Manufacturing Plants' Use of Temporary Workers:
An Analysis Using Census Micro Data

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Abstract

Using plant-level data from the Plant Capacity Utilization (PCU) Survey, we examine how manufacturing plants' use of temporary workers is associated with the nature of their output fluctuations and other plant characteristics. We find that plants tend to hire temporary workers when their output can be expected to fall, a result consistent with the notion that firms use temporary workers to reduce costs associated with dismissing permanent employees. In addition, we find that plants whose future output levels are subject to greater uncertainty tend to use more temporary workers. We also examine the effects of wage and benefit levels for permanent workers, unionization rates, turnover rates, seasonal factors, and plant size and age on the use of temporary workers; based on our results, we discuss various views of why firms use temporary workers.

Key words: temporary workers, output fluctuations

JEL codes: J2, J3

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1. Introduction

The temporary help industry (THS) has grown rapidly over the last quarter century. Indeed, the industry's share of nonfarm employment rose from less than 0.5% in the early 1980s to 2.0% by 2000. The majority of this industry's employees work under the direction of managers at client firms, usually alongside the client's permanent employees.[2]

The industry's rapid growth has attracted substantial attention from researchers (e.g., Segal and Sullivan (1995, 1997), Golden (1996), Polivka (1996), Autor (2003), and Houseman (2001)) who, along with industry analysts, have identified a number of reasons that temporary workers may be attractive to client firms beyond their traditional role of filling in when permanent employees are absent for short periods.

First, it has been suggested that the use of temporary workers may allow client firms to circumvent nondiscrimination requirements in the provision of benefits. Under normal circumstances, in order to secure the tax advantages associated with providing certain benefits, firms need to provide those benefits to all their employees. If the firm would not otherwise want to provide a certain benefit to a particular segment of its work force, one strategy might be to staff that segment with employees of a THS agency. Having such a dual work force may allow it to provide benefits to the remainder of its workforce without jeopardizing their tax status.[3]

[2] For most legal purposes, temporary workers from THS agencies remain employees of the THS agencies, which are responsible for their recruitment and hiring as well as for paying their wages and benefits.

[3] The legal issues surrounding the employment status of temporary workers are complex. A temporary worker can under some circumstances be considered an employee of the client firm. In particular, in the Microsoft case, the U.S. Supreme Court ruled that temporary workers who provided services to Microsoft for a period of several years were entitled to benefits, including stock options, which Microsoft provided to all its permanent employees. The Microsoft decision has limited firms' ability to implement such a strategy of using the same temporary workers for long periods.

The use of temporary workers may also be attractive to firms as a means of screening potential permanent employees. Given the sometimes significant costs of dismissing poorly performing employees, a client firm may want to first observe their performance as temps. If that performance is judged inadequate, they can simply request a new worker from the THS agency. Such a trial period as a temporary worker may be preferable to a formal probationary period as a permanent employee.

Finally, the use of temporary workers may be attractive when a firm believes demand for its product may be lower in the future. A firm would want to avoid the potential costs of dismissing permanent employees should demand turn out to be low. The firm would also want to avoid the costs of training additional permanent employees if the workers are going to be needed only for a short period. The firm may be able to avoid such costs by meeting a portion of its staffing needs with temporary workers. Avoiding such costs may justify the use of temporary workers even if, in the current period, the costs of employing temporary workers are greater than those of permanent workers.

The increased use of temporary workers to accommodate demand fluctuations may have been particularly important in the manufacturing sector. Temporary services industry observers report that THS agencies provided very few "light industrial" workers before the mid-1980s, but by the mid-1990s such workers were a substantial part of their business. At the same time, the prevalence of temporary layoffs by manufacturing firms declined significantly.[4] This suggests that temporary workers may be playing the buffering role that firms' own production workers have historically shouldered. Segal and Sullivan (1997), Katz and Krueger (1999), and others have conjectured that the growth of the temporary services industry increased the efficiency of the labor market search, making it possible for manufacturers and others to vary their output levels without running into bottlenecks due to difficulties hiring enough qualified workers. This, in turn, may have played a role in reducing the natural rate of unemployment during the 1980s and 1990s.

One aim of this paper is to analyze the role of temporary workers in accommodating fluctuations in production levels, a topic on which there is very little empirical work. Houseman (2001) surveyed firms about their use of temporary workers and found that a substantial fraction of firms reported using them to meet fluctuations in demand. Campbell and Fisher (2004) developed a theoretical model describing a firm's decision to adjust employment of two groups of workers with some of the characteristics of temporary and permanent workers and compare their calibration with aggregate level data. However, there are no empirical studies that examine the relationship between a firm's use of temporary workers and its own output fluctuations.

One reason for the scarcity of empirical studies has been limited data. Even among confidential micro Census data sources such as the Annual Survey of Manufactures (ASM) and the Census of Manufactures (CM), it is rare that a survey collects data on the use of temporary workers at the level of the individual business establishment. Such data limitations have prevented researchers from learning the characteristics of firms that use temporary workers.

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[4] See, for example, Aaronson, Rissman, and Sullivan (2004).

In this paper, we use plant-level data from the Plant Capacity Utilization (PCU) Survey, which is conducted annually by the Census Bureau.[5] In 1998, the survey began collecting information on the number of temporary workers utilized by plants. For this study, micro-level data for 1998 and 1999 are available.

Taking advantage of these newly available data, we examine how a plant's temporary worker share is associated with its output fluctuations. In particular, we focus on the relationship between a plant's use of temporary workers and its expected output growth as well as the magnitude of its typical output fluctuations.

Depending on the primary motive for their use, higher expected output growth could be associated with greater or lesser use of temporary workers. On the one hand, if the primary motive for using temporary workers is to reduce the potential costs of dismissing permanent workers due to the lower expected output, then expectations of higher output growth will be associated with less use of temporary workers. In addition, as our stylized model in Section 2 shows, if firing costs are sufficiently high, greater uncertainty about future output leads the firm to cap the number of permanent workers at a lower level, and thus hire more temporary workers. On the other hand, if the primary motive for using temporary workers is to screen future permanent workers, then higher expected output growth is likely to be associated with a greater use of more temporary workers. Given a need to significantly increase permanent employment in the near future, the firm will screen a large number of workers in the current period and may thus employ a large number of temporary workers.

[5] These data are used by the Federal Reserve Board to estimate capacity utilization rates for the manufacturing and publishing industries.

In addition to testing the above conjectures, we also examine how a plant's temporary worker share depends on a number of its other characteristics, such as its size, age, and industry. Plant size may matter for a number of reasons. One might imagine that the use of temporary workers to buffer fluctuations in the labor requirement may require a level of sophistication likely to be found in a large plant. Its larger size may also increase a plant's ability to negotiate a lower margin from a temporary services firm. In addition, a larger plant, with its deeper pockets, may face higher costs in the event of an unjust dismissal lawsuit. On the other hand, the larger scale of such a plant may allow the plant to be flexible without relying on temporary workers, by redistributing its permanent workers across different production processes. Plant age and industry may also matter for use of temporary workers because of their effect on the level of uncertainty and other factors.

Moreover, we investigate the relationship between the use of temporary workers and a plant's wage and benefit levels. A plant whose permanent workers earn high wage rates may be more motivated to use temporary workers. However, what should matter for the choice of temporary worker share is the *ratio* of temporary worker to permanent worker wage rates. Industry observers indicate that THS agencies charge client firms a higher markup over wages in the case of higher skilled workers (Kilcoyne, 2004). Thus, it is possible that a firm with a high wage rate for permanent workers might use temporary workers less. A similar argument applies to a firm that provides generous benefit packages, though the negative effects may be offset because a firm that provides expensive benefits packages may have more incentive to employ temporary workers to keep benefit costs down.

