taylor, 1996; Houseman, Kalleberg, & Erickcek, 2003; Houseman, 2001; Segal & Sullivan, 1997). A long-held result of the domestic outsourcing literature.

The omitted reallocations problem as one of the causes behind the decline in labor market dynamism is also consistent with the characterization of such decline provided by previous studies. Hyatt and Spletzer (2013) find that more than half of the decline in worker reallocations is accounted for by the decline in flows associated with secondary and short-duration jobs (less than three months). These findings agree with the short-tenure nature of the typical assignment in a client business (10 weeks), and this paper's tenure results: the average tenure of temporary help employees in staffing agencies has steadily become longer, even relative to payroll employees. Together, these facts confirm that the number of omitted reallocations is increasing over time. In turn, an increasing number of omitted reallocations implies a reduction in the observed transitions across short-tenure jobs.

The longer tenure result also speaks directly to recent developments in the job tenure and stability literature. Specifically, helps to clarify work by Molloy, Smith, and Wozniak (2020) documenting two seemingly conflicting facts: declining labor market dynamism and a widespread perception that long-term employment relationships are more difficult to attain, even though the data show a decline in short-tenure (less than a year) jobs. The increasing tenure of temporary help employees in staffing agencies documented in this paper, and the short-tenure nature of the typical assignment in client businesses offer an explanation to the puzzle highlighted by Molloy et al. (2020). For outsourced workers, tenure at an employer is not equivalent to tenure at a job; therefore, observing these workers staying longer in staffing agencies does not translate into short-tenure jobs disappearing or job security improving. Outsourced workers continue to fill short-tenure positions in client firms. I show that intermediaries in the matching process as staffing agencies override the equivalency between employer change and job change: a common assumption in job ladder models' calibrations.

OVERVIEW OF THE PAPER The paper is organized as follows. Section 1.2 introduces the omitted reallocations problem, documents its origin, and presents the data used in the paper. Section 1.3 explains the research design to quantify the magnitude of the omitted reallocations problem on aggregate worker reallocations. Section 2.6 concludes.

1.2 The omitted reallocations problem

Domestic outsourcing affects labor market dynamism —its measurement, definition, and observed behavior— through the omitted reallocations problem. The omitted reallocations problem encompasses the errors that arise from not considering the reallocations of outsourced workers, outsourced jobs, and the vacancies they fill. These errors can be classified into two categories: measurement and conceptual. The focus of this paper is the measurement dimension of the omitted reallocations problem, which arises in the data used to track labor markets' activity. These data are, in turn, used to conduct all kinds of labor market analyses and hence to conceptualize how the labor market works. In other words, failure to measure the reallocations of outsourced workers translates into misconceptions about the labor market. This section explains the origin of the omitted reallocations problem and introduces the data used in my empirical analysis.

1.2.1 The origin of the omitted reallocations problem: the measurement dimension

The origin of the omitted reallocations problem is the data. Labor market flows are directly computed from three data sources: the Job Openings and Labor Turnover Survey (JOLTS), the Longitudinal Employer-Household Dynamics (LEHD), and the Business Employment Dynamics (BED). Yet, none of these datasets account for the reallocation of outsourced workers across client businesses or record the outsourced worker-client business pair as a job.

The JOLTS definition of employment, vacancies, and labor flows excludes outsourced workers from the count.[1] Thus, JOLTS' labor fluidity measure (worker reallocations) is likely underestimated. To illustrate this point, consider, for example, a janitor that worked consecutively for two different companies in a year but was legally employed by the same staffing agency during the entire period. Although the reallocation of this janitor across two client businesses entails two hires and two separations, these flows are not observed in JOLTS data.

The LEHD and the BED only record employer-employee relationships. Outsourced workers can reallocate across client businesses while remaining on the contracting firms' payroll throughout. That is, workers change jobs, tasks, and workplaces—but not the employer of record as in traditional employment relationships. Consequently, the reallocations of outsourced workers

[1] The JOLTS has been conducted by the Bureau of Labor Statistics of the U.S. Department of Labor since December 2000. It is a monthly, establishment-level survey that collects information on employment, vacancies, hires, quits, layoffs, and other separations

between client businesses are omitted in labor flows derived from the LEHD and the BED. This situation arises because the LEHD and the BED are primarily derived from state-submitted unemployment insurance (UI) wage records, and the outsourced worker-client business relationship is not captured by UI records: when a business outsources tasks that were previously performed payroll, the employer of record of the employees performing these tasks changes to the contracting firm, i.e., the staffing agency. Staffing agencies are, in consequence, the employers subject to submitting wage information on their outsourced workers even if they are performing tasks on-site for a different establishment —the client business. The LEHD is the source of information for the Quarterly Workforce Indicators (QWI), which publishes aggregated information on worker and job flows quarterly.

Similar to the QWI, the BED statistics are derived from a quarterly census of all establishments under state UI programs, the Quarterly Census of Employment and Wages. Different from the QWI, however, the BED only tracks job flows; it does so by longitudinally linking UI records aggregated at the establishment level since the third quarter of 1992. To the extent that the outsourced worker-client business relationship is not captured in UI records, BED job flows omit client businesses' creation and destruction of jobs filled by outsourced workers, hence underestimating the labor dynamism of these establishments' industries. Moreover, if the client business' creation (destruction) of jobs filled by outsourced workers did not map into the creation (destruction) of jobs in the contracted staffing agencies, the omission results in the underestimation of the *aggregate* BED job reallocation measure of labor fluidity and not only of the client business' industry —the omitted-reallocation problem arises in BED data.

As shown in this section, the omitted reallocations problem is pervasive across data sources, affecting both worker- and employer-side labor market fluidity indicators. The empirical exercise of this paper estimates the magnitude of the omitted reallocations problem on the aggregate worker reallocation. Focusing on the worker reallocation rate allows me to use publicly-available, high-quality, individual microdata to test the omitted reallocation hypothesis.

1.2.2 Data

The biggest challenge to test the omitted reallocation hypothesis is the data and resides on the nature of the problem at hand: *omitted* reallocations. I overcome this challenge by combining multiple establishment and household surveys administered by the Bureau of Labor Statistics (BLS), the American Staffing Association (ASA), and the Census Bureau. Specifically, I use the Current Employment Statistics (CES), the basic module and the tenure supplement of the Current

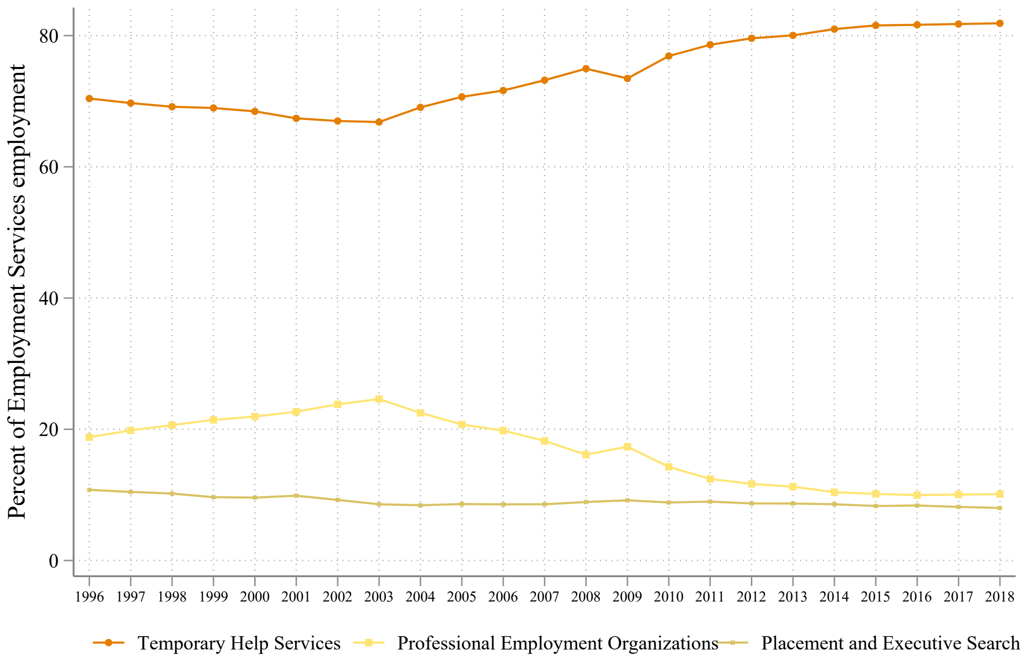
Population Survey (CPS and CPS-JT), the Staffing Employment and Sales Survey statistics, and the QWI.

The CES survey is a monthly establishment survey conducted by the BLS and based on payroll records. The CES program provides employment estimates disaggregated to the six-digit NAICS industry classification, allowing me to retrieve the employment share of the Temporary help services industry: a five-digit sub-classification of the Employment Services industry. I focus on the temporary help industry because it encompasses all establishments whose main activity is supplying workers to client businesses to meet their employment demand —workers that are legally employed by the temporary help services establishment but supervised by the client business, the source of the omitted reallocations problem in QWI and BED data.

The CPS is a monthly household survey, administered by the BLS. Important labor market indicators such as the unemployment rate and labor force participation are computed from this survey. In this paper, I use the basic CPS and its Job Tenure Supplement to investigate how long outsourced workers have been working for the current employer (the staffing agency). I identify outsourced workers in the CPS as workers classified under the Employment Services industry, the most detailed industry classification in the basic CPS. Employment Services, the four-digit category that includes Temp-Help Services, only has three categories in it: Temporary Help Services, Professional Employment Organizations, and Employment Placement Agencies. More importantly, for the period of the empirical analysis, Temp-Help Services accounts for over 60% of the employment in Employment Services (see Figure 1.2).

The CPS-JT provides information on the length of workers' employment spells at the current employer. This CPS supplement has been consistently conducted in January or February of even years since 1996; consequently, my analysis comprises the period between 1996 and 2018. Besides tenure at the staffing agency, my empirical strategy requires information on the length of individual assignments at client businesses, and on the proportion of outsourced workers obtaining a permanent offer in a client business (placement rate). I obtain both from statistics published by the ASA based on their Staffing Employment and Sales Survey. Finally, to compute the corrected worker reallocation rate, I use the QWI; the only worker-side labor fluidity set of statistics available since the 1990s.

Figure 1.2. Temporary Help Services employment has the greatest share of total employment in the Employment Services industry.



Note: Each line displays the corresponding sub-industry's percentage of employment in the Employment Services industry. Source: Author's calculations based on seasonally adjusted data from Current Employment Statistics.

1.3 The omitted reallocations problem on the worker reallocation rate

I estimate the magnitude of the omitted reallocations problem on the worker reallocation rate by implementing a three-step empirical strategy whose cornerstone is the decomposition of this labor market fluidity indicator. The decomposition illustrates that the number of omitted reallocations increases due to either a growing share of outsourced workers in aggregate employment (prevalence) or by outsourced workers staying longer in staffing agencies' payrolls (tenure). I find that (i) outsourced workers' spells in staffing agencies have increased by 18 months (65%) between 1996 and 2018; (ii) on average, the worker reallocation rate omits the equivalent to 14% of the yearly gross worker flows; and (iii) the corrected worker reallocation rate is more sensitive to the cycle.

1.3.1 Decomposing the worker reallocation rate: outsourced worker reallocations depend on prevalence and tenure

For any given point in time, the worker reallocation rate captures the reshuffling of workers across workplaces and employment status (WR_t) as a share of total employment (E_t). Formally, aggregate worker reallocations are the sum of all industries' j hires (H_{jt}) and separations (S_{jt}).

$$wr_t = \frac{WR_t}{E_t} = \frac{H_t + S_t}{E_t} = \sum_j \frac{(H_{jt} + S_{jt})}{E_t}.$$

Therefore, the aggregate worker reallocation rate is equivalent to a weighted average of the industries' worker reallocation rates, the weights being the employment share (e_{jt}):

$$wr_t = \underbrace{\sum_{j \neq o} (e_{jt} \times wr_{jt})}_{f(e_{jt}, wr_{jt})} + \underbrace{(e_{ot} \times wr_{ot})}_{o(e_{ot}, wr_{ot})}, \tag{1.1}$$

where $j = o$ is the staffing industry[2]. Movements of workers across employers that, in a world without staffing agencies, would have increased $f(e_{jt}, wr_{jt})$ in Equation (1.1), are now unobserved transactions between client businesses and staffing agencies: the omitted-reallocation problem. I assume that, if observed, omitted reallocations would be counted in the staffing industry, i.e., $o(e_{ot}, wr_{ot})$ would be higher in the absence of the omitted reallocations problem[3]. Equation (1.1) then illustrates how the omitted reallocations problem depends on both the share of outsourced workers and the measured worker reallocation rate in the staffing industry.

To illustrate this point, consider a guard that worked in three different companies during 2019, all classified under an industry different than the staffing industry ($j \neq o$). If this guard was hired directly by the businesses for which he provided his services, his reallocations would have added three hires and three separations to $wr_{j,2019}$. In contrast, this guard was an outsourced worker, legally employed by a staffing agency in 2019. Therefore, the six gross reallocations of the guard in the example were either (i) completely omitted in the computation of wr_t if he had been

[2]This approach assumes that all establishments whose economic activity is to meet the demand for workers of their client businesses are classified under the same industry.

[3]This assumption shuts down the composition effect of domestic outsourcing on worker reallocations to focus on the aggregate level effect.

working for the staffing agency longer than one year, i.e, if he was hired by the staffing agency before 2019; (ii) counted as only one hire in $wr_{o,2019}$ if the guard was hired by or separated from the staffing agency in the same year in which the six reallocations took place: 2019; or (iii) counted as two gross reallocations, one hire and one separation, in $wr_{l,2019}$ if the guard was both hired by and separated from the staffing agency in 2019.

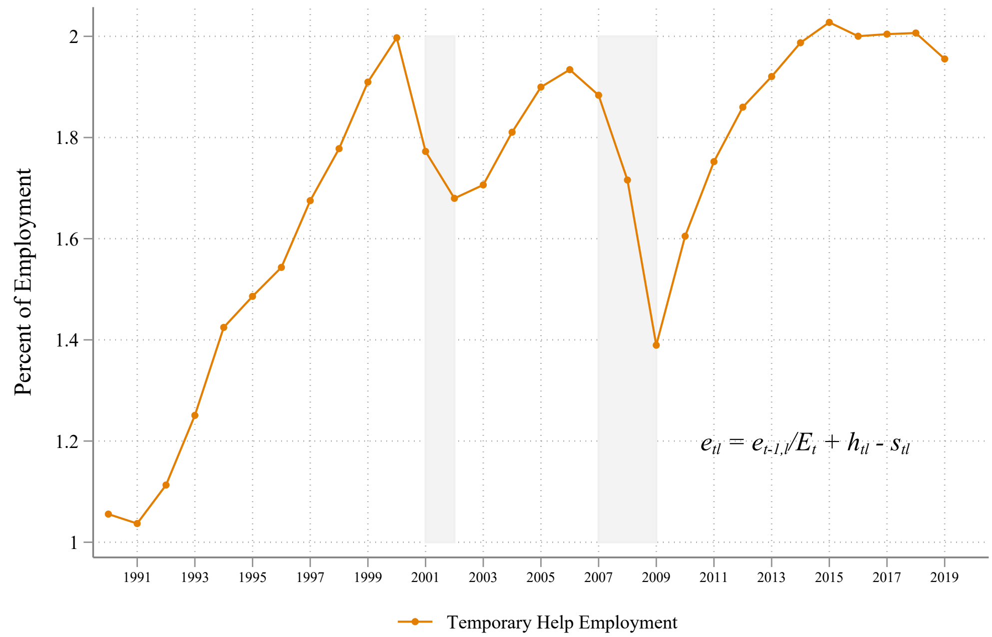
Notice that in the guard example, the number of omitted reallocations ranges from four to six depending on the guard's tenure in the staffing agency. In general, the more an outsourced worker stays employed by a staffing agency, the more reallocations are omitted over time, holding everything else constant. This is the *tenure* channel, one of the two mechanisms through which omitted reallocations could be increasing over time. The second mechanism is *prevalence*. In the guard example, the prevalence channel captures the fact that if an economy had more and more outsourced guards instead of payroll guards, the number of omitted reallocations would no longer range from 4 to 6 but from 400 to 600, say, if this economy had 100 outsourced guards instead of 1. This example stresses the point that each channel can increase total omitted reallocations, even if the other stays constant.

The number of omitted reallocations (OWR_t) in a given year t is then a function of outsourced employment (E_{ot}), the rate at which staffing agencies place outsourced workers in permanent jobs at client businesses, the tenure of outsourced workers at staffing agencies (y_t), and the length of assignments at client businesses ($lenght_t$). The latter must be considered because the extent to which longer spells of outsourced workers in staffing agencies translate into more omitted reallocations depends on the length of individual assignments. If outsourced workers had indeed stayed longer in staffing agencies but the tenure of the jobs to which they were assigned (individual assignments) had increased proportionally, omitted reallocations would not increase over time. For example, consider a janitor that stayed employed by a staffing agency for one year, and during that year he was assigned to two different jobs so that two gross reallocations (out of four) were omitted. If the same janitor had stayed employed by the staffing agency for three years (longer tenure) but during that period he worked the same two jobs, the total number of omitted reallocations would have been the same.

I estimate the number of omitted reallocations as follows[4]:

[4]The omission of the time subscript in the placement rate is intentional: I assume the matching efficiency in pairing outsourced workers (active job seekers) with permanent jobs in client businesses did not change in the studied period; therefore, the placement or permanent job-finding rate is in steady state.

Figure 1.3. The employment share of temporary help agencies has doubled since 1990.



Note: The figure displays the average monthly employment by year as a percentage of the total non-farm employment in the same year. Source: Author's calculations based on Current Employment Statistics series, seasonally adjusted

$$OWR_t = \left[\frac{52\ weeks}{length_t} 2\,\widehat{y_t} - 1\right] \frac{1}{\widehat{y_t}} \times \left[E_{ot}\ (1 - Placement\ rate)\ \right]. \tag{1.2}$$

Equation (1.2) captures the fact that each assignment completed at a client business while legally employed by a staffing agency represents two omitted reallocations: one hire and one separation. The initial hire of the worker by the staffing agency is, however, counted in the aggregate hires of the corresponding period. I conservatively assume that at least one reallocation is counted in the aggregate measure per year spent at the staffing agency. This assumption implies that, for each year at the staffing agency, the average outsourced worker spends at least three consecutive months with no assignment (no payment).

The corrected worker reallocation rate is then,

$$cwr_t = \frac{WR_t + OWR_t}{E_t}. \tag{1.3}$$

Equation (1.3) provides a lower bound of a worker reallocation rate accounting for domestic outsourcing for two reasons. First, I use a higher placement rate (23.1%) than the one reported by the outsourcing literature. Using proprietary data, (Houseman & Heinrich, 2015) estimate that between 2007 and 2011 around 14% of temporary workers obtained at least one job with a client. Additionally, anecdotal evidence points to a decline in the share of outsourced workers hired as payroll employees in client businesses, and I conservatively assume the placement rate is fixed over time (see Equation (1.2)).

Second, I use temporary help employment to approximate outsourced employment E_{ot}. Although the staffing industry definition matches almost perfectly with the Temporary Help Services industry definition, what is believed to be a small proportion of all staffing agencies are specialized firms classified under the industry of the main activity performed by their employees[5]. For example, cleaning services firms whose main activity is to outsource janitors are classified under the Janitorial Services industry. The employment of the Temporary Help Services industry is, in consequence, a subset of the total employment of staffing firms, making my omitted reallocations estimator a lower bound of the true parameter.

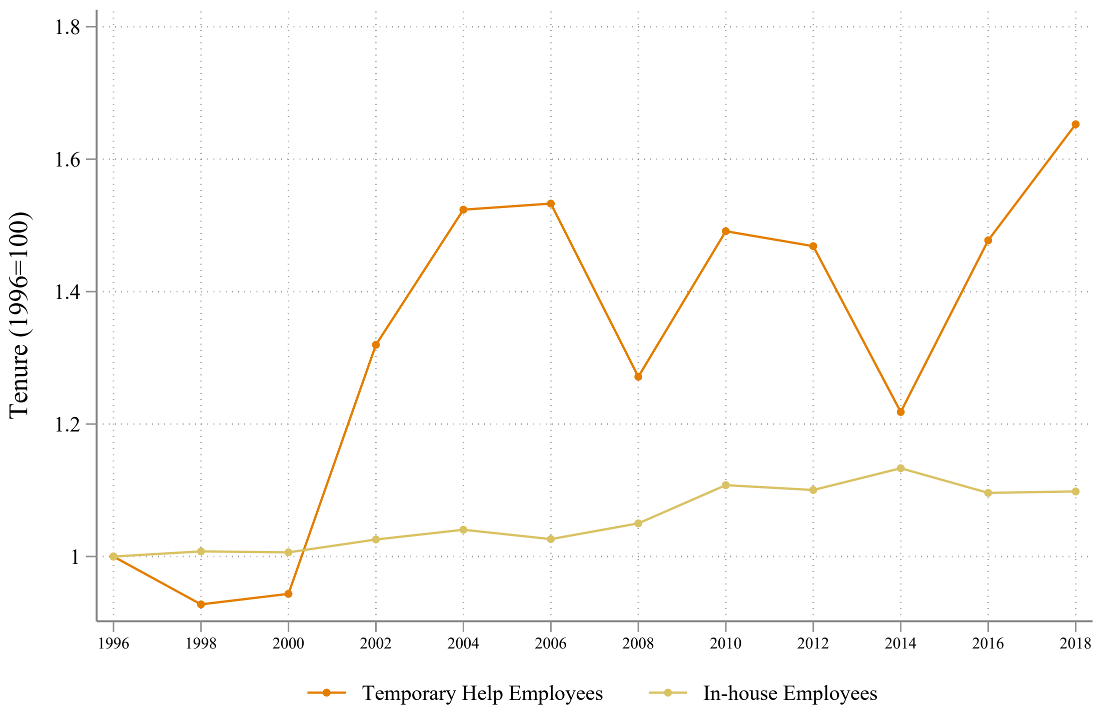
Temporary help services employment (see Figure 1.3), yearly average assignment length, and the placement rate are readily available in the datasets leveraged by this paper (see Section 2.2.1). Tenure at a staffing agency, on the other hand, merits more discussion.

Outsourced workers' tenure at staffing agencies is increasing

As illustrated in the previous section, the longer an outsourced worker stays employed by a staffing agency, the more reallocations across client businesses are omitted in official data sources. However, since there is a negative relationship between tenure and worker reallocations, the omitted reallocations hypothesis implies not only an increasing tenure of outsourced workers but that such growth should not be lower than the one exhibited by payroll employees. This is the *longer tenure prediction*. This section shows that the longer tenure prediction holds both on average and when controlling for demographic and labor market characteristics. Outsourced workers' tenure is increasing even relative to that of payroll employees. This evidence indicates that domestic outsourcing is a key driver underlying the observed decline in worker reallocations (over aggregate increasing tenure).

[5]The North American Industry Classification System defines the Temporary Help Services industry as that comprising establishments primarily engaged in supplying workers to clients' businesses for limited periods of time to supplement the working force of the client. The individuals provided are employees of the temporary help services establishment. However, these establishments do not provide direct supervision of their employees at the client's work sites.

Figure 1.4. The tenure gap between outsourced and payroll employees is closing.



Note: The figure displays the average tenure of outsourced and payroll employees at the time of the survey normalized to the 1996 value. Source: JT-CPS 1996-2018.

The longer tenure prediction holds when comparing outsourced and payroll employees' unconditional tenure averages. Figure 1.4 displays the average tenure of outsourced workers and payroll employees between 1996 and 2018, relative to its value in 1996. Since 1996, the typical outsourced worker tenure has increased by 65%, while payroll employees' tenure has increased by less than 10%. This is equivalent to saying that while outsourced employees' tenure increased by 18 months, payroll employees' tenure increased by less than 8 months. The qualitative result holds across workers' sex, age, and education (see Table A.1).

It is also worth noting that outsourced workers' tenure is considerably more volatile than that of payroll employees. Figure 1.4 shows that the average spell at a staffing agency sharply increased in the aftermath of the 2001 and 2008 recessions, and after 2014. In contrast, no drastic change is observed in the payroll series. This behavior agrees with previous literature pointing out outsourced workers as a potential margin of adjustment for client businesses (Abraham & Taylor, 1996; Autor, 2003; Houseman, 2001; Kalleberg, Reynolds, & Marsden, 2003). I investigate this hypothesis in the second chapter of this dissertation.

I proceed to test the longer tenure hypothesis comparing outsourced and payroll employees within narrow job characteristics and controlling by workers' demographic characteristics. This approach allows me to investigate the difference between outsourced workers' and payroll employees' tenure (the tenure gap) that is not accounted for differences in workers' characteristics, the type of job they perform, or the features of the labor market in which they compete. Specifically, I estimate the following equation:

$$y_{ist} = \alpha_{occ} + \alpha_{edu} + \alpha_s + \alpha_t + \sum_t \beta_t (o_{ist} \times d_t) + \gamma X_{ist} + \varepsilon_{ist}, \tag{1.4}$$

where y_{ist} is the inverse of tenure measured in years for worker i in state s and year t, o_{ist} is a dummy variable for CPS outsourced employee status constructed as described in Section 2.2.1, d_t is a dummy variable for year, and X_{ist} is the vector of control variables which includes age, sex, marital status, and race. Equation (1.4) also includes fixed effects such that its parameters of interest, β_t, capture variation within narrow job characteristics defined by two-digit occupation categories, education level, state, and year[6]. I cluster standard errors at the state, occupation, and year level[7].

