Job Dynamics with Staffed Labor*

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Abstract

This paper quantifies the role of staffing in both plant-level employment adjustments and aggregate job reallocation. Staffing happens when businesses source labor through "renting" workers from staffing agencies, in place of direct hiring. We find that staffing is an important channel to both micro- and macro-economic job dynamics. Leveraging administrative data sources for U.S. manufacturing, we show that staffing is widespread and rising over time. On a yearly basis, one in two manufacturing plants recruits at least some of its workers through staffing, and staffing expenditure as a share of revenue has gone up for most plants. Furthermore, we show that staffing allows plants to be more dynamic in response to demand shocks. In particular, changes in staffing employment are larger and more immediate than changes in payroll employment. The creation and destruction of staffed jobs are also a large and increasing portion of aggregate job flows. Staffed workers perform their tasks at the client business' premises and directives, alongside the client business' own employees, but they remain legally employed by the staffing agency throughout different client assignments. Thus, their job changes are unaccounted for in official tallies. This omission is material: since 2006, correcting the total job reallocation rate for the creation and destruction of staffed jobs accounts for 37% of the decline in the measured aggregate job reallocation rate. We conclude that staffing is a quantitatively relevant channel of adjustment both at the plant-level and in the aggregate, and that the strategic use of staffing by U.S. manufactures underlies a significant *shift*, but not necessarily only a *drop*, in labor market dynamism.

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1 Introduction

The reallocation of workers and jobs across employers, one of the faces of labor market dynamism, is a crucial economic process to foster the efficient distribution of labor resources across productive uses. The literature has raised concerns about the diminished ability of firms to expand or contract following shocks, thus raising the possibility of an increase in the misallocation of resources in the U.S. (Decker et al., 2020). In the aggregate, reallocation flows in the labor market have been documented to be on a downward trend since at least the 1990s, raising questions about a curtailed ability of the labor market as a whole to propel workers towards well-paid jobs and assign labor resources where they can be most productive (Davis et al., 1998; Davis and Haltiwanger, 2014; Moscarini and Postel-Vinay, 2016; Decker et al., 2016).

Our paper documents the growing contribution of staffing to both micro-level and aggregate changes in job dynamics. Staffing is a technology for intermediated hiring, through which employers "rent" workers from a staffing agency, rather than employing them directly. Leveraging a variety of administrative datasets, we document that staffing arrangements are widely and increasingly used in U.S. manufacturing. Then, we illustrate how the strategic use of staffing allows plants to scale up or down flexibly, since staffed labor responds more strongly and quickly than payroll labor to firm-level shocks. The use of staffing is also positively associated with plant-level volatility, suggesting staffing employment is a flexible margin of adjustment for plants. The growing use of staffing employment has important macroeconomic consequences, as well. It accounts for a large portion of the secular decline in the aggregate job reallocation rate (37 percent). Our evidence implies that the use of staffing labor leads to a significant shift — but not necessarily a *drop* — in job dynamics, both at the business and aggregate level.

Staffing offers a flexible way to scale up or down as a business' optimal workforce size changes. Unlike direct hiring and firing, staffing allows a business to sidestep many of the costs an employer normally incurs when adjusting its workforce size. Staffing saves time: staffing agencies typically have a list of suitable candidates "at the ready" and staffing employees can be easily dismissed or replaced — without the need to fire anyone. Staffing agencies also perform much of the screening of new recruits and negotiate the assignment contract. Staffing arrangements, however, are not necessarily cheaper than direct hiring, as staffing agencies charge a fee for their services. When choosing between staffing and direct hiring, a plant trades-off the agency's markup with in-house HR costs.

Staffed workers are typically core workers. In manufacturing, this means production workers. A different type of domestic outsourcing is services outsourcing, which often involves professional figures like safety guards, food preparation workers, or cleaning and maintenance personnel. The outsourcing of services can be seen as a byproduct of firms' specialization process, defining what is a firm's core business (to be performed by in-house employees) and what, instead, are accessory functions (to be outsourced to a specialized service provider). We find that staffing is, instead, a flexible technology to source labor and scale production up (or down) as the need arises. We find convincing evidence that employers use staffing in response to idiosyncratic shocks, especially in high-volatility economic environments.[1]

Staffing is a widespread and growing phenomenon among U.S. employers. The employment share of temporary help firms and professional employer organizations (PEOs) has increased by over 80 percent since the 1990s and, every year, staffing agencies assign to client businesses as many workers as the equivalent of 25 percent of aggregate hires. Manufacturing is the sector with the highest use of staffed workers, and U.S. manufactures regularly source labor via staffing.[2] In the Annual Survey of Manufactures (ASM), our main data source, 8 in 10 establishments report positive yearly expenditure for staffed labor at least once between 2006 and 2017. In the same period, about 4 in 10 establishments report positive yearly expenditure for staffed labor *every year*. Over the period 2006-2017, the share of revenue spent on staffed labor by the average manufacture has grown significantly and faster than the share spent on payroll labor.

Which businesses are especially likely to use staffing for their labor needs? Descriptive evidence illustrates that the use of staffed labor is systematically and positively correlated with revenue growth. Establishments who are growing especially fast are more likely to report any positive expenditure on staffed labor. Fast-growing plants also tend to spend a larger share of their revenue on staffing than establishments with slower growth rates.[3] We also find that larger, older businesses, and those in more technologically advanced sectors, are more likely to report any positive expenditure on staffing arrangements. However, conditional on any positive expenditure, younger and smaller establishments spend a larger fraction of their revenue on staffed labor than older, larger establishments do.

Our descriptive evidence is consistent with staffing providing flexibility for businesses. We then explicitly ask whether businesses adjust their workforce through staffing *in response to* idiosyncratic shocks. In particular, we study how expenditure on staffed labor, and the corresponding staffed employment headcount, vary with plant-level revenue changes and productivity changes.

[1] The outsourcing of workers in these accessory functions also has significant implications for workers and firms, as shown by Goldschmidt and Schmieder (2017), for instance, and Bilal and Lhuillier (2021).

[2] In the Contingent Workers Survey over a third of workers who are working at staffing agencies report being assigned to manufacturing.

[3] However, while the use of staffing arrangements is monotonically increasing in revenue growth, the share of revenue spent on staffed labor is U-shaped in revenue growth. This is reminiscent of the hockey-stick shaped employment growth in Davis, Haltiwanger and Schuh (1996). Establishments that are shrinking fast face high turnover and thus both a higher hires rate and a higher staffed labor accession rate, with respect to firms who are stable in size.

We measure expenses on staffed and leased labor from the ASM, which distinguishes expenses for leased workers and staffing employees from expenditure for other outsourced services.[4] We propose a methodology to convert those expenses into job counts and derive a lower bound on plant-level changes in staffed jobs, that we use alongside expenditure on staffed labor for our empirical analysis. We then leverage a variety of empirical designs to show that staffed labor responds more strongly and quickly than payroll labor to firm-level shocks, be it demand-driven ones or idiosyncratic productivity changes.

The data strongly supports the notion that staffed labor is a flexible and important margin of adjustment for U.S. manufactures. We show this fact across a variety of empirical exercises. We start from a linear regression of changes in staffed labor expenditure on changes in revenue, as suggested by a firm's cost minimization problem. This returns a higher elasticity of staffed labor to revenue changes than payroll labor, especially in the short term. Though intuitive, the naive OLS approach suffers from endogeneity concerns. As a result, we propose two complementary instrumental variables designs. The first exploits exogenous import price changes that affect a firm's cost, but not labor supply. The second IV design restricts attention to exporter businesses, and leverages real exchange rates shocks as a proxy for exogenous product demand shocks. All of these exercises point to larger and more immediate changes of staffed labor than payroll labor in response to demand shocks.

We also investigate how staffed job creation and destruction react to productivity changes. For this, we build upon Decker et al.'s (2020) empirical investigation of business responsiveness. All our empirical exercises point to staffed labor being a more flexible margin of adjustment than payroll labor. Specifically, we find that plant-level staffed employment is twice as responsive as payroll employment to idiosyncratic shocks and adjusts more quickly. Plants respond to shocks by adjusting staffed employment growth within the same year of the shock, while payroll employment reacts sluggishly.

Staffing also has significant macroeconomic consequences for the measurement and interpretation of aggregate labor market flows. The legal characteristics of staffing arrangements affect the measurement of various job aggregates. Staffed workers are the legal employees of the staffing agency — even though they work at the premises of a client firm, under the supervision and directives of the client firm's managers, and alongside the client firm's own employees. On the factory floor, staffed workers are indistinguishable from payroll workers. In the books, however, they can only be found on the staffing agencies' records. The dichotomy between where the job is performed (the client firm's premises) and the employer of record (the staffing agency) imply a potential mis-

[4] We only consider the former, as our focus is on a flexible type of labor, not on a firm's decision to outsource parts of its non-core activities.

measurement issue, which we show is sizeable and affects employment changes both at the plant- and aggregate level.[5]

We propose a *total* reallocation rate measure that includes the creation and destruction of all jobs, those filled and vacated by staffed workers, alongside those filled and vacated by payroll workers (the traditional measure). We then compute the total job reallocation series corrected for the reallocation of staffed jobs. We find that on average, the creation or destruction of staffed jobs can account for as much as 15 percent of the corresponding payroll job flow in any given year. Along the business cycle, including staffed job reallocations is also insightful. For instance, in 2010, the manufacturing sector was creating jobs to be filled by staffed workers at a higher pace than it was creating payroll jobs. At the same time, it was not destroying the existing staffed jobs as quickly as payroll jobs. This suggests that omitting staffed jobs flows potentially affects our assessment of the speed of economic recoveries, as well.

Staffed jobs are created and destroyed at a higher pace than payroll jobs. Their share of total employment is also increasing over time. Correcting job flows to take into account the jobs filled and vacated by staffed workers has, therefore, a significant impact on the measurement of the aggregate job reallocation rate. In particular, we show that the measured decline in the aggregate job reallocation rate would be 37 percent smaller than what it currently is. In other words, staffing can account for 37 percent of the decline in job reallocations since 2006. We conclude that, alongside a drop in labor market dynamism, the U.S. economy has experienced a substantial *shift* towards alternative labor market matching technologies. Though the drop in job reallocation remains, we interpret our results as providing some measure of comfort as to potential increases in misallocation in the U.S. economy. We also conclude that intermediated matching technologies, of which staffing is one, represent a salient but understudied characteristic of the labor market, worthy of consideration by both researchers and policy makers alike.

CONTRIBUTION TO THE LITERATURE. Our work contributes to the macroeconomic literature studying the measurement and interpretation of labor market flows, pioneered by Davis, Haltiwanger and Schuh (1996), Davis and Haltiwanger (1998), and Davis, Haltiwanger and Schuh (1998). The focus of this paper, the impact of staffing on job dynamics, also complements the literature on the determinants of labor adjustments at the firm- and aggregate level, such as Shimer (2012), and Decker et al. (2020). Our paper shows that staffing provides a flexible way for firms to adjust their workforce in the face of shocks.