Finally, we analyze how the temporary worker share at the three-digit NAICS industry level is dependent upon several additional variables. These variables include unionization, labor turnover rates, and seasonality. We expect unions to resist the use of temporary workers. Higher turnover rates would likely increase the value of screening potential employees and thus could lead to greater use of temporary workers. When voluntary turnover is high, the likelihood of a firm needing to fire workers due to insufficient demand would be lower. So, greater turnover could be associated with less use of temporary workers. A stronger seasonal component would also be positively correlated with the higher use of temporary workers, ceteris paribus.

One can view our study as similar in intent to a number of micro-level studies of other forms of firm adjustment to demand shocks. For example, using plant-level data, Copeland and Hall (2005) examine how automakers accommodate shocks to demand by adjusting price, inventories, and labor inputs through temporary layoffs and overtime. Such considerations are closely linked to a firm's decision to adjust temporary worker share. We intend to examine such interactions in future work.

In Section 2, we outline a simple, stylized model that motivates our empirical specification. In Section 3, we describe our data in more detail and discuss empirical implementation. In Section 4, we present our empirical results. Section 5 concludes.

2. Motivational Model

In this section, we present a stylized model of a plant's choice on how many permanent and temporary workers to hire. The model is intended to help motivate and guide our empirical work and to emphasize the role of temporary workers in accommodating output fluctuations.

Specifically, we assume that labor is the only factor of production and that, in each period, the plant manager must hire an appropriate quantity of labor, e_t, to meet an exogenously determined level of output, $y_t = f(e_t)$, where f is a standard, strictly increasing production function. The required labor input can come from a combination of "permanent employees," p_t, and "agency temporary workers," a_t, with the total quantity of labor given by $e_t = p_t + \theta a_t$, where θ is a positive constant representing the productivity of a temporary worker relative to that of a permanent worker. The wage rates for permanent and temporary workers are w_p and w_a, respectively. The plant incurs costs of δ to fire each permanent worker. Thus, the plant's total costs in a period are $w_p p_t + w_a a_t + \delta \max(p_{t-1} - p_t, 0)$. We assume that future levels of output are uncertain and that the firm minimizes the expected present value of total costs given a discount factor, $\beta = 1/(1+r)$, where γ is a real interest rate.

Let the unit labor costs for permanent workers be $u_p \equiv w_p$ and that for temporary workers $u_a \equiv w_a / \theta$. We assume that $\Delta u = u_a - u_p > 0$; absent firing costs, temporary workers are more expensive, either because their wage rate is higher ($w_a > w_p$), they are less productive ($\theta < 1$), or both. We further assume that the cost of firing a permanent worker is greater than the (discounted) difference in unit labor costs, but less than a full period's wage; i.e., $\Delta u / \beta < \delta < w_p$. If $\Delta u > \beta\delta$, the plant never hires any temporary workers; it is cheaper to use permanent workers even if it is certain that they will be fired in the next period. The condition that $\delta < w_p$ is a convenient simplification implying that the firm does not keep any idle workers on the payroll; keeping an idle worker on the payroll costs more than firing the worker in the current period and may also increase firing costs in the future. With this configuration of costs, the plant faces a tradeoff between using more permanent workers, which lowers current wage costs, versus using more temporary workers, which may lower future firing costs.

The Two-Period Case

It is easiest to see the logic of the model when there are only two periods. In this case, the plant is unconcerned about firing costs in the second period. Let y_2 represent a required output level in the second period. The plant meets its entire labor need with permanent workers, $p_2 = f^{-1}(y_2)$, incurring costs

$C_2 = w_p f^{-1}(y_2) + \delta \max(0, p_1 - f^{-1}(y_2))$.

In the first period, given y_1 and knowledge of the distribution of y_2, the firm chooses p_1 and a_1 to minimize total expected discounted costs, TC, which is written as $TC = w_p p_1 + w_a a_1 + \beta E[w_p f^{-1}(y_2) + \delta \max(0, p_1 - f^{-1}(y_2))]$. The quantity of labor that meets the required level of production is $f^{-1}(y_1) = p_1 + \theta a_1$. Thus, we can rewrite TC as a function of p_1 alone: $TC = u_p p_1 + u_a (f^{-1}(y_1) - p_1) + \beta E[w_p f^{-1}(y_2) + \delta \max(0, p_1 - f^{-1}(y_2))]$.

Thus, the derivative of costs with respect to (w.r.t.) permanent labor in the first period is

$$\frac{dTC}{dp_1}(p_1) = -\Delta u + \beta\delta \frac{d}{dp_1} E[\max(0, p_1 - f^{-1}(y_2)] . \qquad (1)$$

Assume that y_2 follows a continuous distribution with density $g(y_2)$ that is strictly positive over the relevant interval; distribution function is $G(y_2)$. Then, the expected number of permanent workers fired in the second period given p_1 is $L(p_1) = E[\max(0, p_1 - f^{-1}(y_2)] = \int_0^{f(p_1)} (p_1 - f^{-1}(y_2))g(y_2)dy_2$. Thus the derivative of the number of permanent workers fired w.r.t. permanent labor in period 1 is

$$L'(p_1) = (p_1 - f^{-1}(f(p_1))g(f(p_1)) + \int_0^{f(p_1)} g(y_2)dy_2 = G(f(p_1)). \qquad (2)$$

From (2), we can rewrite (1) as

$$\frac{dTC}{dp_1}(p_1) = -\Delta u + \beta\delta G(f(p_1)). \qquad (3)$$

Increasing permanent workers by one (and thus lowering the number of temporary workers by $1/\theta$) in period 1 reduces current costs by the difference in unit costs between temporary and permanent workers (Δu), but raises expected firing costs in the second period by the product of the cost of firing a worker (δ) and the probability that the marginal worker is fired ($G(f(p))$).

Because $G(y)$ and $f(p)$ are increasing functions, $\frac{dTC}{dp_1}(p_1)$ is increasing in p_1. Moreover, $\frac{dTC}{dp_1}(0) = -\Delta u < 0$ and $\lim_{p_1 \to \infty} \frac{dTC}{dp_1}(p_1) = -\Delta u + \beta\delta > 0$. Thus, there exists a unique level of permanent employment, $\overline{p}$, such that

$$\frac{dTC}{dp_1}(\overline{p}) = -\Delta u + \beta\delta G(f(\overline{p})) = 0. \qquad (4)$$

See Figure 1 for an illustration of the case in which y_2 is uniformly distributed in the interval from y_{low} to y_{high} and $f(e)$ is linear. If $f^{-1}(y_1) < \overline{p}$, as permanent employment increases, TC decreases until permanent employment reaches the level that satisfies the plant's labor requirements given y_1. Thus, the optimal number of permanent workers is $f^{-1}(y_1)$, and that of temporary workers is zero. On the other hand, if $f^{-1}(y_1) > \bar{p}$, TC falls with p_1 until $p_1 = \bar{p}$, and then begins to rise. Thus the optimal number of permanent workers is $\bar{p}$, and that of temporary workers is $(f^{-1}(y_1) - \bar{p})/\theta$, the level necessary to meet the rest of the labor requirement. We can summarize the solution by writing the optimal numbers of the first period permanent workers, p_1^*, and temporary workers, a_1^*, as

$$p_1^* = \min(f^{-1}(y_1), \bar{p}) \tag{5}$$

$$a_1^* = (f^{-1}(y_1) - p_1^*)/\theta, \tag{6}$$

where $\bar{p}$ satisfies $\beta\delta G(f(\bar{p})) = \Delta u$. The plant hires permanent workers up to a maximum level at which the expected discounted costs of firing an additional permanent worker are equal to the extra current unit labor costs of substituting temporary workers. In Appendix A, we show that in the case of an infinite horizon with independently and identically distributed (i.i.d.) random output levels; the plant's optimal policy is essentially identical to the solution of the first period of the two-period model.