Each coefficient β_t is the year-specific difference between outsourced and payroll employees' inverse tenure. Thus, after estimating Equation (1.4), I observe the trend in the inverse tenure gap between comparable outsourced and payroll employees in terms of individual characteristics and type of job performed. This output lets me determine if the tenure of outsourced workers is increasing *relative* to payroll workers. This analysis is important because, as mentioned above, there is a negative relationship between worker reallocations and job tenure even in the absence of omitted reallocations. Intuitively, the longer a worker stays in a job, the fewer reallocations he makes. This negative association arises naturally in a search-and-matching framework in which job matches are experience goods, and hence, gradual learning about match quality leads to a separation rate that declines with job tenure (Jovanovic, 1979). The theoretical prediction has

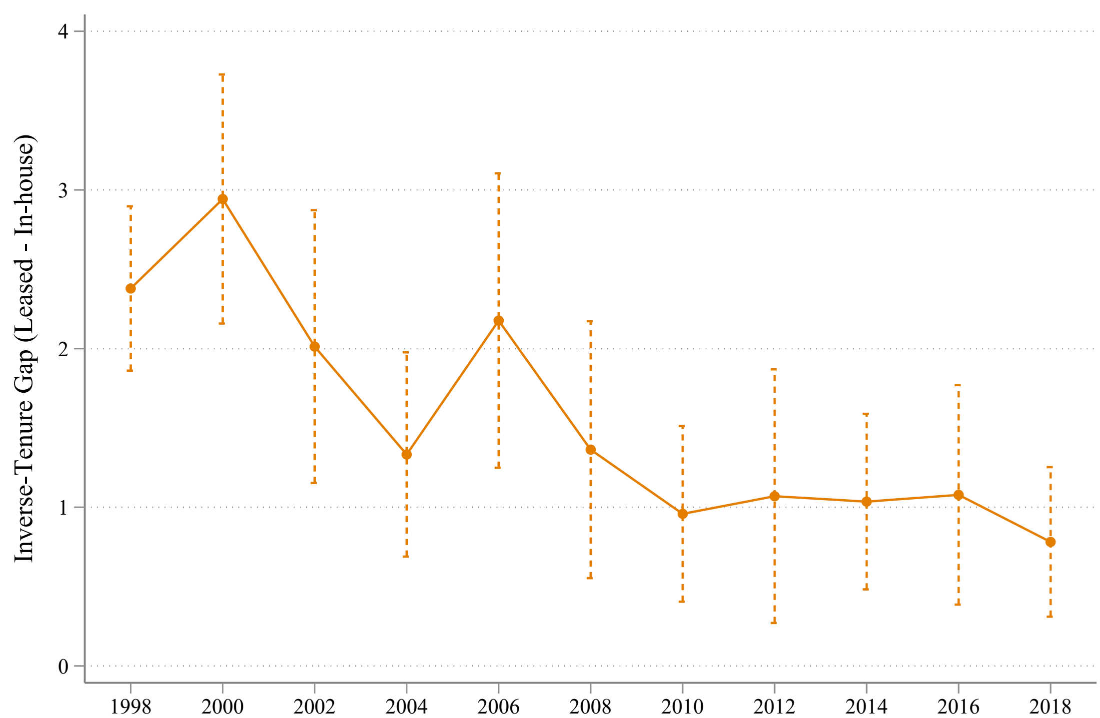
[6] Four education levels: less than high school, high school, some college, and college.

[7] Occupation-education-state-year cells with no outsourced employees are excluded from the analysis. Workers in occupation-industry combinations outside the Temp-Help industry, that have been clearly identified by previous studies as contracted-out workers, are also excluded from the analysis. In particular, I exclude janitors/cleaners (CPS occupation code 453) working in the Services to Buildings and Dwellings industry (CPS industry code 722), and guards (CPS occupation code 426) working in the Protective Services industry (CPS industry code 740) from the analysis (Dube & Kaplan, 2010)

been documented empirically by several papers since at least 1965 (Stoikov & Raimon, 1968; Burton Jr & Parker, 1969; Parsons, 1972; Freeman, 1980).

The longer tenure prediction holds in the data when comparing outsourced and payroll employees within narrow job categories. Figure 1.5 illustrates this finding, depicting $\hat{\beta}_t$, the estimated parameters of interest in Equation (1.4). In 1998, the tenure of outsourced employees represented 28% of that of comparable payroll workers, whereas the same ratio reached 44% in 2018. The tenure gap is also decreasing over time when comparing workers with the same education level, performing the same occupation, and living in the same state, while controlling for demographic characteristics.

Figure 1.5. The tenure gap between outsourced and comparable payroll workers is shrinking over time.



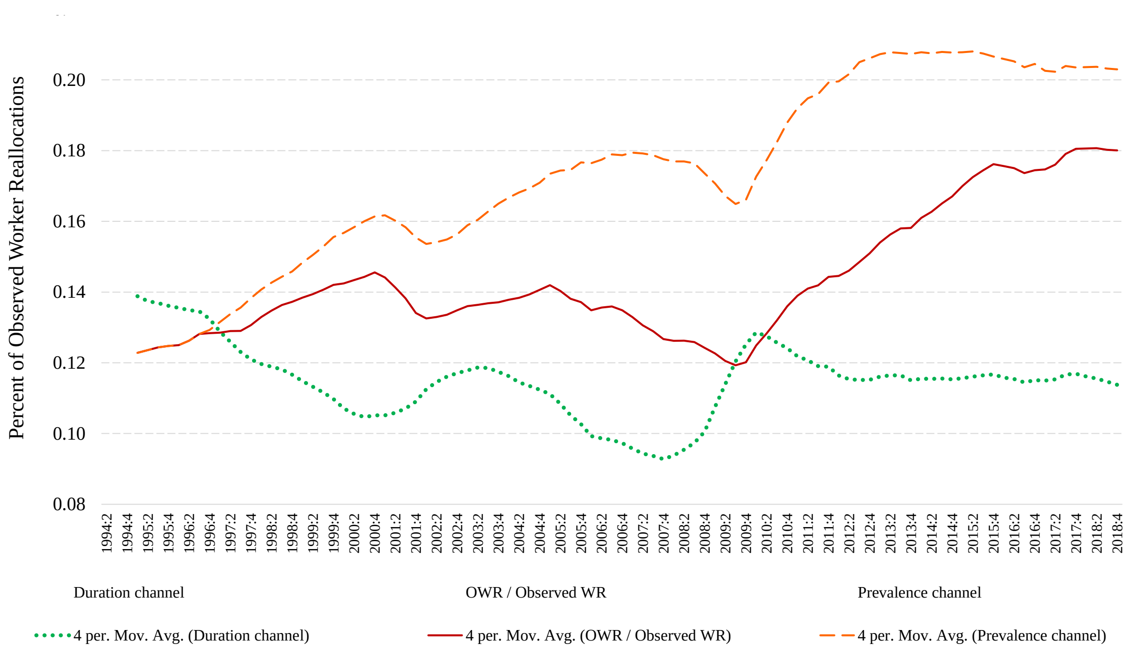
Note: The figure displays estimated coefficients, and 95% CI, of the interaction between outsourced-employee status and year dummies in Equation (1.4). Source: Author's calculations based on CPS-JT 1996-2018.

The CPS's limitations to identify outsourced workers probably explain the wide confidence intervals. Specifically, each year a considerable share of outsourced workers could be mistakenly classified as payroll employees in the sample of my analysis, hence introducing noise to my estimates. This misclassification occurs mainly because individuals report the client business as their employer (Houseman, Dey, & Polivka, 2010). This issue should just introduce noise to my point estimates, $\widehat{\beta}_t$, and flatten the hypothesized upward trend of the tenure gap between outsourced and payroll employees. This is because, combining information from the Contingent Worker Supplement (CWS) and the basic CPS, I find that the share of misclassified Temporary Workers has remained fairly constant over time[8].

Corrected worker reallocations

I estimate the omitted reallocations of outsourced workers OWR_t following Equation (1.2). To that end, I compute predicted tenure $\hat{y}_t$ using the estimated parameters from Equation (1.4). I find that (i) the omitted reallocations problem is sizeable, (ii) it dramatically increased after the Great Recession, and (iii) the corrected worker reallocation is more sensitive to the cycle.

Figure 1.6. The share of omitted reallocations has increased over time.



Note: The figure displays the four-period moving average of the estimated number of omitted reallocations per average quarter in an outsourced-employee spell as a share of QWI payroll worker reallocations. QWI worker reallocation indicator was constructed with the quarterly series of End-of-Quarter Hires and Beginning-of-Quarter Separations. Source: Author's calculations based on CPS-JT, CES, QWI, and ASA statistics.

Figure 1.6 displays outsourced worker reallocations as a share of payroll worker reallocations

[8]The CPS-CWS was designed to overcome the misclassification issue by specifically asking whether the respondent was *paid* by a Temporary Help agency.

(solid line) over time. The dashed line in the same figure represents the share of omitted reallocations had the outsourced workers' tenure remained constant at its 1996 value. The dotted line represents the share of omitted reallocations had outsourced employment remained constant at its 1996 value. The three lines are the moving average of the four quarters preceding the observed data point. Three messages emerge.

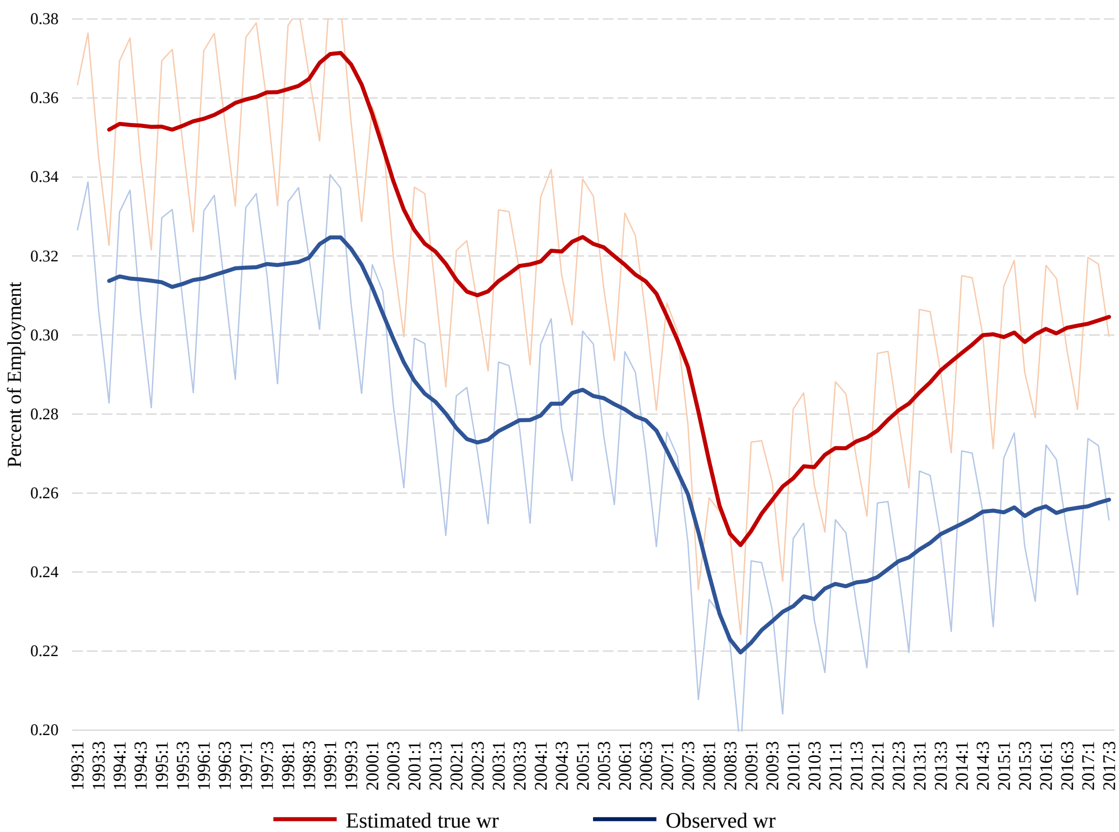
First, worker reallocations are undercounted. Every year, the hires and separations of outsourced workers represent 14% of payroll worker reallocations. That is, in the aggregate, we do not account for 1 in 7 worker transitions. Second, the share of omitted reallocations exhibits significant variation over time going from 13% in 1996 to 18% in 2018. The share of omitted reallocations sharply increased in the aftermath of the Great Recession. This result supports the hypothesis that businesses use outsourced workers as a margin of adjustment. They engaged in outsourcing arrangements to meet their labor needs during the recovery and there is some managerial persistence in this practice. This interpretation matches the fact that the sharp increase in the share of omitted reallocations after 2009 is driven by an increase in the number of outsourced workers (dotted line) rather than by an increase in their tenure at staffing agencies.

Third, omitted reallocations are increasing over time driven by the number of outsourced workers in the economy (prevalence). Prevalence adds variation to the omitted reallocations series while duration adds level. The increasing share of omitted reallocations is driven by an increasing number of outsourced hires and separations and not by a decline in payroll worker reallocations. Figure A.1 shows that the level of omitted reallocations exhibits the same pattern observed in Figure 1.6.

Figure 1.7 shows the corrected worker reallocation rate as computed in Equation (1.3) (red line) and the payroll worker reallocation rate (blue line) over time. This figure shows that the worker reallocation rate is consistently undercounted and misidentified. The corrected worker reallocation rate is, on average, 3% higher than the payroll worker reallocation rate. Moreover, the corrected worker reallocation rate is more sensitive to the cycle. In booms, both series diverge, presumably as client businesses increase their demand for outsourced workers, while in recessions, eventually, both series converge (Figure A.2).

Figure 1.7 also shows that omitted reallocations account for at least one-fifth of the observed drop in the payroll worker reallocation rate between 1993 and 2018. This estimate is a lower bound of the magnitude of the omitted reallocations problem as discussed in Section 1.3.1.

Figure 1.7. The worker reallocation rate is underestimated.



Note: Corrected and observed worker reallocation rates. The lighter series illustrates the quarterly value. The darker series represents the moving average of the previous four quarters. The observed QWI worker reallocation rate was constructed with the quarterly series of End-of-Quarter Hires and Beginning-of-Quarter Separations. Both worker reallocation rates are calculated following QWI formula. Source: Author's calculations based on QWI, JT-CPS, CES, ASA statistics.

1.4 Conclusion

In this paper, I assess the extent to which labor fluidity indicators reflect a rise in domestic outsourcing rather than a decline in underlying dynamism. The mechanism behind this connection is the omitted reallocations of outsourced workers across client businesses. While staying in staffing agencies' payrolls, outsourced workers are continuously reallocated across clients; however, these reallocations are not observed in the datasets traditionally used to compute labor market fluidity indicators. Hence, the observed rates are likely underestimated. The omitted reallocations problem is pervasive across labor fluidity indicators and sectors. This paper focuses, however, on the worker reallocation rate for the empirical analysis, a worker-side measure.

If the omitted-reallocation problem explained the decline in labor fluidity, the number of omitted reallocations must be increasing over time. I provide a decomposition of the worker reallocation rate that illustrates such behavior can be caused by either an increasing share of outsourced employees or payroll fluidity declines within the staffing sector: an increasing job tenure of outsourced employees in staffing agencies. I take this implication to the data using the Job Tenure Supplement of the CPS between 1996 and 2018 to compare the average tenure of similar outsourced and payroll employees over time. I find that for workers with the same education level, performing the same occupation and living in the same state, the average tenure of outsourced employees represented 28% of that of payroll workers in 2000, while this number reached 43% in 2018. This result sheds light on the fact that aggregate tenure is increasing while ob insecurity perception is as well. For outsourced workers, longer tenure does not translate into fewer jobs or more job stability.

I combine the tenure estimates with information provided by the American Staffing Association and the Current Employment Statistics to estimate the number of omitted reallocations. I find that, between 1994 and 2018, the QWI worker reallocation indicator omitted the equivalent to 14% of the observed reallocations. The proportion of omitted reallocations increased dramatically after the 2008 recession. While 3 million of reallocations were omitted in 2009, the same number reached 6 million in 2018. In fact, the worker reallocation rate would have been at least 21% were the hires and separations of outsourced workers factored in.

To my knowledge, this is the first paper studying the connection between domestic outsourcing and labor market fluidity. The magnitude of the number of omitted reallocations highlights a new challenge that different employer-employee relationships impose on our understanding of labor markets and their dynamics. Acknowledging that our labor fluidity indicators are not capturing part of these dynamics is an important step to comprehending recent developments in the U.S. labor market and the response of its agents to shocks.

Chapter 2

Contracting out Labor Market Dynamism*

2.1 Introduction

Since at least the 1990s, U.S. firms have met their labor needs by hiring directly or contracting other firms in the U.S. to "rent" workers —domestic outsourcing. The U.S. manufacturing sector increased the number of outsourced jobs per payroll job by at least 40% between 2006 and 2017. Yet, previous data limitations have prevented this growing phenomenon from being incorporated into analyses of establishment-level and aggregate labor adjustment. This paper shows that (i) outsourced workers are an important margin of adjustment at the micro and aggregate level, and (ii) not accounting for the creation and destruction of jobs filled by outsourced workers biases the measurement of indicators at the center of our understanding of labor markets and the design of public policies targeting firms —job creation, job destruction, hires, separations, vacancies, and employment.

A large literature documents a downward trend in the pace at which jobs and workers move across workplaces in the U.S. in recent decades (Decker, Haltiwanger, Jarmin, & Miranda, 2016a; Molloy, Trezzi, Smith, & Wozniak, 2016; Bjelland, Fallick, Haltiwanger, & McEntarfer, 2011; Akcigit & Ates, 2021)[1]. The decline in labor market fluidity has received considerable attention

[*] Any opinions and conclusions expressed herein are those of the author and not those of the U.S. Census Bureau. The Census Bureau's Disclosure Review Board and Disclosure Avoidance Officers have reviewed this information product for unauthorized disclosure of confidential information and have approved the disclosure avoidance practices applied to this release. This research was performed at a Federal Statistical Research Data Center under FSRDC Project Number 1808. (CBDRB-FY22-P1808-R10049 and CBDRB-FY23-P1808-R10211)

[1] Although the level of the decline largely depends on the data source and the indicator used to measure it, there is a strong agreement about the downward trend (Hyatt & Spletzer, 2013).

because less fluid labor markets result in lower productivity growth through the misallocation of resources: fewer jobs and workers flowing to their more productive uses (Jovanovic & Moffitt, 1990; J. Haltiwanger, Foster, & Krizan, 2001). Decker et al. (2020) finds that reduced plant-level payroll employment responsiveness to revenue productivity underlies the aggregate decline in payroll job reallocations and has been a drag on aggregate productivity. These results added allocative efficiency to the productivity slowdown debate and settled the discussion about the underlying causes of payroll job reallocations beyond changes in the firms' demographic distribution[2]. However, the factors behind declining plant payroll employment responsiveness are still an open question and an important one given its implications for allocative efficiency.

This paper establishes that the increasing use of domestic outsourcing is one of the factors behind the decline in plant-level payroll employment responsiveness and accounts for a significant share of the aggregate decline in payroll job reallocations. The growing availability of labor market intermediaries has broadened the choice set for employers seeking to adjust employment. In particular, these intermediaries specialize in flexible labor sourcing, which is particularly attractive for plants responding to productivity fluctuations.

Domestic outsourcing happens when firms (clients) contract with other firms or individuals in the U.S. to provide goods and services previously performed in-house. Thus, outsourced staff effectively work for client firms but are legally employed by a staffing agency; therefore, these workers may change jobs, tasks, and workplaces —but not the employer of record as in traditional employment relationships. In the U.S., the data used to track labor markets' activity accounts for the labor market transitions of outsourced workers in their agency's sector (services) and omits their reallocations across client establishments altogether. This omission gives rise to (i) a systematic undercount of the aggregate job and worker reallocations (and the vacancies they fill), and (ii) a misrepresentation of the reallocations composition across sectors —this is the *omitted reallocations* problem. The omitted reallocations problem is a measurement issue, pervasive across labor market fluidity indicators and sectors, with non-trivial implications for our understanding of labor markets (Atencio De Leon, 2023).

The biggest challenge to empirically investigate the implications of the omitted reallocations problem lies in the very nature of the problem at hand: *omitted* reallocations. The client firm-outsourced employee relationship is not observable, and thus linking outsourcing and productivity at the micro level has not been possible until now[3]. I overcome this challenge by combining

[2] The discussion about the documented slowdown in the U.S. productivity growth rate focused on technological and measurement explanations (Byrne, Fernald, & Reinsdorf, 2016; Gordon, 2016a; Syverson, 2017).

[3] See Bernhardt, Batt, Houseman, and Appelbaum (2016) and (Houseman & Bernhardt, 2017) for a discussion on the data limitations to study outsourcing and an overview of the existing data.

multiple datasets administered by the U.S. Census Bureau and the U.S. Bureau of Labor Statistics, and developing a procedure to transform plant-level information on expenses on staffing services into plant-level outsourced employment. The Census and Annual Survey of Manufacturers collect plant-level information on expenses on different types of outsourced staff since 2006[4]. I focus on temporary and leased employees because this type of outsourced workers performs tasks on the client's worksite, typically in occupations at the core of the manufacturing business (Houseman et al., 2010). From now on, I use temporary and leased employment and outsourced employment interchangeably for simplification.

I begin my empirical analysis by characterizing the type of manufacturing plants using domestic outsourcing while documenting novel facts on the prevalence and growth of this phenomenon. First, I find that the share of revenue spent on outsourced workers (outsourced labor share) is decreasing in the plant's age and payroll employment size. These patterns are in line with the drop in the share of payroll jobs created by smaller and younger firms partly accounting for the long-term decline in labor market fluidity (Davis & Haltiwanger, 2014; Decker, Haltiwanger, Jarmin, & Miranda, 2014, 2016b). Second, between 2006 and 2017, the outsourced labor share exhibits steeper and more volatile growth compared with the payroll labor share. The average manufacturing plant increased its outsourced labor share by 85%, compared to a 10% increase in the payroll labor share. Third, the decision to use staffing arrangements as well as the intensity with which they use them vary systematically with revenue growth. The share of manufacturing plants using outsourced labor decreases when revenue growth is shrinking and increases when it is expanding. These three facts suggest that plants use domestic outsourcing strategically and that domestic outsourcing is a key component underlying the decline in aggregate job reallocations.

Business dynamics models' result that plants adjust their employment in response to their own ever-changing productivity (H. A. Hopenhayn, 1992; Bergin & Bernhardt, 2004) motivate my empirical strategy to assess outsourced labor responsiveness; a strategy that, in turn, builds on (Decker et al., 2020)'s empirical design to study payroll employment responsiveness to revenue productivity. I then define shocks as revenue productivity growth deviations from own or detailed industry-year average productivity growth.

Outsourced employment is an important margin of adjustment. I find that plant-level outsourced employment is twice as responsive as payroll employment to shocks and adjusts more quickly. Plants respond to shocks by adjusting outsourced employment growth within the same year of the shock, while payroll employment reacts in the following year. The "immediate" response of

[4]Outsourced workers include temporary help workers, leased employees, independent contractors and contracted out workers through business service firms

outsourced employment reflects the flexible nature of this type of worker and is micro evidence for the use of temporary help employment as a leading recession indicator (Peck & Theodore, 2007; Houseman & Heinrich, 2015; Luo, Mann, & Holden, 2021).

I interpret the smaller subsequent response of payroll employment as plants using outsourced workers to adjust their workforce while they learn about the permanency of the shock. In turn, this is consistent with outsourced jobs temporarily substituting for payroll jobs. That is, the evidence suggests that (i) following negative shocks, plants shed outsourced jobs first to retain permanent workers in whom they have invested and who have acquired firm-specific skills, and (ii) following positive shocks, plants outsource new hires, waiting to see whether the shock is long-lasting enough to merit costly investments in new permanent employees. This pattern is consistent with the hypothesis that payroll employment adjustment costs are an important mechanism behind the use of staffing services (Abraham & Taylor, 1996; Segal & Sullivan, 1997; Houseman, 2001; Houseman et al., 2003; Autor, 2003). Consistent with domestic outsourcing being a core factor behind the drop in job reallocations, payroll employment adjustment costs have also been shown to be a relevant mechanism for the decline in labor market flows (Autor, Kerr, & Kugler, 2007; Davis & Haltiwanger, 2014; Cairo & Cajner, 2017; Fujita, 2018).

Domestic outsourcing micro implications have large macroeconomic measurement consequences. On average, every year, we omit the equivalent to 14% of payroll job reallocations. Moreover, the creation or destruction of outsourced jobs can account for as much as one-fifth of the corresponding payroll job flow in a given year —this was the case for outsourced job creation in 2010, the first year after the Great Recession, while omitted job destruction was at its minimum in that year. This contrast means that, in the first year after the Great Recession, relative to payroll jobs, the manufacturing sector was not only creating jobs to be filled by outsourced workers at a higher pace, but it was not destroying the existing ones as quickly. The omitted reallocations problem qualitatively affects our understanding of labor markets' adjustment along the cycle.