[5] Indeed, jobs filled and vacated by staffed workers are not tallied in official job creation and destruction measures, because their creation and destruction do not trigger any payroll variation. To see this, consider how staffed workers cycle through client assignments while remaining always a legal employee of the staffing agency. They may change jobs, tasks, workplaces and colleagues, but not their legal employer — as would instead happen in payroll employment relationships.

Our paper is also related to various works studying the causes and consequences of the decline in aggregate labor market dynamism (Hyatt and Spletzer, 2013; Davis and Haltiwanger, 2014; Decker et al., 2016; Molloy et al., 2016; Peters and Walsh, 2019; Karahan, Pugsley and Şahin, 2019; Akcigit and Ates, 2021). Our results contribute to this literature by proposing and implementing a method to measure total job flows, including those pertaining to the creation and destruction of staffed jobs. We also offer an alternative explanation for the measured decline in aggregate reallocation flows, arguing it reflects instead a shift towards the use of intermediaries in the hiring and firing processes.

We also join a recent literature investigating the micro- and macro-economic consequences of domestic outsourcing. Significant attention has been devoted to staffing's impact on wages. Goldschmidt and Schmieder (2017) leverage German matched employer-employee data to document how the use of staffing arrangements by employers alters the wage structure, and typically results in lower wages for staffed workers. Bilal and Lhuillier (2021) propose a framework to evaluate the trade-off between contingent workers' wage losses, which they also find in French data, and the efficiency gains from reduced frictions in matching. Again in the French context, Bergeaud et al. (2023) finds that the average wage gap between payroll and contingent workers is about 3 percent, that the gap is negative in more than 25 percent of establishment-occupation cells, and largely inefficient. Drenik et al. (2023) exploit a unique data source in Argentina that provides data on both contingent workers' employer of record (the staffing agency) and workplace of assignment (the client firm). They also find a wage penalty for staffed workers vis-à-vis payroll employees.[6] Using administrative data from Mexico, Estefan et al. (2024) show that banning labor outsourcing arrangements and mandating the conversion of staffed workers to in-house employees, as the Mexican government did in 2021, is an effective policy to raise wages and lower labor markdowns, without curtailing overall employment nor output. Our paper complements this literature by providing evidence using plant-level data from the U.S. manufacturing sector and focusing on how staffing impacts business-level and aggregate job dynamics, instead.

OVERVIEW. Section 2 details our measurement strategy, what challenges we face, and the data we use to overcome them. Section 3 documents the prevalence and growth of staffing in the U.S. manufacturing sector, and illustrate heterogeneity in the use of staffing arrangements alongside plant

[6] The literature on staffing is large. Some papers have a narrow focus to only a subset of occupations. Dube and Kaplan (2010) focus on janitors and guards, arguing that "outsourcing seems to have reduced labor market rents for workers". More recently, Felix and Wong (2023) leverage a natural experiment in the legalization of outsourcing in Brazil and studies how it affected compensation and employment rates for security guards. Other papers are chiefly concerned with the negative consequences of staffing, that is the risk of fostering wage discrimination within the firm and exacerbate wage inequality (Houseman, Kalleberg and Erickcek, 2003; Autor and Houseman, 2010; Bloom, Guvenen, Smith, Song and von Wachter, 2018; Dorn, Schmieder and Spletzer, 2018; Bergeaud, Mazet-Sonilhac, Malgouyres and Signorelli, 2021; Weber-Handwerker, 2022).

size and age, and over time. Section 4 quantifies how changes in revenue and revenue productivity affect a plant's workforce size, both in terms of staffed and payroll employment. Section 5 corrects aggregate job flows to properly account for the (previously unmeasured) reallocation flows of staffed jobs. Section 6 concludes.

2 Measurement

This section illustrates how the legal and administrative architecture of staffing arrangements affect the measurement of how many jobs are filled and vacated by temporary or leased workers. We overcome this measurement challenge by exploiting data on staffing in the U.S. manufacturing sector made available by the U.S. Census Bureau. Our administrative micro data sources, chiefly the Annual Survey of Manufactures (ASM), Census of Manufactures (CM), and Longitudinal Business Database (LBD), provide information on yearly plant-level expenses on temporary and leased staff for the period between 2006 and 2017, together with other inputs expenditures, payroll employment counts, and revenue. In addition to using expenditure data, we develop a methodology to calculate job counts from it and use it to estimate plant-level changes in the number of jobs filled and vacated by staffed labor.

2.1 What is staffing?

Staffing is a way for firms to source labor, alternative to direct hiring, which is mediated by a specialized business, the staffing agency. Staffing agencies, legally termed temporary help agencies or Professional Employment Organizations (PEOs), specialize in providing workers who fit a variety of skill profiles and also often offer HR management services with regard to the workers they lease out to clients. Direct hiring is a frictional process, calling for potentially significant resources expenditures. Employers devote specialized labor (HR) to surfacing, recruiting, and screening potential candidates, in addition to spending time in crafting a job description, posting job ads, setting wage policies, negotiating over various aspects of job contracts, organizing teams, and providing on-the-job training for new employees. Staffing arrangements allow employers to sidestep many of these actions, which are accomplished by the staffing agency, and provides a means for firms to quickly scale up or down as their demand fluctuates. To access the flexibility that staffing offers, firms rely on an established relationship with a staffing agency (very much akin to the relationship they may have with a bank who offers an open line of credit, staffing agencies offer an open *line of labor*). Once a relationship between a firm and an agency is established, an employer business trades-off HR costs and the agency's fees.[7]

Staffing poses significant measurement challenges for job flows. Jobs filled by staffing workers are not counted in official job creation tallies, nor are jobs vacated by staffing workers counted as job destruction. This is because these statistics are predicated on payroll changes at the employer's that is creating or destroying jobs. However, temporary workers' assignments do not trigger any legal payroll change. Staffed workers change tasks, co-workers, managers, and workplace as they move from assignment to assignment, but remain legally employed at the staffing agency throughout. Hence no job change is measured. As a result, the more staffed labor is a substitute for payroll labor, the more job flows are underestimated. Furthermore, if job flows are detected at all, it is when staffing agencies themselves create or destroy jobs. Therefore, these job flows are mistakenly ascribed to the service sector — while the jobs will be performed (or no longer performed) in the client business' sector, for instance manufacturing. The mismeasurement is potentially significant. Dey et al. (2012), Dey et al. (2017) show that manufacturing employment between 1989 to 2000 increases by 1.4% (instead of a 4.1% drop), while annual labor productivity growth between 2007 and 2015 is 15% lower (Dey et al. 2017), once staffed labor accessions and separations are properly accounted for. In addition, when we count expenditure on staffed labor, we find that the labor share of value added is 1.2 pp higher on average between 2006 and 2017, a period in which it was mostly flat.

2.2 Data

Data on outsourcing activity is typically not available in administrative sources and has, thus, been missing in our economic analyses. We overcome this challenge by combining multiple administrative datasets from the U.S. Census Bureau. Specifically, we use the Annual Survey of Manufacturers (ASM), the Census of Manufacturers (CM), the Longitudinal Business Database (LBD), and the Revenue-Enhanced Longitudinal Business Database (RE-LBD).

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

The ASM-CM has establishment-level information on output and inputs (allowing us to also con-

[7] Staffing arrangements lend themselves handily to additional screening of potential employees. Indeed, according to the American Staffing Association, 1 in 6 workers employed in staffed jobs then transitions to being a payroll employee.

struct measures of multi-factor revenue productivity), and since 2006, expenses on staffed services.[8] We focus on expenses on temporary and leased staff since, in manufacturing, this type of staffed workers typically work side-by-side payroll employees and are in production occupations (Dey, Houseman and Polivka, 2017).[9] These characteristics of temporary and leased workers are important for our analysis because they suggest that the jobs filled by these types of staffed 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 (through the use of intermediaries) rather than in the task composition of the production process. From now on, we will use temporary and leased workers, and staffed workers interchangeably.

We link the ASM-CM sample with the LBD to retrieve information on plant location, plant age, firm age, and firm payroll employment. In this case, the firm refers to the parent organization that owns the respective plant. The LBD is a census of establishments and firms in the U.S. with paid employees. We use plant location to link each plant with the average labor share (defined as payroll over revenue) of temporary help firms and professional employment organizations in a given state. This information is in the RE-LBD and is important in order to transform expenses on staffing labor to temporary and leased staff headcount.

We restrict the ASM-CM sample to establishments with no missing or imputed information on expenses on temporary and leased staff. Therefore, to ensure that our empirical analysis is still representative of the manufacturing sector, we 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 (see Appendix A.3 for details). The baseline sample for the analysis of this paper is a non-balanced panel of manufacturing plants between 2006 and 2017.

2.3 Measuring staffing expenditure in Census data

The ASM provides data on yearly expenditures on staffed and leased employees, instructing respondents to report "total costs paid to PEOs and staffing agencies for personnel." It includes all charges for payroll, benefits, and services. It is this variable we use to measure temp help expenditure at the plant-level. Importantly, the data distinguishes expenditure on staffing from expenditure on professional and technical services, such as "management consulting, accounting, auditing, bookkeeping, legal, actuarial, payroll processing, architectural, engineering, and other

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

[9] Staffing 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.

professional services". The distinction matters. Staffed and leased employees are more often than not covering "core" positions while on assignment at a manufacture, and work alongside the manufacture's own employees on similar tasks. On the other hand, workers who perform professional services for a firm often take on tasks that are auxiliary to production. Since we are interested in investigating the use of staffed labor as a source of added flexibility when a business faces demand shocks, we restrict our attention to expenditures on staffed and leased employees. We leave the question on how a firm's scope vary with outsourcing auxiliary services for future research.

2.4 Recovering staffing employment from staffing expenses

For some applications, we need to recover staffed job counts rather simply expenses on staffed labor. In this section, we propose a methodology to do so. It is based on the ASM temporary and leased workers expenditure variable and predicated on two assumptions. One, that the wage bill for staffed labor is no higher than for payroll labor. This has vast support in the literature (see for instance, Bilal and Lhuillier (2021) for some recent, compelling evidence). We also let the markup charged by staffing agencies not exceed the agencies' own inverse payroll share.[10] Under these conditions we derive a lower bound for staffed jobs at the plant level, for each plant in the ASM.

Total expenditures on staffing labor, denoted by exp^O, is the sum of the wage bill of staffed workers, $o \times w^O$ plus fixed costs related to outsourcing F.[11] That is, we have:

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

where (client) plants, states and years are indexed by j, s and t, respectively.

Suppose that the fixed costs of outsourcing are proportional to dollars spent on staffed employees, then we can write:

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

where α is the overhead per staffed employee charged by the staffing agency associated with plant j. To estimate plant-level staffed employment o_{jst}, we begin by making two conservative assumptions. First, average earnings per payroll job w^p_{jst} are equal to that of staffed jobs w^O_{jst}. Second, the agency's overhead per staffed employee is equal to the inverse labor share β of the average staffing agency ℓ in state s.[12] This assumption implies that staffing agencies' profits are completely covered

[10]The American Staffing Association estimates this at 15% of the staffed worker wage.

