Federal Reserve Bank of Chicago

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WP 2006-24

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November 2006

Abstract

Using plant-level data from the Plant Capacity Utilization (PCU) Survey, we examine how a manufacturing plant's use of temporary workers is associated with the nature of its output fluctuations. Our empirical evidence suggests that plants choose temps over perms when they expect output to fall, which allows them to avoid costs associated with laying off permanent employees. We also found that plants whose output levels are associated with greater levels of uncertainty use more temps. The effects of other variables are also tested in order to examine the validity of various views about why firms use temporary workers. The variables we look at include wage and benefit levels for permanent workers, unionization rates, turnover rates, seasonal factors, and plant size and age.

Key words: temporary workers, output fluctuations

JEL codes: J2, J3

[1] We thank Randy Becker and John Steven for insightful advice and helping us to augment the data sets. The research in this paper was conducted while the authors were Special Sworn Status researchers of the U.S. Census Bureau at the Chicago Census Research Data Center. Research results and conclusions expressed are those of the authors and do not necessarily reflect the views of the Census Bureau, the Federal Reserve Bank of Chicago, or the Federal Reserve System. This paper has been screened to insure that no confidential data are revealed. Support for this research at the Chicago RDC from NSF (awards no. SES-0004335 and ITR-0427889) is also gratefully acknowledged. Views expressed are those of the authors and not necessarily those of the Federal Reserve Bank of Chicago or the Federal Reserve System.

1. Introduction

The temporary help industry 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 the industry's employees work under the direction of managers at client firms, usually along side the client's regular employees. However, for most legal purposes, they remain employees of the temporary help agency, which is responsible for their recruitment and hiring as well as for paying their wages and benefits.[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); Houseman (2001)) who, along with industry analysts, have identified a number of reasons the use of temporary workers may be attractive to client firms. First, temporary help agencies continue to fill their original function of providing workers who fill in when regular employees are absent for short periods. In addition, 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 obtain the tax advantages of 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 workforce, one strategy might be to staff that segment with employees of a temporary help agency. Having such a dual workforce may allow it to provide benefits to the remainder of its workforce without jeopardizing their tax status.[3]

Two other reasons for using temporary workers stem from the substantial costs that can be associated with worker layoffs. First, given the significant costs of dismissing poorly performing employees, a client firm may want to screen potential regular employees by first observing their performance as temps. If that performance is judged inadequate, they can simply request a new worker from the temporary help agency. Such a trial period as a temp may be preferable to a formal probationary period as a regular employee.

Finally, the use of temporary workers may be attractive when there is substantial uncertainty about the strength of future demand for a firm's product. Under such circumstances, a firm may want to avoid the costs of laying-off regular employees if demand turns out to be low.

[2] The legal issues surrounding the employment status of temporary workers are complex. For some purposes, 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 regular employees.

[3] The Microsoft decision referenced above has limited firms' ability to implement such a strategy using the same temporary workers for long periods. However, they may still want to adopt such a strategy with a workforce of temps that turns over more frequently.

It may be able to do this by routinely meeting a portion of its staffing needs with temporary workers. Or it may respond to what may be a short-term increase in demand by adding mainly temporary workers. In either case, if demand declines, the firm can reduce the size of its workforce by reducing the number of temps, which would allow it to avoid the costs of laying off regular employees. Avoiding such costs may justify the use of temporary workers even if they may generally cost more to employ in the current period due to a wage premium demanded by workers or margin paid to agencies.

The increased usage of temporary workers to accommodate fluctuations in demand may have been particularly important in the manufacturing sector. Temporary services industry observers report that temporary help 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 (1987), Katz and Krueger (1999) and others have conjectured that the growth of the temporary services industry increased the efficiency of labor market search, making it possible for manufacturers and others to vary their output levels without running into bottlenecks due to the difficulty of finding or reluctance to hire regular workers. This may, in turn, have played a role in reducing the natural rate of employment during the 1980s and 1990s.

This paper focus on testing 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 usage of temporary workers and found that a substantial fraction of firms reported using them to meet fluctuations in demand. Campbell and Fisher (2004), on the other hand, develop 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 fluctuation.

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 usage of temporary workers by business establishments. Such data limitations have prevented researchers from learning very much about the characteristics of firms that use temporary workers.

[4] See, for example, Groshen and Potter (2003).

In this paper, we use plant-level data from the Plant Capacity Utilization (PCU) Survey, which is conducted annually by the Census Bureau. These data are used by the Federal Reserve Board to estimate capacity utilization rates for manufacturing and publishing industries. In 1998 the survey began collecting information of the number of temporary workers utilized by plants. However, thus far, only 1998 and 1999 micro-level data are available. Taking advantage of these newly available data, we examine how a plant's temporary worker share is associated with the plant's output fluctuations. In particular, we focus on the relationship between a plant's use of temporary workers and the deviation of realized output from trend or expected output as well as the magnitude of plants' typical output fluctuations. When a firm experiences an increase in demand, to the extent that it is expected to be temporary, the firm may be reluctant to hire additional permanent workers because of the costly process of firing such workers if demand declines. In such situations, firms may rely on temporary workers to meet current employment needs. In addition, as we show in Section 2, if firing costs are sufficiently high, greater dispersion in the distribution of output leads the firm to cap the number of perms at a lower level, and thus hire more temps.

We also analyze how a plant's temp 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 to arrange temporary workers to buffer fluctuations in employment need may require a level of sophistication more likely to be found in larger plants. Larger size may also increase a plant's ability to negotiate a lower margin from a temporary services firm. In addition, larger plants, with their deeper pockets, may face higher costs in the event of an unjust dismissal lawsuit. On the other hand, larger scale may allow plants to facilitate flexibility without relying on temps, by redistributing their permanent workers across different production processes. Plant age and industry may matter for use of temp workers through their effect on the level of uncertainty and other factors.

In addition, we investigate the relationship between temporary worker usage and a plant's wage and benefit levels. One might imagine that a plant whose regular workers earn high wage rates would be more likely to want to use temporary workers. However, what should matter for the choice of temp worker share is the ratio of temporary worker to regular worker wage rates. Industry observers indicate that the charges to client firms represent a higher markup over the wages paid to workers in the case of higher skilled workers (Kilcoyne, 2004). Thus, to the extent that high wages are due to a more skilled labor force rather than simply higher worker rents, we would expect higher wage firms to make less use of temporary workers. A similar argument applies to firms that provide generous benefit packages, though the incentive to employ temps to operate a dual work force will be greater for firms that provide expensive benefits packages.

Finally, we analyze how temp share at the three-digit industry level depends on several additional variables. These include unionization and labor turnover rates. We expect unions to resist the usage of temporary workers. On the one hand, higher turnover rates would likely increase the value of screening potential regular employees and thus could lead to greater use of temporary workers. On the other hand, when voluntary turnover is high, the likelihood of a firm needing to layoff workers due to insufficient demand is reduced. So, greater turnover could be associated with less use of temps. We also look at the effect of industry seasonality and inventory usage in determining temp share. One would expect plants whose output has a strong seasonal component to use more temps, while those for whom inventories tend to be able to absorb significant fluctuations in demand would tend to use fewer temps.

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) examines 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.