More generally, the widespread use of gross job flows to investigate U.S. labor markets, test theories about their behavior, understand cyclical fluctuations in employment, and inform public policy decisions underscores the importance of considering the first-order effects documented in this paper in labor market analyses. A salient example is search models' calibrations —a workhorse model for the empirical research of labor markets, for which gross labor flows are typically key parameters (Pissarides, 1985; Mortensen & Pissarides, 1994, 1999).

ADDITIONAL CONTRIBUTIONS TO THE LITERATURE. My findings contribute to two strands of literature: labor market dynamism and domestic outsourcing. In the literature on the decline in labor market dynamism, the omitted reallocations hypothesis is novel. In the domestic outsourcing body of work, this paper highlights the importance of domestic outsourcing *dynamics* and contributes with administrative client plant-level evidence for the biggest client sector of staffing services, manufacturing.

Domestic outsourcing is increasingly receiving attention by the economic literature due to its consequences for wages, wage discrimination within the firm, and wage inequality (Houseman et al., 2003; Autor & Houseman, 2010; Dube & Kaplan, 2010; Goldschmidt & Schmieder, 2017; Bloom, Guvenen, Smith, Song, & von Wachter, 2018; Dorn, Schmieder, & Spletzer, 2018; Bilal & Lhuillier, 2021; Bergeaud, Mazet-Sonilhac, Malgouyres, & Signorelli, 2021; Weber Handwerker, 2022). Not surprisingly, then, this literature is mostly focused on the worker side. Two notable exceptions to this practice are Houseman (2001) and Anderson and McKenzie (2022). My contribution to this body of work is twofold. First, the descriptive evidence of this paper complements our knowledge about domestic outsourcing from the client business side. The facts on the type of businesses using staffing services more intensively, as measured by the outsourced labor share, are novel in the literature; and those on the prevalence of this phenomenon across plants' characteristics are consistent with Houseman (2001)'s results. Second, my results show that the dynamics in the use of domestic outsourcing also have significant consequences on our understanding of labor markets' functioning. The existing empirical evidence concentrates on the effects of transitioning from not outsourcing to outsourcing. This paper also adds the magnitude of the decline in gross job flows to the list of measurement issues that arise if we do not account for outsourced workers. Previous work has focused on employment and labor productivity patterns, or worker flows (Dey, Houseman, & Polivka, 2012, 2017; Houseman & Heinrich, 2015; Atencio De Leon, 2023).

Accounting for domestic outsourcing complements our knowledge of the decline of labor market dynamism and of labor adjustment at the aggregate and micro level (Shimer, 2012b; Hyatt & Spletzer, 2013; Davis & Haltiwanger, 2014; Decker et al., 2016a; Molloy et al., 2016; Peters & Walsh, 2019; Decker et al., 2020; Akcigit & Ates, 2021). My results suggest that at least part of the decline reflects a transformation of the labor market towards the use of intermediaries in the employment process rather than a decline in underlying dynamism and that allowing a broader definition of employers' responsiveness to include domestic outsourcing enriches our understanding of micro-level adjustments to shocks.

OVERVIEW OF THIS PAPER. Section 2.2 documents the prevalence and growth of domestic outsourcing in the U.S. manufacturing sector. Section 2.3 presents the methodology to estimate plant-level outsourced employment from expenses and assesses the consequences of omitting outsourced workers on plant-level labor responsiveness of plants to changes in revenue productivity. Section 2.4 quantifies the omitted reallocations problem in manufacturing job reallocations. Section 2.5 discusses the results. Section 2.6 concludes.

2.2 Domestic outsourcing in U.S. manufacturing: growth and prevalence

This section describes domestic outsourcing in the U.S. manufacturing sector using administrative micro data on expenses on temporary and leased staff for the period between 2006 and 2017 (see Section 2.2.1). I describe the prevalence of domestic outsourcing by plant employment size, high/low-tech industry, three-digit industry, and revenue growth. I also characterize the types of plants that use outsourced staff more intensively, as measured by the share of revenue spent on this type of workers. Finally, I investigate the use of outsourced employment over time. The results in this section show that domestic outsourcing is increasing over time and exhibits substantial cross-sectional variation along plants' characteristics and revenue growth.

2.2.1 Data

Large data gaps have impeded accurately accounting for outsourced workers in economic analyses. I overcome this challenge by combining multiple administrative datasets from the U.S. Census Bureau. Specifically, I use the Annual Survey of Manufacturers (ASM), the Census of Manufacturers (CM), the Longitudinal Business Database (LBD), and the Revenue Longitudinal Business Database (RE-LBD).

The Annual Survey of Manufacturers contains a sample representative of the manufacturing sector that rotates every five years (in years ending in "4" and "9"). The Census of Manufacturers, on the other hand, contains the universe of manufacturing plants and is conducted in years ending in "2" and "7". For such years, I keep only the plants that are in the corresponding rotating sample of the ASM. The rotating sample feature of the ASM is essential for my empirical analysis since I rely on year-to-year changes.

The ASM-CM has establishment-level information on revenue and revenue productivity and since 2006, on expenses on outsourced services[5]. I focus on expenses on temporary and leased staff since, in manufacturing, this type of outsourced workers typically work side-by-side payroll employees and are in production occupations (Dey et al., 2017)[6]. These characteristics of temporary and leased workers are important for my analysis because they suggest that the jobs filled by these types of outsourced workers are comparable to those filled by payroll employees. This implies that the omission of the creation and destruction of jobs filled by temporary and leased workers reflects a structural change in the employment process (the use of intermediaries) rather than in the task composition of the production process. From now on, I will use temporary and leased workers and outsourced workers interchangeably.

I link the ASM-CM sample with the LBD to retrieve information on plant location, plant age, firm age, and firm payroll employment. The LBD is a census of establishments and firms in the U.S. with paid employees. I use the plant location to link each plant with the average labor share (payroll over revenue) of temporary help firms and professional employment organizations in a given state. This information is in the RE-LBD and is an important component of the estimation of outsourced staff from expenses on temporary and leased staff.

I restrict the ASM-CM sample to establishments with no missing or imputed information on expenses on temporary and leased staff. Therefore, to ensure that my empirical analysis is still representative of the manufacturing sector, I construct propensity score weights based on a logit model of industry, firm size, and firm age to adjust the restricted sample to represent the LBD (Section B3 provides details). The baseline sample for the analysis of this paper is a non-balanced panel of manufacturing plants between 2006 and 2017.

2.2.2 Domestic outsourcing in the cross-section

Table 2.1 describes the use of temporary and leased staff in the manufacturing sector by establishment age, size, and high-tech status. Column (1) displays the percentage of client plants: establishments reporting having spent on outsourced employment in a given year. Column (2) shows expenditures on outsourced employment as a percentage of revenue for client plants. In this way, the outsourced labor share of revenue captures use intensity without confounding the participation decision.

[5] Revenue is defined as the sum of the total value of shipments and variations in inventory.

[6] Domestic outsourcing includes independent contractors, on-call workers, contract company workers, temporary workers, and leased staff. Temporary help agencies assign their workers to client plants, while professional employment organizations (the legal employer of leased employees) completely take over client plants' human resources tasks.

Table 2.1. Outsourced staff in the manufacturing sector: participation in staffing arrangements is more prevalent in older, bigger, and high-tech establishments, but younger, smaller, and low-tech establishments use them more intensively.

	Pct. of establishments *(1)*	Pct. of revenue (clients) *(2)*
Total	47.14	1.70
Establishment age class		
0-4	41.51	2.23
5-9	44.29	1.81
10-29	47.63	1.60
30+	51.97	1.45
Establishment size class		
0-9	27.60	2.54
10-49	39.88	1.99
50-249	67.51	1.31
250+	81.19	1.01
High-tech status		
High-tech	63.62	1.46
Low-tech	46.11	1.72

Notes: Yearly averages by the given establishment characteristic. Column 1 displays the percentage of establishments reporting having spent on temporary workers and leased employees. Column 2 reports the percentage of revenue spent on temporary and leased employees by the average client establishment in each category. High-tech is defined using four-digit NAICS industries as in (Hecker, 2005). Source: Author's calculations from ASM-CM-LBD data in 2006-2017.

The use of domestic outsourcing is common in the manufacturing sector. 70% of the plants reported having spent on outsourced employment between 2007 and 2017 and 47% of the manufacturing plant-year observations in the sample are client plants. The difference indicates that using outsourced staff is not an absorbing state. Manufacturing plants use outsourced staff intermittently. The average client business spent 1.7% of its revenue on professional employment organizations and temporary help agencies.

Outsourcing arrangements are more prevalent in bigger and older establishments, but among clients, smaller and younger establishments use these arrangements more intensively. Panel A of Table 2.1 shows that the percentage of establishments with fewer than 10 payroll employees using staffing arrangements is one-third of that of establishments with more than 250 payroll employees. Conversely, among client establishments, small plants' temporary and leased staff share of revenue more than double that of big establishments.

J. Haltiwanger, Hathaway, and Miranda (2014) have found that the decline in payroll job reallocation between 2003 and 2011 was larger among high-tech manufacturing plants, so I investigate how outsourcing varies between high-tech and other manufacturing plants. High-tech is defined using four-digit NAICS industries as in Hecker (2005). Table 2.1 shows the results. Consistent with the omitted reallocations hypothesis, high-tech establishments are more likely to spend on staffing arrangements than other manufacturing plants. According to Table 2.1, 63.6% of this type of manufacturing plant used staffing arrangements compared to 46.1% of low-tech establishments and 47.14% overall.

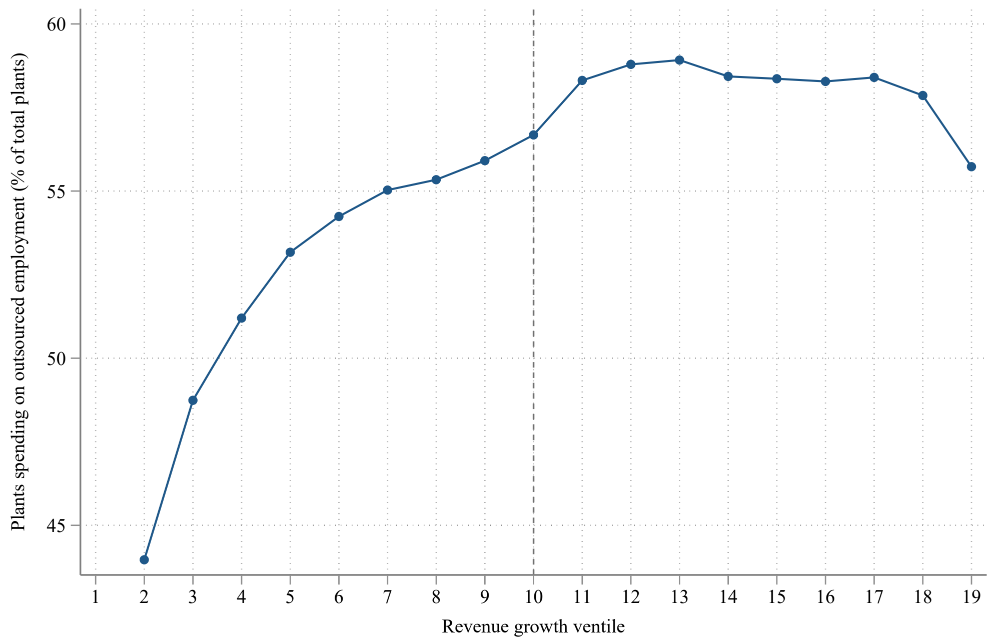
I next consider the cross-sectional relationship between the use of domestic outsourcing and average plant-level revenue growth. This exercise will provide insights on the strategic use of outsourced employment by plants. My hypothesis is that the use of intermediaries allows for lower cost adjustments of labor needs and faster adjustment.

I restrict the sample to establishments observed for at least two consecutive years and compute the symmetric revenue growth rate for each of them.[7] Then, I split the sample into twenty equally-sized groups and compute domestic outsourcing use statistics for each group. Figure 2.1 displays the average share of client establishments for each revenue growth ventile. Similarly, Figure 2.2 depicts average plant-level expenses on outsourced staff as a share of revenue for each revenue growth ventile.

Figure 2.1 shows an increasing, nonlinear relationship between revenue growth and the use of domestic outsourcing. The share of client plants declines sharply when revenue growth is shrinking. Above the median revenue growth, the participation margin rises until it reaches its maximum at 59.5%; then it flattens to finally decline for establishments at the top of the revenue growth distribution. Figure 2.1 indicates that the revenue growth and the decision of using outsourced workers are tightly linked at the business level. The "hook" shape of the relationship

[7] DHS or arc-elasticity widely used in the literature. This measure is inclusive of establishments exiting or entering the market; however; I do not report them in figures 2.1 and 2.2.

Figure 2.1. The share of client plants increases with revenue growth. The increase flattens after the median.



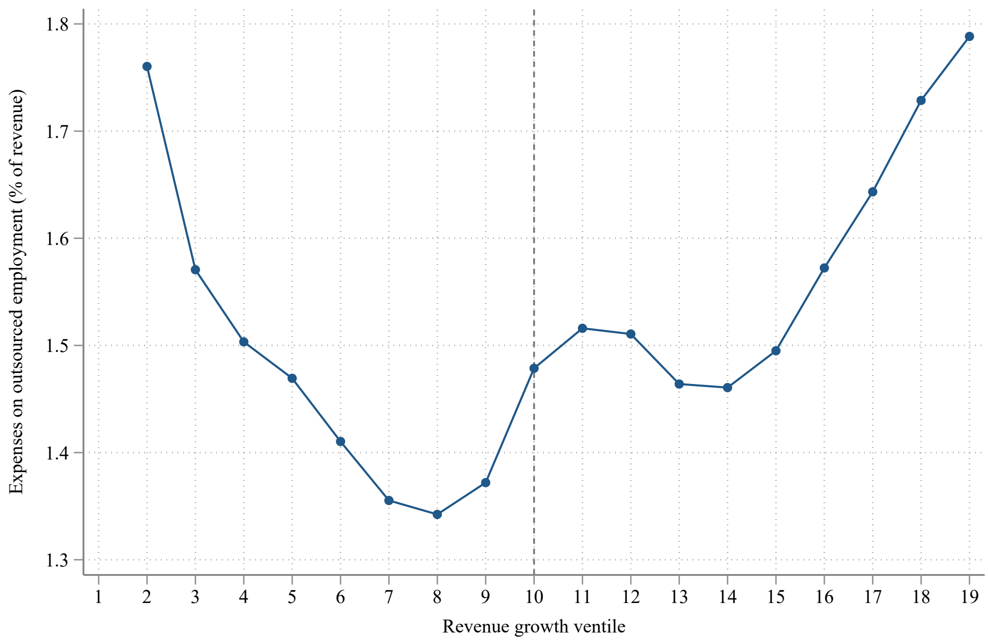
Note: The figure displays the share of client establishment by revenue growth ventile. Each point is the three-point moving average. Source: Author's calculation from ASM-SM-LBD data in 2006-2017.

supports the hypothesis that plants use domestic outsourcing strategically and potentially as a margin of adjustment to variations in revenue growth. The pattern exhibited by the relationship between the intensive margin and revenue growth is consistent with this interpretation (Figure 2.2).

2.2.3 Domestic outsourcing over time

The use of domestic outsourcing is increasing over time. The share of revenue spent on this type of staffing arrangement almost doubled for the studied period, going from 0.65% to 1.21%. This growth is conditional on business age, industry, and payroll employment size, i.e., it is not accounted for changes in the composition of plants along these characteristics. The average client business exhibits the same pattern. Figure 2.3 depicts the temporary and leased staff share of revenue for the average client business over time. Every year, on average, plants that reported having spent a non-zero amount on temporary and leased staff increased the share of revenue spent on this service by approximately 7%, going from 1.49% in 2006 to 2.70% in 2017.

Figure 2.2. There is a U-shaped relationship between the share of revenue spent on outsourced staff and revenue growth.

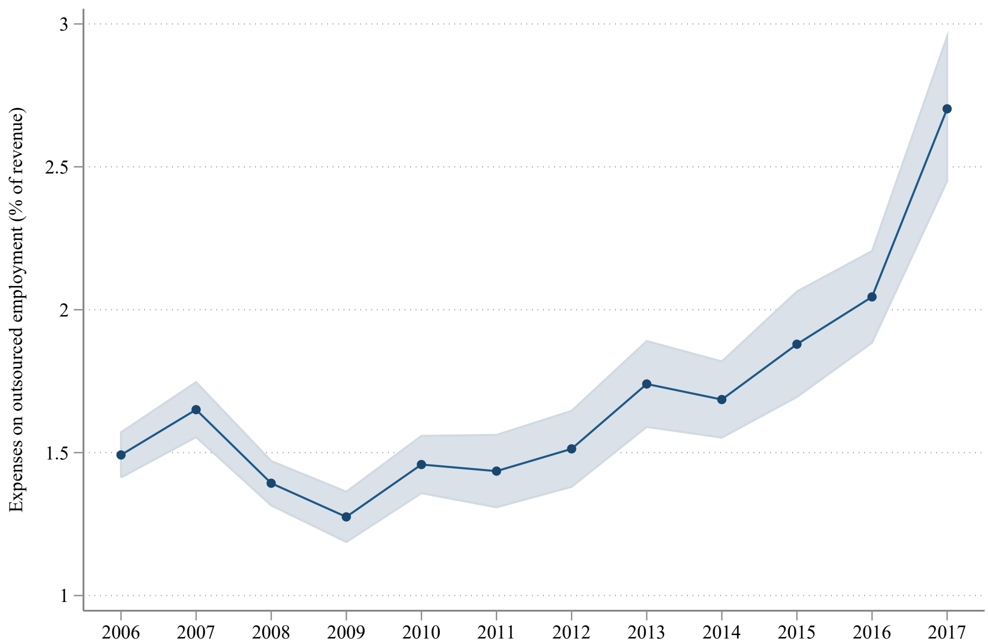


Note: The figure displays the average share of revenue spent on temporary and leased staff by revenue growth ventile. Each point is the three-point moving average. Source: Author's calculation from ASM-SM-LBD data in 2006-2017.

Despite the average positive yearly growth rate, between 2007 and 2009, the outsourced labor share of revenue dropped by 23%. During these years, the U.S. economy was undergoing the Great Recession; thus, the drop is expected but its magnitude is remarkable considering that revenue was also declining. It follows that client plants cut expenses on temporary and leased employment at a higher pace than they saw their revenue decline. Figure 2.4 suggests the same does not hold for payroll employment.

Figure 2.4 displays the labor share of outsourced and payroll employment for the average manufacturing business over time. It shows that, between 2007 and 2009, the average payroll employment share saw a small increase, presumably due to the decline in revenue, whereas the outsourced employment share dropped by 35%. Not surprisingly, the decline for the average manufacturing plants exceeds that of the average client business since the former confounds the fact that plants may decide not to use outsourced workers altogether in response to the adverse economic environment (the participation margin). This evidence is in line with the relationship between domestic outsourcing and revenue growth documented in the previous section. It also

Figure 2.3. The average manufacturing plant increased the outsourced labor share by 85% between 2006 and 2017.



Note: Point estimates and robust standard errors of plant-specific expenditures on outsourced staff as a share of revenue, controlling for employment size, age, and three-digit industry. Source: Author's calculations from ASM-CM-LBD data in 2006-2017.

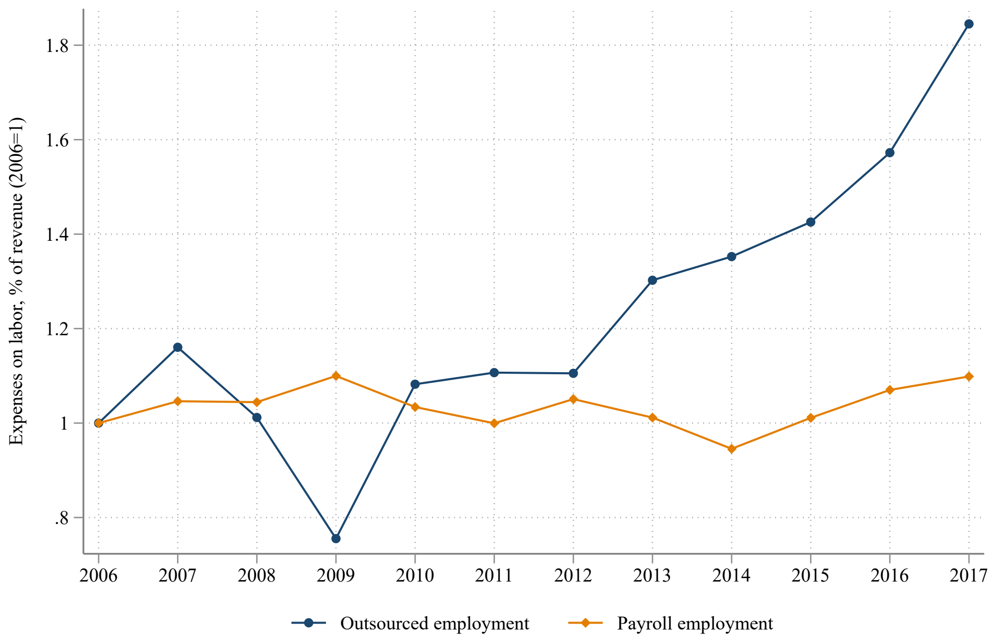
points to outsourced workers being an important margin of adjustment for plants. I investigate the role of outsourced workers as a margin of adjustment in Section 2.3.

Figure 2.4 is also consistent with manufacturing plants increasingly sourcing labor from temporary help agencies and professional employment organizations even relative to direct hires. The figure additionally shows that outsourced labor share variance is significantly higher than that of payroll employment. The evidence suggests that the creation of jobs filled by outsourced workers has increased over time and supports the interpretation of outsourced workers as being an unobserved margin of adjustment. Sections 2.3 and 2.4 confirm these statements.

2.3 Domestic outsourcing and plant-level labor responsiveness

The omitted reallocations problem goes beyond measurement. The failure to account for outsourced workers translates into misconceptions about the labor market and how it works. I

Figure 2.4. Outsourced employment share of revenue is increasing, whereas payroll employment share of revenue remained roughly constant.



Note: Point estimates of plant-specific expenditures on outsourced and payroll employment as a share of revenue, controlling for employment size, age, and three-digit industry. Point estimates normalized to the value in 2006. Source: Author's calculations from ASM-CM-LBD data in 2006-2017.

illustrate this point with the labor adjustment of plants to changes in revenue productivity growth (responsiveness). I show that by not considering outsourced workers in the labor responsiveness of plants we omit a margin of adjustment whose dynamics differ from that of the observed margin (payroll employment), limiting in turn our understanding of employers' strategic behavior. The increasing share of revenue spent on temporary and leased employment (see Section 2.2) suggests that such an omitted margin of adjustment may be one of the underlying causes of the decline in payroll labor responsiveness documented by the literature.

2.3.1 Plant-level outsourced employment from reported expenses

Total expenditures on outsourced staff, exp^o, is a function of the wage bill of outsourced workers, o^o, and the fixed costs related to outsourcing, F:

$$exp^o_{jst} = o_{jst} w^o_{jst} + F_{jst},$$

where a plant is indexed by j, state by s, and year by t.

Suppose that fixed costs are proportional to wages paid for outsourced employees, then

$$exp^{o}_{jst} = (1+\alpha)o_{jst}w^{o}_{jst}, \tag{2.1}$$

where α is the overhead per outsourced employee charged by the staffing agency associated with plant j.

To estimate plant-level outsourced employment o_{jst}, I begin by making two conservative assumptions. First, average earnings per payroll job w^{p}_{jst} are equal to that of outsourced jobs w^{o}_{jst}. Second, the agency's overhead per outsourced employee is equal to the inverse labor share of the average staffing agency ℓ in state s[8]. I then estimate plant-level outsourced employment as follows:

$$\hat{o}_{jst} = \underbrace{exp^{o}_{jst} \times \frac{payroll_{\ell st}}{revenue_{\ell st}}}_{\text{Outsourced wage bill}} \times \frac{1}{w^{p}_{jst}}. \tag{2.2}$$

Equation (2.2) underestimates plant-level outsourced employment as long as

$$\frac{payroll_{\ell st}}{revenue_{\ell st}} < \frac{1}{1+\alpha}, \tag{2.3}$$

α is small, otherwise, the client plant would hire all employees directly instead of outsourcing. Moreover, besides competing with clients' direct hiring, staffing agencies also compete aggressively with each other on price. Consequently, $\frac{1}{1+\alpha} \approx 1$ and whenever outsourcing agencies have profits or expenses other than labor, $\frac{payroll_{\ell st}}{revenue_{\ell st}} << 1$. Thus, condition (2.3) holds and my baseline estimate of plant-level outsourced employment is a lower bound.