[11]These fixed costs could reflect, for example, outsourcing fees charged by the staffing agency.

[12]We 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, denoted by

by client plants' overhead expenditures.[13] Then, we estimate plant-level staffed employment $\hat{o}$ as follows:

$$\hat{o}_{jst} = \underbrace{exp^{O}_{jst} \cdot \beta_{\ell st}}_{\text{staffed wage bill}} \cdot \frac{1}{w^{p}_{jst}}. \tag{2}$$

Our procedure leads to lower bounds for plant-level staffed employment. The reason is twofold. First, we assumed that the wages of staffed workers are equal to that of their payroll counterparts. However, there is evidence indicating that the average wage of staffed workers is a fraction of that of payroll employees in the same occupation. That is, we have:

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

where γ_t denotes the time-variant wedge between payroll and staffed workers. Dube and Kaplan (2010) show that, for low-wage service occupations, γ_t ranges from 4 percent to 24 percent. Using German data, Goldschmidt and Schmieder (2017) show there is an outsourcing wage penalty (ranging between 10 and 15 percent); 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), we find that γ_t varies from 10 and 15 percent as well. Equation (2) effectively assumes that γ_t is constant and equal to zero. As a result, our baseline results are a lower bound. We relax the wage assumption in section 5 and show how our results only get reinforced.

Second, equation (2) underestimates plant-level staffed employment as long as:

$$\beta_{\ell st} < \frac{1}{1 + \alpha}, \tag{3}$$

Note that 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, we must have $\beta_{\ell st} \ll 1$. Thus, condition (3) holds and our baseline estimates of plant-level staffed employment are lower bounds.

β_{st}. We do so because, although we observe the labor share of staffing agencies, the staffing agency-client plant link is not observed.

[13] Alternatively, we could assume that staffing agencies are perfectly competitive and, hence, make no profits. In this case, overhead expenditures cover any non-labor expenses.

3 Staffing in U.S. manufacturing

We describe the prevalence of staffing by plant size and age, high/low-tech industry, three-digit industry, and revenue growth. We also characterize the types of plants that use staffing labor more intensively, as measured by the share of revenue spent on this type of workers. Finally, we investigate the use of staffed employment over time. The results in this section show that staffing is increasing over time and exhibits substantial cross-sectional variation along plants' characteristics and revenue growth.

3.1 Staffing by size and age

Table I describes the use of temporary and leased staff in the manufacturing sector by several establishment-level characteristics such as age, size, and high-tech status. Column (1) displays the percentage of client plants: establishments reporting having spent any positive amount on staffed employment, in a given year. Column (2) shows the amount spent on staffed employment as a percentage of revenue for these client plants.

The use of staffing is common in the manufacturing sector: 70 percent of plants reported having spent on staffed employment at some point in time between 2007 and 2017. Furthermore, on average, 47 percent of manufacturing plants use staffed workers in a given year.[14] The average client business spent 1.7 percent of its revenue on leasing labor through 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. The second panel of Table I 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 are more than double that of large establishments.

3.2 Staffing by high-tech status and revenue growth

Haltiwanger, Hathaway and Miranda (2014) found that the decline in payroll job reallocation between 2003 and 2011 was larger among high-tech manufacturing plants, so we investigate how outsourcing varies between high-tech and other manufacturing plants. High-tech designation is defined as in Hecker (2005) using four-digit NAICS industries. Table I shows the results. High-

[14]The difference indicates that using staffed employment is not an absorbing state. Manufacturing plants, in general, use staffing labor intermittently.

Table I: Older, bigger, and high-tech establishments are more likely to spend on staffed labor; conditional on doing so, however, younger, smaller, and low-tech establishments spend a larger share.[a]

	Share of clients	Share of revenue
Whole sample	**47.14**	**1.70**
Establishment age		
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		
1-9	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

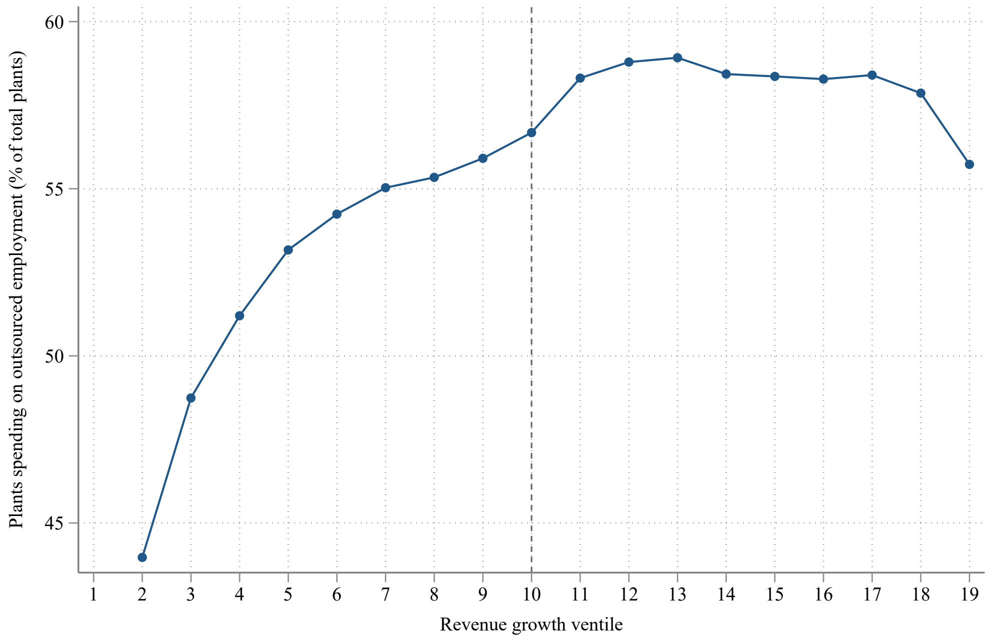
[a]Entries reflect yearly averages within each establishment characteristic. Column (1) displays the percentage of establishments reporting having spent on temporary workers and leased employees. Column (2) reports the percentage of revenue spent on temporary and leased employees by the average client establishment in each category. High-tech status is defined through an establishment's 4-digit NAICS industry as in Hecker (2005). Source: Authors' calculations from ASM-CM-LBD data.

tech establishments are more likely to spend on staffing arrangements than other manufacturing plants. According to Table I, 63.6 percent of this type of manufacturing plants used staffing arrangements, compared to 46.1 percent of low-tech establishments and 47.14 percent overall.

We next consider the cross-sectional relationship between the use of staffing and average plant-level revenue growth. This exercise will provide insights on the strategic use of staffed employment by plants. Our working hypothesis is that the use of intermediaries allows for lower labor cost adjustments and faster adjustment. We restrict the sample to establishments observed for at least two consecutive years and compute the symmetric revenue growth rate for each of them.[15] Then, we split the sample into twenty equally-sized groups and compute staffing use statistics for each group. Figure 1 displays the average share of client establishments for each revenue growth ventile. Similarly, figure 2 depicts average plant-level expenses on staffing labor as a share of revenue for each revenue growth ventile.

[15]The arc-elasticity in Davis, Haltiwanger and Schuh (1998) or Davis-Haltiwanger-Schuh (DHS) growth rate is widely used in the literature. This measure of growth explicitly allows for the inclusion of establishments exiting or entering the market; however, we do not report them in figures 1 and 2.

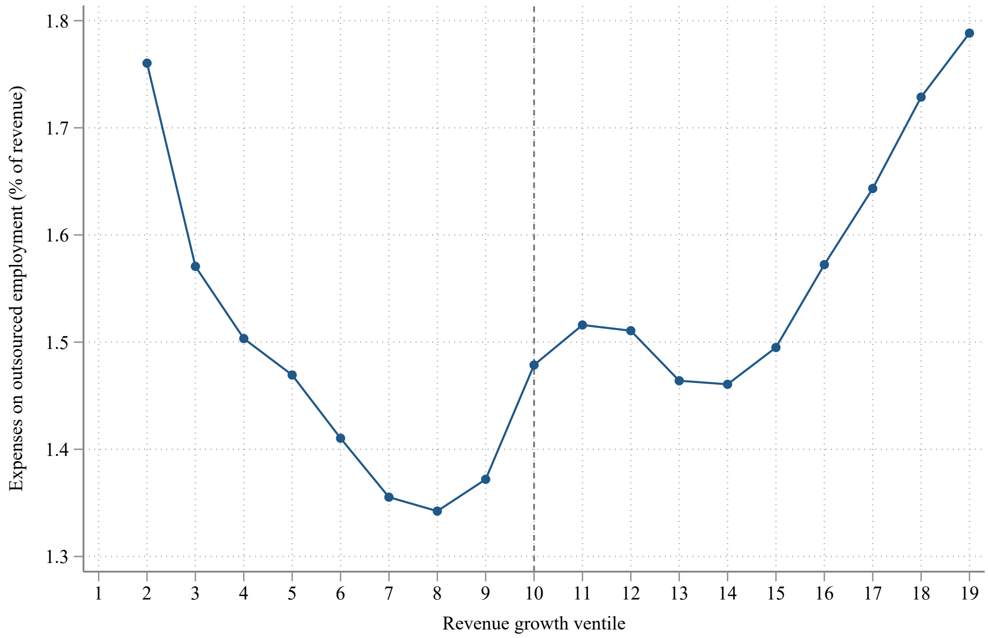
Figure 1: The share of client plants increases with revenue growth. The increase flattens after the median.



The figure displays the share of client establishment by revenue growth ventile. Each point is the three-point moving average. Source: Authors' calculations from ASM-CM-LBD data in 2006–2017.

Figure 1 shows an increasing, nonlinear relationship between revenue growth and the use of staffing. The share of client plants declines sharply when revenue growth is shrinking. Above the level of median revenue growth, the participation margin rises until it reaches its maximum at 59.5 percent. Then, it flattens to finally decline for establishments at the top of the revenue growth distribution. Figure 1 indicates that revenue growth and the decision of using staffed workers are tightly linked at the business level. The "hook" shape of the relationship supports the hypothesis that plants use staffing 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 (also, see figure 2).

Figure 2: There is a U-shaped relationship between the share of revenue spent on staffing labor and revenue growth.