Lognormal Output Levels and Power Production Function

Suppose that the distribution of y_2 is lognormal, $\log y_2 \sim N(\mu_2, \sigma^2)$ and that the production function takes the power form,

$$f(e) = Ae^{\alpha}. \tag{7}$$

Then, based on (4), $\bar{p}$ is such that (s.t.) $\Delta u = \beta\delta\Phi(\frac{\log A + \alpha \log \bar{p} - \mu_2}{\sigma})$, where $\Phi(x)$ is the standard normal distribution function. Alternatively, we can write

$$\log \bar{p} = \alpha^{-1}[\mu_2 - \log A + \sigma\Phi^{-1}(\frac{\Delta u}{\beta\delta})]. \qquad (8)$$

The impact of σ on $\bar{p}$ depends on Δu and firing costs δ.[6] If firing costs are sufficiently high so that $\Delta u < \frac{1}{2}\beta\delta$, then $\Phi^{-1}(\frac{\Delta u}{\beta\delta}) < 0$, and the probability of needing to fire the marginal worker is less than one half. In this case, greater uncertainty increases the probability, moving it toward one half. The increased probability of firing causes the plant to use fewer permanent workers and more temporary workers to produce the given output.[7]

Implications for Empirical Analysis

The simple model sketched above suggests that expected output growth, $g^e \equiv \mu_2 - \log y_1$, is an important determinant of a plant's use of temporary workers. When g^e is lower, the model suggests that firms tend to use more temporary workers in order to avoid future firing costs. The model also says that if firing costs are high enough, higher uncertainty, σ, increases the use of temporary workers. These are two key hypotheses we test in the

[6] Because α and δ are positive constants and $\Phi^{-1}(\cdot)$ is an increasing function, a higher value of Δu is associated with a greater level for $\bar{p}$, leading to the use of fewer temporary workers. On the other hand, a higher value of the firing cost, δ, is associated with a lower level of $\bar{p}$, leading to the use of more temporary workers.

[7] Note that the opposite is true if firing costs are low so that $\Delta u > (1/2)\beta\delta$. It is somewhat counterintuitive that an increase in uncertainty could lead to the use of fewer temporary workers. When firing costs are low, the plant worries little about firing and thus hires so many permanent workers that the probability of firing a marginal permanent worker in the second period exceeds one half. In such a situation, an increase in the uncertainty in the second period labor requirements lowers the probability of firing to the level closer to one half. This reduces the marginal expected firing costs and gives the plant the incentive to hire more permanent workers.

empirical section. As noted above, if screening is the primary reason why firms use temporary workers, then in contrast to the above model, higher expected output growth would be associated with greater use of temporary workers.

3. Empirical Implementation and Construction of Variables

Empirical Specification

Using (7) and (8) and assuming for simplicity that α and A are one, the condition that a plant hires temporary workers is

$$f^{-1}(y_1) > \overline{p} \Leftrightarrow Z = -g^e - \sigma\Phi^{-1}(\frac{\Delta u}{\beta\delta}) > 0\,. \qquad (9)$$

Introducing heterogeneity across plants through a normally distributed random components in log output, ν_i, and assuming (9) can be well approximated by a linear function, we can rewrite the condition that a plant uses temporary workers as $Z_i = [g_i^e, \sigma_i, \mathbf{X}_i]\boldsymbol{\beta} + \nu_i > 0$, where $\mathbf{X}_i$ contains other control variables. The plant uses no temporary workers when Z_i is negative; once Z_i is positive, the plant begins using temporary workers, and its temporary worker share increases as Z_i continues to increase. Both a plant's likelihood of using temporary workers and its temporary worker share increases with g_i^e and σ_i.

To examine a plant's discrete choice to use any temporary workers, we estimate the Probit model. We also estimate Tobit models to examine how the temporary worker share is associated with our key variables. The Tobit model is consistent with our framework in that plants start using temporary workers once Z_i becomes positive and continue to increase their use of temporary workers as Z_i increases further. Using the observations on plants with positive numbers of temporary workers, we also fit linear regression models relating the continuous part of temporary worker share to our key variables, thus relaxing a restriction imposed by Tobit analysis. $\mathbf{X}_i$ includes industry dummies as well as other plant characteristics such as plant size and age that may proxy for variation in the level of firing costs and wage differentials between temporary and permanent workers, which the model says should also influence the use of temporary workers.

Data

The main data set for this study is the survey of Plant Capacity Utilization (PCU), which is used by the Federal Reserve Board to estimate capacity utilization rates of manufacturing and publishing plants.[8] In addition to variables related to a plant's operation status and capacity utilization, the survey collects data on workers, including the number of production workers, their hours of work, and overtime hours. Since 1998, the survey has collected data on the number of temporary production workers and their hours of work, which are the key variables in our study. In the PCU questionnaires, temporary production workers are defined as "production workers not on the payroll (hired through temporary help agencies or as their own agent)".[9] The 1998 and 1999 PCU

[8] http://www.census.gov/econ/overview/ma0500.html (August 2006)

[9] In the PCU questionnaires, "production workers" are defined as workers (up through the line-supervisor level) engaged in fabricating, processing, assembling, inspecting, receiving, packing, warehousing, shipping (but not delivering), maintenance, repair, janitorial, guard services, product development, auxiliary production for plant's own use (e.g., power plant), record keeping, and other closely associated services. They also include truck drivers delivering ready-mixed concrete (U.S Census Bureau, 2000). Note that while the PCU provides employment and hours data for each shift, examining the allocation of permanent and temporary workers between different shifts is beyond the scope of this paper. We focus on a plant's overall use of temporary workers for all shifts in total.

micro data are available for this study;[10] the surveys collect information for the only fourth quarter of each year.

In our empirical work, we include only manufacturing plants that are in operation and that provide valid answers to the key employment questions including the number of temporary production workers. We exclude plants that reported inconsistent responses for key variables. Among the remaining plants, we further select those for which we can calculate measures of the expected level and volatility of production. As we describe below, we calculate such measures using annual shipment data from ASM and CM. The ASM and CM are available to us for the period from 1976 to 2001. Our sample is limited to the plants which appeared in the ASM-CM panel for a sufficient number of years for us to estimate key parameters of their time series process for output. We are also limited to plants that appear in the ASM for enough consecutive years prior to being in the PCU to allow us to use lagged variables in the regressions. Appendix B provides more details about which plants are included in our sample. Combining both years of available PCUs leaves us with about 5,000 plants.

Measure for g_i^e

As our stylized model shows, expected output growth is a key variable in determining a plant's use of temporary workers. In order to create an empirical measure of this variable, we have to make three choices. In particular, we have to specify the current period, the future period, and how the expectation of the future period's output is estimated. Because information on temporary worker employment from the PCU is that of the fourth quarter, we take the current period to be the fourth quarter of the survey year

[10] Approximately 17,000 plants are surveyed each year.

In particular, we use the annualized fourth quarter total value of shipments (TVS) reported on the PCU survey as the current output; the ASM and the CM, which we use to estimate time series process for TVS, report annual TVS As a future period, one could view the length of the horizon considered by the plant as an empirical question to be investigated thoroughly. However, given that no monthly or quarterly output series at plant-level are available, we take the entire year following the survey to be the future period.

Let us define the annualized fourth quarter output for plant i in year t as $ltvs_{it}^{AQ4} \equiv \ln(4 \times tvs_{it}^{Q4})$, where tvs_{it}^{Q4} is the TVS of plant i's fourth quarter in year t. We define $g_{it}^{e,Q4} \equiv E_t[ltvs_{it+1}] - ltvs_{it}^{AQ4}$, where $E_t[ltvs_{it+1}]$ is plant i's expected TVS in year $t+1$. $g_{it}^{e,Q4}$ reflects the difference between the current quarter's output and the expected average quarterly output over the next year. We estimate $E_t[ltvs_{it+1}]$ using several specifications for the time series of log annual output levels in the ASM-CM panel.