2. Motivational Model

In this section we discuss a stylized model of a plant's choice of temp worker share that is intended to help motivate and guide our empirical work. The model emphasizes the role of temporary workers in accommodating fluctuations in output without increasing future costs associated with layoffs of permanent employees.

Specifically, the model assumes that labor is the only factor of production and that in each period, the plant manager must hire an appropriate quantity of labor services, 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 regular, or "perm," employees, p_t, and "agency temps," a_t, with the total quantity of labor services given by $e_t = p_t + \theta a_t$, where θ is a positive constant representing the relative productivity of perm and temp workers. The wage rates for perms and temps are w_p and w_a, respectively. In addition, the plant incurs firing costs of δ for each perm worker that is laid off. 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 costs given a discount factor, $\beta = 1/(1+r)$.

Let the unit labor costs associated with hiring perms and temps be, respectively, $u_p = w_p$ and $u_a = w_a / \theta$. We assume that $\Delta u = u_a - u_p > 0$. That is, absent firing costs, temp workers would be more expensive to employ, 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 perm worker is greater than the (discounted) difference in unit labor costs, but less than a full period's wage, $\Delta u / \beta < \delta < w_p$. If $\Delta u > \beta\delta$, then the plant will never want to hire any temps; it will be cheaper to use perms even if it is certain that they will be laid off next period. The condition that $\delta < w_p$ is a convenient simplification that implies that the firm will not keep any idle workers on the payroll; keeping an idle worker on the payroll costs more than laying him off in the current period and may also increase layoff costs in the future. With this configuration of costs, the plant faces a tradeoff between using more perms, which lowers current wage costs, versus using more temps, which may lower future firing costs.

Two Period Case

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

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

The plant's choice is less trivial in the first period. Specifically, 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 taking into account how they will behave in the second period. Those total costs are $TC = w_p p_1 + w_a a_1 + \beta E[w_p f^{-1}(y_2) + \delta \max(0, p_1 - f^{-1}(y_2))]$. In order to meet the required level of production, $f^{-1}(y_1) = p_1 + \theta a_1$. Using the latter constraint, costs can be written 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, $\dfrac{dTC}{dp_1}(p_1) = -\Delta u + \beta\delta \dfrac{d}{dp_1} E[\max(0, p_1 - f^{-1}(y_2)]$.

Assume that the distribution of second period output is continuous with density $g(y_2)$ and distribution function $G(y_2)$. Then the expected number of layoffs in the second period given that p_1 perms were hired in the first period is

$L(p_1) = \int_0^{f(p_1)} (p_1 - f^{-1}(y_2)) g(y_2) dy_2$. Thus,

$L'(p_1) = (p_1 - f^{-1}(f(p_1)) g(f(p_1)) + \int_0^{f(p_1)} (1) g(y_2) dy_2 = G(f(p_1))$, which implies that

$\dfrac{dTC}{dp_1}(p_1) = -\Delta u + \beta\delta G(f(p_1))$. That is, increasing the number of perms by one (and thus lowering the number of temps by $1/\theta$) lowers costs in the current period by the difference between temp and perm unit costs (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 will need to be fired ($G(f(p))$).

$G(y)$ and $f(p)$ are increasing functions. Thus, $\dfrac{dTC}{dp_1}(p_1)$ is also increasing. Moreover, $\dfrac{dTC}{dp_1}(0) = -\Delta u < 0$ and $\lim\limits_{p_1 \to \infty} \dfrac{dTC}{dp_1}(p_1) = -\Delta u + \beta\delta > 0$. Thus there is a unique level of perms, $\overline{p}$, such that $\dfrac{dTC}{dp_1}(\overline{p}) = -\Delta u + \beta\delta G(f(\overline{p})) = 0$. See the top panel of Figure 1 for an illustration of the case in which y_2 is uniformly distributed on the interval from y_{lo} to y_{hi} and $f(e)$ is linear.

On the one hand, if $f^{-1}(y_1) < \overline{p}$, then total expected discounted costs are decreasing in the number of perms all the way up to the value that completely satisfies the plant's employment need. Thus, in this case, the optimal number of perms is $f^{-1}(y_1)$ and the optimal number of temps is zero. On the other hand, if $f^{-1}(y_1) > \overline{p}$, then total expected discounted costs fall with p_1 until $p_1 = \overline{p}$, and then begin to rise. Thus the optimal number of perms is $\overline{p}$, and the optimal number of temps is $(f^{-1}(y_1) - \overline{p})/\theta$, the number necessary to meet the remaining necessary level of labor services. We can summarize the solution by writing the optimal numbers of first period perms and temps as $p_1^* = \min(f^{-1}(y_1), \overline{p})$ and $a_1^* = (f^{-1}(y_1) - p_1^*)/\theta$ where $\overline{p}$ satisfies $\beta\delta G(f(\overline{p})) = \Delta u$. In words, the plant hires perms up to a maximum value at which the expected discounted firing costs of hiring an additional perm are equal to the extra current wage costs of substituting an equivalent number of temps.

Lognormal Output Levels and Power Production Function

Suppose the distribution of y_2 is lognormal, $\log y_2 \sim N(\mu, \sigma^2)$ and the production function takes the power form, $f(e) = Ae^{\alpha}$. Then, the equation characterizing $\overline{p}$ is $\Delta u = \beta\delta G(f(\overline{p})) = \beta\delta\Phi(\frac{\log A + \alpha \log \overline{p} - \mu}{\sigma})$, where $\Phi(x)$ is the standard normal distribution function, and μ and σ^2 are the mean and variance of the log of the output distribution. Alternatively, $\log \overline{p} = \alpha^{-1}[\mu - \log A + \sigma\Phi^{-1}(\frac{\Delta u}{\beta\delta})]$. Because α and σ are positive constants and $\Phi^{-1}(p)$ is an increasing function, a higher value of the gap between temp and perm unit wage costs, Δu, increases the maximum perm employment level, leading to the use of fewer temps. On the other hand, a higher value of the firing cost, δ, lowers the cap on perm workers, leading to the employment of more temps. The impact of the dispersion parameter, σ, on the maximum number of perms depends on the ratio of the gap between unit wage costs and firing costs. If firing costs are sufficiently high that $\Delta u < \frac{1}{2}\beta\delta$, then $\Phi^{-1}(\frac{\Delta u}{\beta\delta}) < 0$ and greater dispersion in the distribution of $\log y_t$ will lead the plant to cap the number of perms at a lower level and, thus, hire more temps for a given level of output. The opposite is true if $\Delta u > \frac{1}{2}\beta\delta$.

That an increase in the uncertainty measure, σ, could lead to the use of fewer temps is, perhaps, somewhat counter intuitive. However, when firing costs are low, the plant will worry little about layoffs. As a result, it will hire so many perms that the probability of needing to lay off the last one will be greater than one half. Increasing the uncertainty in the number of workers needed in period 2 will move the probability closer to one half, which represents a decrease in the probability of needing to fire the marginal worker. This decline in marginal expected firing costs gives the plant the incentive to higher more perms. When firing costs are high, the effect of uncertainty works the other way. The fact that firing costs are high implies that the plant will keep the probability that the marginal worker needs to be laid off less than one half. Increasing uncertainty again leads to the probability moving closer to one half, but in this case, the probability increases. The increased probability that the marginal worker will need to be laid off in turn causes the plant to use fewer perms and more temps to produce the given output.