Let me elaborate on the wage assumption. The average wage of outsourced workers is a fraction of that of payroll employees in the same occupation:

$$w^{p}_{t} = (1+\gamma_t)w^{o}_{t}.$$

[8] I leverage location information on both staffing agencies and client plants to approximate an agency's labor share with the labor share of the average staffing agency in the state s in which the client plant is located β_{st}. I do so because, although I observe the labor share of staffing agencies, the staffing agency-client plant link is not observed.

Dube and Kaplan (2010) show that for low-wage service occupations γ_t ranges from 4% to 24%. Using German data, (Goldschmidt & Schmieder, 2017) show there is an outsourcing wage penalty (ranging between 10% and 15%) even for jobs that are moved outside the boundary of the firm to contracting firms. Using data from the Occupation and Employment Wage Statistics (OEWS), I find that in my setting, γ_t varies from 10% to 15%. Equation (2.2) effectively assumes that γ_t is constant and equal to zero. Once again, my baseline results are a lower bound. I relax the wage assumption in Section 2.4.

2.3.2 Outsourced employment and revenue productivity changes

I investigate outsourced workers as a margin of adjustment estimating a fixed-effects panel equation of outsourced employment growth on revenue productivity change ($log(a_t) - log(a_{t-1})$). My empirical strategy is motivated by business dynamics models' result that plants adjust their employment in response to their own ever-changing productivity (H. A. Hopenhayn, 1992; Bergin & Bernhardt, 2004) and builds on the empirical design of Decker et al. (2020)[9]. Specifically, I estimate the following equation:

$$\Delta_\tau y_j = \alpha_{it} + \beta_1 \Delta_t a_{jt} + controls + \varepsilon_{j\tau} \quad \text{where} \quad \tau \in \{t-1, t \quad t, t+1 \quad t+1, t+2\}, \tag{2.4}$$

α_{it} are six-digit industry-year fixed effects, j denotes establishments and t denotes year. The outcome $\Delta_\tau y$ is the symmetric (or DHS) growth rate of outsourced employment between any pair of years in τ.[10] The variable of interest is $\Delta_t a_{jt}$, the change in log revenue productivity between t and $t-1$. I estimate equation (2.4) for plants that stayed in the sample for at least five years.

Outsourced employment DHS growth rates, $\Delta_\tau y$, are inclusive of plants that stopped using this type of workers at any time during the studied period. This feature is important in my empirical design because plants may respond to revenue productivity changes by adjusting the intensity in which they use outsourced workers or they may stop using them altogether. DHS growth rates capture both responses computing outsourced employment annual changes relative to average outsourced employment for the two periods involved. However, this measure is not defined whenever such average is zero, i.e., non-client plants that decided to stay as such for the

[9] These authors study plant-level labor responsiveness as a cause for the decline in job reallocation.

[10] This growth rate concept is commonly used in the literature on firm dynamics. DHS refers to Davis, Haltiwanger, and Schuh (1996).

subsequent period. I define the outcome as zero in these cases. In particular, for $\tau = t-1, t$

$$\Delta_t y_j = \begin{cases} 2 \times \frac{\hat{o}_{jt} - \hat{o}_{jt-1}}{\hat{o}_{jt} + \hat{o}_{jt-1}}, & \text{if } \hat{o}_{jt} + \hat{o}_{jt-1} > 0 \\ 0, & \text{otherwise} \end{cases}$$

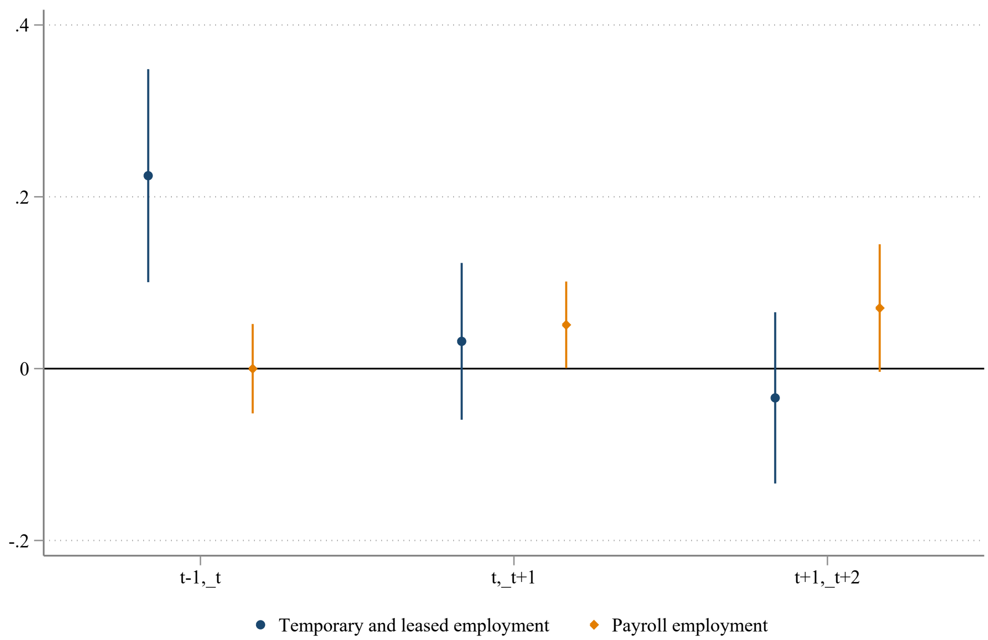
where $\hat{o}_{jt}$ is the plant-level outsourced employment estimated using equation (2.2). Setting to zero the growth rate of plants that "dropped out" from using temporary and leased staff but did not exit the market allows me to capture, for example, situations in which the plant "hired" outsourced workers to fulfill a big order with a short deadline (less than one year) and then "laid them off": a common situation for the use of outsourced workers in manufacturing. The outcome would also capture the opposite case: plants that "opted in" from using the studied margin after the productivity change. It also permits me to follow the same set of establishments from $t-1$ to $t+2$, the periods involved in the estimation of equation (2.4).

The parameter of interest, β_1, estimates outsourced labor responsiveness shocks. The average plant-level response of outsourced staff growth to *deviations* from industry-year average revenue productivity growth. The difference specification already nets out the estimated responsiveness of time-invariant factors at the establishment level; therefore, the inclusion of industry-year fixed effects makes β_1 the responsiveness to changes on plant-level deviations from the average revenue productivity growth in their detailed industry in a given year. I control for factors, common to all plants, inducing a linear trend in revenue productivity growth by including change in log productivity interacted with a linear trend in $controls$.

In addition to the interaction between log revenue productivity change and a linear trend, $controls$ includes a variety of covariates informed by the results in Sections 2.2 and 2.4. These include initial establishment log employment size, initial firm log employment size, firm age, and establishment age; in line with heterogeneity in the use of outsourced workers documented in Section 2.2. The control set also includes a third-degree polynomial of log revenue productivity change, recognizing that the relationship between outsourced staff growth and revenue productivity growth is not linear as shown by Figure B.6. Other covariates in the control set are state fixed effects, ASM rotating sample fixed effects, and cyclical indicators: change in state unemployment rates, and change in state unemployment rates interacted with log revenue productivity change. I include cyclical indicators to avoid $\hat{\beta}_1$ being driven by the pro-cyclical feature of temporary and leased employment since the Great Recession is in the period of analysis.

I also estimate payroll labor responsiveness to deviations from average revenue productivity growth. Specifically, I estimate equation (2.4) with payroll employment DHS growth rate as the outcome.[11] Figure 2.5 displays the estimated responsiveness of outsourced employment (blue) and payroll employment (red) to revenue productivity changes ($\hat{\beta}_1$), as well as 95% confidence intervals. Standard errors are clustered at the establishment level. The first column of Table 2.2 displays the results as well.

Figure 2.5. Plant-level outsourced employment growth is twice as responsive as payroll employment growth to revenue productivity shocks and adjusts more quickly.



Note: The figure shows point estimates and 95-percent confidence intervals of plant-level payroll, and outsourced employment growth rate on revenue productivity change (see Equation (2.4)). Source: Author's calculations based on ASM-CM-LBD and RELBD from 2006-2017.

Plants use outsourced employment as a margin of adjustment. The response of outsourced employment DHS growth rate is sizable, statistically significant, and "immediate". For the average manufacturing business in the sample, a 1% deviation in its revenue productivity growth from the industry-year average is associated with a 0.22% increase in the outsourced employment growth rate in the same year of the productivity change. This is 4% of the average outsourced employment growth. The comparable payroll employment responsiveness is half of that of outsourced employment (2% of the average).

[11] In contrast with outsourced employment, the average payroll employment between two periods (denominator of the DHS growth rate) is only zero if the business exited the market in the preceding year. This case is ruled out by the five-year sample restriction mentioned above.

Table 2.2. Plant-level outsourced employment growth is twice as responsive as payroll employment growth to revenue productivity shocks and adjusts more quickly.

Dependent variable	Prod. Change $\Delta_t a_{jt}$		Dep. Var Mean
	(1)	(2)	(3)
Payroll employment growth			
t-1, t	-0.0001	-0.0521	2.66
	(0.0266)	(0.0111)	
t, t+1	0.05095	0.0286	2.57
	(0.0257)	(0.0145)	
t+1, t+2	0.07052	0.0072	3.79
	(0.0379)	(0.0173)	
Outsourced employment growth			
t-1, t	0.2246	0.2557	6.04
	(0.0633)	(0.0563)	
t, t+1	0.0318	0.0211	4.66
	(0.0466)	(0.0474)	
t+1, t+2	-0.0341	-0.0229	5.09
	(0.0509)	(0.0528)	
Observations	102,000	102,000	102,000
Industry-year fixed effects	Yes		
Establishment fixed effects		Yes	

Notes: Plant-level labor responsiveness estimates to revenue productivity shocks. Standard errors clustered at the establishment level in parenthesis. Column (1) displays results for the baseline specification: shocks defined as plants' revenue productivity growth deviations from NAICS six-digit industry-year average. Column (2) displays results when the shock is defined as plants' productivity growth deviations from their own productivity growth average. Source: Author's calculations based on ASM-CM-LBD.

Plants accelerate the use of outsourced workers only in the period of the shock (t), whereas their response through payroll employment occurs in the following period ($t+1$). The correlation between the outsourced employment growth rate for the two periods following the productivity change and the productivity change is small and not statistically different from zero. Conversely, the average business increases its payroll employment growth rate by 0.05% in $t+1$, when presumably it has more information on the persistence of the productivity change. Like outsourced employment, the payroll employment growth rate in $t+2$ is positive, but not statistically different from zero. Table 2.2 shows that the qualitative result holds for a different definition of the shock: deviations from own average productivity growth.

Table 2.3 shows that the responsiveness result is robust to different specifications and not restricting the sample to five-period continuers.

The immediate response of outsourced staff reflects the flexible nature of this type of employment. Client plants can renegotiate staffing agreements within weeks. In fact, it is standard for staffing agencies to bill depending on the workers provided, allowing the client business to adjust temporary and leased workers at a moment's notice, so that renegotiating the arrangement may not be even needed. I study yearly changes due to the frequency of the data available. The lagged plant-level response of outsourced staff relative to payroll staff is also in line with the pattern exhibited by the share of employment of outsourced workers at the aggregate level. This series drops sharply in the year preceding a recession as shown in Figure B.1. Therefore, this result provides micro-level evidence supporting the use of employment in the temporary help sector as a predictor of aggregate economic conditions. It also suggests that plants use outsourced and payroll employment as substitutes.

Table 2.3. Outsourced employment growth is more responsive than payroll employment growth.

Dependent variable	Revenue Productivity Level a_{jt} (1)	Change $\Delta_t a_{jt}$ (2)	(3)	(4)
Payroll employment growth	0.1782	0.1742	0.1061	0.1164
$t,t+1$	(0.0110)	(0.0203)	(0.0395)	(0.0410)
Dependent variable mean			-14.22	
Outsourced employment growth			0.1374	0.1703
$t,t-1$			(0.0467)	(0.0526)
Dependent variable mean			2.87	
Observations	1,630,000	1,181,000	150,000	150,000
1981-2013	Yes	Yes		
2006-2017			Yes	Yes
Third-degree polynomial				Yes
Total initial employment				Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes

Notes: Plant-level labor responsiveness estimates to revenue productivity shocks for 1981-2013 and 2006-2017 and different specifications. Standard errors clustered at the establishment level in parenthesis. Columns (1) and (2) display results for 1981-2013, the period of analysis of (Decker et al., 2020). Columns (3) and (4) display results for 2006-2017, the period for which outsourced employment estimates are available. Column (1) reports payroll employment growth responsiveness to productivity level following (Decker et al., 2020)'s specification. Column (2) reports payroll employment growth responsiveness to productivity change following a specification otherwise identical to that of Column (1). Column (3) additionally reports outsourced employment growth responsiveness. Column (4) adds a productivity third-degree polynomial and initial outsourced employment to the control set. All coefficients are statistically significant with $p < 0.01$. Source: Author's calculations based on ASM-CM-LBD.

2.4 Domestic outsourcing and the measurement of aggregate job reallocations

The previous section showed that plants use outsourced employment as a first-line margin of adjustment to shocks, and the increasing outsourced labor share documented in Section 2.2 suggests this has been occurring at an increasing rate; thus, supporting the hypothesis that the increasing use of domestic outsourcing is one of the underlying causes of manufacturing payroll employment becoming increasingly stable —payroll declining dynamism. In particular, the mismeasurement of labor market flows, as the dynamism is increasingly concentrated in the unmeasured mobility of outsourced workers. In this section, I show that, in fact, manufacturing outsourced jobs reallocate at a higher pace than payroll jobs. For job reallocations in the U.S. manufacturing sector between 2006 and 2017, I will show that the omitted reallocations problem is sizeable, exhibits considerable variation over time and across average plant-level revenue growth, and is tightly linked to the cycle.

I begin by defining job reallocations. Job reallocations capture the reshuffling of job opportunities across workplaces. Formally, they are the sum of plant-level employment gains and losses that occur between two years. Therefore, plant-level outsourced employment is the main ingredient to quantify how the creation and destruction of jobs filled by outsourced workers bias the measurement of the aggregate job reallocation. I calculate gross outsourced job reallocations OJR_t using plant-level outsourced employment $\hat{o}_{jt}$ estimated in Section 2.3.1 as per Equation (2.2),

$$\begin{aligned} OJR_t &= \sum_j |\hat{o}_{jt} - \hat{o}_{jt-1}| \\ OJR_t &= OJC_t + OJD_t \end{aligned} \tag{2.5}$$

OJR_t captures the reallocation of outsourced jobs across manufacturing plants and it also equals the sum of the total number of outsourced jobs created OJC_t and destroyed OJD_t in a given year. Analogously, payroll job reallocations are the sum of payroll jobs created and destroyed in a given year.

Table 2.4. The omitted reallocations problem is sizeable and varies significantly over time.

	Job Creation JC (1)	Job Destruction JD (2)	Job Reallocations JC+JD (3)
Panel A: Yearly outsourced job flow (% payroll job flow)			
Average	16.20	13.66	**14.61**
Std. Dev.	2.47	3.68	2.66
2017 - 2007	4.19	8.57	6.48
Panel B: Yearly job flow rate (%)			
Payroll			
Average	7.52	7.98	15.49
Std. Dev.	1.29	2.86	2.07
2017 - 2007	12.31	-12.35	**-0.46**
Outsourced			
Average	30.38	25.99	56.36
Std. Dev.	6.12	6.70	10.01
2017 - 2007	-1.42	6.21	**1.90**
Total			
Average	8.39	8.66	17.05
Std. Dev.	1.38	2.88	2.11
2017 - 2007	14.81	-6.87	3.80
Panel C: Job flow percentage change (2017 - 2007)			
Payroll	-2.14	-23.62	-13.27
Outsourced	22.99	32.50	27.12
Total	1.39	-17.76	-8.33
Obs	259,500	259,500	259,500

Notes: Job creation is the employment change sum of expanding plants. Job destruction is the employment change sum of shrinking plants. Job reallocations is the sum of jobs created and jobs destroyed (see Equation (2.5)). A job flow rate is the job flow expressed as a share of employment. Source: Author's calculations from ASM-CM-LBD data in 2006-2017.

Table 2.4 summarizes the results. Panel A presents summary statistics for yearly outsourced jobs created, outsourced jobs destroyed, and outsourced gross job reallocations as a percentage of the corresponding payroll job flow between 2007 and 2017. They paint a clear picture: aggregate job flows are underestimated and the extent of mismeasurement varies significantly over time.

On average, every year, we omit the equivalent to 16% of the payroll jobs created and 13% of the payroll jobs destroyed. Both indicators display significant variation over time accounting for as much as one-fifth of the payroll job flow in a given year. Moreover, for the studied period, the share of outsourced jobs destroyed more than doubled, ranging from 8 to 20 outsourced jobs destroyed per every 100 payroll jobs destroyed. The reported variation is tightly linked to aggregate economic conditions, a point that I explore later in this section and that has non-trivial consequences on our understanding of labor market adjustment along the cycle.

Outsourced jobs reallocate at a higher pace than payroll jobs across plants. Panel B of Table 2.4 displays summary statistics for yearly outsourced and payroll job reallocation rates. That is, the corresponding job flow as a share of payroll or outsourced employment. For every job flow, the outsourced rate is at least two times higher than the corresponding payroll rate. The measurement of aggregate job flows not only omit the reallocations of a certain type of jobs, but these jobs also reallocate at a higher pace —a necessary condition for the omission of outsourced jobs reallocations to account for part of the documented decline in the payroll job reallocation rate. If the manufacturing sector were outsourcing longer-tenure jobs (relative to payroll jobs), the omitted reallocations problem would imply an overestimation of the payroll job reallocation rate.

For the studied period, the payroll job reallocation rate dropped by 0.46%. In contrast, the outsourced job reallocation rate increased by 1.90% (Table 2.4, Panel B). Panel C of Table 2.4 presents the percentage change in outsourced and payroll job reallocations.

I find that the documented increase in the outsourced job reallocation rate is driven by outsourced job reallocations increasing at a higher pace than outsourced employment (27.1% vs. 23.3%). Similarly, the drop in the pace at which payroll jobs reallocate across worksites is driven by payroll job reallocations decreasing at a higher pace than payroll manufacturing employment (13.3% vs. 11.9%). The positive long-difference in the reallocation of jobs filled by outsourced workers represents 28% of the long-difference decline in payroll job reallocations. If the reallocation of outsourced jobs were considered in manufacturing job reallocations, the 13.27% decline would be 4.9 percentage points smaller. This is 37% of the drop.

These findings support the hypothesis that a large part of the decline in payroll job reallocations reflects a transformation of the labor market toward the use of intermediaries in the employment process, rather than a decline in underlying dynamism. Consistent with this hypothesis, I find evidence that supports domestic outsourcing as one of the causes behind the drop in payroll job reallocations even while focusing on the period between 2007 and 2017 and the manufacturing sector. Publicly available indicators point to domestic outsourcing having its steepest increase in the 1990s (see Figure B.1) and abundant anecdotal evidence suggests the use of staffing arrangements becoming increasingly popular in other sectors such as health.

According to evidence from the Contingent Worker Supplement of the Current Population Survey (CPS-CWS), manufacturing has been the biggest client industry since we collect this information, 1995. Every year in which the CPS-CWS was conducted, around one-third of temporary help employees reported performing tasks in a manufacturing business (Appendix Table B.2). Interpreting domestic outsourcing as an innovation of the labor market, this evidence is consistent with manufacturing plants having learned how to incorporate the new technology in their production process faster than businesses in other industries, thus, leaving less room for growth in the sector. Given the flexible nature of outsourced employment, I conclude that the magnitude of the omitted reallocations problem in the measurement of job reallocations may be even greater in sectors that started adopting this technology more recently.

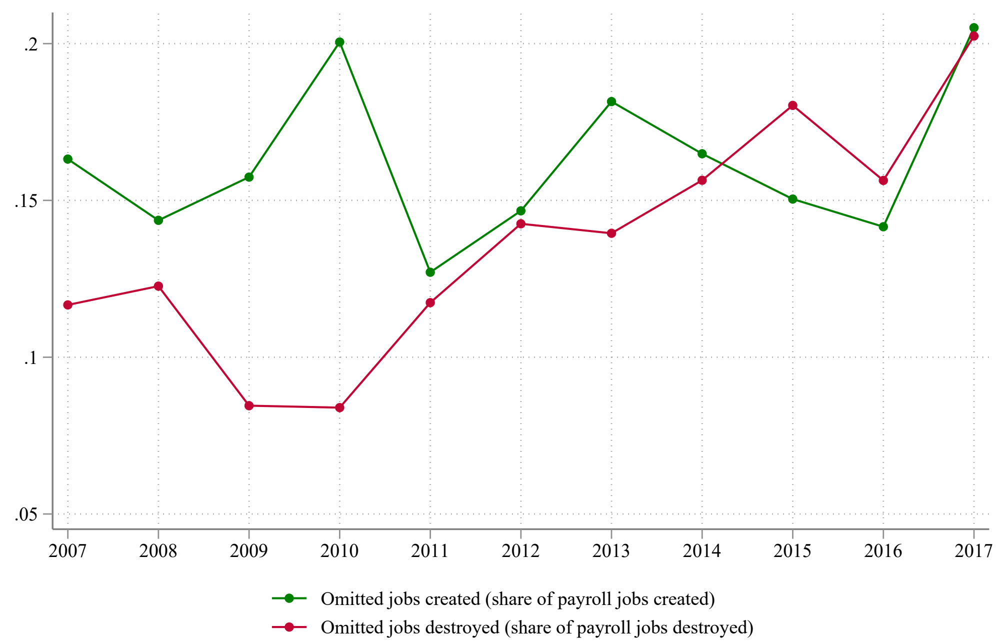
The fact that outsourced employment increased by 23.3% while payroll employment dropped by 11.9% is yet another manifestation of the importance of outsourced workers for our understanding of labor markets[12]. One that has received more attention for its implications on measured labor productivity, and the influence of factors such as technological changes in the decline in manufacturing payroll employment and labor demand in general. While confirming the increasing use of domestic outsourcing using client plant information, the results in this section also suggest a relevant role of domestic outsourcing *dynamics* for our understanding of labor markets' adjustment given the considerable variation exhibited by outsourced job flows.

The variation in the extent of aggregate job flows mismeasurement is tightly linked to aggregate economic conditions. Figure 2.6 displays omitted jobs created (green line) and destroyed (red line) as a share of the corresponding payroll job flow over time. The omitted job creation reached

[12] The employment trends documented in this section are not at odds with those in previous literature. In line with the representativeness of my analysis sample, the drop in manufacturing employment is comparable to that published by the Census Bureau for the manufacturing sector (11.5%). Moreover, reaffirming the validity of the methodology developed in this paper to estimate outsourced employment, the increase in outsourced employment in manufacturing between 2007 and 2017 is remarkably close to that found by Dey et al. (2017) between 2007 and 2015 (23.1%). The authors follow a different methodology to estimate outsourced employment assigned to manufacturing combining employment-occupation information provided by staffing agencies (from the OEWS) with average occupation-industry of assignment distribution derived from worker-level data (CPS-CWS).

its maximum in 2010, implying that the total number of jobs created in manufacturing that year was 1.2 times the measured figure. In contrast, the omitted job destruction was at its minimum in the same year. This contrast means that, in the first year after the Great Recession, relative to payroll jobs, the manufacturing sector not only was creating jobs to be filled by outsourced workers at a higher pace but it was not destroying the existing ones as quickly. It follows that the omitted reallocations problem qualitatively affects our understanding of recoveries.

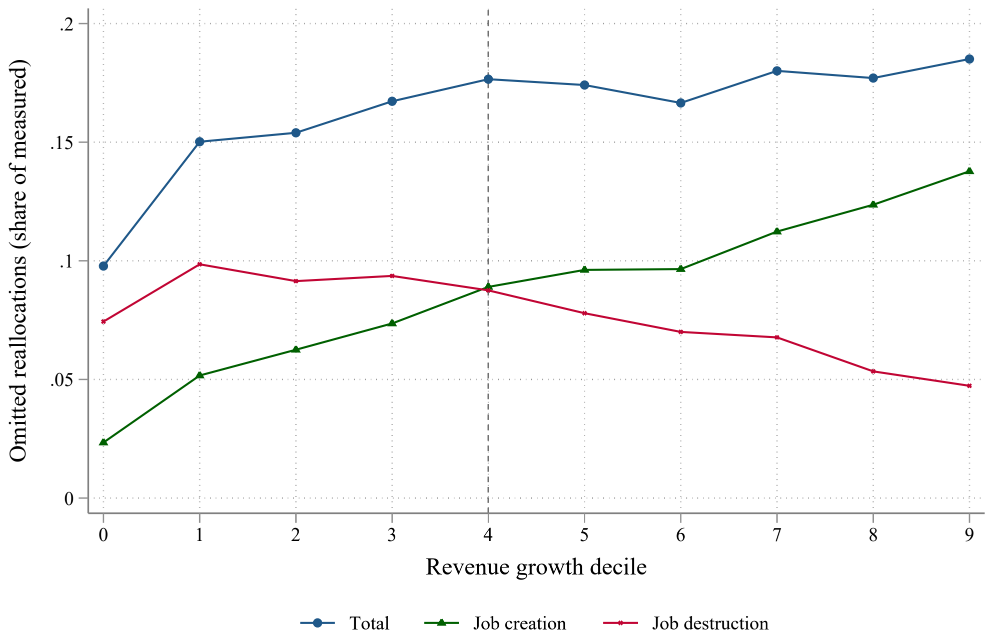
Figure 2.6. Aggregate job flows mismeasurement varies with the cycle. The share of omitted jobs created dropped entering the Great Recession and started increasing just before the recovery, reaching its maximum in 2010. The share of omitted jobs destroyed increased entering the recession and dropped just before the recovery, reaching its minimum in 2010.