Specification for the Expected Output Level and the Uncertainty Level

To measure expected future output, $E_t[ltvs_{it+1}]$, as well as the uncertainty, σ, for each plant, we use the time series data of the plant's TVS from the ASM and the CM. The combination of ASM and CM, often called the Longitudinal Research Database (LRD), provides us annual time series data for the U.S. manufacturing plants, and we can match these data to PCU by plant identification number. As we previously noted, monthly and quarterly series on plant level TVS are not available in the ASM, CM, or any other sources that can be matched to PCU. Thus we analyze output fluctuations at the annual frequency.

While the CM is a population survey and is conducted every five years, the ASM is a sample survey in off-census years. Thus, we observe the TVS of all manufacturing plants in a census year as long as they exist, but in off-census years, we observe only for plants sampled in the ASM. Using a plant identification number, which is given based on the physical location of the plant, we create an ASM-CM plant-level unbalanced panel data. To use a consistent plant identifier, we limit ourselves to the ASM and CM observations from 1976 and after.[11] We focus on real TVS by employing the TVS deflator for each of 4-digit SIC calculated by Bartelsman, Becker, and Gray.[12]

Note that to measure demand fluctuations, one might also consider using a plant's employment given by the Longitudinal Business Database (LBD), which provide annual employment data for virtually all U.S. business establishments (that have employees). However, like most other data sources, the employment reported in the LBD includes only workers on a plant's payroll and thus excludes temporary workers. To the extent that a plant uses temporary workers to accommodate output fluctuations, permanent employment fluctuations should be smoother than the fluctuation of all workers including temporary workers. Thus, any unobserved or uncontrolled factors that increase a plant's use of temporary workers may be translated into a smaller fluctuation in permanent

[11] As a plant identifier, we use the Longitudinal Business Database (LBD) number, which is a revised version of the Permanent Plant Number (PPN) used for manufacturing plants in the Longitudinal Research Data. Similar to the PPN, the LBD number does not change in the event of merger and acquisition and is specific to a plant's physical location. The LBD number is created as a part of the effort by Census to create the LBD data set, which reviews and updates the longitudinal linkage as well as the operation status of the establishments/plants in the Standard Statistical Establishment List. While the Census of Manufactures goes back to 1963, the LBD begins in 1976.

[12] The data sets for the deflators through 1991 are posted at http://www.nber.org/nberces/nbprod96.htm. We thank Randy Becker for letting us use the preliminary version of the TVS deflators for the later period.

employment, which biases our estimation. Thus, in this paper, we use TVS from the ASM-CM panel to capture output fluctuations.[13]

If plant production levels were i.i.d. random variables, then expected future output could simply be taken to be the mean of the log TVS in the ASM-CM data. Moreover, the standard deviation of the residuals (deviation between actual and expected TVS in logarithm) could be used as a measure of the uncertainty a plant faces. However, there are several obvious problems with such a procedure. First, for most plants, output levels have long-term trends, either up or, less frequently, down over time. Second, an issue arises from the fact that the ASM-CM panel is unbalanced, with plants observed in different sets of years. The measure of uncertainty based on a sample mean of log TVS would depend on the particular set of years in which the plant exists and in which the data are available for that plant, because of the volatility due to macroeconomic factors across years. Lastly, the simple mean of log TVS from our sample would also depend on where in a life cycle the plant is when it is included in the sample.

Given these considerations, we specify a method to estimate the mean and standard deviation of future output growth. We assume that output growth follows a first order autoregressive process. We control for the change in macroeconomic conditions. Denoting the growth rate of TVS by $gtvs$, we estimate:

$$gtvs_{it} = \tilde{\beta}_i + \rho_i gtvs_{it-1} + \gamma dn_t + \upsilon_{it} , \qquad (12)$$

where $dn_t \equiv n_t - n_{t-1}$; n_t is a macroeconomic variable that captures the business cycle. Any linear plant-specific time trend is captured by $\tilde{\beta}_i$. In this specification, a plant uses the past realized output level and growth rate to form its expectation for its future output.

[13] Note that labor hours reported in ASM and CM suffer the same problem, as they include only the hours

The uncertainty measure σ_i is the standard deviation of the residuals of the model, which is written as $gtvs_{it} - E_{t-1}[gtvs_{it}] = ltvs_{it} - E_{t-1}[ltvs_{it}] = \upsilon_{it}$ and represents unforeseeable events after a plant observes the output or growth rate from the previous year. For n_t, we use the deviation of log real gross domestic products (GDP) from log potential GDP provided by the Congressional Budget Office. Note that $E_t[ltvs_{it+1}]$ depends on expectations of n_{t+1}. However, because γn_{t+1} is common across plants and does not affect relative variation across plants, we simply use n_{t+1} to estimate $E_t[ltvs_{it+1}]$, and thus $g_{it}^{e,Q4}$.[14]

Summary Statistics of Key Variables

Applying the above specification to our ASM-CM panel, the distribution of $g_{it}^{e,Q4}$ for plants in our sample is roughly symmetrical and mostly contained between -2 and 2. We exclude plants with $g_{it}^{e,Q4}$ below -2 or above 2, considering to be outliers. Our measure of uncertainty, σ_i, is distributed between 0 and 2 except for a small number of outliers, which again are removed. After dropping these observations, our sample contains 4,909 (plant-period) observations. On average, $g_{it}^{e,Q4}$ is 0.10 and varies widely across plants. σ_i is on average 0.189. Large heterogeneity in σ_i across plants is observed. An average plant's realized annual output deviates from its expectation based on (12) by 18.9%. A plant with σ_i that is one standard deviation (s.d.) larger than the mean experiences annual output levels that typically deviate from expected values by 30% (=0.189+0.11).

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worked by permanent employees. The LBD does not provide any data on labor hours.

[14] We also performed our estimation using a simpler specification for output levels: $ltvs_{it} = \alpha_i + \beta_i T + \gamma n_t + \varepsilon_{it}$, where $\beta_i T$ absorbs any linear effect of plant age. We obtain qualitatively the same results based on both specifications.

On average in our sample, $g_{it}^{e,Q4}$ is equivalent to 63% of the volatility (σ_i) that plants face. Summary statistics are in Table 1.

In our sample, the fraction of plants employing a positive number of temporary workers in a particular year is 42%. The remaining 58% of plants operate without using any temporary workers. Of plants with temporary workers, on average, the temporary worker share of total production workers is 0.119.

Other Control Variables in Analyses

We also include a number of additional control variables. The most important of these is a variable that controls for the previous level of permanent employees. As we mentioned above, our two-period model does not address how the previous level of permanent workers influences a plant's current use of temporary workers. However, in reality, if a plant's permanent employment in the previous period is greater than the level required to produce the current output, then to respond to any positive shock to the current output, a plant would be more likely to rely on already hired permanent workers and less likely to rely on temporary workers. Indeed, in a version of our model with more realistic time series processes for output, the number of permanent workers from the previous period is a state variable. As a remedy, one might consider controlling for the level of permanent employment, p_{t-1}, in the previous period. However, in the cross-section, such a variable may capture other factors. While the model assumed a homogenous production function, plants are, in fact, heterogeneous. A high level of p_{t-1} may simply mean that the plant is unproductive, rather than that it has a binding level of permanent workers on its payroll.

As an alternative way to control for variation in the previous number of permanent workers relative to current output levels, we include plants' recent output growth rates.[15] If a plant's output has been growing, it is unlikely that the number of permanent workers in the last period is binding. However, if output has been falling, the number of permanent workers inherited from the previous period may constrain the plant; in this case, even when a plant's current output is greater for a given future expected level, the plant would be unlikely to use temporary workers.