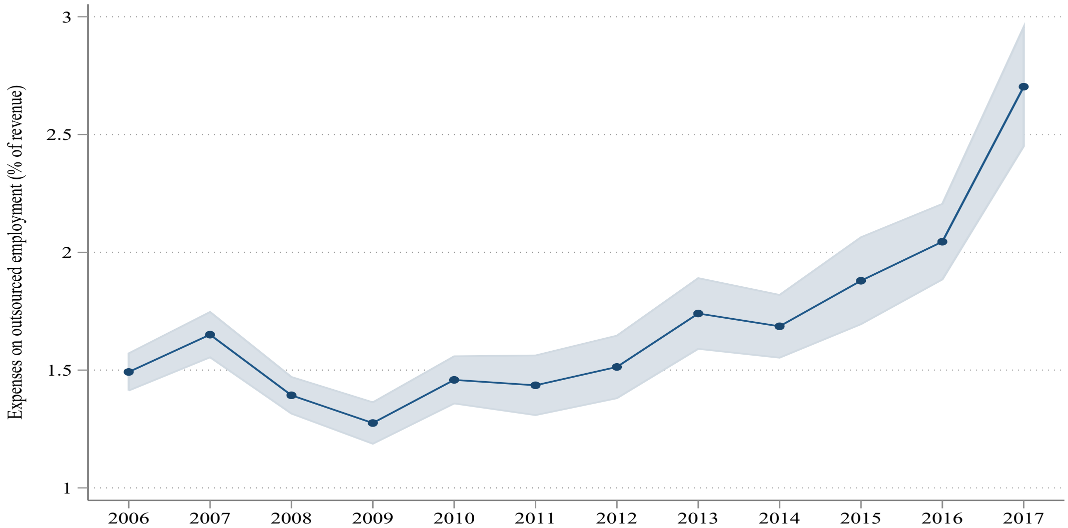
The figure displays the average share of revenue spent on temporary and leased staff by revenue growth ventile. Each point is the three-point moving average. Source: Authors' calculations from ASM-CM-LBD data in 2006–2017.

3.3 Staffing employment over time

In the previous section, we highlighted the importance of staffing across plant-level observables. In the following, we show that the use of staffing is increasing over time.

Figure 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 about 85%, going from 1.49 percent in 2006 to 2.70 percent in 2017. This growth is conditional on business age, industry, and payroll employment size; it is not accounted for by changes in the composition of plants along these characteristics.

Figure 3: Conditional on sourcing labor through staffing, the average manufacturing plant increased its staffed labor share by 85% between 2006 and 2017.



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

Growth in the aggregate staffed labor share, which changes from 0.48 to 0.62 percent, is also not accounted for by shifts in industry composition, nor the reallocation of economic activity towards businesses who spend a larger share of their revenue on staffed labor — if anything, in fact, reallocation is a force for a diminishing staffed labor share. It is, in fact, an increase in staffed labor share of the average plant that explains most of the variation over time. To see this, we turn our attention to an accounting decomposition à la Olley-Pakes (see table II):

$$\begin{aligned} S_t^{\text{staffing}} &= \sum_{p \in P_t} \omega_{pt} \cdot s_{pt}^{\text{staffing}} \\ &= \underbrace{\frac{1}{|P_t|} \sum_{p \in P_t} s_{pt}^{\text{staffing}}}_{\text{OP–MEAN}} + \underbrace{cov(\omega_{pt}, s_{pt}^{\text{staffing}})}_{\text{OP–COV}} \end{aligned}$$

where S_t^{staffing} indicates the aggregate expenditure on staffed labor as a share of revenue in year t, s_{pt}^{staffing} is the plant-level staffed labor share of revenue, and ω_{pt} are plant-level revenue weights. When looking at the different terms of this decomposition, we see that the covariance term is negative. In other words, plants which account for a larger share of aggregate revenue did not see an especially large increase in their staffed labor share (the opposite, in fact, column 4 of Table II).

It is, instead the mean term (column 3) that accounts for the aggregate increase. We conclude that the aggregate growth in the staffed labor share is accounted for not by reallocation, but rather by an across-the-board increase.

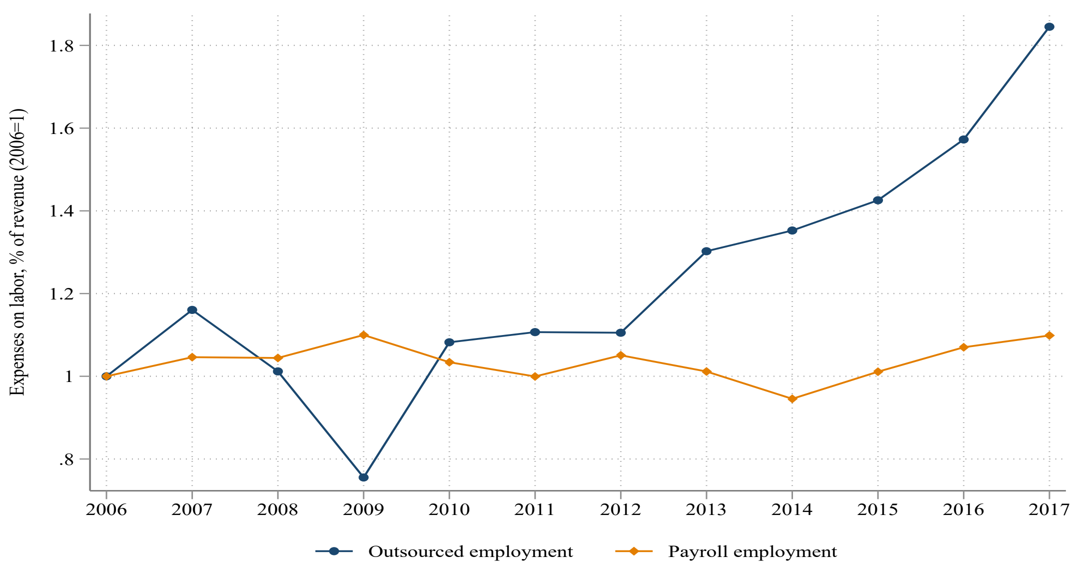
Finally, column 5 in table II computes a counterfactual in which we hold fixed the within-manufacturing industry composition in 2007 and compute the resulting change in the aggregate staffed labor share. There is very little difference from the actual data, which leads us to conclude that shifts in industry shares are not a major driver of the aggregate changes.

Table II: Aggregate revenue share of staffed labor is increasing over time due to an across-the-board increase, not reallocation nor industry composition effects.[b]

		OLLEY-PAKES DECOMPOSITION		FIXED INDUSTRY SHARES
Year	**Data**	**OP–MEAN**	**OP–COV**	**Counterfactual**
2007	0.4850	0.7936	-0.3085	0.4850
2012	0.5172	0.8993	-0.382	0.5189
2017	0.6176	0.9962	-0.3786	0.6023

[b] All numbers are multiplied by 100 to improve readability. Source: authors' calculations for ASM-CM-LBD data.

Figure 4: Staffed employment share of revenue is increasing, whereas payroll employment share of revenue remained roughly constant.



Point estimates of plant-specific expenditures on staffed 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: Authors' calculations from ASM-CM-LBD data.

Figure 4 displays the labor share (relative to revenues) of staffed and payroll employment for the average manufacturing business over time, normalized to be equal to 1 in 2006. The labor share of payroll employment is largely flat, while that of staffed labor increases by 85 percent.

Figure 4 emphasizes how manufacturing plants in the U.S. are increasingly sourcing labor from temporary help agencies and professional employment organizations relative to direct hires. The figure additionally shows that the variance of the staffed labor share over the business cycle is higher than that of payroll employment. Between 2007 and 2009, the Great Recession years, the staffed labor share of revenue drops by over 20 percent. While the drop is expected because of the economic downturn, its magnitude is remarkable considering that revenue is also declining at the same time. This is consistent with the evidence we provide in section 4 that staffed labor is a more flexible input than payroll labor.

4 Staffing employment as a flexible margin of adjustment

In this section, we investigate whether plants change payroll and staffed labor differentially in response to shocks. We propose two different empirical exercises. The first is based on the cost minimization problem a plant faces when choosing its optimal input mix. This problem implies that changes in the expenditure of labor types respond to change in revenues. The second investigates the labor adjustment of plants after changes in revenue productivity growth (that is, plants' "responsiveness", following Decker, Haltiwanger, Jarmin and Miranda, 2020). We show that by not considering staffed workers in the labor responsiveness of plants we omit a margin of adjustment whose dynamics differ from that of the typically observed margin (i.e., payroll employment). In turn, this limits our understanding of employers' strategic behavior. The increasing share of revenue spent on temporary and leased employment (see section 3) 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.

4.1 How does staffing expenditure change with revenue growth?

Let categories of labor be denoted by $c \in \{O, P\}$ (staffing and payroll), then a plant's first-order conditions for these two types of labor are:

$$\frac{F_{it}^{\ell^P}}{\text{exp}_{it}^{\ell^P}} \cdot \text{rev}_{it} = \mu_{it} \cdot \nu_{it} \tag{4}$$

$$\frac{F_{it}^{\ell^S}}{\text{exp}_{it}^{\ell^S}} \cdot \text{rev}_{it} = \mu_{it} \tag{5}$$

where we assume that payroll labor can be subject to monopsony forces (hence, the markdown ν), but this is not the case for outsourced (staffing) labor. Indeed, staffing labor can be purchased on a "spot" market through staffing agencies, hence it can be interpret as a flexible input.[16]

Given the above-mentioned cost minimization conditions, it is straightforward to show that (log) changes in labor expenditures are proportional to changes in revenues. Then, we can a regression specification of the form:

$$\Delta \text{exp}_{it}^{\ell c} = \beta \cdot \Delta \text{rev}_{it} + \mathbf{X}_{it}' \boldsymbol{\gamma} + \varepsilon_{it} \tag{6}$$

for $c \in \{O, P\}$.

Endogeneity issues are apparent in regression specification (6) since there can be unobserved factors driving both $\Delta \text{exp}_{it}^{\ell c}$ and Δrev_{it} (e.g., physical productivity). As a result, OLS regressions give us an imperfect picture.

Ideally, we would like to run a regression with a (quasi-)exogenous revenue shifter:

$$\Delta \text{exp}_{it}^{c} = \beta \cdot \Delta \text{revenue}_{it}^{\text{EXO}} + \mathbf{X}_{it}' \boldsymbol{\gamma} + \varepsilon_{it}$$

for $c \in \{O, P\}$. Furthermore, $\Delta \text{revenue}_{it}^{\text{EXO}}$ reflects that component in revenue changes orthogonal ("exogenous") to any omitted variable in the above regression specification. We can obtain this exogenous component through a valid instrument Z_{it} for $\Delta \text{revenue}_{it}$. As usual, this requires $cov(\Delta \text{revenue}_{it} \cdot Z_{it} | \mathbf{X}_{it}) \neq 0$ and $\mathbb{E}(Z_{it} \cdot \varepsilon_{it} | \mathbf{X}_{it}) = 0$. To do so, we construct two instrumental variables that exploit trade linkages of manufacturing plants. For this purpose, we use administrative transaction-level data from the Longitudinal Firm Trade Transactions Database (LFTTD). The LFTTD contains the universe of import and export transactions for 1992 and 1994–2017.

First, we construct an instrument that captures an industry's import price inflation index.[17] The identifying assumption is that unobserved idiosyncratic factors do not affect import prices since these are mostly determined in international markets.[18] At the same time, they plausibly affect a plant's production costs and input composition — through substitution patterns across (imported) intermediate inputs, and between (imported) intermediate inputs and labor.

[16]For simplicity, we did not consider adjustment costs for payroll labor. However, this does not affect the result that changes in the expenditure of each labor type are proportional to changes in revenues.