Note: Job reallocations of outsourced employees as a share of the job reallocations of payroll employees over time. Source: Author's calculations based on ASM-CM-LBD and RELBD from 2006-2017.

Since 2010, manufacturing plants destroyed payroll jobs at a slower pace than outsourced jobs, so that the omitted share of jobs destroyed more than doubled between 2010 and 2017 (from 8.4% to 20%). The same pattern does not hold for omitted job creation. Between 2011 and 2013, manufacturing plants created outsourced jobs at a faster pace than payroll jobs but the opposite is true between 2014 and 2017. This evidence is consistent with manufacturing plants handling the uncertainty in the aftermath of the Great Recession creating outsourced employment and then subsequently substituting it with increased payroll employment.

Figure 2.7. The destruction of jobs filled by outsourced workers accounts for most of the omitted reallocations in plants with negative revenue growth, while the creation of jobs filled by temporary and leased workers accounts for the omitted reallocations in plants with positive revenue growth.



Note: The figure displays the average job reallocations of temporary and leased employees relative to measured job reallocations by revenue growth ventile. Each point is the three-point moving average. Source: Author's calculations based on ASM-CM-LBD and RELBD from 2006-2017.

Figure 2.7 shows the average share of total outsourced reallocations by plant-level revenue growth decile. In general, the share of outsourced reallocations is increasing in revenue growth. However, the qualitative relationship between the share of outsourced jobs created and revenue growth contrasts starkly with that between the share of outsourced jobs destroyed and revenue growth: relative to the corresponding payroll job flow, outsourced job creation increases with revenue growth while outsourced job destruction decreases with revenue growth. On average, for plants experiencing negative (positive) revenue growth the share of omitted reallocations is mostly accounted for the destruction (creation) of jobs filled by temporary and leased workers. This evidence further supports the interpretation that employers use outsourced workers strategically and shows that at the plant level, the sign of labor growth mismeasurement is not evident. At the aggregate level, gross job flows are undercounted; however, average plant-level employment growth might be under or overestimated depending on revenue growth.

One threat to the results presented in this section is the composition of the jobs filled by outsourced workers over time. Plants may be outsourcing more expensive jobs over time. In this case, expenses on staffing services would exhibit the increasing trend documented in section 2.2 without translating into an increase in the number of temporary and leased workers employed in manufacturing. I address this concern in two ways. First, I show that the occupation distribution of temporary workers assigned to manufacturing in 2005 is comparable to that in 2017 (Table B.2). Second, the average earnings of temporary workers relative to that of payroll workers did not increase between 2007 and 2017, the period of my analysis.

The results presented in this section support domestic outsourcing as one of the factors behind the decline in payroll job reallocations. Moreover, the significant variation in the extent of mismeasurement of job flows along the cycle highlights the importance of not only accounting for the use of outsourced workers but for its dynamics. They enrich our understanding of labor market adjustment to aggregate economic conditions.

2.5 Discussion

Labor flows and vacancies are key parameters in most search models —a workhorse model for the empirical research of labor markets— and thus central to their calibration. The omitted reallocations problem leads to an underestimation of labor flows and the number of vacancies in the economy or in the client sector; thus, the measurement dimension of the omitted reallocations problem will translate into misconceptions about the labor market. The results in this paper illustrated this statement showing that the omitted reallocations problem hinders our understanding of plants' behavior when facing unexpected conditions and even of the margins of adjustment available to them —the labor responsiveness of plants to productivity.

The use of intermediaries, such as staffing agencies, in the search process for job candidates destroys the equivalency between a job change and an employer change in the data, masking both the behavior of firms and the behavior of a certain type of job seeker in the search process. Omitting the reallocations of outsourced workers across client plants masks labor market frictions in the hiring process. The omitted reallocations problem renders invisible in the data the rungs filled by outsourced workers, hindering our understanding of job ladders.

Therefore, the results on the size, growth, and cyclical variation of the omitted reallocations problem provide insights into macroeconomic puzzles such as the break of the standard matching function and of the job ladder after the Great Recession (Davis, Faberman, & Haltiwanger, 2013a; Moscarini & Postel-Vinay, 2016). Similarly, the fact that outsourced employment increased between 2007 and 2017, while payroll employment dropped during the same period provides insights into the magnitude of what the literature has called “jobless recoveries” in the manufacturing sector in line with what previous work on domestic outsourcing has found (Shimer, 2007; Houseman & Bernhardt, 2017).

2.6 Conclusion

This paper shows that domestic outsourcing affects plant-level labor responses to revenue productivity shocks and biases the measurement of aggregate job reallocations. To do so, I assess the *omitted reallocations problem* on job reallocations in the U.S. manufacturing sector between 2006 and 2017. In previous work, I define the omitted reallocations problem as the errors that arise from not accurately accounting for the hires and separations of outsourced workers, the creation and destruction of outsourced jobs, and the vacancies these workers fill. Outsourced staff effectively work for client plants but are legally employed by a staffing agency; therefore, the data used to track labor markets’ activity accounts for the labor market transitions of outsourced workers in the services sector, and omits their reallocations across client plants altogether. This omission has two implications (i) a systematic undercount of the aggregate job and worker reallocations (and the vacancies they fill), and (ii) a misrepresentation of the reallocations composition across sectors (Atencio De Leon, 2023).

The importance of the omitted reallocations problem hinges on the growth and prevalence of domestic outsourcing. Consequently, I describe the use of temporary and leased staff in the cross-section and over time. I document that the participation and intensity in the use of staffing services exhibit significant variation across size, industry, and revenue growth categories. Over time, the average manufacturing establishment increased the share of revenue spent on temporary and leased staff by 85% for the studied period. The growth of the outsourced labor share of revenue is eight times that of payroll and exhibits more variation.

At the sector level, the omitted reallocations problem undoubtedly leads to a systematic undercount of job reallocations, suggesting that part of the measured decline in job reallocations is a sign of a structural change in the way plants source labor instead of an actual decline in underlying dynamism. At the business level, however, the direction of the employment growth bias is not evident. I find that while the share of omitted jobs destroyed is declining along average plant-level revenue growth categories, the share of omitted jobs created is increasing. This evidence suggests that plant-level employment growth is overestimated whenever revenue is shrinking but underestimated when is growing. I investigate the omitted reallocations problem at the plant level (employment growth) studying the relationship between deviations from average revenue productivity growth and outsourced staff growth. I find that outsourced workers are a margin of adjustment that reacts more quickly than the measured margin (adjustment of payroll employment). This provides plant-level micro-evidence for the use of temporary help employment as a leading indicator and calls for a more comprehensive measure to study the labor responsiveness of plants. Policies targeting firms commonly define eligibility and compliance conditions on payroll jobs destroyed or created and this paper showed plants may adjust destroying or creating jobs filled by outsourced workers, who work side-by-side payroll typically performing the same jobs.

The micro implications have significant aggregate consequences. The reallocation of jobs filled by temporary and leased workers across manufacturing plants accounts for 37% of the decline in payroll employment job reallocations. The omitted reallocations problem is sizeable, exhibits significant variation over time, and is tightly linked to aggregate economic conditions. The share of omitted jobs created peeked in 2010, the first year after the Great Recession. In contrast, the share of omitted jobs destroyed was at its minimum in the same year. Relative to payroll jobs, the manufacturing sector was not only creating jobs to be filled by outsourced staff at a faster pace, but it also was not destroying the existing ones. This evidence shows that the omitted reallocations problem hinders our understanding of recoveries and thus limits the effectiveness of recovery policies.

Further research is required on the implications of the omitted reallocations problem. This paper documented that the omitted reallocations problem is pervasive across labor market fluidity flows, vacancies, and economic sectors. Therefore, it has potential implications for our understanding of the search process and firm behavior. Thus, a contribution of this paper is the estimation of plant-level temporary and leased employment from expenses data that opens the door to deepen our knowledge of the interaction of domestic outsourcing and current developments in the labor market.

Chapter 3

Recruiting and Mismatch in Peru

Joint with Munseb Lee and Claudia Macaluso†*

3.1 Introduction

In Caracas, they are called *toderos* (do-it-alls), because they indeed do everything; these marginalized workers live on occasional jobs, nibbling work bit by bit: they are servers or servants, stone-cutters or occasional masons, salespeople or street vendors, occasional electricians or plumbers or wall painters, car attendants, and sometimes beggars, or thieves; simply labor, available for whatever comes.

Eduardo Galeano, Las venas abiertas de Latinoamerica, Inter-American Court of Human Rights

In the context of studying economic development, the process of firm growth, by which an entrepreneur develops a business idea, becomes an employer business and expands her firm's operations through hiring, has received considerable attention. The attention is well-justified: employer businesses in poorer countries are consistently smaller and less productive than in richer ones, a stylized fact that contributes to the aggregate productivity gap between poor and rich countries (Tybout, 2000; Hsieh & Klenow, 2014). Furthermore, a promising mean of alleviating poverty is to provide employment opportunities for the poor: an economy's capacity to create

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The views expressed in this article are those of the authors and do not necessarily reflect the position of the Federal Reserve Bank of Richmond nor the Federal Reserve System.

and sustain a sufficient volume of "good" jobs is central to its ability to improve its population's living standards (Krueger, 1983). However, insofar as employers in poorer countries are smaller and less productive than those in rich countries, one can expect employment opportunities to be limited and hold little promise for income growth. Recent scholarship has also highlighted how labor markets in poor countries are characterized by higher rates of worker reallocation and turnover, higher unemployment and under-employment risk, and lower returns to human capital (Donovan, Lu, & Schoellman, 2023; Bick, Fuchs-Schündeln, Lagakos, & Tsujiyama, 2022; Feng, Lagakos, & Rauch, 2021). However, what is still lacking is direct evidence on employers' recruiting behavior in poor countries, how it differs from employers in richer countries, and whether these disparities translate into aggregate differences in job dynamics and human capital accumulation.

In this paper, we take a first step towards documenting employers' recruiting behavior in poor countries. We develop a new survey — the Survey of Employers Recruiting Behavior (SERB) — that investigates several steps of the matching process, including how employers advertise for open jobs, recruit and screen potential candidates, craft contracts and carry out bargaining, and finally train new employees. We implement our survey with a nationally-representative sample of workers and firms in urban Peru and use the data to shed light on key aspects of the matching process in the context of a developing economy. To the best of our knowledge, we offer the first direct evidence on the prevalence of different recruiting methods, their relationship with firm size, and the incidence of skill deficits and mismatch in resulting matches.

We focus first on documenting stylized facts about employers' recruiting behavior in Peru and start by describing how employers advertise their open jobs. We find that most Peruvian employers use more than one recruiting method at a time, often combining more formal avenues like posting ads on a job board with less standardized channels like recommendations from friends and family, or employee referrals. Jobs requiring less than a college degree, and jobs at smaller firms, are more likely to recruit candidates only via informal channels. Network recruiting, which exploits family, friends, or co-workers' connections to surface candidates for open jobs, is by far the most popular recruiting channel, alone or alongside other instruments, with over one in two employers reporting the use of networks to recruit candidates for their jobs.

The efforts employers expend in advertising their open jobs and scouting candidates suggest that the recruiting process is frictional. Do these frictions result in a high rate of unfilled jobs and long-lived vacancies? We find no evidence of that in the Peruvian context. Jobs fill quickly, in fact, with an average vacancy duration of just over a week — and only 10% (1%) of vacancies not filled after two weeks (4 months). The high job-filling rate is due to a combination of short job advertising duration and high filling rates. Well over two-thirds of Peruvian firms post their vacancies within 4 weeks of the desired start date, and the vast majority of these vacancies are filled within this time frame, with little heterogeneity across sectors or firm size categories. A negligible number of firms report unfilled vacancies after 3 months since the start of their recruiting effort. We interpret this result as suggesting that, in poor countries, the labor market *is* fluid but, unlike what one may think based on evidence from richer countries, labor market fluidity does *not* necessarily go hand-in-hand with income and productivity growth[1].

While the job-filling rate is high, previous scholarship has documented that matches are not necessarily long-lived nor especially conducive to wage and human capital growth (Donovan et al., 2023; Bick et al., 2022). One potential explanation, that we investigate, is mismatch. To do so, we collect data on the education and experience requirements of jobs, and the corresponding attainment of new hires. We find that over-qualification is remarkably common in Peru, with at least a quarter of jobs requiring a high school diploma being filled by a college graduate instead[2]. Despite the large heterogeneity in the quality of educational institutions, the incidence of over-education is not accounted for by heterogeneity in education quality. In fact, our result generalizes to measuring qualifications using labor market experience.

We then dig deeper and complement the analysis of mismatch in Peru by collecting detailed data on the specific skills used in various positions. Specifically, we document the importance of 10 distinct skill dimensions for over 600 detailed occupations. The dimensions we consider are loosely based on Deming and Kahn (2018) and fully comparable with U.S. sources like O*NET: cognitive, social, organizational, writing, customer service, project management, people management, financial, basic computer skills, and advanced computer skills.

From the perspective of skills, the data offers plenty of suggestive evidence of informational frictions and mismatch. For instance, 1 in 4 new hires underestimates the skill requirements of the job in which they are employed. The mismatch between the importance of different skill sets expected by employees and required by employers is stronger for organizational and customer service skills. More evidence of skill mismatch builds up as we consider that, among the (few) firms leaving their vacancies unfilled, candidates' lack of specific skills and abilities is a prevalent reason for the unrealized match. Furthermore, the most important reason to train new hires, as

[1]Our result on short vacancy duration and high job-filling rates can be interpreted as the mirror image to higher worker flows, as documented by Donovan et al. (2023) who reach a similar conclusion regarding the relationship between labor market dynamism and growth.

[2]We also have detailed information on the college and course of study attended by new hires. To bolster the narrative of mismatch, for example, we document that 50% of college-educated new hires graduated from a course of study that is not what the employer deems "ideal" (e.g. a degree in engineering for an engineer position, in management for a managerial position, etc.).

most Peruvian employers do, is to increase industry-specific knowledge or soft skills.[3]

Finally, we investigate human capital usage on the job and find that for the average job in Peru, 6 out of 10 skill dimensions are important, very important, or extremely important. In fact, all 10 skills are at least "important" for 38% of the jobs in the sample, and over 9 in 10 jobs report at least 5 out of 10 skill dimensions as important, very important, or extremely important. We interpret these figures as evidence of skill flattening or lack of specialization.

We then relate the stylized facts we uncover in our data — employers' use of multiple recruiting instruments, a short average vacancy duration, and evidence of mismatch, —to the question of economic growth. To do so, we compare our results to the U.S. benchmark. We build upon data from the O*NET, Job Openings and Labor Turnover Survey (JOLTS), and the DHI indicators developed by (Davis, Faberman, & Haltiwanger, 2013b). We also leverage a new data source, the Survey of Employer Recruiting Behavior USA (SERB-USA). SERB-USA is a small establishment-level survey of employers in the Southeastern United States, which we designed and fielded in cooperation with the Federal Reserve Bank of Richmond.[4] It contains detailed information on recruitment methods U.S. employers use to fill vacancies.

There are overall few differences in employers' choices of hiring methods. In both countries, firms use a variety of recruiting avenues, often at the same time. Recruiting via recommendations, referrals, or direct contracts with educational and training institutions (which we refer to collectively as "network recruiting") is utilized by over 50% of firms in both the U.S. and Peru. About 50% of both Peruvian and American employers also advertise their jobs via explicit job postings. By comparison, less than 10% of either Peruvian or American employers engages in recruiting processes reminiscent of random matching, such as job fairs or mass recruitment campaigns. We view these facts as informative for validating common labor market models. On the one hand, the job posting behavior we document is akin to a wage-posting model a la (Burdett & Mortensen, 1998). On the other hand, network recruiting is a largely under-explored mechanism in theory that, we show, is prevalent in the data and especially salient in the context of a poorer economy.

To investigate disparities in vacancy duration and the aggregate job-filling rate between Peru and the U.S., we rely on JOLTS/DHI measurements for the U.S. and the SERB-Peru data we

[3]Relatedly, we find that Peruvian employers make extensive use of signals — observable characteristics that are correlated (though not perfectly) with unobservable ability. We document, for example, the role of affinity. Nearly one in ten hiring managers prefers candidates of his/her same gender or who were educated in the same university and course of study. Even more tellingly, candidates who are of the same gender or university as the hiring manager, are at least 50% more likely to be eventually hired.

[4]We thank Sonya Waddell and Jason Kosakow at the FRBR for their invaluable help and support.

collected for Peru. We find that the average daily job-filling rate in 2017 is 0.115 for Peruvian firms, and 0.035 for U.S. firms (equivalent to 8.7 and 28.5 days of vacancy duration at a constant daily filling rate). While at first surprising, this pattern is in line with the well-documented higher amount of worker churn in poor countries' labor markets than rich countries' ones (Donovan et al., 2023).

Finally, we exploit the skill portion of the SERB-Peru survey, together with the O*NET data for the U.S., and explicitly investigate differences in the skill profiles of different occupations between Peru and the U.S.. We view this as a way to understand the origin of the widespread over-qualification we observe in the data, together with patterns on wage growth (or lack thereof) documented in the literature. Our main result is that jobs in Peru tend to be less specialized than similar ones in the U.S. Specifically, we find that the average (filled) job in Peru displays a larger dispersion in the importance of various skills, than a job within the same occupational category in the U.S.

CONTRIBUTION TO THE LITERATURE. The paper is most related to the macro literature seeking to document and understand cross-country patterns of labor market conditions and outcomes. Bick et al. (2022) documents that returns to experience are much lower in poor countries than in rich ones. A recent comprehensive effort by Donovan et al. (2023), who uses surveys from 45 countries, shows that some of those differences are accounted for by the fact that worker flows are two to three times higher in the poorest countries as compared to the richest. Our paper complements the picture these authors paint, and confirms the view of poor countries' labor markets as high-paced but low rewarded, by providing evidence from the firm side. Feng et al. (2021) document that unemployment is increasing with GDP per capita, and Poschke (2019) study the relationship between self-employment and the ratio of unemployment to wage employment (an important theme in Donovan et al. (2023) as well). All these papers draw on existing surveys in many countries. Our paper has a narrower geographical scope, but offers more detailed information on the recruiting and hiring process.

Our paper is also closely related to the micro literature on the importance of labor market frictions in developing countries. The efficient functioning of labor markets crucially depends on the information available to both employers and job seekers, and on the search costs they incur to find each other. A large body of theoretical and empirical work has emphasized the role of information frictions on skills as a potential source of inefficiency (e.g. Pallais (2014) and Farber and Gibbons (1996), among others). Several randomized experiments have also tested various interventions designed to reduce information and search frictions (Abebe et al., 2020; Bassi

& Nansamba, 2022).[5] We complement those findings by providing survey evidence on search processes and realized matches.

3.2 Data

3.2.1 SERB - Peru

The Survey of Employers' Recruiting Behavior (SERB) Peru is based on two surveys of Peruvian individuals and firms carried out between November 2017 and March 2018. Our data, collected in cooperation with the MINEDU, the Peruvian Ministry of Education, and IPA (Innovations for Poverty Action), are representative of workers and firms in urban labor markets. The survey is articulated in two stages: a first questionnaire is addressed to a cohort of individuals who have obtained their college degree within 6 years of the survey date, and may or may not be currently employed (referred to as the *graduates*).[6] A second survey collects information from a sample of 1,000 firms randomly drawn from the 2017 Census of Enterprises (referred to as the *employers*).[7] About a third of jobs in the employers survey can be reliably traced back to a worker in the graduates sample, thus providing a small matched employer-employee sample that allows us to study job-specific skill mismatches.

Our data is extremely rich and covers many aspects of hiring, meeting, matching, and sorting between workers and jobs. The employers' survey contains information on employers' size, sector, and main products/services sold, in addition to information about the most recent position the firm recruited for, including the position's job title, required skills, education and experience levels, methods used to recruit, vacancy duration and yield, obstacles to hiring or contracting, and on-the-job training. We also collect demographic details, such as age and sex, about both the employee hired for the position of interest (if present) and the hiring manager. Finally, we conducted a survey of managers to assess implicit bias. Workers in the graduates survey further report information on their major and university of graduation, their current employment status, usual hours worked, current wage, and past wages for the last 10 jobs. They also are interviewed

[5] McKenzie (2017) provides a summary of 9 recent randomized experiments which have tested various interventions on search and matching assistance.

[6] A first survey collects data on students currently enrolled at Peruvian higher education establishments (the *estudiantes* survey). We do not use this data in the present paper, but we inherit from it the focus on college-educated workers.

[7] We excluded non-employer firms. To ensure representativeness, we oversampled small enterprises (less than 3 employees) and explicitly included employers in the public sector — both public administration and state-owned enterprises.

about their job search methods and satisfaction level on their current job, in addition to several measures of self-reported skill mismatch. We match a third of the individuals in the graduates survey to the jobs in the employers one and denote this smaller dataset as our *matched* sample.

The graduates' and employers' samples are extracted from frames based on administrative sources: the Census of Population and the Census of Enterprises, respectively. The final datasets are stratified random samples of 5,000 workers and 1,000 employers/jobs. Because the survey of graduates by definition only contains college-educated individuals, our worker sample is heavily skewed towards more educated workers. However, we do not necessarily restrict firms in the employers survey to report information for jobs that require a college degree or are matched with a college-educated worker. Specifically, the employers' survey is designed so that 50% of the firms are sampled purely based on the employment distribution in their province-sector-size cell as per the Peruvian Census of Enterprises. We occasionally refer to this as our "geographic" subsample. The remaining 50% of firms in the employers' survey are drawn from the sample of employers reported by respondents in the graduates' survey. This subsample, which we refer to as "matchable", is thus a random sample of employers in the urban provinces of Peru according to the provinces' working age population distribution. We consider 16-65 as the working age and restrict our attention to provinces where the labor force features at least 1% of college graduates. The latter restriction is largely unconsequential for urban markets. Our final sample includes the province of Ancash, Arequipa, Cajamarca, Callao, Cusco, Huanuco, Ica, Junin, La Libertad, Lambayeque, Lima, Piura and Puno — covering over 75% of Peruvian labor force. Of the 500 firms in the matchable sample, about 300 can be reliably matched with a worker in the graduates' survey — thus giving rise to our matched sample.[8]

We do not regard our focus on college-educated workers necessarily as a drawback since we intend to abstract from literacy and numeracy deficits. These factors, though common in low-income economies, are not the focus of our analysis. Moreover, as in many other low-income countries, Peru has seen a sustained increase in college graduates over the last 20 years without a corresponding improvement in the percentage of formal workers or employment prospects for its youth.[9] For this reason, we deem that measuring skill mismatches and skill deficits for college-educated workers is particularly relevant in the Peruvian context. We furthermore concentrate on urban areas only, thus we abstract from the large socio-economic divide between

[8]The discrepancy mostly arises from time discrepancies between the graduates' interview date (when the individual reports her current employer) and the date of the firm interview (when the manager is asked about the firm's last hire).

[9]College enrollment rose, from just below 23% in 2000 to about 35% of adults aged 17-24 in 2017, while formal employment is stable at 40% and the unemployment rate among young Peruvians, at about 10% in 2017, is almost three times higher than that for adults, according to the ILO.

urban and rural areas. In this sense, our paper is about the sorting and matching of workers and firms as understood in modern urban environments.

The core of our data is the information on the supply and demand of skills by occupation. To the best of our knowledge, this is the first representative source of data on detailed occupational skills — not just basic literacy and numeracy — that covers all occupations in a large developing economy. Our data is also one of the very few sources that combine information on occupational skills with establishment-level recruiting and hiring behavior.[10]

We estimate skill supply by asking recent college graduates to assess the skills they acquired during their education on a scale from 0 to 100, according to a ten-dimensional vector loosely based on ()deming2018skill. The ten skill items we consider are cognitive, social, organizational, writing, customer service, project management, people management, financial, basic computer skills, and advanced computer skills. We also interview managers in the employers' survey and collect information on skill demand. Specifically, we ask what skills managers deem necessary to perform the last position they recruited for. As an additional check, we collect similar information from the graduates who report the skills needed to perform their current job (when employed). As a consequence of the surveys' design, our data is primarily a source of information on occupational skill mismatches, because we match supply and demand for skills by job title/occupation. As previously mentioned, however, for a small subset of matched employer-employee relationships, we can estimate skill discrepancies at the more detailed job level.

Descriptive statistics Table 3.1 provides some summary statistics on our employee sample (the *graduates*). They are relatively young, as they have typically completed college only a few years before the interview date. Despite their young age, about 2 in 3 have been employed in at least one job since graduation. Despite being college educated, 2 out of 3 workers in our graduates' sample are employed in an occupation that does not require a college degree. Table 3.1 also shows that over 1 in 4 graduates is working informally.[11] We define informality as (i) not having a contract, or (ii) having a contract but no access to employer-sponsored benefits such as health insurance, pension savings, and unemployment insurance.