IID Output Levels

If the plant's horizon is infinite, but the exogenous levels of required outputs over time are i.i.d. random variables, then we show in the appendix that the plant's optimal policy is essentially identical to that just derived for the first period of the two period model.[5] The intuition is that given future optimal behavior, the choice of p_τ at time τ determines the number of perms laid off at time $\tau+1$. However, subsequent layoffs depends on the independent choice of $p_{\tau+1}$, $p_{\tau+2}$, etc. and not p_τ. Thus in considering the optimal choice of perms at time 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 the plant starts with a level of perms, $p_{\tau-1} < \overline{p}$, from the previous period, the marginal change in expected costs from employing an additional perm differs 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.[6] 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 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 the bottom panel of Figure 1.

Implications for Empirical Strategy

In the empirical section, we analyze the cross sectional determinants of the use of temp workers. The simple model sketched above suggests that one important determinant is the level

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[5] The only qualification is that the plant must start with a level of perms that is less than or equal to, the cap derived in the last section. As long as this is the case, it will be optimal to follow the rule that $p_\tau^* = \min(f^{-1}(y_\tau), \overline{p})$. If this was not the case, that is, the plant started with $p_{\tau-1} > \overline{p}$, then it is possible for it to be optimal to choose $p_\tau > \overline{p}$. 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.

of current output relative to the expectation of future output. When output levels are high relative to what is expected in the future, the model suggests that firms tend to use more temps in order to avoid firing costs. We also look at the effects of cross-plant variation in the uncertainty of future output. The model says that, in principle, higher uncertainty could either increase or decrease the use of temp workers. In the empirical work we control for industry as well as plant characteristics such as plant size and age that may proxy for variation in the level of firing costs and temp wage differentials that the model says should also influence the use of temps.

From the model, a plant hires a positive number of temps if $f^{-1}(y) = (y/A)^{1/\alpha} > \bar{p}$. This holds when $\log y - \mu - \sigma\Phi^{-1}(\frac{\Delta u}{\beta\delta})$ >0. Introducing heterogeneity across plants, let us write $\tilde{Z}_i^* = \log y_i - \mu_i - \sigma_i\Phi^{-1}(\frac{\Delta u_i}{\beta\delta_i}) + \nu_i$, where ν_i is a random component. A plant uses temps if $\tilde{Z}_i^* > 0$, and the plant does not use any temps, otherwise. As we mentioned above, under the assumption that δ_i is large enough that $\Phi^{-1}(\frac{\Delta u_i}{\beta\delta_i})$ is negative, the plant's likelihood to use temps increases with $\log y_i - \mu_i$ and σ_i. If the random component enters in such a way that a plant has temps when $\frac{\log y_i - \mu_i}{\sigma_i} - \Phi^{-1}(\frac{\Delta u_i}{\beta\delta_i}) + \nu_i$, the effect of σ_i would depend on the singn of $\log y_i - \mu_i$. In the empirical section, we examine plants' use of temps using a specification where we include $\frac{\log y_i - \mu_i}{\sigma_i}$ and the other specification where we include $\log y_i - \mu_i$ and σ_i separately.

3. Empirical Analyses

Above, we outline how a plant's use of temporary workers is associated with the difference between its current and expected future production levels, which we denote by d, as well as the level of uncertainty associated with its future production level, which we denote by σ. To analyze the relationship between these variables and a plant's use of temp workers, we estimate probit models linking a plant's likelihood of using temporary workers in a given period

[6] 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 perms laid off in the first period.

to the measures of d and σ as well as other plant characteristics. In addition we estimate tobit models that link the share of temp workers to plant characteristics.

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.[7] In addition to variables related to plants' operation status and capacity utilization, the survey collects data on work patterns by shift, including the number of production workers and their hours of work. The survey also collects information on overtime hours. Such information is provided for each of the shifts that a plant operates during the fourth quarter of the year. 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).[8] Currently the 1998 and 1999 PCU micro data are available for this study.

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 also exclude plants that reported inconsistent responses for key variables. Among them, we further select plants, for which we can calculate measures of the expected level and volatility of production. As we describe below, we calculate such measures using annual output data from Annual Survey of Manufactures (ASM) and Census of Manufactures (CM). Thus, our sample is limited to the plants which previously appeared in the ASM-CM (1976~2001) panel for enough years that we could estimate some key parameters of their time series process for output.[9] Combining both years of available PCUs leaves us with about 5,000 plants. Appendix A.1 provides more details about which plants are included in our sample. Note that while the PCU provides employment and hour data for each shift, examining the allocation of perm and temp workers between different shifts is beyond the scope of this paper. In what follows, we focus on a plant's overall use of temporary workers for all shifts in total.

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

[8] In 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. Include truck drivers delivering ready-mixed concrete. (US Census Bureau, 2000)

[9] While approximately 17,000 plants are surveyed each year, many plants are beyond our focus or do not respond to the key items for our study.

In our sample, the fraction of plants employing a positive number of temporary production workers in a particular year is about 42%. The remaining 58% of plants operate without using any temporary workers. This is consistent with our stylized model, which predicted that when output is below a certain threshold, a plant uses only permanent workers. Of plants with temporary workers, on average, the temp share in total production workers is 0.119. Plants in our sample are much bigger and older than that of average manufacturing plants in Census of Manufactures (1997). Plant TVS is on average 59 million dollars based on 1987 dollar. 65% of the plants in our sample exist in 1975 or before, and among those which are born after 1975, the average age is about 16.

Measure for d

The theory identified the deviation of current output from expected future output as a key variable determining a plant's use of temp workers. In order to create an empirical measure of this variable we have to make three choices. First, we have to identify what we mean by the current period. Second, we have to identify what we mean by the future period. Finally, we have to explain how the expectation of the future period's output is estimated. On the first question, we take the current period to be the fourth quarter. Because, the measure of temporary worker that we seek to explain is for the fourth quarter (the PCU provides information on only fourth quarter), it seems the fourth quarter is the natural choice as the current period. We use the annualized figure for the fourth quarter total value of shipments (TVS) reported on the PCU survey. It is somewhat less clear what to choose as the future period. Indeed, one could view the length of the horizon considered by the plant as an empirical question to be investigated more 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 $d_{it}^{Q4} \equiv ltvs_{it}^{AQ4} - E_t[ltvs_{it+1}]$. That is, d_{it}^{Q4} is the difference between the current quarter's output and the expected average of the output levels over the next four quarters. We estimate the expectation of next year's output that appears in the definition of d_{it}^{Q4} using three different specifications for the time series of log annual output levels in the ASM-CM panel.

Before discussing those three specifications, it is helpful to establish some additional notation and discuss a decomposition for d_{it}^{Q4}. Specifically, let us write the fourth quarter's annualized output as

$$ltvs_{it}^{AQ4} = E_{t-1}[ltvs_{it}] + f_i^{Q4} + v_{it}^{Q4}, \tag{1}$$

where f_i^{Q4} is a seasonal component for the fourth quarter, v_{it}^{Q4} is a random disturbance in the fourth quarter in year t. That is, the log level of annualized output in the fourth quarter is the level of output expected for the whole year based on last year's data plus the standard seasonal effect for the fourth quarter plus a "shock" term that represents the surprise in the level of fourth quarter output.