In addition to the control for the previous level of permanent employees, we control for several other variables that may influence a plant's use of temporary workers. Such variables include plant size and age, the wage rate of permanent workers, the ratio of benefit payments to wages, the unionization rate, and the seasonal factor for the fourth quarter. The rationales for including these variables were discussed earlier.

For plant size, we use $ltvs_{it}^{AQ4}$. Age is measured based on the first year that a plant's identifier for its physical location appeared in the LBD. To calculate the permanent production worker wage rate, w_{it}^{P}, for each plant, we use the ASM; the PCU does not provide any wage information. Note that we cannot distinguish overtime hours from total production hours in the ASM. Thus the calculation for w_{it}^{P} is influenced by wage premium for overtime; w_{it}^{P} would be greater for plants that use more overtime. If a plant's use of overtime is motivated by a reason similar to why they use temporary workers, it would induce the positive correlation between w_{it}^{P} and temporary worker share. Thus, we calculate the straight rate permanent worker wage, $w_{it}^{SP} \equiv w_{it}^{P}(1+.5s_{it}^{over})$,

[15] A dummy variable for a survey year is also included.

using the overtime share, s_{it}^{over},[16] from the PCU, and use this measure in our regressions. We also use the ASM to calculate supplemental labor costs for each dollar of wage payments.[17]

The unionization rate, turnover rate, and seasonal component are all calculated at the three-digit SIC level, as plant-level information is not available. The data on the unionization rate among production workers are derived from the monthly outgoing rotation files of the Current Population Survey (CPS). We pooled data from 1996 through 2000 to estimate the rate of unionization for each three-digit SIC industry. As a proxy for turnover, we use job-to-job transition rates based on the non-outgoing rotation groups of CPS.[18] Again we pool all data since 1996 for each detailed CPS industry. We also calculate seasonal components for each 3-digit SIC based on the industrial production (IP) quarterly series (not seasonally adjusted) for the period between 1987 and 2005 from the Federal Reserve Board of Governors. Using IP_{jt}^{q} to denote the IP of industry j in qth quarter in year y, we specify the seasonal component of qth quarter for industry j, f_j^q, as $f_j^q \equiv \sum_t \{\ln(4 \times IP_{jt}^q) - \ln(IP_{jt})\}$. When we include the above 3-digit

[16] The PCU data provide information on hours for all production workers (including temporary workers), hours worked by temporary workers (including overtime if any), and total overtime. Assuming that overtime is performed only by permanent workers, we use the ratio of the overtime to the hours worked by permanent workers. We also used the ratio of overtime to hours worked by all workers, which did not qualitatively change our results.

[17] Supplemental labor costs are not provided separately for production and non-production workers in the ASM/CM. We divide such a total number by wage payments to all employees. Note that some years in the micro data provide the decomposition of supplemental labor costs into voluntary and non-voluntary parts. Such data are not available for the years relevant to this study.

[18] Specifically, we matched each observation in the non-outgoing rotations to the corresponding observation in the following month using the household ID and line numbers. In addition, we required that the sex of respondents match and that the reported ages be within one year of each other. We then determined which workers remained employed at the same firm as in the previous month using the employment status variable and the indicator for whether an employed worker remained at his previous employer. This latter variable is available starting in 1996 and makes possible the identification of job-to-job transitions. See Fallick and Flieshman (2004).

SIC level variables in our models, we report standard errors that account for clustering at the 3-digit SIC level.

Again, the summary statistics are in Table 1. Plants in our sample are much bigger and older than that of average manufacturing plants in the CM for 1997. Plant TVS is on average 59 million based on the 1987 dollar. Sixty-five percent of the plants in our sample exist in 1975 or before, and among those which are built after 1975, the average age is 16.

4. Results

In Table 2, we report results with our base specification. The net effects of $g_{it}^{e,Q4}$ is negative and significant, and σ_i is positive and significant. The data seem to support the view that higher expected growth decreases both a plant's likelihood of using temporary workers and, for a plant that uses temporary workers, decreases its temporary worker share. The model in section 2 illustrated that the expectation of growth reduces the probability for a marginal permanent worker to be fired, which in turn reduces the expected future firing costs and motivates a plant to use more permanent workers. Our results are consistent with such a view, rather than the alternative discussed earlier in which a higher expectation of growth might necessitate more screening of future permanent workers and thus more current temporary workers.[19]

Based on the results of the Probit analysis, if $g_{it}^{e,Q4}$ increases by a one s.d. from its average, moving from .0977 to .460, the probability of employing temporary workers decreases from 0.42 to 0.39; about a 7 % decrease. For plants using temporary workers, the Tobit results suggest that a one s.d. increase in $g_{it}^{e,Q4}$ decreases the temporary worker share by 1.6 percentage points, which is 13% of the average temporary worker share. The ordinary leased squares (OLS) results in which we exclude the observations on plants without any temporary workers suggests a smaller effect than the Tobit. A one s.d. increase in $g_{it}^{e,Q4}$ decreases the temporary worker share by 0.8 percentage point based on OLS.[20]

Plants that face more uncertainty appear to use more temporary workers. As we also discussed, when firing costs are large enough, greater uncertainty level increases the probability of marginal permanent worker to be fired, discouraging plants to hire permanent employees. For a plant whose uncertainty level is one s.d. greater than average plant, the plant's likelihood to use temporary workers is 1.7 percentage points greater, and for plants using temporary workers, the temporary worker share increases by 1 percentage point, based on Tobit and by 0.8 percentage point based on OLS.[21]

We also performed quantile regression analysis using the data of plants with any temporary workers to see whether the magnitude of effects vary between plants in different portions of the distribution of the temporary worker share. The quantile regressions showed that, among plants with temporary workers, the magnitudes of the

[19] It is possible that screening matters for short-run growth prospects. Our data, however, do not allow us to capture plant-level growth rates at the monthly or quarterly levels.

[20] We also perform the analysis, controlling for a variable representing a current year shock, $ltvs_{it} - E_{t-1}[ltvs_{it}]$, to see if our data identify any effect of current shock separate from that of $g_{it}^{e,Q4}$. We find that the measure of current shock obtains a positive and significant coefficient, while the coefficient for the expected growth rate remains negative and significant. The size of the effect of $g_{it}^{e,Q4}$ remains almost the same. Note that, in this regression, we exclude $gtvs_{it}$ as it is highly correlated with the current year shock measure.

[21] We also performed Probit and Tobit analyses replacing expected annual output level in $t+1$ with its realized value. For this exercise, out of 4,909 plants used in Table 3, we used the data of 4,617 plants,

effects of our key variables are much greater for plants with higher temporary worker shares. Our OLS result was similar to that for plants with high temporary worker shares. Once we replace our dependent variable with log of the temporary worker share, however, the quantile regressions obtain almost the same coefficients across all quantiles. It seems that the effects of our key variables are constant in terms of the percentage by which they increase the share.

The results generally suggest that bigger plants are more likely to use temporary workers, and if they do, the temporary worker share is greater than smaller plants. It is possible that fixed costs are involved in using temporary workers for, perhaps, negotiating with temporary help agencies. The results may also be reflecting that larger plants are more likely to face greater penalty in the event of an unjust dismissal lawsuit. Such effect seems to offset possible negative effect, if any, from the larger plants' ability to redistribute workers within itself. A one s.d. increase in $ltvs_{it}^{AQ4}$ raises a plant's likelihood to use temporary workers by 2.0 percentage points. Note that the ability to negotiate or allocate workers should be better captured at firm level rather than plant level. Thus we also performed our analyses, adding a dummy indicating whether the plant is affiliated with multi-plant firm and, if so, its firm's size.[22] Neither variable obtains a significant coefficient, and the qualitative results of other variables remained the same.