Table 3.2 shows the distribution of the firms in our sample in terms of size and economic sector, along with the national distribution as computed by the Peruvian National Institute of Statistics

[10]A similar two-pronged survey is available for a representative sample of firms in Germany, but we are unaware of similar data in any low- or middle-income country.

[11]We have information on contractual benefits and informality for a little less than half of our sample.

and Information (INEI for its initials in Spanish) in their 2016 Business Structure report. The two distributions are different. Compared to the national distribution, in our sample, small firms are underrepresented. While at the national level, three of every four firms are small, in our sample, this share is less than 24%. However, these numbers must be compared with caution since in Peru, firm size classification depends on sales and not on the number of employees.

3.2.2 SERB - U.S.A.

The Federal Reserve Bank of Richmond's Survey of Employer Recruiting Behavior (SERB) is a quarterly survey series that aims to provide timely insight into current labor market dynamics by surveying employers across the Southeastern United States (the Federal Reserve's 5th District). To throw new light on recruiting methods and the hiring process, the Federal Reserve Bank of Richmond ran three special survey waves between 2020 and 2021, sampling 308 distinct employers across various firm size categories and industries. Although the sample focuses on the Southeastern U.S., we find remarkable parallels to aggregate labor market conditions and a similar industry and firm-size composition to the aggregate economy.[12]

The February 2020 wave, which ran from Jan. 31 to Feb. 19, focused on what employers do to source candidates for their open jobs and asked respondents about recruiting efforts for the position their firm most recently recruited for in the prior 12 months. The subsequent wave, which ran May 28-June 17 2020, covered the same topics as the February 2020 wave but asked employers about the most recent position recruited for over the previous *three* months. The third and final survey wave, which ran March 17-31 2021, asked about recruiting efforts for the typical open position in the last 12 months and measured changes in recruiting methods and efforts since February 2020.

[12] See https://www.richmondfed.org/publications/research/economic_brief/2021/eb_21-28 for details. Note that SERB-USA undersamples smaller firms with less than 50 employees (over 75% in BDS data, but less than 40% in our surveys) and oversamples manufacturing firms (about double the national average, at 30% of the sample).

3.3 Facts on the Peruvian labor market

3.3.1 Recruiting channels

Our first empirical contribution is documenting the recruiting process, that is the employer's actions between the moment when the need for a new hire arises (the job becomes vacant) and the moment a new hire walks in through the establishment's doors (the job is filled). We focus our attention on recruiting methods: what do Peruvian firms do to advertise and attract suitable candidates to their open jobs? Theory suggests wage posting as a natural candidate, and we find robust evidence that many employers use such a recruiting method to fill their vacancies. We also find evidence of less formal channels based on professional and personal networks, which are as widespread in the data as they are virtually unexplored in economic literature. This data help shed light on possible obstacles and bottlenecks that render recruiting and hiring particularly costly in poor countries.

Firms in Peru use various recruiting methods, often many at a time, including some that do not use the intermediation of vacancies. Figure 3.1 shows that around 60% of the firms in our sample use more than one method to recruit employees. This fact underscores how recruiting is a technology akin to production, in which employers optimally choose inputs and expend effort to recruit and hire new employees. Figure C.1 shows the distribution of firms across the number of recruitment methods used by firm size. While firms with less than 10 employees use a maximum of six recruitment methods, a small proportion of the firms with more than 100 employees can rely on up to nine recruitment methods to fill their job postings. Moreover, more than 70% of small and medium firms rely on only two recruitment methods, while around half of large firms decide to do the same. We conclude that the complexity of recruiting, as captured by recruiting channels used, increases with the employer size.

The most popular recruiting methods rely on networks: referral from current employees or other professional contacts, recommendations from friends and family, and direct partnerships with educational institutions. Among the 40% of firms that use only one recruiting channel, for example, 1 in 3 firms relies entirely on networks to fill their vacancies. Jobs requiring less than a college degree and jobs at smaller firms are more likely to recruit candidates only via informal channels. Table 3.3 further illustrates that informal search methods based on networks play an outsized role in recruiting. In fact, these hiring methods, alone or in conjunction with other more formal venues, are used by over half of the firms in Peru. Job posting methods come in as a close second, with about 50% of employers explicitly advertising their open jobs on a public or semi-public job board. Methods reminiscent of random search, like job fairs or mass recruitment campaigns, are instead used only by less than 10% of employers. We view these facts as especially informative for the validation of common labor market models.

Comparison to the U.S. Table 3.3 also illustrates the comparison between employer recruiting in Peru and the U.S. The picture it paints is not unlike the one we described for Peru: network recruiting, and especially recommendations from friends and family together with employee referrals, is by far the preferred method to surface candidates for open jobs while posting ads on a job board comes a close second (60% and 50% of firms use these two recruiting channels, respectively). One difference pertains to recruiting with the help of labor market intermediaries such as staffing agencies: 1 in 5 firms takes advantage of this channel in the U.S., while virtually none does so in Peru.

3.3.2 Job-filling rate

The efforts employers expend to fill vacancies suggest that the recruitment process is frictional. A long-standing hypothesis is that such frictions may be particularly severe in poor countries, thus preventing jobs from being filled and firms from growing in size. Is that so? We exploit our data and compute the job-filling rate to investigate this question.

Let e denote the establishment and t time, and f_{et} the job-filling rate for employer e in period t (or the share of filled jobs at employer e during time t). We do not directly observe f_{et} in the data. However, we do observe the share of vacant jobs at e, which are filled at various deadlines since their first advertising. We refer to this time as the (expected) "recruiting period length", which is derived from the time between the day the employer starts recruiting activities and the day the employer expects the job to be filled. We now derive a condition to relate what we observe in the data to f_{et}.

Consider the daily hires flows at employer e, h_{est}, and the flow for period t of length τ, h_{et}. The flow of hires is equal to the stock of vacancies in the previous period by the employer-level job-filling rate, cumulated over the period's length τ:

$$\sum_{s=1}^{\tau} h_{est} = h_{et} = \sum_{s=1}^{\tau} f_{et} v_{es-1,t} \tag{3.1}$$

In turn, the daily vacancy stock is equal to the sum of previous-period unfilled vacancies and the flow of new vacancies. Denote the latter by θ:

$$v_{est} = (1 - f_{et})(1 - \delta_{et})v_{s-1,t} + \theta_t$$

Notice that the first term encompasses all vacancies that (i) were not filled between t and $t-1$ (with probability $1 - f_{et}$), and (ii) all unfilled vacancies that did not expire between t and $t-1$ (with probability $1 - \delta_{et}$).

Cumulating over s and substituting recursively for v_{est-1} gives us:

$$\sum_{s=1}^{\tau} v_{est} = v_{et} = [(1 - f_{et})(1 - \delta_{et})]^{\tau} v_{et-1} + \theta_{et} \sum_{s=1}^{\tau} [(1 - f_{et})(1 - \delta_{et})]^{s-1} \quad (3.2)$$

where $[(1 - f_{et})(1 - \delta_{et})]^{\tau}$ is what we observe in the Peruvian data for different τs.[13]

For Peru, we have data on vacancy duration by (expected) recruiting period length (Table 3.4). We postulate a constant daily filling rate and assume that the rate at which unfilled vacancies elapse is zero (this is largely inconsequential and can be relaxed following (Davis et al., 2013b)). Therefore, exploiting (3.2) and (3.3), we get that the daily filling rates for vacancies with different recruiting period lengths (short f_s^d, medium f_m^d, and long f_ℓ^d) are:

$$(1 - f^{2w}) = (1 - f_s^d)^{10} = 0.09 \rightarrow f_s^d = 0.11$$

$$(1 - f^{8w}) = (1 - f_m^d)^{40} = 0.10 \rightarrow f_m^d = 0.06$$

$$(1 - f^{32w}) = (1 - f_\ell^d)^{160} = 0.10 \rightarrow f_l^d = 0.01$$

where we assume there are 5 working days per week and take medians.

Using the proportion of jobs in different recruiting period categories ranging from 2 to 32 weeks, we find that the aggregate daily filling rate and vacancy duration in Peru are:

$$\tilde{f}^{d,P} = 0.115 \rightarrow 8.70 \text{ days}$$

A vacancy duration of a little over a week is relatively short. Therefore, there seems to be

[13] Relatedly, we can substitute (3.2) into (3.1) and obtain:

$$h_{et} = f_{et} v_{t-1} \sum_{s=1}^{\tau} [(1 - f_{et})(1 - \delta_{et})]^{s-1} + f_{et}\theta_{et} \sum_{s=1}^{\tau} (\tau - s)[(1 - f_{et})(1 - \delta_{et})]^{s-1} \quad (3.3)$$

Equations (3.2) and (3.3) constitute a system in θ_{et}, f_{et}, given $h_{et}, v_{et}, v_{et-1}, \delta_{et}$.

little evidence of time-to-fill frictions that result in lengthy recruiting or a high share of unfilled vacancies for Peruvian employers.

Comparison to the U.S. We now compare these numbers, which to our knowledge are the first such estimates of their kind outside a rich country, to estimates for the U.S. and find that U.S. vacant jobs are filled at a slower pace than jobs in Peru. For the U.S., we rely on (Davis et al., 2013b)'s calculations. DHI indicators in 2017 report an average of 3.5% daily filling rate[14]; therefore, we get an average vacancy duration of approximately a month, over three times what we documented for Peru:

$$f^{d,US} = 0.035 \rightarrow 28.5 \text{ days}$$

In Peru, furthermore, the recruiting period length diminishes with employer size, and a greater share of large firms' job postings are filled by the expected date (Table 3.5). According to DHI indicators, the opposite is true in the U.S. We conclude that the relatively fast job-filling rate in Peru is consistent with the picture of a fast-paced labor market, as it is also observed from the worker side and documented by (Donovan et al., 2023) using hire and separation flows.

3.3.3 Skills

Over-qualification and mismatch

In the last part of our empirical analysis, we set out to investigate how, in a poor country like Peru, a dynamic labor market where jobs are promptly filled can co-exist with significant costly recruiting efforts by firms and the literature's evidence of stunted firm growth and limited individual income's growth. One possible explanation is mismatch: filling vacant jobs may not be especially hard in Peru; what is difficult is filling them *with the right worker*. To investigate this hypothesis we first collect data on the education and experience requirements of jobs and the corresponding attainment of new hires. We find that over-qualification is remarkably common in Peru, with at least a quarter of jobs requiring a high school diploma being filled by a college graduate instead (Table 3.6, panel A).

An alternative explanation to matching frictions for hiring over-qualified workers is low education quality. Despite the large heterogeneity in the quality of educational institutions in Peru, however,

[14](Davis et al., 2013b) report 0.050 as an average for the period 2001-2006 from JOLTS microdata, though the notion of vacancy is more restrictive in JOLTS than in DHI and our own surveys.

we find that the incidence of over-education is not accounted for by heterogeneity in education quality. In fact, our result generalizes to measuring qualifications using labor market experience (Table 3.6, panel B) and still persists if we look at graduates from the employer's preferred top 3 universities (Table 3.7). Specifically, out of the firms for which we have information about the last hire's characteristics, 65% of the most recent hires have a higher level of education than required by the position *ex ante*. Table 3.7 shows that 3 in 5 of these over-qualified employees graduated from one of the top three universities preferred by their current employers.[15] We conclude that there isn't sufficient evidence to support a low-education quality explanation for the observed over-qualification in realized matches.

Our data also allow us to directly measure skill importance in the performance of various jobs, as perceived by both the employee supplying the skills while working and by the employer recruiting for the job. We can then compare the assessment of the importance of various skills between the former and the latter. We find that between 1 in 4 and 1 in 3 workers underestimate how important at least one skill dimension is in the performance of their job, with respect to what the employer estimates. The gap is largest for organizational skills, with 36% of employees estimating they are less important than their employer's judgment (Table 3.8). More evidence of skill mismatch builds up as we consider that, among the (few) firms leaving their vacancies unfilled, candidates' lack of specific skills and abilities is a prevalent reason for the unrealized match (Table 3.9). Furthermore, the most important reason to train new hires, as most Peruvian employers do, is to increase industry-specific knowledge or soft skills (Table 3.9).

Relatedly, we find that Peruvian employers make extensive use of signals — observable characteristics that are correlated (though not perfectly) with unobservable ability. We document, for example, the role of affinity. Nearly one in ten hiring managers prefers candidates of his/her same gender or who were educated in the same university and course of study. Even more tellingly, candidates of the same gender or university as the hiring manager, are at least 50% more likely to be eventually hired.

Skill flattening

Our data allow us to investigate further the skill composition of jobs in Peru, by explicitly measuring the importance of ten skill dimensions for the performance over 600 occupations

[15]Additionally, 5 in 7 would have not chosen a different university given their current information and the same financial constraints. Given full scholarship, however, 48% of the mismatched employees would have chosen a different university and 24% a different major. Notwithstanding, 82% think that are better prepared than colleagues who graduated from a different university.

(roughly equivalent to the U.S. SOC 4 digits level, such as Retail Salespersons (*vendedores*) and Accountants (*Contadores*)). We survey both workers and employers about the usage of the following skill categories: cognitive, social, organization, writing, customer service, project management, people management, financial skills, basic computer skills, and advanced computer skills. We provide survey participants with examples of each skill category, based on O*NET and (Deming & Kahn, 2018) (see Table 1 in their paper). For instance, cognitive skills involve problem-solving, research, or critical thinking, together with math and statistics. Social skills pertain to collaboration and negotiation. Organization skills are related to time management, instead (Appendix C3).

We measure importance of skill usage at the occupation level using a scale between 1 (not important at all) and 5 (extremely important) and find that for the average job in Peru, 6 out of 10 skill dimensions are important (3 out of 5), very important (4 out of 5), or extremely important (5 out of 5). All 10 skills are at least "important" for 38% of the jobs in the sample, and over 9 in 10 jobs report at least 5 out of 10 skill dimensions as important, very important, or extremely important. We interpret these figures as evidence of skill flattening or lack of specialization and verify that, indeed, the corresponding occupational wage distribution is remarkably flat with a significant portion of workers in each occupational category in each wage quartile (Figure 3.4).

Comparison with the U.S. We retrieve skill profiles for occupations in the U.S. using O*NET data for 2017, and compare importance ratings for each skill dimension across 6-digits occupations. Because the skill survey in Peru was modeled on O*NET, this comparison is appropriate (see Appendix C3). We find that, on average, occupational skill profiles are flatter in Peru, with different professional figures doing "a little bit of everything". This can be clearly seen in the examples we provide in Figure 3.5, where the histogram on the left depicts occupational profiles in the U.S. and the one on the right in Peru, for the same occupational title (here Salesperson and Accountant). Profiles in Peru are flatter.

3.4 Conclusions

A well-functioning labor market is an essential component of economic development. However, direct evidence on labor market dynamism, recruiting behavior, and matching outcome in poor countries is still lacking. Are those different from rich countries? If so, is it hampering firm growth and economic development? We overcome the data limitation in poor countries by designing the original survey and implementing it in Peru and the Southeastern U.S.

We provide three important findings. First, various recruiting channels are equally widely used in the two countries. Second, jobs fill more quickly in Peru than in the U.S. Third, over-qualification and skill flattening are common in Peru. We can use our empirical findings to guide theories of hiring under labor market frictions. Our first result suggests that the lack of hiring channels or lower recruiting efforts is not necessarily an issue in the Peruvian context. As in (Donovan et al., 2023), our second result is inconsistent with modeling labor market frictions as a cost to switching jobs, which will make the labor market flows and job-filling rate in poor countries lower. Our third result highlights important differences in the labor market across countries. In the labor market with higher turnover, it is optimal for establishments to avoid input specification.

Figures and Tables

Table 3.1. *Graduates'* characteristics (SERB-Peru)

	%[i]
Female	47.60
Aged 20-25 years	45.26
Aged 26+ years	27.64
Graduated 1 year ago or sooner	30.60
Graduated between 1 and 2 years ago	37.14
Graduated 3 years ago or earlier	5.61
Exactly one job since graduation	44.71
At least one job since graduation	64.93
Self-employed since graduation	2.68
Current occupation: professional[ii]	47.85
Current occupation requires college	33.14
Formal job	22.46
Informal job (no benefits, no contract)	25.88
Observations	**11,287**

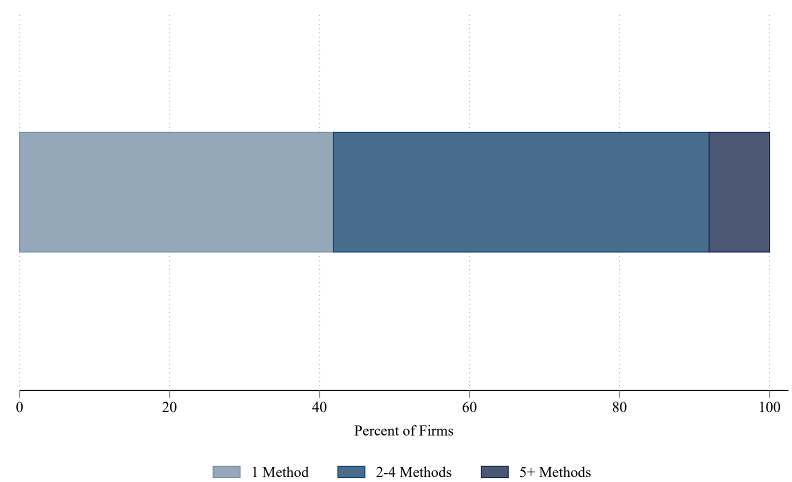
Notes: Percentage of workers (*graduates*) by selected characteristics. [i]Percentages may not add up to 100% because of unreported missing values or because categories are not exclusive. [ii]Professional occupations may or may not require a college degree. Those that do not require a college degree include private sector managers and public officials, professional positions requiring technical degrees, and administrative bosses/employees. Non-professional occupations include service/retail workers, agriculture workers, construction workers, mechanical workers, and elementary jobs. Source: Authors' calculations based on the SERB-Peru graduates' sample.

Table 3.2. *Employers'* characteristics (SERB-Peru)

	Sample	National(i)
Size		
1-10 employees	23.60	76.0
11-100 employees	47.90	20.0
100+ employees	28.40	4.0
Sector		
Services & Private Education	39.5	33.9
Wholesale and Retail Trade	17.0	45.09
Public Administration & Health	11.2	14.75
Construction	7.9	2.75
T&TLC	6.1	7.59
Manufacturing	5.0	7.97
Region		
Lima	66.7	46.0
Coastal (excl. Lima)	11.8	21.9
Mountain	20.2	24.4
Jungle	1.3	6.7
Observations	994	2,124,280

Notes: Distribution of firms across size, sector, and region. Source: Authors' calculations based on the SERB-Peru employers' sample and (i) INEI micro-data for 2016.

Figure 3.1. In Peru, 60% of firms use at least two recruiting methods.



Notes: Distribution of firms across the number of recruiting methods used to fill their vacancies. Source: SERB-Peru *Employers'* sample.

Table 3.3. Recruiting methods in Peru and the U.S. Search methods based on networks play an outsized role in recruiting in both countries.

	% of firms	
	SERB Peru	SERB USA
Networks	*53.0*	*58.5*
Recommendations (friends and family)	30.8	38.7
Referrals from employees	42.3	43.2
Job posting	*47.5*	*50.5*
Job Boards (non-university)	32.3	–
Job Boards at universities	25.2	–
Random search	*58.0*	*56.8*
Partnerships with universities	7.0	20.7
Social media	34.1	42.3
Traditional media	28.7	10.0
Job fairs	8.5	8.1
Mass recruitment campaigns	6.6	
Recall/rehire & staffing agencies	0.7	18.9
N	*994*	*111*

Notes: Percentage of firms using the given recruiting method as part of their recruiting strategy. The numbers in italic represent the percentage of firms using at least one of the recruiting methods in the corresponding group as part of their recruiting strategy. Source: Authors' calculations based on SERB-Peru employers' sample and SERB-USA.

Table 3.4. The aggregate daily filling rate in Peru is 0.115, which means that the aggregate vacancy duration is 8.7 days, one-third of that in the U.S.

Expected start - posting date ("recruiting period")	% not filled by expected start date	% of jobs	Daily filling rate f^d
0-20 days	9	64	0.11
21-60 days	10	25	0.06
61-260 days	10	1	0.01
Aggregate	-	100	0.115

Notes: Percentage of vacancies not filled, distribution of realized matches, and daily job filling rate, by (expected) recruiting period length. Source: Authors' calculations based on SERB-Peru employers' sample.

Table 3.5. In Peru, the recruiting period length diminishes with employer size, and a greater share of large firms' job postings are filled by the expected date. The opposite is true for the U.S.

Panel A: SERB-Peru

	Firm size		
	1-10	11-100	101+
Recruiting period (days)	*Percentage of job postings*		
0-20	60.2	69.2	69.1
21-60	34.0	23.1	25.9
61-260	5.8	7.8	5.0
	Percent filled by expected date		
0-20	91.2	90.2	93.1
21-60	90.0	88.5	93.9
61-260	87.7	89.2	95.3
	Daily job filling rate		
0-20 (median: 10)	0.216	0.207	0.235
21-60 (median: 40)	0.056	0.053	0.068
61-260 (median: 160)	0.013	0.014	0.019
Average daily job filling rate	**0.150**	0.157	**0.181**
Inverse daily job filling	7	6	6
Average recruiting period (raw)	27	26	23
Average recruiting period (residual)	**24**	20	**19**

Panel B: DHI-JOLTS (U.S.)

	1-9	10-49	50-249	250+
Average daily job filling rate	0.036	0.039	0.037	0.023
Inverse daily job filling	27	26	27	43

Notes: Panel A displays the percentage of job postings, the percentage of vacancies filled, and the daily job filling rate by recruiting period and firm size in Peru. Panel B displays the average and inverse daily job filling rate by firm size in the U.S. Numbers computed as explained in section 3.3.2. Source: Authors' calculations based on SERB-Peru employers' sample and DHS-JOLTS data for the U.S..

Table 3.6. In Peru, new hires have more education and experience than jobs require.

Required by job	Attained by new hire	(%)
Panel A: Education		
	High school or less	57.10
High school or less (N=198)	Technical school	15.70
	BA or more	27.30
	High school or less	2.20
Technical school (N=322)	Technical school	30.40
	BA or more	67.40
	High school or less	0.00
BA or more (N=260)	Technical school	1.20
	BA or more	98.80
Panel B: Experience		
	Less than one year	16.6
Less than one year (N=157)	1-3 years	59.9
	4 years or more	23.6
	Less than one year	15.3
1-3 years (N=111)	1-3 years	53.2
	4 years or more	31.5

Notes: Percentage of new hires that attained the given education level by the education level required by the job. Attained experience is measured as the difference between age and years of education minus six (potential experience). Source: Authors' calculations based on SERB-Peru employers' sample (Panel A) and SERB-Peru matched sample (Panel B).

Table 3.7. No evidence of low-education quality for the observed over-qualification in realized matched. 3 in 5 over-qualified workers graduated from one of the top three universities preferred by their current employers.

Characteristic	% workers
Graduated from firm's top 3 universities	60.2
Would not change university or major	
No scholarship	72.6
Full scholarship	45.2
Given scholarship, would have changed	
University	47.8
Major	24.2
Think that are better prepared than grads from other universities	81.7
N	186

Notes: The sample of this table is workers with higher education attainment than required for the job, and it displays the percentage of these workers by selected characteristics. Source: SERB-Peru matched sample.

Table 3.8. Skill mismatch in Peru. Workers underestimate how important at least one skill dimension is to perform their job, with respect to what the employer estimates.

Skill type	Importance level reported by graduates	
	< Employer's	< Attainment
	(1)	*(2)*
Cognitive	24.2	84.4
Social	30.2	80.2
Organizational	35.8	78.0
Writing	32.3	79.0
Customer Service	31.9	74.6
Project Manag.	22.8	81.3
People Manag.	27.4	79.4
Financial	19.6	80.1
Basic Computational	22.8	85.6
Advanced Computational	28.8	81.7
N	112	3,090

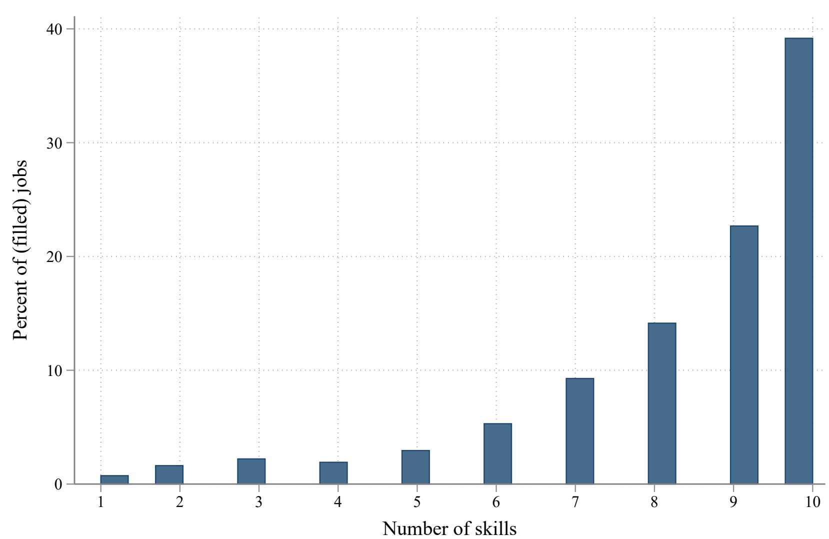
Notes: Percentage of workers reporting the skill level required to perform their job is lower than the one reported by the employer (column 1) or lower than the level attained at college (column 2). Source: Authors' calculations based on SERB-Peru matched sample (column 1) and graduates' sample (column 2).