We can further write

$$\begin{aligned} ltvs_{it}^{AQ4} - E_t[ltvs_{it+1}] &= \{ltvs_{it}^{AQ4} - E_{t-1}[ltvs_{it}]\} - \{E_t[ltvs_{it+1}] - E_{t-1}[ltvs_{it}]\} \\ &= \{f_i^{Q4} + v_{it}^{Q4}\} - \{E_t[ltvs_{it+1}] - E_{t-1}[ltvs_{it}]\}. \end{aligned} \tag{2}$$

The term in the first bracket is the deviation of the realized fourth quarter annual output from the expected output of the current year. It can be further decomposed into a time-invariant seasonal component and a random component. The term in the second bracket is the change in the expected future outputs. In our empirical work, we examine how each of these components is related to a plant's temp share. To the extent that a plant's current output level exceeds the previous trend or what was anticipated in the previous period, we expect the plant to be more likely to hire temporary workers and have a greater temporary worker share. If a plant finds its current output level below past trends or expected levels and decides to lower the level of labor, it would layoff temps before it dismisses permanent workers. If firing costs are an important consideration and fast growing plants are less likely to need to layoff workers in the future, one would expect plants that have been consistently fast growing to hire a lower share of temp workers.

Note that we would like to control for f_i^{Q4} to separate the effect of a surprise in the level of current output from the seasonality effect. Due to the lack of time series quarterly data, however, it is not feasible to estimate a seasonal component for each plant. Thus, we run the analysis with 3-digit SIC industry dummies to control for the typical industry level seasonality and any other factor that varies only at the 3-digit SIC level. We also calculated seasonal components based on quarterly series for industrial production (IP) for each 3-digit SIC and used this industry-level measure as a proxy for the plant-level factor in models with 2-digit SIC dummies. (More detail about how the seasonal component was calculated are given below.)

Models for expected output levels and uncertainty level, σ

To measure expected levels of current and future output and the uncertainty for each plant, we use the time series data of plant TVS from the ASM and the CM. The CM is a population survey and is conducted every five years. In contrast, the ASM is a sample survey and is conducted annually.[10] We observe the TVS of all manufacturing plants in a Census year as long as they exist, but in off-Census years, we only observe the TVS of plants sampled for the ASM. Using a plant identification number, which is given based on a physical location of the plant, we create ASM-CM plant-level unbalanced panel data. Note that, 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 values by employing the TVS deflator for each of 4-digit SIC calculated by Bartelsman, Becker, and Gray.[12] As we previously noted, monthly and quarterly series on plant level TVS are not available in the ASM or CM. Thus we analyze output fluctuations at the annual frequency.

One might also consider measuring the demand fluctuations facing a plant using the employment totals given by the Longitudinal Business Database (LBD). The LBD provides annual employment levels for all establishments (that have employees) every year. However, like most other surveys, the employment measure in the LBD data included only workers on a plant's regular payroll and thus excludes temp workers. To the extent that a plant uses temporary workers to accommodate output fluctuations, variation in permanent employment would be less that variation in overall employment, including that of temp workers. Moreover, any unobserved or uncontrolled factors that increase a plant's use of temporary workers may be translated into a lower level of permanent employment fluctuations. Thus, in this paper, we use TVS data from the ASM-CM panel to capture output fluctuations.

Below, we describe three specifications for the time series process for log output. For each of the models we use the standard deviation of the residuals as a measure of the uncertainty a plant faces about future output. First (Model 1), we estimate a simple mean of the log TVS in the ASM-CM data and take this to be the expected output in all periods. In this case, since the expected output is the same across years, the second term in (2) disappears, and d_{it}^{Q4} reduces to the shock v_{it}^{Q4}, after controlling for seasonal component. If the plant's production levels are i.i.d. random variables, this model would adequately reflect the long-run level and volatility of the plant's output.

[10] The ASM is performed as a part of CM in the Census year. Plants in ASM samples are asked to fill a longer questionnaire.
[11] As a plant identifier, we use LBD number, which is a revised version of Permanent Plant Number (PPN) used in much research on manufacturing data base such as Longitudinal Research Data (LRD). Like PPN, the LBD number does not change at the event of merger and acquisition and is specific to a plant physical location. LBD number is created as a part of the effort for a Census to create the LBD, which review and update the longitudinal linkage as well as the operation status of the establishments/plants in the SSEL. While the Census of Manufacturing goes back to 1963, the LBD starts from 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.

However, there are some obvious reasons to question the adequacy of such measures. First output levels at most plants have long-term trends, either up or, less frequently, down over time. Second, the data are unbalanced, with plants observed in different sets of years. Because years differ in their volatility due to macroeconomic factors, the value of σ_i might depend on the particular set of years available for a particular plant. In addition, there might be factors, such as age, which are systematically associated with a plant's output level. Since we do not observe TVS for all the years that a plant exists, the simple mean of TVS observed in our sample would depend on where in a life cycle the plant is when it is included to the sample.

Considering these issues, we estimate the following specification (Model 2);

$$ltvs_{it} = \alpha_i + \beta_i T + \gamma n_t + \varepsilon_{it}\,, \qquad (3)$$

where $ltvs_{it}$ is log TVS of plant *i* in year *t*. T captures a plant specific time trend that absorbs any linear effect of plant age, and n_t is a macroeconomic variable that captures business cycle. As n_t, we use the deviation of log real GDP from log potential GDP provided by the CBO. Note that in this model, expected future output depends on expectations of n_t. However, γn_t is common across plants and thus does not affect relative expectations across plants. We simply use the realized value for n_t in calculating the expected outputs. The value for σ_i is the standard deviation of the error terms from the model. This measure does not reflect the particular period or particular part of a plant's life cycle that appears in the ASM-CM sample.

Note that in this specification, unlike Model 1, the expected output changes over time, and d_{it}^{Q4} is decomposed as in (2). The term in the second bracket representing the change in expected outputs is equal to β_i the time trend for the plant.

Finally, our last model (Model 3) assumes that output growth follows a first order autoregressive process. We again control for the change in macroeconomic conditions. Denoting the growth rate of TVS (the change in the log of TVS) by $gtvs$, we estimate;

$$gtvs_{it} = \tilde{\beta}_i + \rho_i gtvs_{it-1} + \gamma dn_t + \upsilon_{it}\,, \qquad (4)$$

where $dn_t \equiv n_t - n_{t-1}$. Unlike Model 2, here, a plant uses the past realized output level and growth rate to form its expectation for its future output level. The uncertainty measure σ_i is again the standard deviation of the residuals of the model. Thus, it reflects uncertainty about output levels one period ahead. In this specification, the term in the first bracket in (2) is unforeseeable events after a plant observes the output/growth rate in the previous year, which we capture by the residual term from (4).[13]

Using the above three methods, we calculate d_{it}^{Q4}, σ_i, and the components of the decomposition in (2) and use these as variables in the probit and tobit models.