[17]This index is constructed as follows. First, we assign each firm a 3-digit NAICS code through the modal NAICS code across its plants in a given year; similar to Haltiwanger et al. (2016). Then, for each industry, we aggregate real prices within 10-digit HS product-country cells through quantity weights. As a result, we end up with a product-level data set where products are defined at the 10-digit HS product-country level. For each product, we calculate real price changes through natural log differences and we aggregate these price changes within each industry through import expenditure weights.

[18]Implicitly, we are assuming that U.S. firms are not large enough so that they are able to "dominate" global-level demand for certain 10-digit HS products.

Table III: Plant-level growth in staffing expenditure is significantly more responsive than payroll expenditure growth on impact.[c]

Dependent variable	OLS	IV – Import price	IV – Exchange rate
TYPE OF EXPENDITURE GROWTH			
Payroll			
$t-1,t$	0.3327	0.4603	0.4174
	(0.0061)	(0.1073)	(0.1575)
$t,t+1$	0.0375	0.4002	0.5858
	(0.0047)	(0.1447)	(0.2132)
$t+1,t+2$	−0.0001	−0.0959	−0.8149
	(0.0043)	(0.1236)	(0.2608)
Staffing			
$t-1,t$	0.6708	2.092	5.053
	(0.0170)	(0.580)	(1.247)
$t,t+1$	−0.1403	0.0624	0.7697
	(0.0150)	(0.5116)	(0.7881)
$t+1,t+2$	−0.0874	−0.2383	−2.691
	(0.0155)	(0.5665)	(0.9977)
First-stage F-statistic		41.27	19.27
Controls/fixed effects			
Size	Yes	Yes	Yes
Age	Yes	Yes	Yes
Industry	Yes	Yes	Yes
State	Yes	Yes	Yes
Year	Yes	Yes	Yes
OBSERVATIONS	115,000	115,000	101,000

[c]The table contains estimates for plant-level staffing real expenditure and payroll real expenditure changes, associated with plant-level revenue changes (OLS) or with quasi-exogenous shocks to plant-level revenue (IV), for the period 2006-2017. Standard errors are clustered at the establishment level and denoted in parentheses. Source: Authors' calculations based on ASM-CM-LBD data.

The second instrumental variable exploits (quasi-)exogenous changes in real exchange rates. It is constructed in the tradition of shift-share instruments, as a weighted sum of an industry's foreign demand shocks. In practice, we use an expenditure-weighted average of real exchange rate shocks across an industry's export destinations.[19] Changes in exchange rates alter foreign clients' demand for an industry's array of products: as exchange rates with the U.S. dollar depreciates, importing U.S. goods are relatively more expensive for these consumers and total quantity demanded declines. At the same time, unobserved idiosyncratic factors at the plant level are unlikely to affect real exchange rates fluctuations, which are determined in international (currency) markets.

[19]Real exchange rate shocks are defined as natural log changes in real exchange rates. The latter is constructed by dividing nominal exchange rates by a country's CPI. Country-year level data on nominal exchange rates and CPI are obtained from World Bank Open Data.

Our regression results can be found in Table III. The first column contains our OLS estimates and indicates that expenditure on staffing labor responds more quickly and more strongly than that on payroll labor; supporting the idea that staffing functions as a flexible margin of adjustment for firms faced with shocks.

Both of our IV estimation strategies yield a similar conclusion. In fact, staffing labor responds even more strongly on impact (that is, when the shock happens at t) when compared to our OLS estimates — as one would expect from a flexible input. Importantly, both instruments seem valid since their first-stage F-statistics are always sufficiently above the threshold of 10.

4.2 Plant-level responsiveness à la Decker et al. (2020)

We investigate staffed workers as a margin of adjustment estimating a fixed-effects panel equation of staffed employment growth on revenue productivity changes; denoted by $\Delta_t a_{jt} = \ln(a_{jt}) - \ln(a_{jt-1})$. Our empirical strategy is motivated by business dynamics models' result that plants adjust their employment in response to their own ever-changing productivity (Hopenhayn, 1992) and builds on the empirical design of Decker, Haltiwanger, Jarmin and Miranda (2020).[20] Specifically, we estimate the following equation:

$$\Delta_\tau y_j = \alpha_{it} + \beta_1 \Delta_t a_{jt} + \mathbf{X}'_{jt}\boldsymbol{\gamma} + \varepsilon_{j\tau} \tag{7}$$

where $\tau \in \{(t-1, t), (t, t+1), (t+1, t+2)\}$ denotes differences along different times. Furthermore, 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 staffed employment between any pair of years in τ.[21] The variable of interest is a plant's idiosyncratic productivity shock $\Delta_t a_{jt}$ which we approximate through the change in natural log revenue productivity between t and $t-1$. We estimate equation (7) for plants that stayed in the sample for at least five years since we are considering difference in the outcome along different horizons.

Staffed 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 our empirical design because plants may respond to revenue productivity changes by adjusting the intensity in which they use staffed workers or they may stop using them altogether. DHS growth rates capture both responses computing staffed employment annual changes relative to average staffed 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 subsequent period. We define the outcome

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

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

as zero in these cases. In particular, for $\tau = (t-1, t)$, we have:

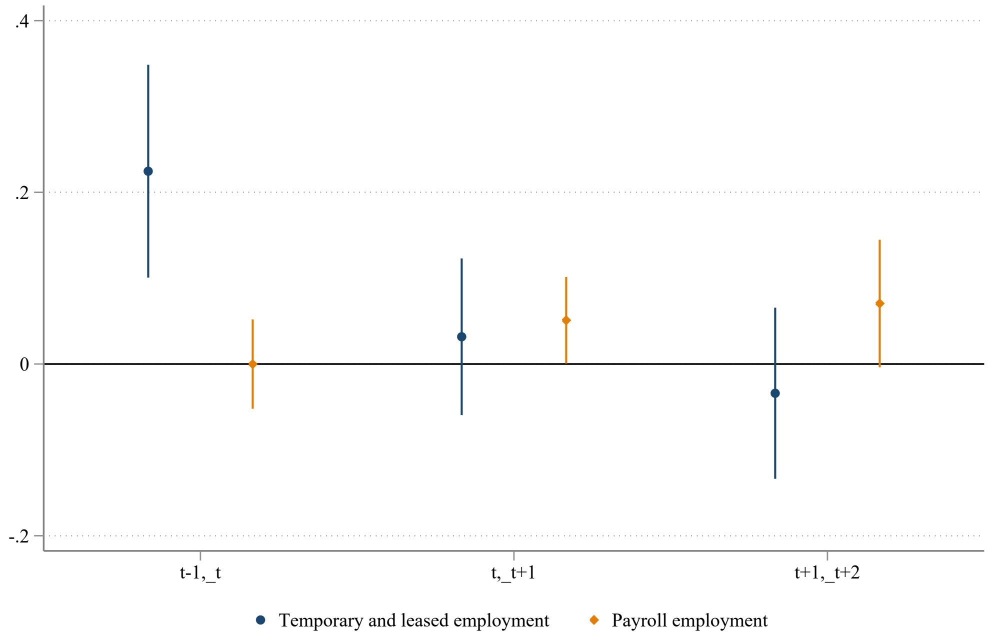
$$\Delta_\tau y_j = \begin{cases} \frac{\hat{o}_{jt} - \hat{o}_{jt-1}}{\frac{1}{2}(\hat{o}_{jt} + \hat{o}_{jt-1})} & \text{if } \hat{o}_{jt} + \hat{o}_{jt-1} > 0, \\ 0 & \text{otherwise} \end{cases}$$

where $\hat{o}_{jt}$ is plant-level staffed employment as estimated through equation (2). By setting the growth rate to zero for plants that "dropped out" from using temporary and leased staff but did not exit the market allows us to capture, for example, situations in which the plant "hired" staffed workers to fulfill a big order with a short deadline (e.g., less than one year) and then "laid them off". This is a common scenario in which staffed workers in manufacturing are used. 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 (7).

The parameter of interest, β_1, estimates a plant's labor responsiveness to idiosyncratic productivity shocks. In particular, we will be focusing on a plant's staffed labor responsiveness. More precisely, it captures the average plant-level response of staffing labor 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. We control for several other factors; including those common to all plants by including a linear trend in revenue productivity growth.

In addition to this common factor, our set of controls (denoted by $\mathbf{X}_{jt}$) includes a variety of covariates informed by the results in sections 3 and 5. These include initial establishment log employment size, initial firm log employment size, firm age, and establishment age; in line with the heterogeneity in the use of staffed workers as documented in section 3. The control set also includes a third-degree polynomial of log revenue productivity change, recognizing that the relationship between staffing labor growth and revenue productivity growth is not linear as shown by figure A.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. We include cyclical indicators to avoid $\hat{\beta}_1$ being driven by the procyclical feature of temporary and leased employment since the Great Recession is in the period of analysis.

Figure 5: Plant-level staffed employment growth is twice as responsive as payroll employment growth to revenue productivity shocks and adjusts more quickly.



The figure shows point estimates and 95-percent confidence intervals of plant-level payroll, and staffed employment growth rate on revenue productivity change (see equation (7)). Source: Authors' calculations based on ASM-CM-LBD data and revenue-enhanced LBD from 2006–2017.

We also estimate payroll labor responsiveness to deviations from average revenue productivity growth. Specifically, we estimate equation (7) with payroll employment DHS growth rate as the outcome.[22] Figure 5 displays the estimated responsiveness of staffed employment (blue) and payroll employment (red) to revenue productivity changes ($\hat{\beta}_1$), as well as 95 percent confidence intervals. Standard errors are clustered at the establishment level. The first column of table IV displays the results as well.

Our results indicate that plants use staffed employment as a margin of adjustment; in particular, in the short run. The response of staffed employment DHS growth rate is sizable, statistically significant, and "immediate". For the average manufacturing business in the sample, a 1 percent deviation in its revenue productivity growth from the industry-year average is associated with a 0.22 percent increase in the staffed employment growth rate in the same year of the productivity change. The comparable payroll employment responsiveness is half of that of staffed employment.

[22] In contrast with staffed 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 IV: Plant-level staffed employment growth is twice as responsive as payroll employment growth to revenue productivity shocks and adjusts more quickly.[d]

Dependent variable	Productivity shock $\Delta_\tau a_{jt}$		Mean
TYPE OF EMPLOYMENT GROWTH			
Payroll			
$t-1, t$	0.0001 (0.0266)	−0.0521 (0.0111)	2.66
$t, t+1$	0.05095 (0.0257)	0.0286 (0.0145)	2.57
$t+1, t+2$	0.07052 (0.0379)	0.0072 (0.0173)	3.79
Staffed			
$t-1, t$	0.2246 (0.0633)	0.2557 (0.0563)	6.04
$t, t+1$	0.0318 (0.0466)	0.0211 (0.0474)	4.66
$t+1, t+2$	−0.0341 (0.0509)	−0.0229 (0.0528)	5.09
Fixed effects			
Industry-year	Yes		
Establishment		Yes	
OBSERVATIONS	102,000	102,000	

[d]The table contains plant-level labor responsiveness estimates to revenue productivity shocks. Standard errors are clustered at the establishment level and denoted in parentheses. Column (1) displays results for the baseline specification: shocks are defined as plants' revenue productivity growth deviations from 6-digit NAICS industry-year averages. Column (2) displays results when the shock is defined as plants' productivity growth deviations from their own productivity growth average. Column (3) displays the mean of the respective dependent variable (in percentage terms). Source: Authors' calculations based on ASM-CM-LBD data.