Table 3.9. Peruvian firms train new workers mostly to remedy skill deficits, and candidates' lack of specific skills and abilities is a prevalent reason for the unrealized match among the (few) firms leaving their vacancies unfilled.

	Firms (%)
Obstacles to hiring: Candidates lack...	
Education	36.0
Abilities	48.3
Experience	28.1
N	89
Firms training new workers	86.70
N	994
Reasons to train	
Increase industry knowledge	61.90
Increase soft skills	38.50
Correct common errors	29.90
Increase language skills	13.80
N	862

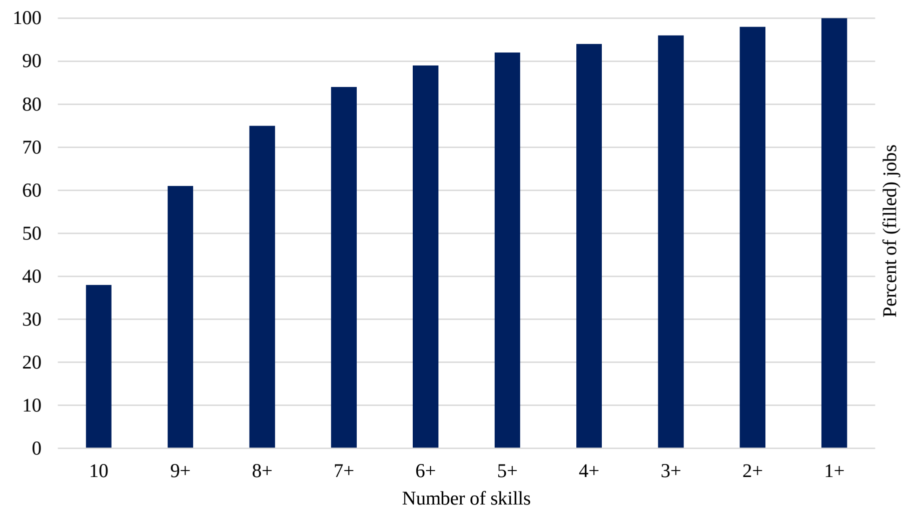
Notes: Percentage of firms by selected characteristics. Source: Authors' calculations based on SERB-Peru employers' sample.

Figure 3.2. In Peru, all skills are at least important for 38% of the jobs.



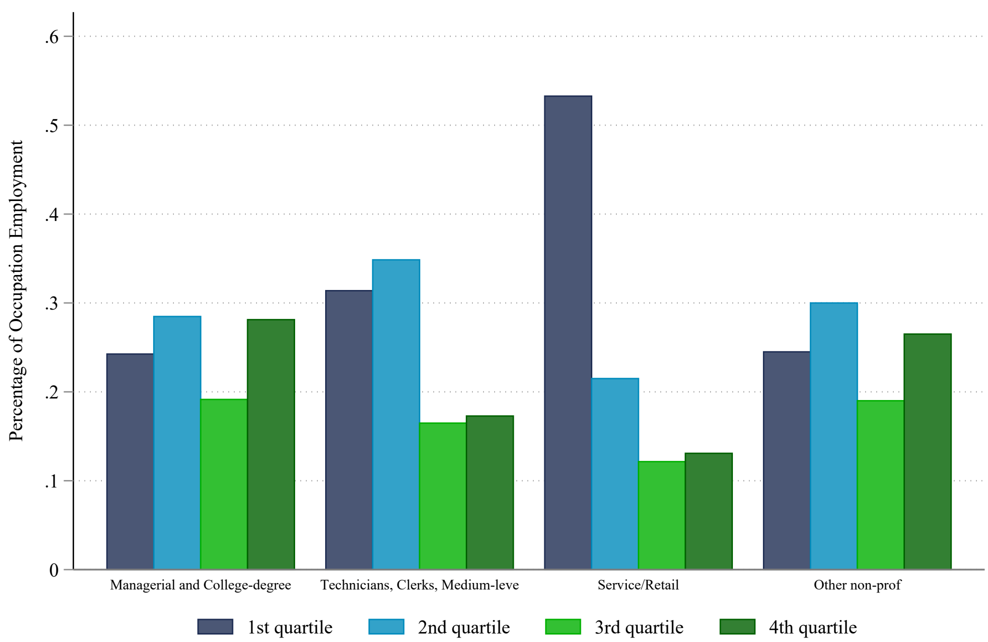
Notes: Each bar represents the percentage of filled jobs for which the given number of skills is important, very important, or extremely important. Source: Authors' calculations based on SERB-Peru employers' sample.

Figure 3.3. In Peru, over 9 in 10 jobs report at least 5 skill dimensions as important, very important, or extremely important.



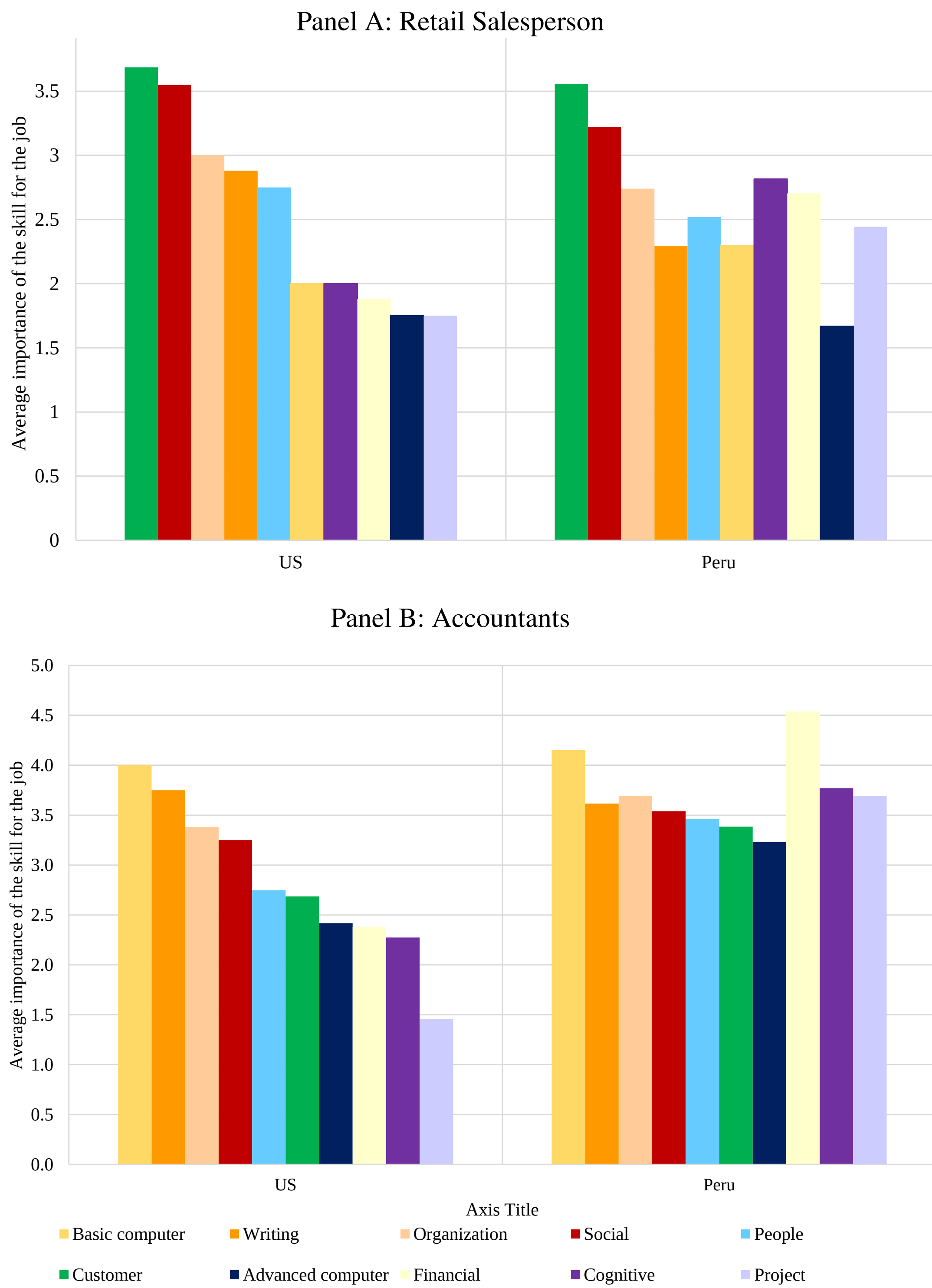
Notes: Each bar represents the percentage of filled jobs for which the given number of skills is important, very important, or extremely important. Source: Authors' calculations based on SERB-Peru employers' sample.

Figure 3.4. In Peru, there are workers in each wage quartile for every major occupational group.



Notes: Each bar represents the percentage of workers of the given occupation whose wage is in the corresponding aggregate wage quartile. Source: Authors' calculations based on SERB-Peru graduates' sample.

Figure 3.5. Peruvian workers do a little bit of everything, they are "toderos" regardless of the current occupational title



Notes: Each figure displays the skill profile for retail salespersons (panel A) and accountants (panel B) for the U.S. and Peru. Each bar represents the average importance of the skill. Source: SERB-Peru employers' sample and O*NET 2017.

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Appendix A

Supplementary Material for Chapter 1

A1 Additional tables

Table A.1. Outsourced and payroll employees' average tenure, by selected characteristics.

	1996	**1998**	**2000**	**2002**	**2004**	**2006**	**2008**	**2010**	**2012**	**2014**	**2016**	**2018**
Panel A: Outsourced employees												
Total	2.3	2.14	2.17	3.04	3.51	3.53	2.93	3.43	3.38	2.8	3.4	3.8
Sex												
Women	2.1	2 .00	2.19	3.03	3.83	3.89	3.35	3.53	3.85	2.98	3.47	3.83
Men	2.59	2.33	2.15	3.04	3.08	3.04	2.22	3.3	2.88	2.55	3.32	3.77
Age												
18-24	0.85	0.6	0.62	0.76	0.93	0.7	0.99	0.87	0.91	0.74	1.17	0.97
25-44	1.81	1.86	1.64	2.62	2.78	2.42	2.55	2.87	2.67	2.4	2.83	2.87
45-54	3.87	3.66	4.09	5.14	4.88	5.89	4.71	5.07	5.2	4.54	3.24	5.78
55-64	5.29	3.69	4.86	4.81	6.8	6.17	3.21	6.14	4.78	3.39	8.4	5.38
Education												

Continued on next page

Table A.1 – continued from previous page

	1996	**1998**	**2000**	**2002**	**2004**	**2006**	**2008**	**2010**	**2012**	**2014**	**2016**	**2018**
No college graduate	2.17	1.64	1.83	2.29	2.81	2.63	2.87	2.61	3.08	2.34	2.45	3.25
College graduate	2.51	2.92	2.89	4.06	4.47	4.61	2.99	4.51	3.85	3.51	4.67	4.3
N	243	307	340	301	347	346	330	291	287	283	260	255
Panel B: Payroll employees												
Total	6.9	6.96	7.02	7.21	7.42	7.2	7.39	7.74	7.77	7.93	7.81	7.52
Sex												
Women	6.33	6.58	6.58	6.67	7.09	6.98	7.04	7.47	7.5	7.92	7.69	7.35
Men	7.58	7.37	7.53	7.84	7.81	7.44	7.76	8.05	8.04	7.93	7.94	7.7
Age												
18-24	1.3	1.33	1.26	1.38	1.47	1.46	1.41	1.59	1.5	1.4	1.42	1.33
25-44	5.74	5.42	5.4	5.39	5.41	5.31	5.21	5.35	5.43	5.11	5.07	4.97
45-54	10.87	10.52	10.56	10.61	10.61	10.39	10.37	10.6	10.34	10.67	10.46	10.11
55-64	11.88	12.52	12.21	12.07	12.2	11.49	12.75	12.96	12.71	14.07	13.6	13.3
Education												
No college graduate	6.97	6.81	6.84	6.92	7.18	6.71	7.03	7.66	7.7	7.65	7.57	7.45
College graduate	6.81	7.16	7.26	7.47	7.65	7.66	7.72	7.79	7.84	8.15	7.97	7.54
N	8,493	10,550	10,952	10,706	11,280	11,337	10,855	9,854	8,947	9,595	9,384	7,868

Notes: Average tenure at employer by selected characteristics. Job Tenure Supplement weights used to compute the averages.

Source: Author's calculations based on CPS-JT 1996-2018.

Table A.2. Tenure difference between comparable outsourced and payroll employees.

	1996	**1998**	**2000**	**2002**	**2004**	**2006**	**2008**	**2010**	**2012**	**2014**	**2016**	**2018**
Panel A: Baseline specification												
Baseline	1.760***	2.379***	2.943***	2.013***	1.333***	2.177***	1.363***	0.958***	1.070***	1.036***	1.078***	0.781***
	(0.240)	(0.235)	(0.357)	(0.391)	(0.292)	(0.422)	(0.368)	(0.251)	(0.363)	(0.251)	(0.314)	(0.214)
Observations	123,411											
Panel B: Heterogeneous effects by sex												
Women	1.660***	2.704***	3.021***	1.868***	1.381***	2.086***	1.064***	0.919***	0.839**	0.714**	0.993**	0.651***
	(0.393)	(0.369)	(0.357)	(0.408)	(0.325)	(0.531)	(0.309)	(0.265)	(0.365)	(0.264)	(0.323)	(0.202)
Observations	66,886											
Men	1.906***	1.898***	2.827***	2.232**	1.274**	2.290***	1.882**	0.998***	1.325**	1.479***	1.182***	0.932**
	(0.302)	(0.435)	(0.613)	(0.821)	(0.414)	(0.475)	(0.732)	(0.230)	(0.532)	(0.312)	(0.376)	(0.334)
Observations	56,525											
Panel C: Heterogeneous effects by occupation groups												
Manufacture	2.514**	2.685**	4.984***	4.005***	2.758***	4.180***	3.327**	1.879**	1.882*	1.847**	2.209	0.836
related occs	(0.479)	(0.472)	(0.575)	(1.051)	(0.789)	(0.562)	(0.617)	(0.446)	(0.598)	(0.530)	(1.039)	(0.384)
Observations	22,563											
Services	1.616**	2.107**	2.523***	1.682***	0.820*	1.700	0.616**	0.622	0.777	0.834	0.970*	0.407
related occs	(0.337)	(0.597)	(0.405)	(0.433)	(0.334)	(0.817)	(0.174)	(0.311)	(0.641)	(0.612)	(0.389)	(0.202)
Observations	77,387											

Notes: Estimated coefficients of the interaction between outsourced-employee status and year dummies in Equation (1.4). The equation was estimated separately for the corresponding group. Robust standard errors in parenthesis, clustered at the year, occupation, education level, and state level. *** p<0.01, ** p<0.05, * p<0.1. Source: Author's calculations based on CPS-JT 1996-2018.

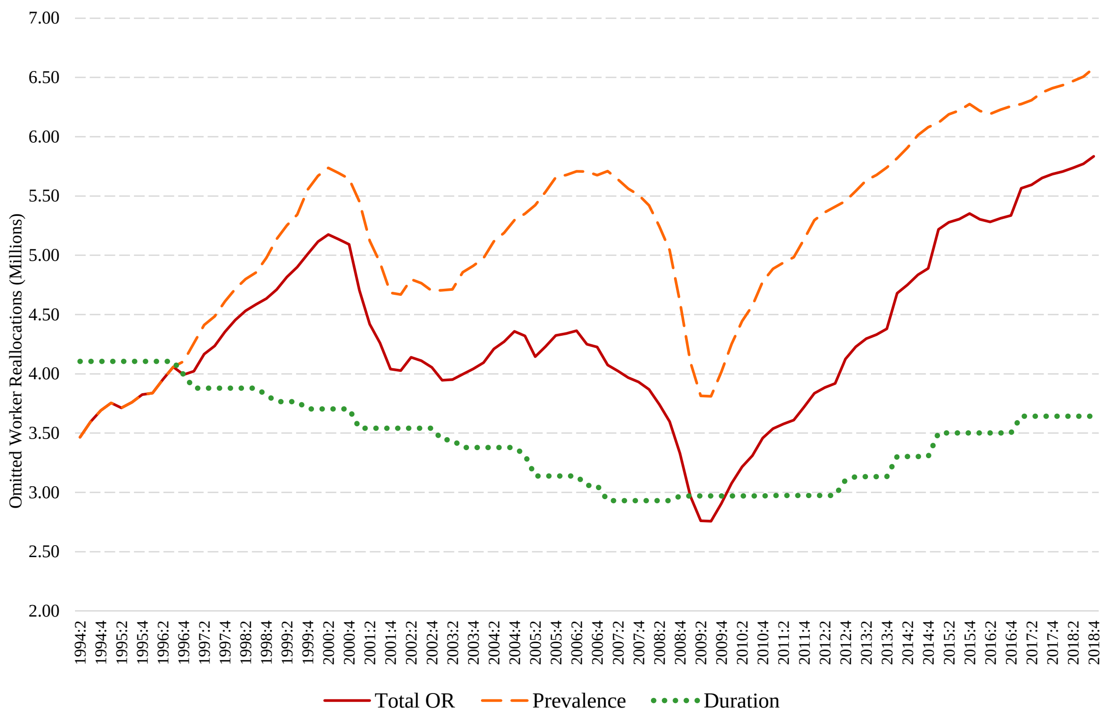
Table A.3. Tenure difference between comparable outsourced and payroll employees, by age and education level

	1996	1998	2000	2002	2004	2006	2008	2010	2012	2014	2016	2018
Panel A: Heterogeneous effects by age												
18-24	1.771**	1.931**	4.779***	1.887**	0.380	3.565***	0.692	1.805*	1.834*	1.653**	1.214	0.750
	(0.773)	(0.633)	(1.009)	(0.697)	(0.624)	(0.866)	(0.890)	(0.922)	(0.985)	(0.690)	(0.882)	(0.558)
Observations	9,737											
25-44	2.142***	2.450***	2.474***	2.616***	1.688***	1.988***	1.515**	0.803***	1.125**	0.941**	1.240*	0.439**
	(0.290)	(0.321)	(0.296)	(0.551)	(0.366)	(0.465)	(0.590)	(0.217)	(0.364)	(0.341)	(0.584)	(0.175)
Observations	61,954											
45-54	1.058**	2.190***	2.155***	0.780**	1.034**	1.873***	1.182**	0.942**	0.595*	1.214**	0.862**	1.232**
	(0.452)	(0.679)	(0.395)	(0.315)	(0.411)	(0.526)	(0.406)	(0.390)	(0.288)	(0.403)	(0.370)	(0.546)
Observations	32,634											
55-64	0.407	3.876*	2.961**	0.760	0.938***	1.890*	1.692***	0.655	1.109*	1.300***	0.658*	1.168***
	(0.231)	(1.869)	(1.124)	(0.767)	(0.248)	(0.943)	(0.324)	(0.443)	(0.563)	(0.298)	(0.302)	(0.329)
Observations	19,086											
Panel B: Heterogeneous effects by education												
No college	1.864***	2.697***	3.419***	2.602***	1.377***	3.359***	1.588***	1.409***	1.398***	1.408***	1.355**	0.688***
	(0.283)	(0.269)	(0.388)	(0.497)	(0.383)	(0.522)	(0.498)	(0.307)	(0.413)	(0.279)	(0.494)	(0.196)
Observations	58,298											
College	1.614***	1.863***	1.941***	1.236***	1.249***	0.759**	1.120***	0.414**	0.567	0.506	0.724*	0.850**
	(0.325)	(0.349)	(0.508)	(0.338)	(0.340)	(0.292)	(0.296)	(0.171)	(0.317)	(0.286)	(0.338)	(0.302)
Observations	65,113											

Notes: Estimated coefficients of the interaction between outsourced-employee status and year dummies in Equation (1.4). The equation was estimated separately for the corresponding group. Robust standard errors in parenthesis, clustered at the year, occupation, education level, and state level. *** p<0.01, ** p<0.05, * p<0.1. Source: Author's calculations based on CPS-JT 1996-2018.

A2 Additional figures

Figure A.1. The number of outsourced workers drives the increase in omitted reallocations.



Note: The figure displays the estimated number of omitted reallocations per average quarter in an outsourced-worker spell. Source: Author's calculations based on CPS-JT, CES, and ASA statistics.

Figure A.2. The corrected worker reallocation rate is more sensitive to the cycle.

Note: The figure displays the corrected and payroll QWI worker reallocation rates normalized to their 1994 value. The QWI worker reallocation rate was calculated as in Figure 1.7. Source: Author's calculations based on QWI, CPS-JT, CES, and ASA statistics.

Appendix B

Supplementary Material for Chapter 2

B1 Additional tables

Table B.1. The use of domestic outsourcing varies greatly across three-digit manufacturing industries.

	Pct. of establishments *(1)*	Pct. of revenue (clients) *(2)*
Food Manufacturing	47.33	1.81
Beverage and Tobacco	48.06	1.92
Textile Mills	51.03	1.60
Textile Product Mills	34.37	1.73
Apparel	26.98	1.81
Leather and Allied Product	33.03	1.27
Wood Product	37.17	2.11
Paper	70.78	1.14
Printing	44.14	1.93
Petroleum and Coal Products	25.36	1.27
Chemical	59.63	1.32
Plastics and Rubber	67.48	2.07
Nonmetallic Mineral	26.29	1.52
Primary Metal	59.24	1.05
Fabricated Metal	47.22	1.81
Machinery	52.69	1.46
Computer and Electronic	61.83	1.58
Electrical Equipment	62.44	1.44
Transportation Equipment	60.64	1.55
Furniture and Related	40.35	1.86
Miscellaneous	41.17	1.97
Total	47.14	1.70

Notes: Yearly averages by the given establishment characteristic. Column 1 displays the percentage of establishments reporting having spent on temporary workers and leased employees. Column 2 reports the percentage of revenue spent on temporary and leased employees by the average client establishment in each category. Industry groups correspond to the 3-digit NAICS classification. Source: Author's calculations from ASM-CM-LBD data in 2006-2017.

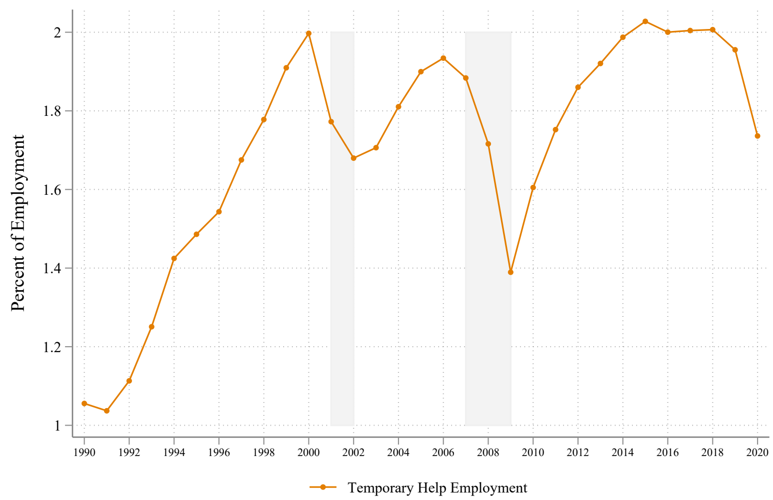
Table B.2. Industry of Assignment Distribution of Temporary Help Workers

	1995	1997	1999	2001	2005	2017
Agriculture, forestry, fishing	0.30	0.00	0.40	0.90	0.80	0.80
Mining	0.20	0.70	0.10	0.90	0.50	0.70
Construction	2.90	2.60	2.70	3.50	3.50	3.40
Manufacturing	34.10	32.10	31.20	22.70	29.50	34.90
Transportation, Communications	7.40	6.40	6.30	8.00	3.80	5.30
Wholesale trade	2.90	4.40	4.10	3.10	5.70	4.00
Retail trade	5.30	3.30	4.10	4.10	3.30	2.90
Finance, Insurance, and Real Estate	6.90	8.40	7.10	7.00	3.80	4.30
Business and repair services	22.60	25.90	25.60	30.30	29.20	23.20
Personal services	2.70	1.90	3.40	1.00	3.30	0.90
Entertainment and recreation services	0.70	0.90	0.50	1.90	0.00	0.60
Professional and related services	12.60	13.20	13.20	14.10	13.80	18.10
Public administration	1.30	0.00	1.20	2.40	2.90	1.00

Note: Calculations based on major industry of assignment (1990 codification) reported by those in the CWS who indicate being paid by a temporary help agency. CWS weights used. Source: Author's calculations based on the CP-CWS.