Specification of Probit and Tobit Models

Here we specify probit and tobit models for the usage and share of temps. Let us denote the net benefit for a plant of using a positive number of temps in fourth quarter in year t by Z_{it}^{Q4*}. We then specify;

$$Z_{it}^{Q4*} = (d_{it}^{Q4}, \sigma_i, X_{it})\boldsymbol{\lambda} + u_{it}, \quad (5)$$

where σ_i is the average level of uncertainty of the plant, X_{it} is a vector of other control variables, including 3-digit SIC industry dummies, and a survey year dummy. Assuming that a plant hires temporary workers when $Z_{it}^{Q4*} > 0$, we estimate (1) by maximum likelihood.

Let S_{it}^{Q4} stand for the temporary worker share in plant i in the fourth quarter in year t. Analogously to the probit models, we specify;

$$S_{it}^{Q4} = (d_{it}^{Q4}, \sigma_i, X_{it})\tilde{\boldsymbol{\lambda}} + \tilde{u}_{it}, \quad (6)$$

where S_{it}^{Q4} is censored at the value zero.

Note that for both probit and tobit models, we include plants' recent output growth rates.[14] These are intended to control for variation in the initial number of permanent workers relative to current output levels. Our simple 2-period model did not address how the initial level of permanent workers influences a plant's current use of temp. However, in reality, if a plant already has more permanent workers than it needs to produce the current output, its labor requirement is unlikely to be met by using temporary workers. Indeed, in versions of our model with more realistic time series processes for output, the share of perm workers from the previous period is a state variable.

As a way to incorporate the effects of varying levels of initial numbers of permanent workers, we control for past output growth rates. If a plant's output has been growing, it is likely that the number of perms in the last period is not biding. However, if output has been falling, the

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[13] $ltvs_{it} - E_{t-1}[ltvs_{it}] = gtvs_{it} - E_{t-1}[gtvs_{it}] = \upsilon_{it}$

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

number of perms inherited from the previous period may constrain the plant; in this case, even when a plant expects production levels to fall further, it is unlikely to hire many temps.

Another possibility would be to actually include information on the number of permanent workers from the previous period. However, in the cross-section, it is difficult to interpret the level of permanent employment. While the model assumed homogenous productivity (A), it is, in fact, heterogeneous. A high level of p_{t-1} may mean that the plant is unproductive, rather than that it has a binding level of permanent workers on its payroll.

Applying each model to our ASM-CM panel, d_{it}^{Q4} is almost symmetrically distributed between -2 and 2 for most plants. We exclude plants with d_{it}^{Q4} below -2 or above 2, considering them as outliers. Our measure of uncertainty, σ_i, is distributed between 0 and 2 for Model 1 and 0 to 1 for Models 2 and 3, except for a small number of outliers, which are again removed. After dropping these observations, our sample size is 4909.

As shown in Table 1, d_{it}^{Q4} is on average 0.20 based on Model 1, -0.15 based on Model 2, and -0.10 based on Model 3. In Model 1, since we use a simple mean of the real outputs until 2001 as a plant's expected output, d_{it}^{Q4} also captures the growth of a plant compared to its history since 1976. This explains the greater mean based on Model 1 as compared to that of Models 2 and 3. In Models 2 and 3, under which the annualized fourth quarter output is about 10 to 15% smaller than the expected annual output for the following year in our sample. The deviation, however, varies a lot across plants. A minus one to plus one s.d. change from the mean level for d_{it}^{Q4} ranges from -0.308 to 0.239 for Model 2, and from -0.460 to 0.264 for Model 3.

Estimates of σ_i are smaller when we control for more variables. The mean level for σ_i is 0.427, 0.262, and 0.189 for Models 1, 2, and 3, respectively. Estimates of σ_i also vary a good deal across plants. Based on Model 3 where we incorporate the previous growth rate in the expectation, an average plant's realized annual output deviates from its expectation by 18.9%. However, a plant with σ_i one s.d. higher than the mean experiences annual output levels that typically deviate from expected values by 30% (=0.189+0.11). As one can see from the mean for $\frac{d_{it}^{Q4}}{\sigma_i}$, on average in our sample, d_{it}^{Q4} is equivalent of 35, 64, and 63% of the volatility (σ_i) that plants face, respectively for Models 1, 2, and 3.

Other Variables

In addition to the variables measuring actual and expected output fluctuations, our probit and tobit models include several other variables that may be closely linked to firms' 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. The rationales for including these variables were discussed earlier.

Since the PCU does not provide any wage information, we use the ASM to calculate the permanent production worker wage rate, w_{it}^{P}, for each plant. We then use overtime share, s_{it}^{over}, from the PCU to calculate the straight rate permanent worker wage, $w_{it}^{SP} = w_{it}^{P}(1+.5s_{it}^{over})$.[15] We also use ASM to calculate supplemental labor costs for each dollar of wage payments.[16]

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 3-digit industry covered in the CPS. The data on turnover are also derived from the CPS, but are based on the non-outgoing rotation groups.[17] Our industry level estimates of turnover rates pool all data since 1996 for each detailed CPS industry.

The seasonal component is calculated based on the non-seasonally adjusted IP quarterly series of the period between 1987 and 2005 from the Federal Reserve Board of Governors. More specifically, let IP_{jt}^{q} stand for the IP of industry j in qth quarter in year y. Let us denote the seasonal component of qth quarter for industry j as f_j^q. We calculate f_j^q as

$$\sum_t \{\ln(4 \times IP_{jt}^{q}) - \ln(IP_{jt})\}.$$

The unionization rate, turnover rate, and seasonal component are all captured at the 3-digit SIC level. We pursue two strategies for including them in our models. First, we simply include them in the model, but replace 3-digit SIC dummies with 2-digit dummies. In this

[15] PCU data provide hour information for all production workers (including temps), hours worked by temps (including overtime if any), and any overtime. Assuming that overtime is performed only by permanent workers, we use the ratio of the overtime and 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.

[16] 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.

[17] 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 respondents sex 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

specification, we report standard errors that account for clustering at the 3-digit SIC level. In addition, we estimate models with 3-digit dummies and then estimate separate industry-level regressions in which we examine the dependence of the 3-digit dummy coefficients on unionization, turnover, and seasonality.

4. Results

Table 1 shows the results for a specification in which we look plants' use of temporary workers with measures of d_{it}^{Q4}/σ_i, a form that is suggested by the simple model of section 2. For both probit and tobit models, d_{it}^{Q4}/σ_i obtains a positive and significant coefficient based on expectations calculated using all three models for the ASM-CM time series. Based on Model 3, for a plant with average characteristics, a one s.d. increase in d_{it}^{Q4}/σ_i increases the probability that a plant uses some temps by 2.8 percentage points. For a plant with temporary workers, a one s.d. increase in d_{it}^{Q4}/σ_i increases the share of temps by .013, which is equivalent of over 10% of the average temp share of plants with any temp production workers.

In Table 3, we perform probit and tobit analyses with a more flexible specification, including d_{it}^{Q4} and σ_i separately. The net effects of both d_{it}^{Q4} and σ_i are positive and significant in all models. The maximized likelihoods are also greater with this specification than the previous one. For the case of Model 3, the log likelihood increase from -3059.16 to -3053.68 for probit and from -695.17 to -678.45 for tobit. In both cases, the information criteria prefers the less constrained specification.