Plants accelerate the use of staffed 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 staffed employment growth rate for the two periods following the productivity change is small and not statistically different from zero. Conversely, the average business increases its payroll employment growth rate in $t+1$, when presumably it has more information on the persistence of the productivity change. Like staffed employment, the payroll employment growth rate in $t+2$ is positive, but not statistically different from zero. Table IV shows that the qualitative result holds for a different definition of the shock: deviations from own average productivity growth. Table V shows that the responsiveness result is robust to different specifications and not restricting the sample to five-period continuers.

The immediate response of staffing labor reflects the flexible nature of this type of employment.

Table V: Staffed employment growth is more responsive than payroll employment growth.[e]

Dependent variable	Mean	Level a_{jt}		Change $\Delta_\tau a_{jt}$	
TYPE OF EMPLOYMENT GROWTH					
Payroll $t, t+1$	-14.22	0.1782 (0.0110)	0.1742 (0.0203)	0.1061 (0.0395)	0.1164 (0.0410)
Staffed $t-1, t$	2.87			0.1374 (0.0467)	0.1703 (0.0526)
Period					
1981–2013		Yes	Yes		
2006–2017				Yes	Yes
Controls					
Third-degree polynomial					Yes
Total initial employment					Yes
Industry-year fixed effects		Yes	Yes	Yes	Yes
OBSERVATIONS		1,630,000	1,181,000	150,000	150,000

[e]The table contains estimates for plant-level labor responsiveness estimates to revenue productivity shocks for the periods 1981–2013 and 2006-2017 and different regression specifications. Standard errors are clustered at the establishment level in parentheses. Column 1 contains average values for the dependent variable. Columns (2) and (3) display results for 1981–2013; the period of analysis in Decker, Haltiwanger, Jarmin and Miranda (2020). Columns (4) and (5) display results for 2006–2017; the period for which staffed employment estimates are available. Column (2) reports payroll employment growth responsiveness to productivity levels following Decker, Haltiwanger, Jarmin and Miranda's 2020 specification. Column (3) reports payroll employment growth responsiveness to productivity changes following a specification otherwise identical to that of column (2). Column (4) reports additional specifications for staffed employment growth responsiveness. Column (5) adds a third-degree polynomial in productivity and initial staffed employment to the control set. All coefficients are statistically significant at the 1 percent level. Source: Authors' calculations based on ASM-CM-LBD data.

Client plants can renegotiate staffing agreements within weeks. In fact, it is standard for staffing agencies to bill flexibly. That is, depending on the workers provided, contracts between staffing agencies and client plants are not rigid. This allows the client business to adjust temporary and leased workers at a moment's notice, so that renegotiating the arrangement may not be even needed at all. We study yearly changes due to the frequency of the data available. The lagged plant-level response of staffing labor relative to payroll staff is also in line with the pattern exhibited by the share of employment of staffed workers at the aggregate level. This series drops sharply in the year preceding a recession as shown in figure A.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 staffed and payroll employment as substitutes.

4.3 Staffing and idiosyncratic volatility

Why do plants use staffed labor? In the previous section, we argued that staffing is a tool that plants use when confronted with idiosyncratic shocks in their demand or productivity changes. It allows production to be scaled up or down as the needs arise, circumventing many of the frictions that direct hiring is subject to. In this section, we provide some direct evidence of this mechanism by illustrating the relationship between plant employment volatility and the revenue share of staffing employment. We find a positive relationship between volatility and staffing revenues shares. Importantly, this relationship is more pronounced for positive shocks.

Table VI: Plants with higher volatility have higher staffing revenue shares.[f]

	Standard volatility	Positive-biased volatility
Staffing revenue share	0.2448 (0.0320)	0.3377 (0.0441)
Controls/fixed effects		
Size	Yes	Yes
Age	Yes	Yes
Industry-year	Yes	Yes
State	Yes	Yes
OBSERVATIONS	350,000	350,000

[f] All coefficients are multiplied by 100 to improve readability. Our measure of "standard" volatility is a 5-year window of rolling volatilty as in Thesmar and Thoenig (2011). The measure of "positive-biased" volatility is constructed similarly but positive outliers are multiplied by a weight $B = 0.6$ (instead of 0.5). Source: authors' calculations based on ASM-CM-LBD data.

We adopt a "rolling" measure of volatility in the spirit of Thesmar and Thoenig (2011). More precisely, we define a plant i's volatility with window length $W = 2w + 1$ in year t as:

$$\sigma_{it} = \left(\frac{1}{W-1} \sum_{\tau=t-2w}^{t+2w} (g_{i\tau} - \overline{g}_{it})^2 \right)^{1/2} \quad \text{with} \quad \overline{g}_{it} = \frac{1}{W} \sum_{\tau=t-2w}^{t+2w} g_{i\tau} \tag{8}$$

where g_{it} denotes a plant's annual growth rate in payroll employment.[23] In our baseline specifications, we will adopt 5-year windows. Thus, we set $w = 2$. We also construct measures of volatility that are biased towards positive outliers, i.e. we have:

[23] We construct $g_{it} = \ln(\text{emp}_{it}) - \ln(\text{emp}_{it-1})$ with the LBD in order to avoid missing observations due to the rotating sampling nature of the ASM. Our results are not affected when growth rates are instead calculated through arc-elasticities as in Davis, Haltiwanger and Schuh (1998).

$$\sigma_{it}^{B}=\left(\frac{1}{W-1}\sum_{\tau=t-2w}^{t+2w}b(g_{i\tau}-\overline{g}_{it})(g_{i\tau}-\overline{g}_{it})^{2}\right)^{1/2}\quad\text{with}\ \ b(x)=\begin{cases}B>\frac{1}{2} & \text{if } x>0,\\ \frac{1}{2} & \text{otherwise.}\end{cases}\tag{9}$$

Our measures of volatility display substantial variation in the cross-section: standard deviations for σ_{it} and σ_{it}^{B} are 44 and 40 percentage points, respectively. This is not entirely surprising since volatility can differ substantially in, for example, size. Averages are equal to 40 and 30 percent.

In this exercise, we regress the revenue share of staffing employment on volatility at the plant level and a rich set of controls. These includes size and age but also fixed effects at the state, and industry-year level. We find that there is a positive association between plant-level volatility and expenditure on staffing. A one standard deviation increase in volatility is associated with an increase in the staffing share of revenue of about 0.12 percent, which is about one-eight of its mean.

Our analysis suggests that plants adjust staffed labor in response to demand shocks. While this is true whether they are positive or negative shocks, negative shocks are subject to a natural "zero lower bound". One cannot contract with a staffing firm for a negative amount of workers, only refrain from renewing the previous agreement and hire no workers through staffing agencies. For this reason, we hypothesize that the response of the staffing revenue share to volatility would be more pronounced if we gave a larger weight to positive shocks than to negative ones. For this reason, we employ a positive-biased volatility measure as detailed above. To keep the bias at a conservative level, we set $B = 0.6$. In the end, as expected, we find a larger effect for volatility on the staffing revenue share. When we use a positive-biased volatility measure as a regressor, we find an effect equivalent approximately one-sixth of the mean for the staffing revenue share.

5 Staffing and the aggregate job reallocation rate

The previous section showed that plants use staffed employment as a first-line margin of adjustment to shocks. Furthermore, the staffed labor share has been increasing over time; suggesting that plants have been using staffed labor at an increasing rate. Thus, this supports the hypothesis that the increasing use of staffing is one of the underlying causes of manufacturing *payroll* employment becoming increasingly stable; a phenomenon also known as declining payroll dynamism. In particular, our results imply that labor market flows are mismeasured, and this problem is become larger over time since dynamism seems to be increasingly more concentrated in the (unmeasured) mobility of staffed workers.

In this section, we show that manufacturing staffed jobs reallocate at a higher pace than payroll jobs. For job reallocations in the U.S. manufacturing sector between 2006 and 2017, we 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.

5.1 Reallocation rate of staffed and payroll jobs

We 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 staffed employment is the main ingredient to quantify how the creation and destruction of jobs filled by staffed workers bias the measurement of the aggregate job reallocation. Using plant-level staffed employment $\hat{o}_{jt}$ (as estimated in per equation (2)), we calculate gross staffed job reallocations OJR_t:

$$\begin{aligned} OJR_t &= \sum_{j \in \mathcal{J}_t} |\hat{o}_{jt} - \hat{o}_{jt-1}| \qquad (10) \\ OJR_t &= \sum_{j \in \mathcal{J}_t^+} (\hat{o}_{jt} - \hat{o}_{jt-1}) + \sum_{j \in \mathcal{J}_t^-} |\hat{o}_{jt} - \hat{o}_{jt-1}| \\ &= OJC_t + OJD_t \end{aligned}$$

where $\mathcal{J}_t = \mathcal{J}_t^+ \cup \mathcal{J}_t^-$ denotes the set of plants active in either year $t-1$ or t. OJR_t captures the reallocation of staffed jobs across manufacturing plants and it also equals the sum of the total number of staffed jobs created OJC_t and destroyed OJD_t in a given year.[24] Analogously, payroll job reallocations are the sum of payroll jobs created and destroyed in a given year.

Table VII summarizes the results. Panel A presents summary statistics for yearly staffed jobs created, staffed jobs destroyed, and staffed 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.

5.1.1 Staffed job reallocations over the business cycle

The variation in the extent of aggregate job flows mismeasurement is tightly linked to aggregate economic conditions. Figure 6 displays omitted jobs created (green line) and destroyed (red line) as a share of the corresponding payroll job flow over time. Omitted job creation reached its maximum

[24] Formally, we define the set $\mathcal{J}_t^+ = \{j \in \mathcal{J}_t | \hat{o}_{jt} - \hat{o}_{jt-1} > 0\}$. The set for staffed job destruction is defined similarly.

in 2010, implying that the total number of jobs created in manufacturing that year was 1.2 times the measured figure. In contrast, 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 staffed 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 economic recoveries.