We found that older plants tend to use temporary workers less. The likelihood for plants built pre-1975 to use temporary workers is 9.3 percentage points smaller than

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which appear in ASM sample in the year following their PCU survey. The results remain qualitatively the same.

[22] We use the log of total employments of all plants affiliated with a firm; TVS is not available for all plants.

newer plants. For plants using temporary workers, the temporary worker share for older plants is 4.1 percentage points lower than newer plants based on Tobit, and 2.1 percentage points lower based on OLS. Plant age may reflect an uncertainty level that is not captured by σ. While σ is an average measure of uncertainty over the lifecycle of a plant, the degree of uncertainty may change over time.

Next we explore the effect of other variables, including wage, unionization rate, job-to-job transition rates, and seasonality. The results are summarized in Table 3. First, we include two variables that summarize the compensation paid to permanent workers. As discussed earlier, one might expect that plants that pay high wages or high benefits would have an incentive to use temporary workers to reduce labor costs. In contrast, industry analysts report that the markup that staffing agencies charge over wages for temporary workers tends to be higher for high wage occupations. Thus, higher wage plants may use fewer temporary workers. The latter story seems to hold, as shown in Columns 1, 2, 3 in Table 3. Based on our sample, the straight rate wage for permanent production workers and the supplemental labor costs per dollar of permanent worker wages are both negatively correlated with plants' use of temporary workers. Note that when we control for these two variables, the significance of the positive coefficient obtained for plant size increases. Since bigger plants tend to pay higher wages, once we separate the negative effect of wage, the scale effect seems to be more pronounced.

Next we add the unionization rate, the turnover rate, and the fourth-quarter seasonal component, which we measure at the three-digit SIC level. Columns 4, 5, 6 in Table 3 show the results where we replace three-digit SIC dummies with these three continuous variables. Based on Probit and Tobit analyses, we find that the unionization rate is negatively correlated with a plant's use of temporary workers. This is counter to the idea that unions might increase the use of temporary workers through their effect in increasing wages as well as firing costs relative to productivity. Similar results are found in the study by Houseman (2001). Analogous to what she argues, it is possible that our results reflect the fact that unions oppose the use of non-standard employment relationships to secure regular employment positions. Note that the coefficient for unionization rate is not significant in OLS result. The unionization rate may not influence temporary worker share once plants decide to use temporary workers.

Using Probit analysis, we also examined whether the unionization rate has any interaction effect with $g_{it}^{e,Q4}$. The coefficient for the interaction term seems to suggest that greater union pressures against the use of temporary work arrangements also enhance the negative effect of $g_{it}^{e,Q4}$ on a plants' likelihood to use temporary workers.

Coefficients for the job-to-job transition rate are not significant in any specification. This is different from our original conjecture that higher turnover reduces the probability of needing to fire permanent workers in the future and thus increases the permanent worker share. Note that our measure of the job-to-job transition rate may not be a good proxy for the turnover rate. In the CPS, we cannot distinguish a voluntary quit from a transition motivated by layoff among people who have different jobs between two periods. The Bureau of Labor Statistics (BLS) produces a voluntary quit rate, but only at the level of broad industry category, which does not provide us enough detail for our study. Our result may alternatively be explained by the role of temporary employment in screening. It is possible that greater turnover increases the on-going need to recruit workers through temporary employment, and this might have offset the effect of the decreased probability of needing to fire permanent workers.

The coefficients for the fourth-quarter seasonal component are not significant in Probit but are significant in the Tobit and OLS. We consider the coefficient of the seasonal component to capture the effect of time-invariant fourth quarter component on the share of temporary workers.[23]

Note that in the specifications with the above additional controls, the coefficients for our key variables, $g_{it}^{e,Q4}$ and σ, are still consistent with our conjectures. It would be, however, instructive to note that the variations of our control variables such as plants' size, wage, benefit, and unionization rate seem to have large contribution to the overall variation of the plants' use of temporary workers. Based on the Probit analysis in Column 4 in Table 3, one s.d. increases of wage, benefit, and unionization rate respectively decrease the probability for a plant to use some temporary workers by 7.1, 2.6, and 4.2 percentage points, and that of plant size increases the probability by 7.7 percentage points, where one s.d. increases in $g_{it}^{e,Q4}$ and σ increase the probability by 2.6 and 1.2 percentage points, respectively. In terms of the variation of temporary worker shares across plants, based on the Tobit analysis in Column 5 in Table 3, one s.d. increases in wage, benefit, and unionization rate respectively decrease the share by 2.8, 1.1, and 1.4 percentage points, and that of plant size increases the share by 2.7 percentage points, where one s.d. increases in $g_{it}^{e,Q4}$ and σ increase the share by 1.1 and 0.9 percentage

[23] As a robustness check, we also use a different method to estimate the coefficients for three-digit SIC-level variables. We first estimate three-digit SIC dummies based on the specification in Columns 1, 2, 3 in Table 3, and then run weighted least square to relate the coefficients for dummies with these three-digit SIC level variables. The results show the negative coefficients for unionization and positive coefficients for

points, respectively. The effects of our key variables are larger than that of seasonal factor; a one s.d. increase in fourth-quarter seasonal factor increases the share by 0.7 percentage point.

Finally, we examine whether our key results hold when we control for the effects of geographical variables. In Columns 1, 2, 3 in Table 4, we show the results based on our base specification, adding a dummy indicating urban plants (plants in metropolitan areas). We then limit our sample to urban plants and control for metropolitan fixed effects in addition to three-digit industry effects. We find that in both cases, the effect of our key variables stay qualitatively the same. We also found that plants in urban area are more likely to use temporary workers. To the extent that markets for temporary worker are local, there are many geographic variables such as the unemployment rate and the degree of local concentration of temporary agencies, which would be associated with a plant's use of temporary workers. Examining the effect of these variables requires a thorough consideration of local labor markets. We leave it to our future research to explore the influence of local demand and supply of the temporary workers on a plant's use of temporary workers.

5. Conclusion

We have provided some evidence in support of the proposition that temporary work arrangements facilitate flexibility in a firm's use of labor and allow it to accommodate output fluctuations at lower cost. Our stylized model identifies the expected output growth rate and the uncertainty in that expectation as two key variables in a firm's

fourth-quarter seasonal component. R-squared from these regressions are, however, not very high, showing that much of the industry-specific effects are left unexplained.

decision to use temporary workers. We approximated both of these variables using the ASM and the CM. We used Probit, Tobit, and OLS analyses to examine the relationship between these two variables and plants' actual use of temporary workers.

First, we found that plants make greater use of temporary workers when their expected output growth is lower. This suggests that a plant chooses temporary workers over permanent workers when it expects its output to fall and thus wants to avoid costs associated with dismissing permanent employees. This effect remains identified after netting out the effect of a seasonal factor in a plant's output, which itself had a positive relationship with a plant's use of temporary workers, as well as other variables.

Second, we found that a plant with greater uncertainty over its future output level uses more temporary workers. Firing costs appear to be large enough to induce a more volatile plant to make greater attempts to minimize the costs of firing permanent workers; this might have made the plant rely more on temporary workers even though the current unit costs of using temporary workers is greater than those for permanent workers.

In addition to output fluctuations, we also examined the effect of several other motivations that are thought to play an important role in a plant's decision to use temps. First, we found evidence that a plant's that requires high-skill workers are less likely to use temporary workers, likely because the wage premium or the margin paid to agencies for high-skill temporary workers may be higher than that for low-skill temporary workers. Second, a plant in an industry that is highly unionized seems to use fewer temporary workers, possibly because unions are successful in resisting the use of nonmembers' labor.