In the case of Model 3, if d_{it}^{Q4} increases by a one s.d. from its average, moving from -.0977 to 0.264, the probability of employing temps increases from 0.42 to 0.455; about a 3.5 percentage point increase. For plants with temporary workers, such a change increases the share by 1.6 percentage points, which is 15% of the average share. In addition, plants that experience more uncertainty in general seem to use temps more. For a plant that experiences realized output about one s.d. greater than average, the plant's likelihood of hiring some temps increases by 1.7%, and for plants using temps, the temp share increases by .01.[18]

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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).

[18] We also performed probit and tobit analyses replacing expected annual output level in $t+1$ with its realized value. For this exercise, out of 4909 plants used in Table 3, we used the data of 4617 plants, which appear in ASM sample in the year following their PCU survey. The results remain qualitatively the same.

Next, in Table 4, we show the results of probit and tobit analyses in which we decompose d_{it}^{Q4} to examine the effect of the "current" shock and the change in expected output level separately (see (2)). Based on Model 3, with the specification in Table 4, the effects of d_{it}^{Q4} appear to be dominated by the deviation of realized output to the expected output of the same period. It is possible, however, that a plant has private information about its own growth prospects. For the subset of the plants appearing in ASM in the subsequent year to their PCU survey, we can perform the same analyses replacing the change in the expected output with the change in outputs that are actually realized. Interestingly, we find that, after controlling for other variables, plants' use of temp workers is positively correlated with the growth of their output from the current to the next year. This runs counter to our conjecture that plants that expect to grow hire a greater fraction of perms because they face a smaller probability of needing to fire them in future.

It is possible that short-run growth prospects have different effects on plants' use of temps as compared to the growth prospects that are captured based on our various specifications (Models 1, 2, and 3). When a plant grows faster, it is possible that, it becomes difficult for plants to find enough perms with appropriate skills in a timely fashion, given the plant's own capacity to recruit. In such a case, the plant may initially hire temporary workers to screen them with a possibility of hiring them as perms in future. This effect of screening might be dominating the effect of the increased probability to fire perms, causing the positive and significant coefficients for $gtvs_{t+1}$.

Next we explore the effect of wage variables as well as unionization rate, seasonality, and turnover rates. The results are summarized in Table 5 and 6. 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 temps to reduce labor costs. However, as we discussed, industry analysts report that the markup that temp agencies charge over what temp workers are paid tend to be higher for high wage occupations. Thus higher wage plants may use fewer temps. The latter story seems to hold, as shown in Columns 1 and 4 in Table 5. 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 temps. Note also 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, it is possible that size effects were off set by the negative effects of skill levels in the previous analyses. Bigger plants may have greater negotiation power with temporary agencies.

Next we add the unionization rate, the turnover rate, and the fourth quarter seasonal component, which we measure at 3-digit SIC level. Columns 2 and 5 in Table 5 show the results where we replace 3-digit SIC dummies with these three continuous variables. We then add 2-digit SIC dummies in Column 3 and 6, to see whether any effects of these 3-digit level variables remain after controlling for 2-digit SIC industry specific effects.

We find that the unionization rate is negatively correlated with a plant's use of temps. While the coefficient is not significant for probit with 2-digit SIC dummies, for other specifications, the coefficients are negative and significant. While unions might be thought to increase the use of temps through their effect in increasing wages relative to productivity, we find a negative relationship between unions and the use of temps, similar to that found in the study by Houseman (2001). As she argues, it is possible that the results reflect the fact that unions oppose the use of non-standard employment relationships.

Coefficients for turnover are not significant in any specification. It is possible that the increased need to recruit workers through a period as a temp offsets the decreased probability of needing to fire permanent workers.

The coefficients for the fourth quarter seasonal component are significant in the tobit models without any industry dummies, which we consider capture the effect of time-invariant fourth quarter component on the use of temporary workers.[19]

As a robustness check, we also use our full sample to estimate 3-digit SIC dummies, and directly relate these 3-digit SIC level variables to the industry-specific variables. Using the dummy variable coefficients from the specification in Table 3 (Model 3), we run weighted least squares. The results are in Table 6, which again show the negative coefficients for unionizations and positive coefficients for fourth quarter seasonal component. R-squared from these regressions are, however, not very high, showing that much industry specific effects are left unexplained.

5. Conclusion

We have provided some evidence in support of the proposition that temporary work arrangements facilitate flexibility in firms' use of labor and allow them to accommodate output fluctuations at lower cost. Our stylized model suggested two quantities that were crucial to a firm's decision to use temporary workers and that we could approximate using the ASM-CM panel – the gap

[19] We also control for the inventory-to-shipment ratio calculated at 3-digit SIC level using CMs in past years. The qualitative results for key variables remind the same.

between current and expected future output and the uncertainty in that expectation. We used probit and tobit analyses to examine the relationship between estimates of these two quantities based on three models of the time series process for output and plants' actual use of temps conformed to the prediction of the theory.

First, we found that plants make greater use of temps when their current output levels are high relative to expected future output levels. This suggests that plants choose temps over perms when they expect their output to fall and thus want to avoid costs associated with dismissing permanent employees. This effect was identified after netting out the effect of a seasonal factor in plants' output (calculated at 3-digit SIC level), which itself had a positive relationship with plants' use of temps.

Second, we found that plants with greater uncertainty over their future output levels use more temps. Firing costs appear to be big enough to induce more volatile plants to make greater attempts to minimize the costs of firing permanent workers; this might have made them rely more on temps even though the current period costs of using temps is higher than for permanent workers. We also found evidence suggesting that temporary help arrangement may play an important role in helping firms to screen future permanent workers. Such a role may explain why actual output increases were often associated with greater use of temps.

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

Table 1. Summary Statistics

A. Key variables (4,909 obs.)

	Model 1		Model 2		Model 3	
	Mean	(S.d.)	Mean	(S.d.)	Mean	(S.d.)
d_{it}^{Q4}	0.200	(0.482)	-0.154	(0.393)	-0.0977	(0.362)
σ_i	0.427	(0.254)	0.262	(0.150)	0.189	(0.111)
$\frac{d_{it}^{Q4}}{\sigma_i}$	0.349	(1.300)	-0.638	(1.734)	-0.627	(2.187)

B. Other plant characteristics (4,909 obs.)

	Mean	(S.d.)
$ltvs_{it}^{AQ4}$	11.0	(1.26)
$gtvs_{it}$: growth rate of annual real output in survey years	0.00710	(0.203)
$gtvs_{t-1}$: growth rate of annual real output in previous years	0.0202	(0.224)
Fraction of plants that existed from 1975 or before	0.646	
Fraction of plants from 1999 PCU	0.476	

3-digit SIC level variables included in the study		
Unionization Rates	0.236	(0.117)
Turnover rates	0.0197	(0.00559)
Fourth quarter seasonal factor	0.00608	(0.0398)

Wage variables†		
Ln. straight wage of perm production worker	2.66	(.348)
Benefit per $1 perm wage	.275	(.104)

†: Used for the restricted sample with 3,716 obs. due the missing observations of overtime used to calculate straight wage.