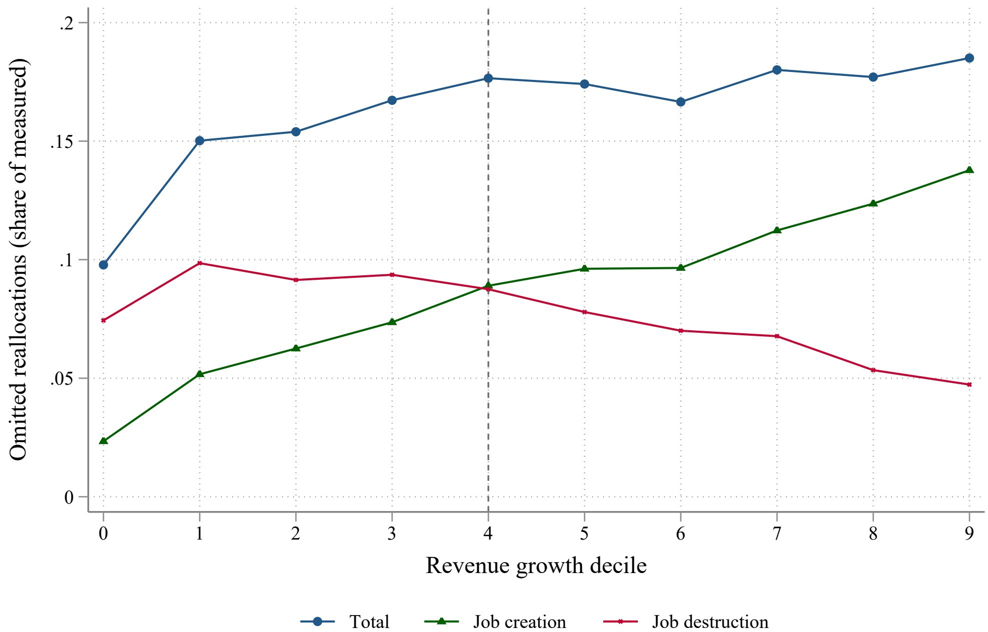
Figure 6: Aggregate job flows mismeasurement varies with the cycle. The share of omitted jobs created dropped entering the Great Recession and started increasing just before the recovery, reaching its maximum in 2010. The share of omitted jobs destroyed increased entering the recession and dropped just before the recovery, reaching its minimum in 2010.

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

Since 2010, manufacturing plants destroyed payroll jobs at a slower pace than staffed jobs, so that the omitted share of jobs destroyed more than doubled between 2010 and 2017 (from 8.4 percent to 20 percent). The same pattern does not hold for omitted job creation. Between 2011 and 2013, manufacturing plants created staffed 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 by outsourcing employment and then subsequently substituting it with (increased) payroll employment.

5.1.2 Staffed job reallocations by plant-level revenue growth

Figure 7: The destruction of jobs filled by staffed 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.



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: Authors' calculations based on ASM-CM-LBD data and revenue-enhanced LBD from 2006–2017.

At the plant level, we find asymmetries in the omission between staffed jobs created and destroyed that depend on a plant's revenue growth. Figure 7 shows the average share of total staffed reallocations by plant-level revenue growth decile. In general, the share of staffed reallocations is increasing in revenue growth. However, the qualitative relationship between the share of staffed jobs created and revenue growth contrasts starkly with that between the share of staffed jobs destroyed and revenue growth: relative to the corresponding payroll job flows, staffed job creation increases with revenue growth while staffed job destruction decreases with revenue growth. On average, for plants experiencing negative (positive) revenue growth the share of omitted reallocations is mostly accounted for by the destruction (creation) of jobs filled by temporary and leased workers. This evidence further supports the interpretation that employers use staffed 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.[25]

5.2 Staffed jobs reallocations and the decline in aggregate dynamism

On average, every year, we omit the equivalent of 16 percent of the payroll jobs created and 13 percent 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 staffed jobs destroyed more than doubled, ranging from 8 to 20 staffed jobs destroyed per every 100 payroll jobs destroyed. The reported variation is tightly linked to aggregate economic conditions, a point that we explore later in this section and that has non-trivial consequences on our understanding of labor market adjustment along the cycle.

staffed jobs reallocate at a higher pace than payroll jobs across plants. Panel B of table VII displays summary statistics for yearly staffed and payroll job reallocation rates. That is, the corresponding job flow as a share of payroll or staffed employment. For every job flow, the staffed 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 staffed 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) on the other hand, 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 percent. In contrast, the staffed job reallocation rate increased by 1.90 percent (table VII, Panel B). Panel C of table VII presents the percentage change in staffed and payroll job reallocations.

We find that the documented increase in the staffed job reallocation rate is driven by staffed job reallocations increasing at a higher pace than staffed employment (27.1 percent vs. 23.3 percent). 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 percent vs. 11.9 percent). If the reallocation of staffed jobs were considered in manufacturing job reallocations, the 13.27 percent decline would be 4.9 percentage points smaller. Thus, accounting for staffed job reallocations can rationalize 37 percent of the drop in the aggregate job reallocation rate.

[25] If plants are outsourcing more expensive jobs over time, expenses on staffing services would exhibit the increasing trend documented in section 3 but this would not translate into an increase in the number of temporary and leased workers employed in manufacturing. We address this concern in two ways. First, we show that the occupation distribution of temporary workers assigned to manufacturing in 2005 is comparable to that in 2017 (see Appendix Table A.2). Second, the average earnings of temporary workers relative to that of payroll workers did not increase between 2007 and 2017; the period of our analysis.

Table VII: Staffing job flows are a large and growing portion of aggregate job flows. Correcting the total job reallocation rate for staffed job flows lowers the secular decline by 37 percent, from -13.27% to -8.33%.[g]

	JOB CREATION (1)	JOB DESTRUCTION (2)	JOB REALLOCATION (3)
	Panel A: Yearly staffed job flow		
Average	16.20	13.66	**14.61**
SD	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
SD	1.29	2.86	2.07
2017−2007	12.31	−12.35	**−0.46**
Staffed			
Average	30.38	25.99	56.36
SD	6.12	6.70	10.01
2017−2007	−1.42	6.21	**1.90**
Total			
Average	8.39	8.66	17.05
SD	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
Staffed	22.99	32.50	27.12
Total	1.39	−17.76	−8.33
OBSERVATIONS	259,500	259,500	259,500

[g] Job creation is the sum of employment changes across expanding plants. Job destruction is the sum of employment changes across shrinking plants. Job reallocation is the sum of jobs created and jobs destroyed (see equation (10)). staffed job flows in panel *A* are expressed as a percentage of payroll job flows. Job flow rates in panel *B* are expressed as a share of employment. Source: Authors' calculations from ASM-CM-LBD data in 2006−2017.

6 Conclusion

This paper shows that staffing is becoming an increasingly more important margin of adjustment for U.S. manufacturing plants. We provide comprehensive evidence from Census administrative data of the prevalence of staffing arrangements and their strategic use by plants. In particular, we document that the use of staffing is systematically and positively correlated with plant-level revenue growth. This association goes beyond correlation: when faced with demand or revenue productivity shocks, manufacturing plants adjust their staffed labor more quickly and more strongly than payroll labor. We also document that this micro-level behavior has aggregate consequences. On average, the creation and destruction of staffed jobs is equivalent, on a yearly basis, to over 15 percent of the corresponding payroll job flows. Because staffed jobs churn at a much higher rate and their share of all jobs has been increasing, we also find that the reallocation of jobs filled by temporary and leased workers across manufacturing plants accounts for 37 percent of the measured decline in the aggregate job reallocation rate. This results offers a novel explanation for the drop in aggregate dynamism, i.e. a technological shift in how employers source labor.

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A Appendix

A.1 Additional Tables

Table A.1: The use of staffing 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

Note: 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: Authors' calculations from ASM-CM-LBD data in 2006–2017.

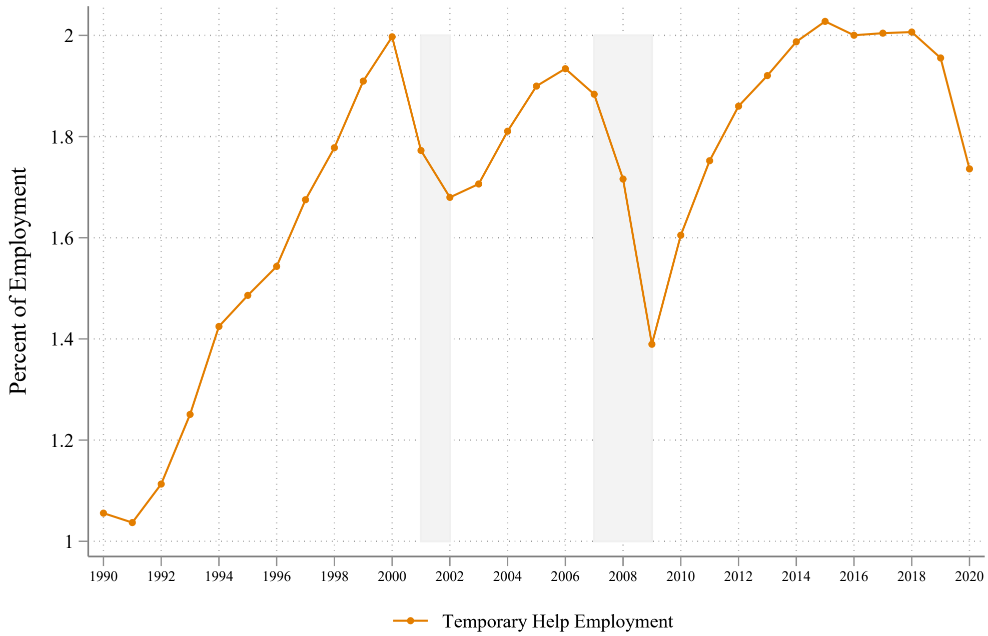
Table A.2: Industry of Assignment Distribution of Temporary Help Workers

	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: Authors' calculations based on the CP-CWS.