Table 1. Summary Statistics

Plant characteristics (4,909 observations)		
	Mean	(S.d.)
$g_{it}^{e,Q4}$	0.0977	(0.362)
σ_i	0.189	(0.111)
$ltvs_{it}^{AQ4}$	11.0	(1.26)
$gtvs_{it}$: growth rate of annual real output in survey years	0.00710	(0.203)
$gtvs_{it-1}$: growth rate of annual real output in previous years	0.0202	(0.224)
ln. straight wage of perm production worker†	2.66	(0.348)
Benefit per $1 perm wage†	0.275	(0.104)
Fraction of plants that existed from 1975 or before: 0.646		
Fraction of plants from 1999 PCU: 0.476		

Three-digit SIC level variables included in the study (3,716 observations)†		
Unionization rates	0.236	(0.117)
Job-to-job transition rates	0.0197	(0.00559)
Fourth quarter seasonal factor	0.00608	(0.0398)

†: The sample is restricted due to the missing observations of overtime used to calculate straight wage. It is used in Table 3.

Table 2. Base specification

	Probit dF/dX	Tobit	OLS
$g_{it}^{e,Q4} := E_t[ltvs_{it+1}] - ltvs_{it}^{AQ4}$	-0.097***	-0.044***	-0.023***
	[4.42]	[5.56]	[3.11]
σ_i	0.152**	0.087***	0.072***
	[2.16]	[3.61]	[3.42]
$ltvs_{it}^{AQ4}$	0.016**	0.004	-0.0008
	[2.15]	[1.54]	[0.33]
$gtvs_{it} := ltvs_{it} - ltvs_{it-1}$	0.218***	0.089***	0.036***
	[5.68]	[6.45]	[2.68]
$gtvs_{it-1} := ltvs_{it-1} - ltvs_{it-2}$	0.106***	0.045***	0.017
	[3.10]	[3.71]	[1.52]
D=1 for plants born pre 1975	-0.093***	-0.041***	-0.021***
	[-5.92]	[-7.27]	[4.21]
D=1: Survey Year 1999	0.027*	0.011**	0.005
	[1.83]	[2.08]	[1.14]
3-digit SIC dummies	Yes	Yes	Yes
Observations	4,909	4,909	2,067

[ ]: Robust z-statistics for Probit, t-statistics for Tobit, and robust t-statistics for OLS;
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 3. Specification with wage and other variables

	(1)	(2)	(3)	(4)	(5)	(6)
	Probit dF/dX	Tobit	OLS	Probit dF/dX	Tobit	OLS
$g_{it}^{e,Q4} := E_t[ltvs_{it+1}] - ltvs_{it}^{AQ4}$	-0.095***	-0.036***	-0.016**	-0.073***	-0.029***	-0.0101
	[3.59]	[4.17]	[1.98]	[2.58]	[3.36]	[1.25]
σ_i	0.140*	0.077***	0.070***	0.117	0.081***	0.0779***
	[1.68]	[2.96]	[2.99]	[1.30]	[3.13]	[3.13]
$ltvs_{it}^{AQ4}$	0.042***	0.014***	0.0035	0.060***	0.021***	0.0049
	[4.50]	[4.40]	[1.17]	[4.62]	[7.92]	[1.52]
$gtvs_{it} := ltvs_{it} - ltvs_{it-1}$	0.218***	0.081***	0.032**	0.209***	0.083***	0.034*
	[4.73]	[5.36]	[2.11]	[3.89]	[5.41]	[1.96]
$gtvs_{it-1} := ltvs_{it-1} - ltvs_{it-2}$	0.077*	0.034**	0.014	0.083*	0.036***	0.017
	[1.85]	[2.55]	[1.16]	[1.91]	[2.61]	[1.39]
D=1 for plants built pre-1975	-0.084***	-0.035***	-0.019***	-0.087***	-0.039***	-0.022***
	[-4.53]	[-5.71]	[3.52]	[-3.76]	[-6.45]	[4.04]
D=1: Survey year 1999	0.034*	0.011*	0.002	0.038**	0.012**	0.00096
	[1.96]	[1.87]	[0.46]	[2.28]	[2.11]	[0.23]
ln. straight rate wage rate for perm workers	-0.222***	-0.094***	-0.053***	-0.205***	-0.081***	-0.032***
	[-7.26]	[-9.62]	[5.38]	[-4.74]	[-8.68]	[3.20]
Supplemental labor costs per $1 perm wage	-0.220**	-0.083***	-0.0375	-0.254**	-0.104***	-0.0503*
	[-2.43]	[-2.82]	[1.36]	[-1.99]	[-3.53]	[1.79]
Unionization rate				-0.361**	-0.121***	-0.023
				[-2.01]	[-4.21]	[0.69]
Job-to-job transition rate				-2.161	-0.359	0.523
				[-0.82]	[-0.67]	[0.84]
Fourth-quarter seasonal factor				0.331	0.181**	0.140*
				[1.27]	[2.45]	[1.95]
3-digit SIC dummies	Yes	Yes	Yes	No	No	No
Observations	3,716	3,716	1,727	3,716	3,716	1,727

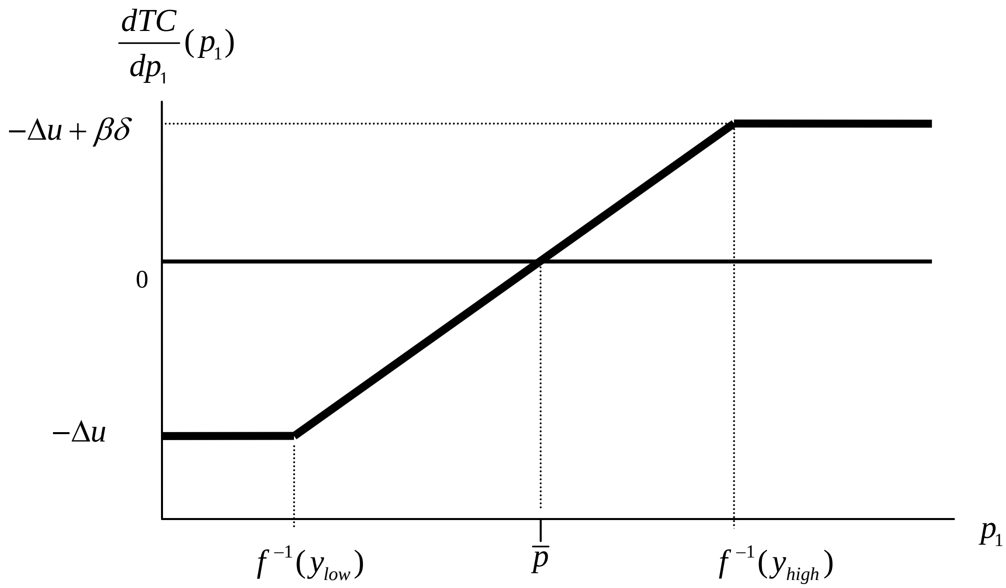
[ ]: Robust z-statistics for Probit, t-statistics for Tobit, and robust t-statistics for OLS (errors are clustered for plants in the same three-digit SIC for Columns 4 and 6); * significant at 10%; ** significant at 5%; *** significant at 1%