Table 2. Results of Probit and Tobit: Specification A

	Probit: dF/dX			Tobit		
	Model1	Model 2	Model 3	Model1	Model 2	Model 3
d_{it}^{Q4} / σ_i	0.044***	0.010**	0.013***	0.016***	0.005***	0.006***
	[6.53]	[2.19]	[3.61]	[6.89]	[3.26]	[4.53]
$ltvs_{it}^{AQ4}$	0.006	0.020***	0.018**	0.001	0.006**	0.005*
	[0.85]	[2.73]	[2.40]	[0.44]	[2.12]	[1.82]
$gtvs_{it} := ltvs_{it} - ltvs_{it-1}$	0.137***	0.183***	0.204***	0.057***	0.072***	0.082***
	[3.53]	[4.75]	[5.28]	[4.04]	[5.22]	[5.93]
$gtvs_{it-1} := ltvs_{it-1} - ltvs_{it-2}$	0.043	0.070**	0.091***	0.019	0.029**	0.038***
	[1.28]	[2.10]	[2.70]	[1.62]	[2.40]	[3.17]
D=1 for plants born pre 1975	-0.095***	-0.097***	-0.095***	-0.042***	-0.043***	-0.041***
	[-5.99]	[-6.15]	[-6.00]	[-7.44]	[-7.58]	[-7.37]
D=1: Survey Year 1999	0.022	0.028*	0.026*	0.009*	0.011**	0.011**
	[1.49]	[1.86]	[1.77]	[1.72]	[2.13]	[2.03]
3-digit SIC dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4909	4909	4909	4909	4909	4909

[ ]: Robust z statistics (based on robust standard errors for Probit case)
* significant at 10%; ** significant at 5%; *** significant at 1%
$d_{it}^{Q4} \equiv ltvs_{it}^{AQ4} - E_t[ltvs_{it+1}]$

Table 3. Results of Probit and Tobit: Specification B – with d and sigma separately

	Probit: dF/dX			Tobit		
	Model1	Model 2	Model 3	Model1	Model 2	Model 3
$d_{it}^{Q4} := ltvs_{it}^{AQ4} - E_t[ltvs_{it+1}]$	0.149***	0.058***	0.097***	0.057***	0.027***	0.044***
	[7.46]	[2.84]	[4.42]	[7.95]	[3.68]	[5.56]
σ_i	0.063*	0.194***	0.152**	0.031***	0.093***	0.087***
	[1.84]	[3.76]	[2.16]	[2.65]	[5.18]	[3.61]
$ltvs_{it}^{AQ4}$	-0.001	0.019***	0.016**	-0.002	0.005**	0.004
	[-0.10]	[2.63]	[2.15]	[-0.84]	[2.06]	[1.54]
$gtvs_{it} := ltvs_{it} - ltvs_{it-1}$	0.116***	0.189***	0.218***	0.046***	0.075***	0.089***
	[2.95]	[4.90]	[5.68]	[3.32]	[5.41]	[6.45]
$gtvs_{it-1} := ltvs_{it-1} - ltvs_{it-2}$	0.021	0.069**	0.106***	0.01	0.028**	0.045***
	[0.61]	[2.05]	[3.10]	[0.82]	[2.37]	[3.71]
D=1 for plants born pre 1975	-0.089***	-0.093***	-0.093***	-0.039***	-0.040***	-0.041***
	[-5.59]	[-5.86]	[-5.92]	[-6.94]	[-7.20]	[-7.27]
D=1: Survey Year 1999	0.016	0.027*	0.027*	0.006	0.011**	0.011**
	[1.05]	[1.84]	[1.83]	[1.19]	[2.10]	[2.08]
3-digit SIC dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4909	4909	4909	4909	4909	4909

[ ]: Robust z statistics (based on robust standard errors for Probit case)
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 4. Decomposing d_{it}^{Q4}

	With change in expected output		With change in realized output	
	Probit: dF/dX	Tobit	Probit: dF/dX	Tobit
	Model 3	Model 3	Model 3	Model 3
$ltvs_{it}^{AQ4} - E_{t-1}[ltvs_{it}]$	0.098***	0.044***	0.090***	0.038***
	[4.46]	[5.58]	[3.95]	[4.71]
$E_t[ltvs_{it+1}] - E_{t-1}[ltvs_{it}]$	-0.012	-0.022		
	[-0.13]	[-0.63]		
$gtvs_{t+1} := ltvs_{it+1} - ltvs_{it}$			0.121***	0.051***
			[3.38]	[4.04]
σ_i	0.152**	0.088***	0.166**	0.094***
	[2.17]	[3.62]	[2.26]	[3.74]
$ltvs_{it}^{AQ4}$	0.016**	0.004	0.015*	0.004
	[2.13]	[1.52]	[1.89]	[1.61]
$gtvs_t := ltvs_{it} - ltvs_{it-1}$	0.145*	0.070**	0.137***	0.051***
	[1.67]	[2.21]	[3.23]	[3.43]
$gtvs_{t-1} := ltvs_{it-1} - ltvs_{it-2}$	0.091**	0.041***	0.101***	0.043***
	[2.41]	[3.06]	[2.85]	[3.48]
D=1 for plants born pre 1975	-0.093***	-0.041***	-0.093***	-0.040***
	[-5.92]	[-7.27]	[-5.67]	[-6.93]
D=1: Survey Year 1999	0.029*	0.011**	0.033**	0.014***
	[1.91]	[2.14]	[2.16]	[2.60]
3-digit SIC dummies	Yes	Yes	Yes	Yes
Observations	4909	4909	4617	4617

[ ]: Robust z statistics (based on robust standard errors for Probit case)
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 5. Specification with wage and other variables: Model 3

	(1)	(2)	(3)	(4)	(5)	(6)
	Probit			Tobit		
$d_{it}^{Q4} := ltvs_{it}^{AQ4} - E_t[ltvs_{it+1}]$	0.095***	0.095***	0.073***	0.036***	0.029***	0.032***
	[3.59]	[3.59]	[2.58]	[4.17]	[3.36]	[3.78]
σ_i	0.140*	0.140*	0.117	0.077***	0.081***	0.070***
	[1.68]	[1.68]	[1.30]	[2.96]	[3.13]	[2.68]
$ltvs_{it}^{AQ4}$	0.042***	0.060***	0.052***	0.014***	0.021***	0.018***
	[4.50]	[4.62]	[4.02]	[4.40]	[7.92]	[6.50]
$gtvs_t := ltvs_{it} - ltvs_{it-1}$	0.218***	0.209***	0.205***	0.081***	0.083***	0.080***
	[4.73]	[3.89]	[3.83]	[5.36]	[5.41]	[5.23]
$gtvs_{t-1} := ltvs_{it-1} - ltvs_{it-2}$	0.077*	0.083*	0.082*	0.034**	0.036***	0.036***
	[1.85]	[1.91]	[1.86]	[2.55]	[2.61]	[2.69]
D=1 for plants born pre 1975	-0.084***	-0.087***	-0.087***	-0.035***	-0.039***	-0.038***
	[-4.53]	[-3.76]	[-3.81]	[-5.71]	[-6.45]	[-6.35]
D=1: Survey Year 1999	0.034*	0.038**	0.036**	0.011*	0.012**	0.011*
	[1.96]	[2.28]	[2.21]	[1.87]	[2.11]	[1.93]
Ln. straight rate wage rate for perm workers	-0.222***	-0.205***	-0.235***	-0.094***	-0.081***	-0.098***
	[-7.26]	[-4.74]	[-6.35]	[-9.62]	[-8.68]	[-10.20]
Supplemental labor costs per $1 perm wage	-0.220**	-0.254**	-0.251**	-0.083***	-0.104***	-0.098***
	[-2.43]	[-1.99]	[-1.98]	[-2.82]	[-3.53]	[-3.35]
Unionization Rate		-0.361**	-0.154		-0.121***	-0.087**
		[-2.01]	[-0.98]		[-4.21]	[-1.98]
Turnover Rates		-2.161	-1.543		-0.359	-0.087
		[-0.82]	[-0.61]		[-0.67]	[-0.14]
Fourth Quarter Seasonal Factor		0.331	-0.062		0.181**	0.045
		[1.27]	[-0.26]		[2.45]	[0.52]
3-digit SIC dummies	Yes	No	No	Yes	No	No
2-dgit SIC dummies	N/A	No	Yes	N/A	No	Yes
Observations	3716	3716	3716	3716	3716	3716