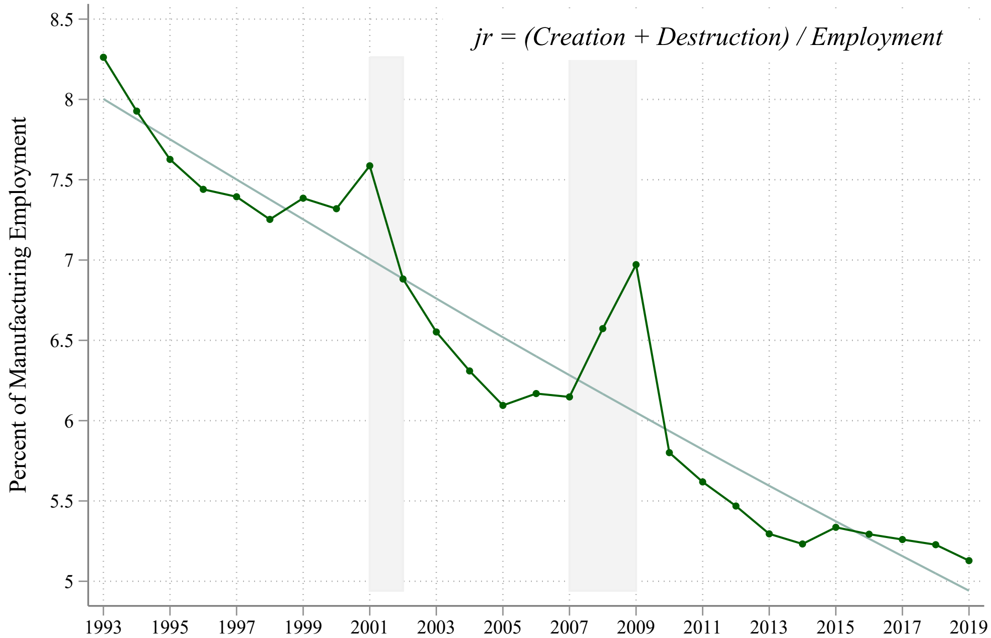
A.2 Figures

Figure A.1: The use of staffing dramatically increased in the 1990s



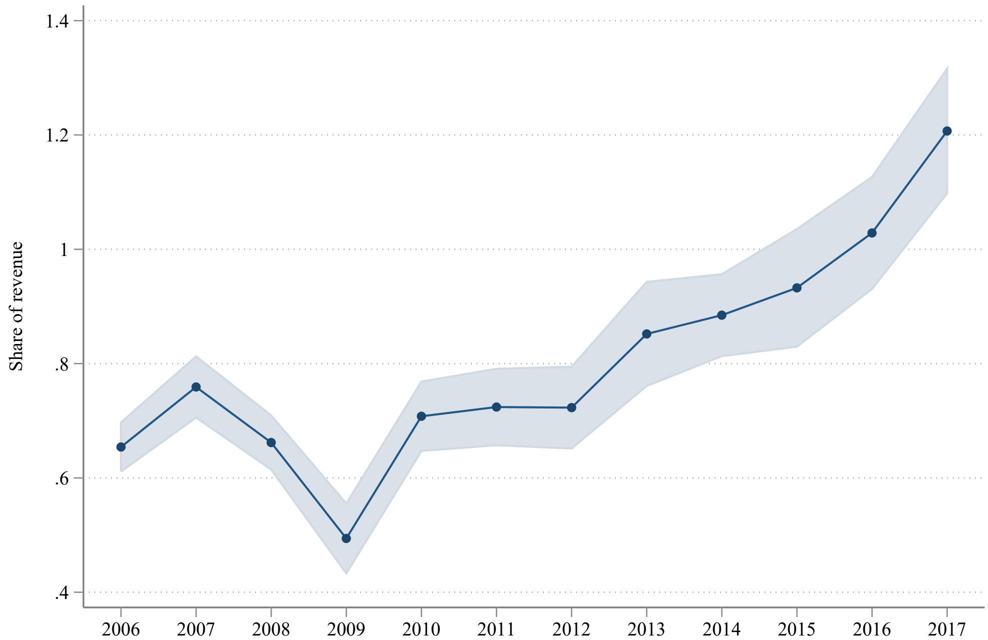
Note: The figure displays the average monthly employment in temporary help agencies relative to non-farm employment over time. Temporary help services is a six-digit NAICS industry comprised of establishments whose main activity is supplying workers to clients' plants. Source: Authors' calculations based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

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



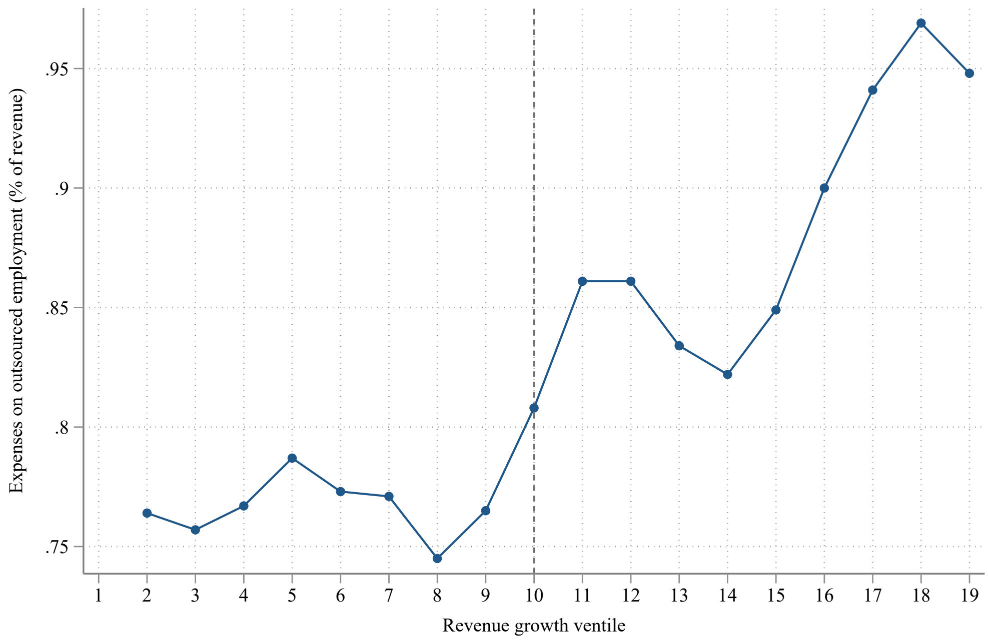
Note: The figure displays yearly averages of the quarterly job reallocation rate in the manufacturing sector and its HP trend. Source: Authors' calculations based on Quarterly Workforce Indicators, seasonally adjusted.

Figure A.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: Authors' calculations from ASM-CM-LBD data in 2006–2017.

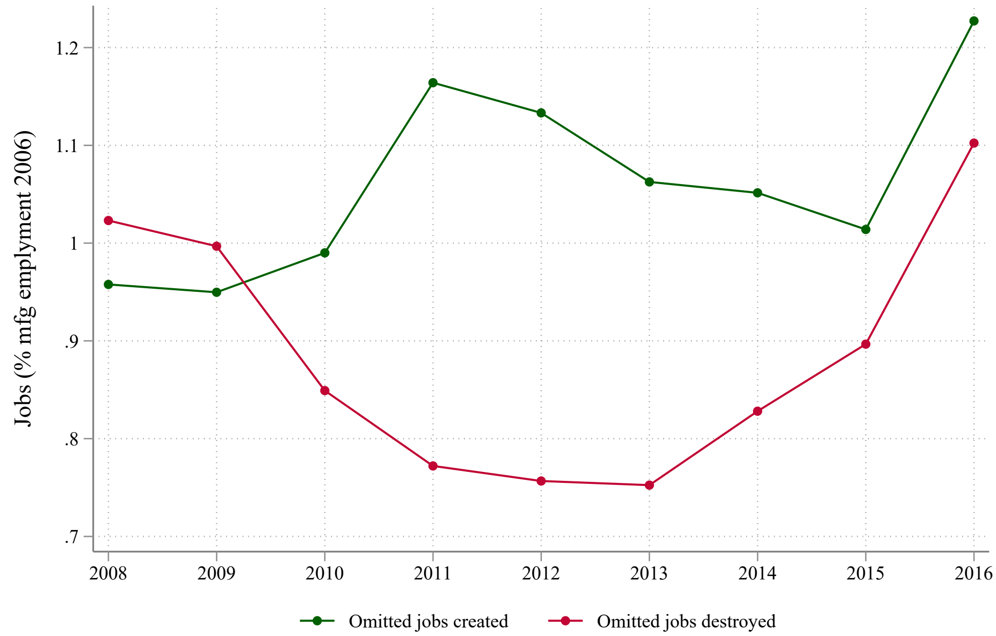
Figure A.4: staffed labor share along plant-level revenue growth for all establishments.



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: Authors' calculation from ASM-SM-LBD data in 2006–2017.

Figure A.5: The manufacturing sector created more staffed jobs than it destroyed

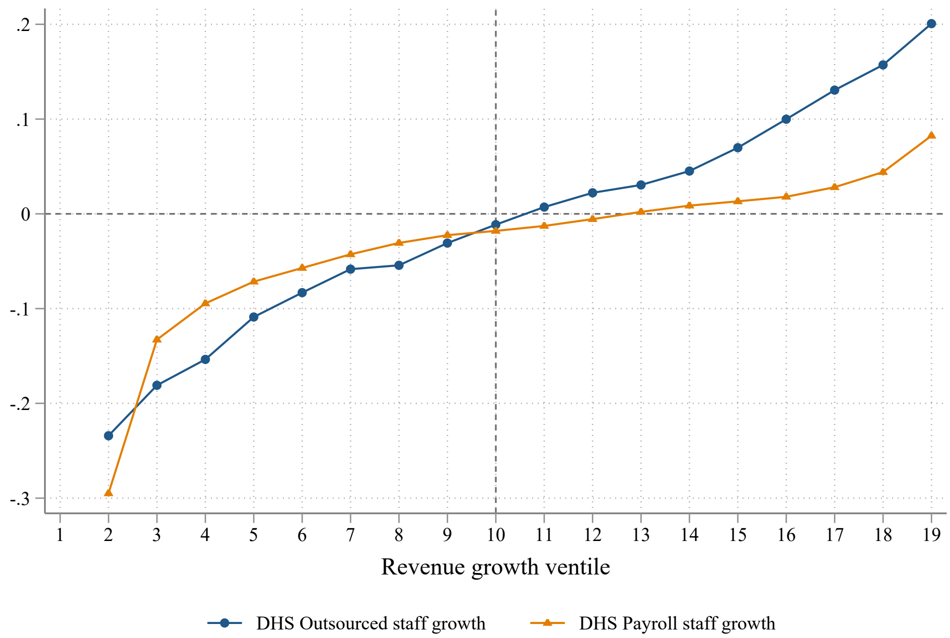
Panel A: Omitted job reallocations



Panel B: Payroll job reallocations

Note: Each point is a three-year average. Omitted job reallocations computed following equation (10). Payroll job creation (destruction) is the sum of employment changes in expanding (shrinking) establishments. Source: Authors' calculation based on ASM-CM-LBD data and revenue-enhanced LBD from 2006–2017.

Figure A.6: The qualitative relationship between staffed 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: Authors' calculations based on ASM-CM-LBD data and revenue-enhanced LBD from 2006–2017.

A.3 Data appendix

Sample restrictions

We limit the analysis in Census years (years ending in 2 and 7) to those establishments that are part of the current rotating sample in the ASM. This is to ensure longitudinal consistency. Also, we drop observations that seem imputed. To do so, we identify plants whose payroll and cost of materials share (relative to revenues) deviate a lot from industry-level averages.

Exclusion criteria (based on other studies) (Dunne, 1998; Roberts and Supina, 1996)

1. Compute the ratio of total value of shipments and cost of materials to payroll for each establishment with a payroll greater than zero.
2. Drop establishments in which either of the ratios is zero or missing.
3. For each year in the sample, we drop establishments whose ratios equal the six-digit industry modal ratio.
4. For each year, we 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.
5. We delete establishments with zero or negative values in either of the TFP components: revenue, capital, total hours, materials and energy.
6. We winsorize capital at the 99.5 percentile.

Weights

We use an ASM-CM-LBD sample for our 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.

We restrict the sample to establishments with information on outsourcing expenses. Therefore, to ensure that the analysis sample is representative of the manufacturing universe, we compute weights based on the probability of being sampled in the ASM and having reported staffed expenses given that the establishment is in the LBD (through propensity scores). We run a logit 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 observed 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. Weights are then constructed through the inverse of the predicted logit probabilities.