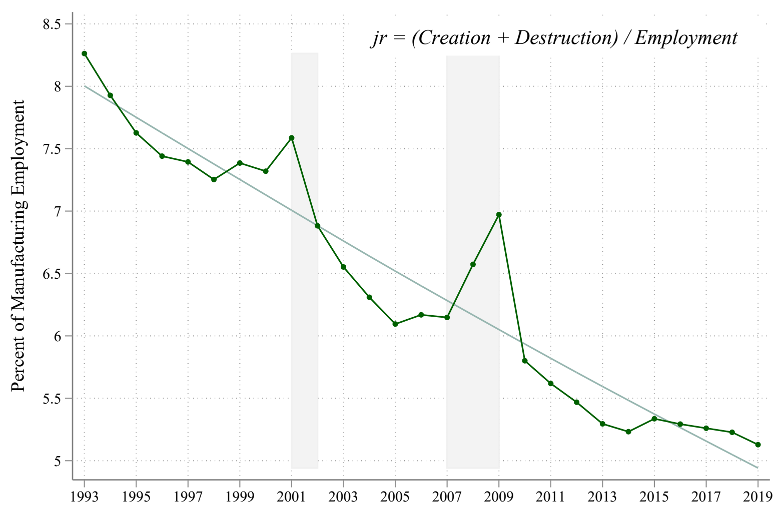
B2 Additional figures

Figure B.1. The use of domestic outsourcing dramatically increased in the 1990s



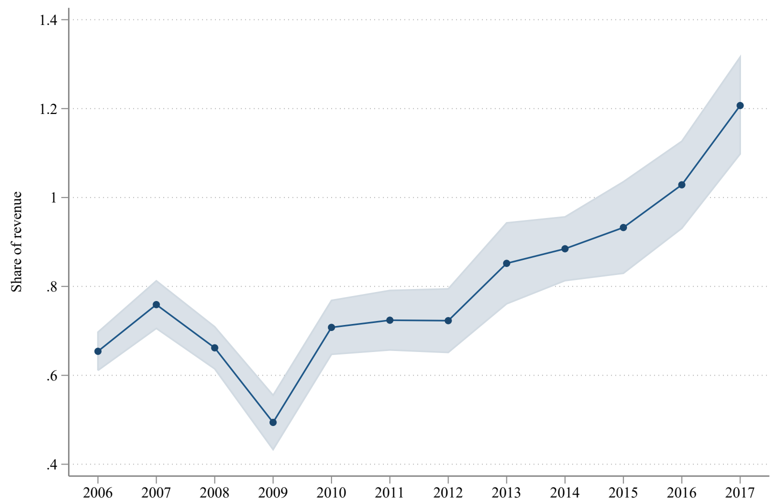
Note: The figure displays the average monthly employment in temporary help agencies relative to non-farm employment over time. Temporary help services is a six-digit NAICS industry comprised of establishments whose main activity is supplying workers to clients' plants. Source: Author's calculations based on the Current Employment Statistics series, seasonally adjusted.

Figure B.2. The job reallocation rate in manufacturing has declined 40% since 1993.



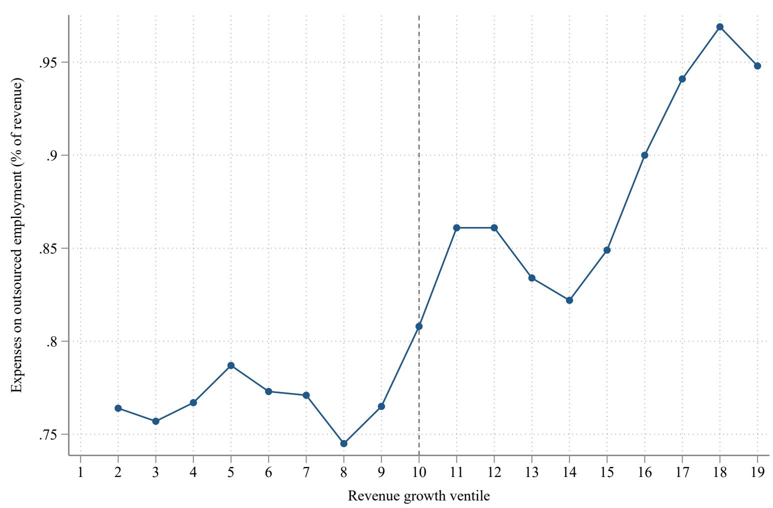
Note: The figure displays yearly averages of the quarterly job reallocation rate in the manufacturing sector and its HP trend. Source: Author's calculations based on Quarterly Workforce Indicators, seasonally adjusted.

Figure B.3. The share of revenue spent on temporary and leased staff by the average establishment increased by 86% between 2006 and 2017.



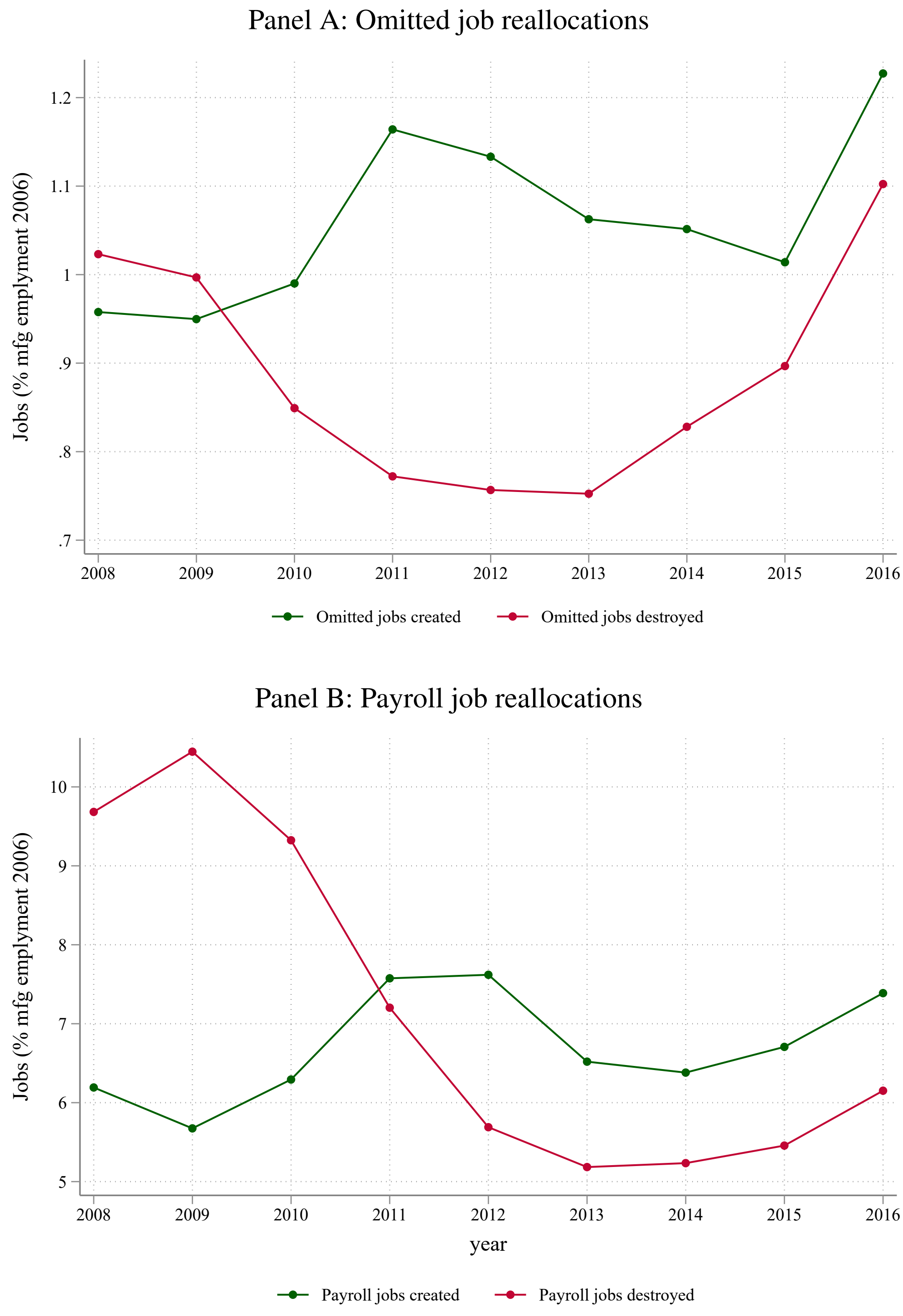
Note: Table shows point estimates and robust standard errors of business-specific expenditures on temporary and leased staff as a share of revenue, controlling for employment size, age, and three-digit industry. Source: Author's calculations from ASM-CM-LBD data in 2006-2017.

Figure B.4. Outsourced labor share along plant-level revenue growth for all establishments.



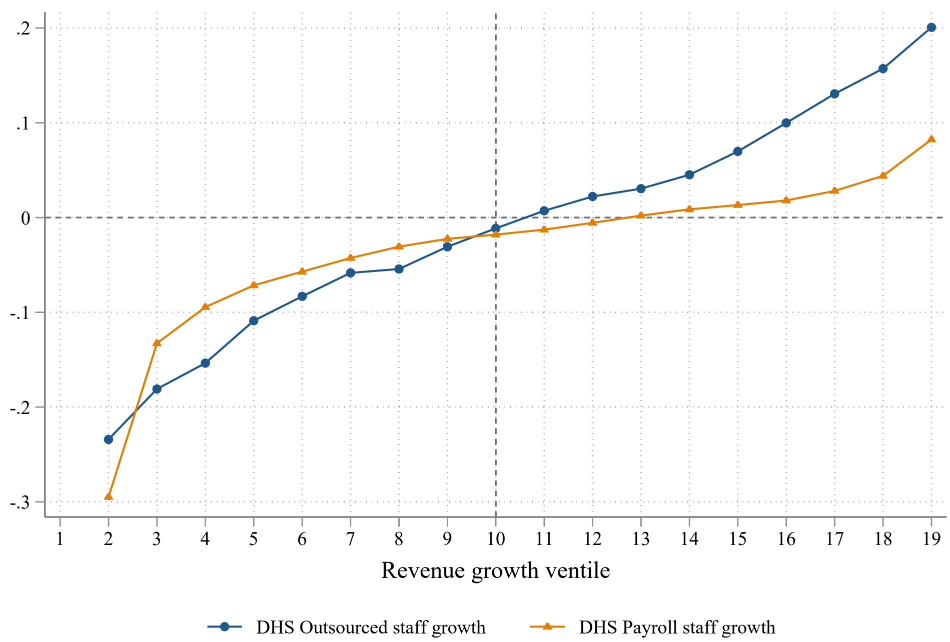
Note: The figure displays the average share of revenue spent on temporary and leased staff by revenue growth ventile. Each point is the three-point moving average. Source: Author's calculation from ASM-SM-LBD data in 2006-2017.

Figure B.5. The manufacturing sector created more outsourced jobs than it destroyed



Note: Each point is a three-year average. Omitted job reallocations computed following equation (2.5). Payroll job creation (destruction) is the sum of employment changes in expanding (shrinking) establishments. Source: Author's calculation based on ASM-CM-LBD and RELBD data from 2006-2017.

Figure B.6. The qualitative relationship between outsourced employment growth and revenue growth exhibits more variation than that of payroll employment.



Note: The figure displays the average DHS growth rate of temporary and leased employment and payroll employment by revenue growth ventile. Each point is the three-point moving average. Source: Author's calculations based on ASM-CM-LBD and RELBD from 2006-2017.

B3 Data appendix

Sample restrictions

I limit the analysis to "ASM establishments" in Census years (years ending in 2 and 7) to ensure longitudinal consistency.

I drop observations that seem imputed using the industry average ratios of the value of shipments and cost of materials to payroll.

Exclusion criteria (Dunne, 1998; Roberts and Supina, 1996)
- Compute the ratio of total value of shipments and cost of materials to payroll for each establishment with a payroll greater than zero.
- Drop establishments in which either of the ratios is zero or missing.
- For each year in the sample, I drop establishments whose ratios equal the six-digit industry modal ratio.

For each year, I trim the industry-year TFP distribution by dropping establishments whose TFP deviate from the six-digit industry average by more than 2 in absolute value.

I delete establishments with zero or negative values in either of the TFP components: revenue, capital, total hours, materials and energy.

Winsorize capital to the 99.5 percentile.

Weights

I use an ASM-CM-LBD sample for the analysis. The ASM-CM provides the main variable of interest —expenses in outsourcing services, and the information to construct revenue productivity —main dependent variable. The LBD, on the other hand, has accurate establishment-level data on location, age, and firm characteristics.

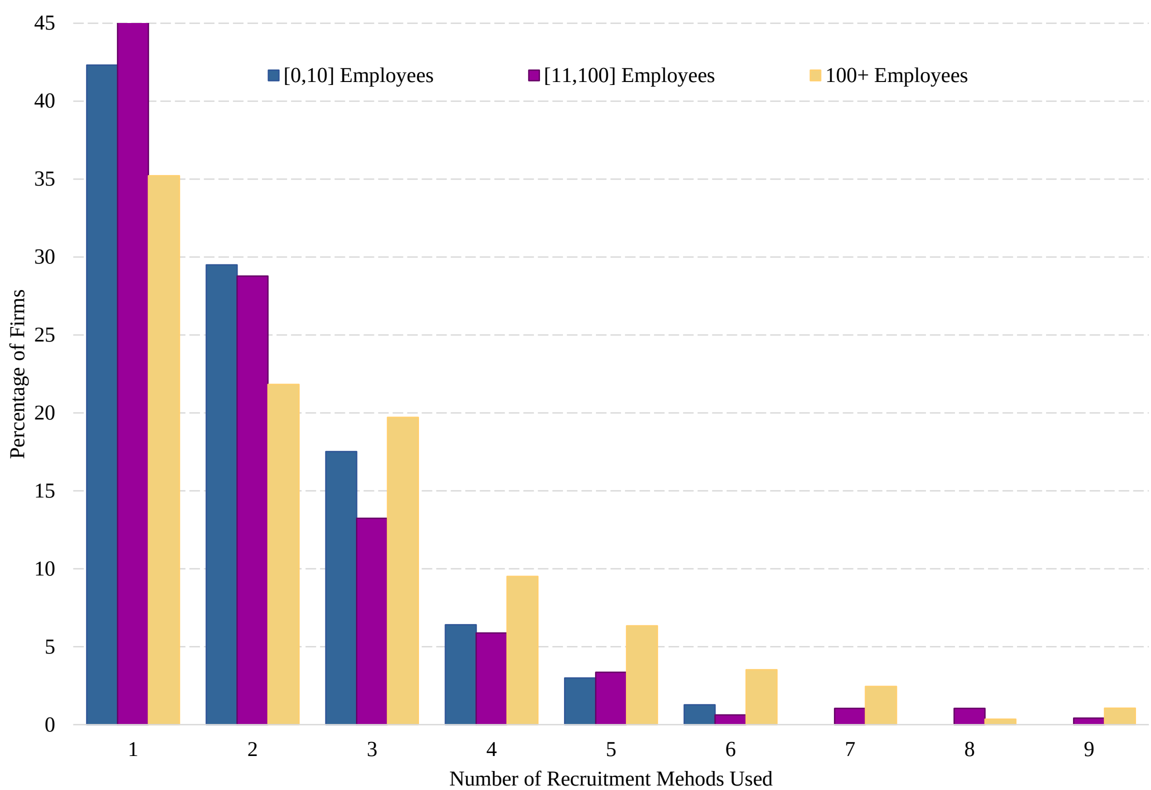
I restrict the sample to establishments with information on outsourcing expenses. Therefore, to ensure that the analysis sample is representative of the manufacturing universe, I compute weights based on the probability of being sampled in the ASM and having reported outsourced expenses given that the establishment is in the LBD (propensity score). I run a logistic regression in which the dependent variable is a dummy equal to one if the establishment is in both the ASM-CM and the LBD for that year and equal to zero if the establishment is only in the LBD. The independent variables are a multi-unit firm dummy, establishment size class dummies (measured by employment), payroll category dummies, and LBD detailed industry codes. The weight is the inverse of the predicted probability.

Appendix C

Supplementary Material for Chapter 3

C1 Heterogeneity across firm size

Figure C.1. Larger firms use more recruiting methods.



Notes: Distribution of firms across the number of recruiting methods used to fill their vacancies, by size. Source: SERB-Peru *Employers'* sample.

Table C.1 shows the percentage of vacancies filled on time in the last 12 months by posting date and firm size. Although small firms post their vacancies earlier than big firms, a greater share of big firms' vacancies are filled on time. The differences in time to fill vacancies across firm sizes are, nonetheless, moderate. 34% of the firms with less than 10 employees usually post vacancies between two and three months of the desired starting date; 90% of the vacancies posted by these firms are filled on time. 70% of the firms with more than 100 employees usually post their vacancies just within four weeks of the desired starting date, and 93% of the vacancies posted by these firms in the last year were filled on time.

Table C.1. The share of vacancies filled on time is higher for larger firms.

		Time before start date (months)			
Firm Size	%	0-1	2-3	> 3	Total
≤ 10	Firms Posting (N=226)	60.18	34.07	5.75	
	Vacancies filled on time	91.23	89.97	87.69	90.6
11-100	Firms Posting (N=464)	69.18	23.06	7.76	
	Vacancies filled on time	90.23	88.49	89.28	89.76
>100	Firms Posting (N=278)	69.06	25.90	5.04	
	Vacancies filled on time	93.06	93.86	95.29	93.38
Overall	Firms Posting (N=968)	67.05	26.45	6.51	
	Vacancies filled on time	91.28	90.45	90.29	90.99

Notes: Percentage of vacancies filled on time by firm size and (expected) recruiting time. Source: SERB-Peru employers' survey.

Table C.2 shows the education level and potential experience of the last hired worker by firm size. When the education level required by the job is lower than BA, the share of hired workers with a college degree or more is greater in firms with less than 10 workers. However, the proportion of over-educated workers is roughly the same across firm sizes suggesting that the over-qualification pattern may be related to a market-level inefficiency rather than firm-specific demand heterogeneity.

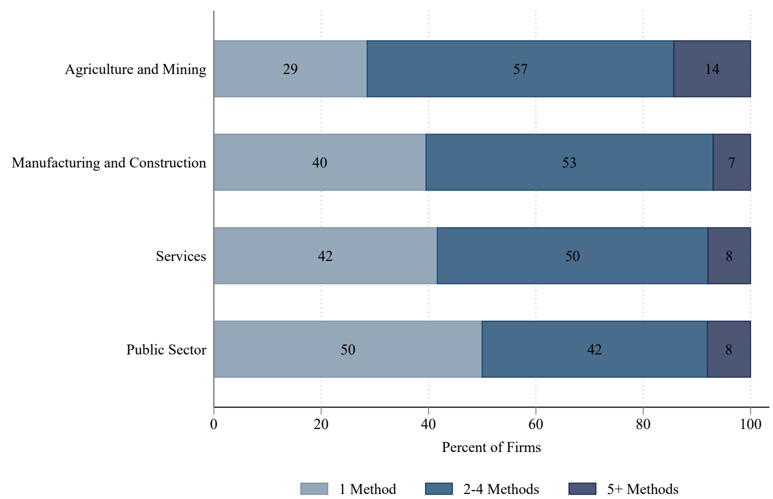
Table C.2. Over-qualification by firm size.

Required by job		Attained by new hire, by firm size (%)			
		≤10	11-100	>100	Overall
Panel A: Education					
	High school or less	54.00	60.00	52.60	57.10
High school or less	Technical school	10.00	15.50	23.70	15.70
	BA or more	36.00	24.50	23.70	27.30
N Firms		*50*	*110*	*38*	198
	High school or less	1.40	2.80	1.90	2.20
Technical school	Technical school	28.40	33.10	28.30	30.40
	BA or more	70.30	64.10	69.80	67.40
N Firms		*74*	*142*	*106*	322
	High school or less	0.00	0.00	0.00	0.00
BA or more	Technical school	1.90	0.90	1.00	1.20
	BA or more	98.10	99.10	99.00	98.80
N Firms		*54*	*107*	*99*	260
Panel B: Experience					
	Less than one year	13.70	20.00	13.90	16.60
Less than one year	1-3 years	58.80	60.00	61.10	59.90
	4 years or more	27.50	20.00	25.00	23.60
N Firms		*51*	*70*	*36*	*157*
	Less than one year	10.70	18.40	15.60	15.30
1-3 years	1-3 years	60.70	47.40	53.30	53.20
	4 years or more	28.60	34.20	31.10	31.50
N Firms		*28*	*38*	*45*	*111*

Note: Percentage of new hires that attained the given education level by the education level required by the job and firm size. Attained experience is measured as the difference between age and years of education minus six (potential experience). Source: Authors' calculations based on SERB-Peru employers' survey (panel A) and SERB-Peru matched sample (panel B).

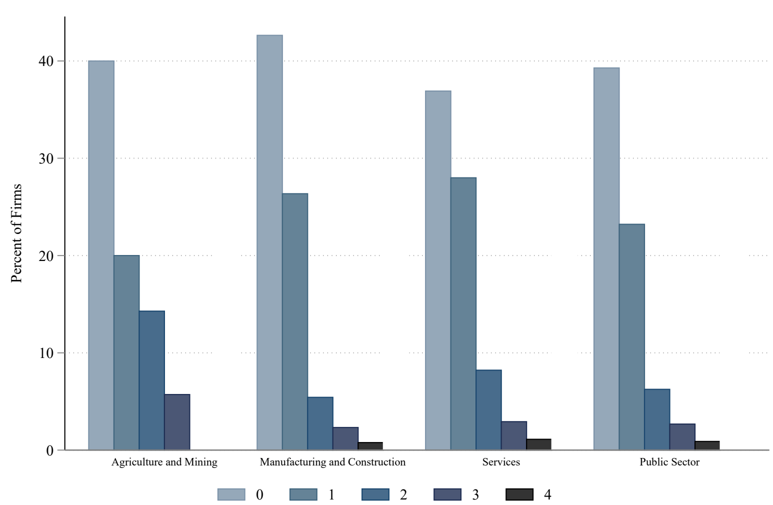
C2 Heterogeneity across firm sector

Figure C.2. Firms use many methods at a time independently of the sector.



Notes: Distribution of firms across the number of recruiting methods used to fill their vacancies, by sector. Source: Authors' calculations based on SERB-Peru employers' sample.

Figure C.3. Number of methods besides networks by sector. Network hiring is pervasive in all sectors.



Source: Authors' calculations based on SERB-Peru employers' sample.

C3 Job skills

We create 10 job skill dimensions that could be useful across a wide range of jobs following O*NET skills classification and Deming and Kahn (2018). We survey employers and workers about the importance of each skill category for the job using a scale between 1 (not important at all) and 5 (extremely important). Table C.3 lists the 10 skill dimensions, the examples we provided to the survey participants, and the correspondent O*NET skills. In an effort to guarantee comparability between U.S. and Peru skill profiles, we based the examples provided to survey participants on O*NET skills as shown in columns 2 and 3 of Table C.3.

The first two skills listed in table C.3 are "cognitive" and "social." The description of these dimensions are meant to match the definition of "non-routine analytical" job tasks used in Autor (2003). The third skill, "organization/ self-efficacy," refers to non-cognitive or "soft" skills such as "organized," "detail-oriented," and "time management." The other seven job skill categories are common to a wide range of jobs Deming and Kahn (2018). We include categories for general and specific computer skills. The former encompasses common software, such as Microsoft Excel, while the latter includes specialized software.

We measure the importance of each job skill dimension for 6-digit occupations. In Peru, the importance of a given job skill dimension for an occupation is the average importance reported by employers for such occupation. In the U.S., the importance of a given job skill dimension for an occupation is given by the average importance of the O*NET skills contained in the skill dimension (column 3 in table C.3).

Table C.3. Description of Job Skills

Job Skill Dimension	Questionnaire Examples	O*NET Skills
Cognitive	Problem solving, research, analysis, critical thinking, mathematics, statistics	Reading comprehension, mathematics, science, critical thinking, active learning, learning strategies, complex problem solving, operations analysis, technology design, equipment selection, installation, equipment maintenance, troubleshooting, repairing, quality control analysis, judgment and decision making
Social	Communication, teamwork, collaboration, negotiation, presentation skills	Active listening, speaking, social perceptiveness, coordination, negotiation
Organization/ Self-efficacy	Time management, organized, detail-oriented, multi-tasking, meeting deadlines on time, energetic	Time management
Writing	Writing skills	Writing
Customer service	Sales, patient	Persuasion, service orientation
Project management	Project management	Operation monitoring, operation and control, management of material resources
People management	Monitoring, leadership, management (not project), advisory, personnel	Monitoring, instructing, management of personnel resources
Financial	Budgeting, accounting, finance, costs projection	Management of financial resources
Basic computer skills	Spreadsheets, common software (e.g., Microsoft Excel, PowerPoint).	Common software technology requirement
Advanced computer skills	Programming language or specialized software (e.g., SAP, SPSS, R, Corel, Java, SQL, Python)	Programming systems analysis, systems evaluation, specialized software

Note: Authors' categorization of job skills and correspondence to O*NET skills.