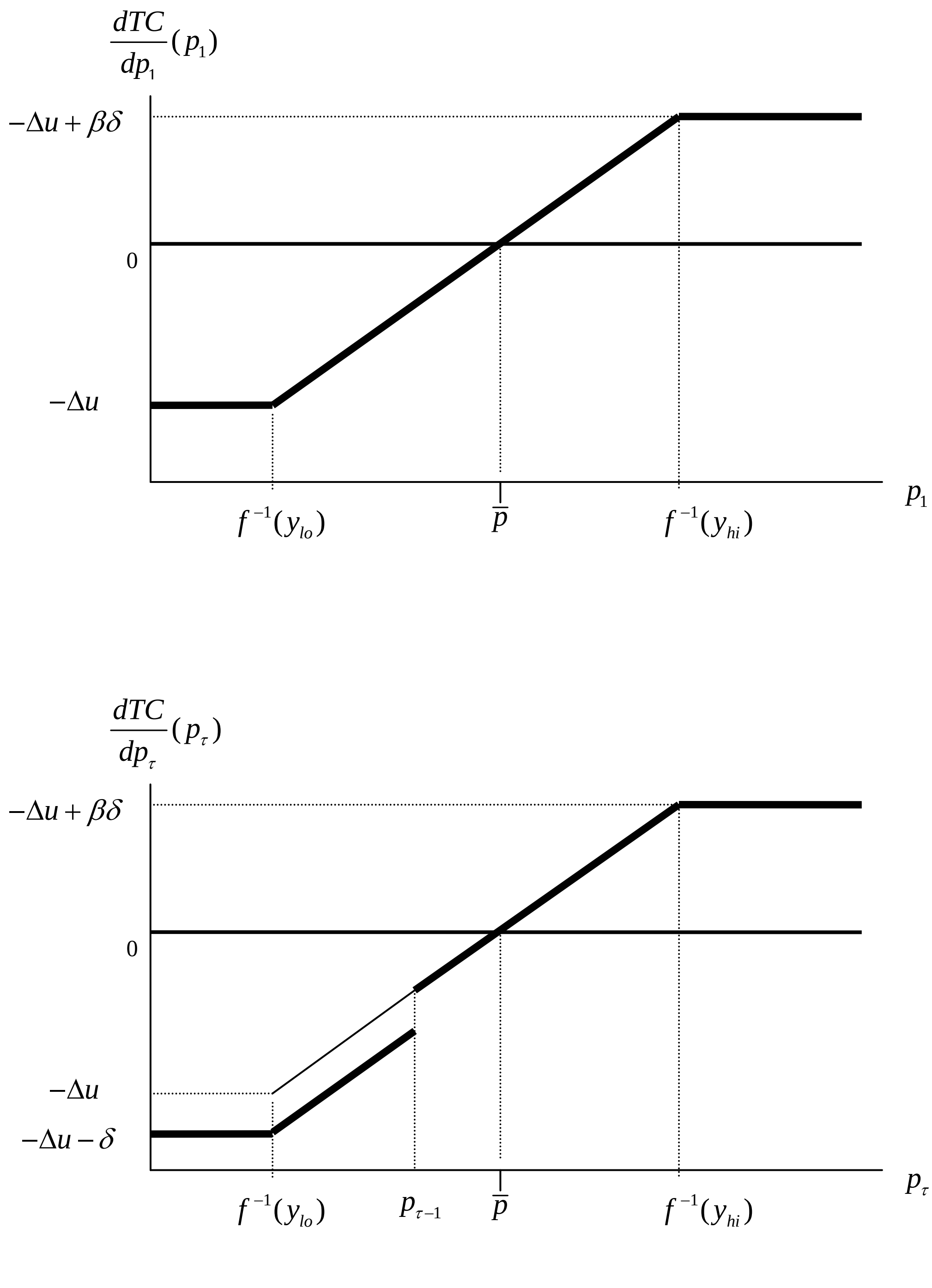
Robust z statistics in brackets: errors are clustered for plants in the same 3-digit SIC for Columns 2, 3, 5, and 6.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 6. Weighted least squares with 3-digit SIC level variables

	Dependent variable: 3digit SIC dummy Coef. from Probit Analysis based on Model 3 in Specification B	Dependent variable: 3digit SIC dummy Coef. from Tobit Analysis based on Model 3 in Specification B
Unionization Rate	-.489**	-.137**
	[-2.52]	[-2.51]
Turnover Rates	1.0646	.375
	[0.29]	[0.38]
Fourth Quarter Seasonal Factor	.792**	.292***
	[2.50]	[3.57]
Constant	.0765	.0319
	[0.64]	[1.02]
R-squared	.1402	.1257
Obs.	116	116

[ ]: t-statistics based on robust standard errors

Figure 1: Determination of the cap on perm workers: Two period and infinite horizon i.i.d. models



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Appendix

A. Our sample based on the PCU data

In the questionnaire, for each shift, plants are asked to report the total number of production workers, temporary production workers, total hours worked by production workers, hours worked by temporary workers, and over time hours (See Item 3 in the questionnaire). 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 instruction of the questionnaire given to the plant. Among plants operating a particular shift, however, many left the information on temporary production workers unfilled, and often, such plants do not provide the 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 instruction for the PCU survey explicitly tells them (with several examples) to write zero when plants operate a given shift but do not use temporary workers. We exclude such plants with missing temporary employment for any of their active shifts (i.e. shifts for which the plant reports positive total number of production workers).

In addition, by definition given in the instruction, when a given shift exists, the total number of production workers should be greater 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 d and σ based on ASM-CM sample as discussed above. Among models we discussed in Section 3, Model 3 put more restriction to our sample. In Model 3, for a plant to be included in estimation, the plant has to appear in consecutive three years at least once in ASM-CM panel. However, plants with only one or two consecutive three year observations typically become outliers in terms of the estimated values for d and σ. Thus we limit our sample to plants that appear in three years consecutively at least three times. We then match these plants with the cleaned PCU sample and use the observations of the plants for which we have the estimates our key variables. Some further outliers are excluded.

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