Table 4. Analyses with MSA fixed effects

	All plants with urban dummy			Urban plants with MSA fixed effects		
	Probit dF/dX	Tobit	OLS	Probit dF/dX	Tobit	OLS
$g_{it}^{e,Q4} := E_t[ltvs_{it+1}] - ltvs_{it}^{AQ4}$	-0.0979***	-0.0438***	-0.0229***	-0.128***	-0.0528***	-0.0274***
	[4.44]	[5.59]	[3.14]	[4.37]	[5.65]	[2.77]
σ_i	0.149**	0.0861***	0.0704***	0.141	0.0851***	0.0643**
	[2.14]	[3.56]	[3.35]	[1.52]	[2.92]	[2.17]
$ltvs_{it}^{AQ4}$	0.0157**	0.00399	-0.00088	0.00996	0.00207	0.000275
	[2.11]	[1.49]	[0.35]	[0.99]	[0.62]	[0.08]
$gtvs_{it} := ltvs_{it} - ltvs_{it-1}$	0.219***	0.0893***	0.0369***	0.208***	0.0787***	0.0347*
	[5.70]	[6.48]	[2.73]	[4.04]	[4.75]	[1.94]
$gtvs_{it-1} := ltvs_{it-1} - ltvs_{it-2}$	0.106***	0.0449***	0.0166	0.120***	0.0393***	0.00869
	[3.12]	[3.73]	[1.53]	[2.59]	[2.74]	[0.63]
D=1 for plants born pre-1975	-0.0942***	-0.0411***	-0.0211***	-0.0781***	-0.0317***	-0.0186**
	[5.96]	[7.35]	[4.30]	[3.55]	[4.47]	[2.52]
D=1: Survey year 1999	0.0280*	0.0116**	0.00547	0.0291	0.0100	0.00139
	[1.88]	[2.18]	[1.22]	[1.50]	[1.57]	[0.23]
D=1 for urban plants	0.0306*	0.0179***	0.0137***			
	[1.78]	[2.91]	[2.76]			
3-digit SIC dummies	Yes	Yes	Yes	Yes	Yes	Yes
MSA dummies	No	No	No	Yes	Yes	Yes
Observations	4,909	4,909	2,067	3,275	3,275	1,431

[ ]: Robust z-statistics for Probit, t-statistics for Tobit, and robust t-statistics for OLS;
* significant at 10%; ** significant at 5%; *** significant at 1%

Figure 1. The determination of the cap on permanent workers: Two-period model



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Appendix

A. A More General Model

Here, we consider the case in which the plant's horizon is infinite and the exogenous levels of required outputs over time are i.i.d. random variables. The plant's optimal policy is essentially identical to the solution of the first period of the two period model.[24]

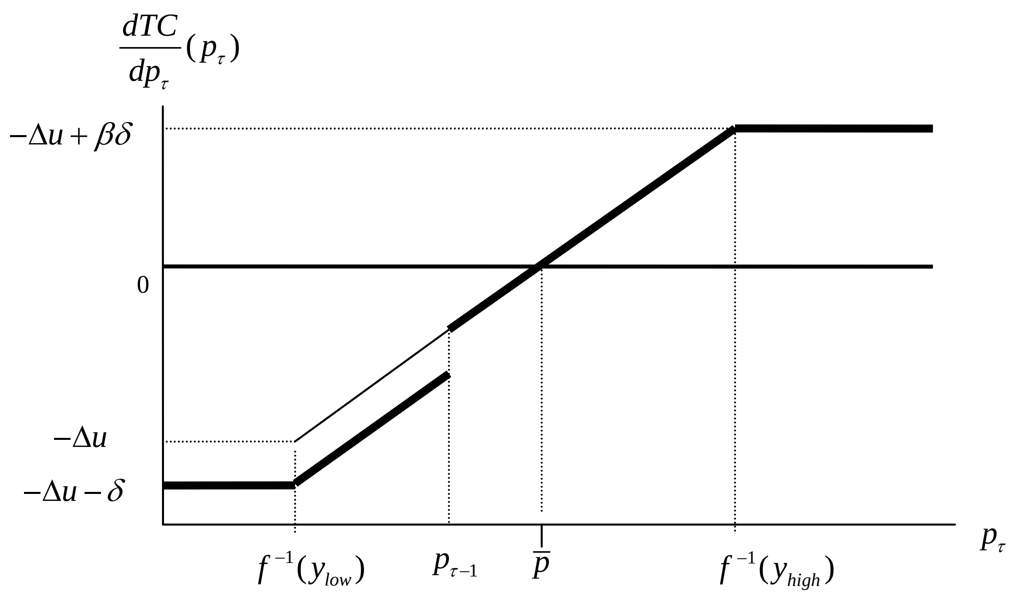
The intuition is that given future optimal behavior, the choice of p_τ at time τ determines the number of permanent workers fired at time $\tau+1$. However, subsequent layoffs depend on the independent choice of $p_{\tau+1}$, $p_{\tau+2}$, etc. and not p_τ. Thus in considering the optimal choice of permanent employment level at τ, future firing cost considerations are identical to those in the first period of the two-period model. That is, the marginal expected discounted firing cost associated with an increase in p_τ is $\beta\delta G(f(p_\tau))$. Given that a plant starts with a level of permanent workers in the previous period such that $p_{\tau-1} < \overline{p}$, the marginal change in expected costs from employing an additional permanent worker differs only slightly from the two-period case. This is because, if $p_\tau < p_{\tau-1}$, then increasing p_τ saves on firing costs in the current period.[25] Thus, in the i.i.d. case, $\frac{dTC}{dp_\tau}(p_\tau) = -\Delta u - \delta I[p_\tau < p_{\tau-1}] + \beta\delta G(f(p_\tau))$, where $I[p_\tau < p_{\tau-1}]$ is an indicator function for $p_\tau < p_{\tau-1}$. This function has a discrete jump

[24] The only qualification is that the plant must start with a level of permanent workers that is less than or equal to, the cap derived in the two-period model Section 2. As long as this is the case, it is optimal to follow the rule that $p_\tau^* = \min(f^{-1}(y_\tau), \overline{p})$. If this were not the case (i.e., the plant started with $p_{\tau-1} > \overline{p}$), it is possible that the optimal level is such that $p_\tau > \overline{p}$. However, once a realization of the y_τ comes in below $f(\overline{p})$, the rule $p_\tau^* = \min(f^{-1}(y_\tau), \overline{p})$ becomes optimal for the rest of time.

[25] In the two-period case, we implicitly assumed that the plant started the first period with no perms. Thus, we did not have to consider the effect of its decision on the number of permanent workers laid off in the first period.

at $p_\tau = p_{\tau-1}$. However, it is still strictly increasing and given that $p_{\tau-1} < \overline{p}$, it still is equal to zero at $p_\tau = \overline{p}$ (See Appendix Figure 1).

Appendix Figure 1: Determination of the Cap on Permanent Workers: Infinite Horizon i.i.d.



B. Our sample based on the PCU data

In the questionnaire, plants are asked to report, for each shift, the total number of production workers, temporary production workers, total hours worked by production workers, hours worked by temporary workers, and overtime hours. We consider that a plant operates a given shift if it reports positive total production workers for the shift, which are defined to include temporary workers in the instructions for the questionnaire given to the plant. Among plants operating a particular shift, however, many left the information for temporary production workers unfilled, and often, such plants do not provide a temporary worker number for any shifts. In such a case, it is not clear whether the plant did not use temporary workers or did not fill out the item. We consider that they did not fill out the item, since the instructions for the PCU survey explicitly instructs them both in words and with visual examples of the tables to write zero when plants operate a given shift but do not use temporary workers. We exclude such plants with missing temporary employment data for any of their active shifts (i.e., shifts for which the plant reports positive total number of production workers).

In addition, by the definition given in the instructions, when a given shift exists, the total number of production workers should be greater than or equal to the number of temporary workers. We exclude plants with any inconsistency regarding these figures. We also exclude a few plants reporting the same number for both total and temporary workers for some shifts. It is possible that these shifts are actually supported by only temporary workers. However, such incidents are rare and we cannot tell whether these are miss data entry.

Once we clean the PCU data, we limit the sample to those for which we can estimate our key variables based on the ASM and the CM as discussed in the main text. Based on the method discussed in Section 3, for a plant to be included in estimation, the plant has to appear in consecutive three years more than once in ASM-CM panel. We limit our sample to plants that appear in three years consecutively at least three times to avoid outliers. Some further outliers based on other variables are excluded.