Measuring Temporary Labor Outsourcing in U.S. Manufacturing

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ABSTRACT

Several analysts claim that firms have been using more flexible work arrangements in order to contain the costly adjustment of labor to changes in economic conditions. In particular, temporary help supply (THS) employment has increased dramatically in the last ten years. However, there is only scant evidence on the industries that are hiring this type of worker. In particular, some anecdotal evidence points to the fact that manufacturing industries have substantially stepped up their demand for THS workers since the mid-1980s. If this is true, not accounting for this flow of workers from the service sector to manufacturing may lead to misleading conclusions about the cyclical and long-term path of manufacturing employment and hours of work. We close this gap by providing several estimates of the number of individuals employed by temporary help supply (THS) firms who worked in the manufacturing sector from 1972 to 1997. One estimate, in particular, is based on a new methodology that uses minimal assumptions to put bounds on the probability that a manufacturing worker is employed by a THS firm. The bounds rely on readily available data on workers' individual characteristics observable in the CPS. We show that manufacturers have been using THS workers more intensively in the 1990s. In addition, the apparent flatness of manufacturing employment in the 1990s can be explained in part by this type of outsourcing from the service sector. Finally, not accounting for THS hours overstated the increase in average annual manufacturing labor productivity by ½ percentage point during the 1991-1997 period.

JEL codes: E2, J2, D2, C14

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1 Introduction

The recent debate on the extent of labor outsourcing by manufacturing firms has been hampered by the absence of good data. In this paper we estimate the number of temporary workers in manufacturing firms that are *not* hired directly by the firm but instead work under contract with firms that are primarily engaged in supplying temporary help to other businesses. More specifically, we estimate the number of "temporary help supply" (THS) workers—employees on the payrolls of service sector firms—working in manufacturing firms. We construct annual estimates from 1972 to 1997 and use them to trace the evolution of this form of labor outsourcing. We also use estimates of the number of THS hours in manufacturing to correct the official measures of manufacturing labor productivity.

The hiring of THS workers is one aspect of the general trend toward flexible, market-mediated, work arrangements by firms. Tasks that formerly were performed by workers hired directly by the firm are now done under contract with firms in the business service sector. Such arrangements include outsourcing of various support services (e.g., computer maintenance, accounting, etc.), subcontracting specific tasks in the production process, and using temporary employees. There are several reasons for the spread of flexible work arrangements: 1) the potential for implementing a two-tier wage structure by contracting with firms that pay lower wages; 2) the possible realization of scale economies due to specialization in the provision of specific tasks; 3) the potentially higher productivity of THS workers relative to directly hired temporary workers due to the better screening and training provided by the THS firms (Polivka, 1996, Autor, 1998); and 4) the ability to adjust the level of employment rapidly in response to temporary and/or uncertain changes in demand (Abraham and Taylor, 1996; Golden, 1996).

The increased use of THS workers is evident in the payroll data published by the Bureau of Labor Statistics (BLS). In the last decade, employment in the temporary help supply industry has more than tripled in the United States.[1] Although employment in the THS industry represented only about 2 percent of total nonfarm employment in 1997, it accounted for 10 percent of the net increase in nonfarm employment between 1991 and 1997. Since 1972, employment in the THS industry has risen at an annual rate of more than 11 percent while total nonfarm employment has expanded only 2 percent (Figure 1).

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[1] The use of temporary workers also grew rapidly in most OECD countries (International Herald Tribune, September 1997).

In addition, THS jobs are highly cyclical. While annual changes in nonfarm employment have fluctuated between -1.8 and +5.1 percent since the 1970s, employment changes in the THS industry have ranged from –25 to +32 percent. Moreover, economists have found THS employment to be a leading indicator of overall employment conditions (Segal and Sullivan, 1995).

The BLS classifies employees by the industry where they are employed rather than the industry where they are working. Thus, most past studies attempting to measure the impact of the THS industry on the performance of other sectors of the economy were necessarily based on very strong assumptions regarding the usage distribution of these workers. Here we address this problem by combining different sources of information on THS workers. In particular, we develop a non-parametric methodology for estimating the number of THS workers by industry. This new methodology also has a more general appeal: Other researchers may use it when trying to identify conditional probabilities from observed marginal probabilities.

The paper is organized as follows. After a brief description of the THS industry we formally define the measurement problem to be tackled in the paper (Section 3). In Section 4, we discuss the different data sources used to analyze recent developments in the THS industry. In Section 5, we estimate a discrete choice model of whether a THS worker is actually working in the manufacturing sector using the Contingent Worker Supplement to the CPS of February 1995 and February 1997--these surveys constitute the only direct evidence on where THS employees actually work. Subsequently, we use the estimated coefficients to compute the proportion of THS workers in that sector in other years using the CPS March tapes. The advantage of this methodology is that it uses well-know statistical methods to get point identification for the parameters under study. The disadvantage is that the parameters of the model are assumed to be constant over time. Given the radical changes in the composition of the pool of workers hired by THS firms in the last decade, this assumption could be incorrect.

To address this last concern we present, in Section 6, a new non-parametric procedure that estimates *bounds* for the proportion of THS workers in an industry at any level of aggregation and in any year. This methodology uses minimal assumptions and exploits the richness of the March CPS tapes and of the Contingent Worker Supplements. It also allows for breaks in the composition of the pool of workers hired by THS firms. This is the main methodological contribution of the paper. In Section 7, we estimate these bounds for the number of THS employees working in the manufacturing sector as a whole during the 1972-1997 period. We find that the bounds are non-trivial and that they trend upward. In addition, the logic behind the estimation of the bounds allows for the calculation of point estimates based on explicit identifying assumptions. We also combine the estimated bounds with information from the input-output tables of 1977, 1982, 1987, and 1992 to generate alternative point estimates for the number of THS workers in the manufacturing sector.

A simple analysis of the reported manufacturing payroll employment data suggests that the expansionary period between 1992 and 1997 generated, on net, only about 550,000 manufacturing jobs. The inclusion of THS workers elevates this figure to as few as 890,000 and as many as 1,060,000 depending on the assumption made to generate point estimates for the proportion of THS workers in manufacturing (Section 8). Manufacturers' are estimated to have employed between 620,000 and 740,000 THS workers in 1997. Moreover, the decline in manufacturing hours between the local peak in 1989 and 1997—about 1-½ percent— disappears once THS workers are taken into account. In fact, depending on the point estimates used, manufacturing hours increased as much as 1-¼ percent between 1989 and 1997. We also show that the year-to-year variation in manufacturing THS employment and hours is of an order of magnitude larger than for manufacturing non-THS employment and hours.

We also discuss the magnitude of the upward bias in manufacturing labor productivity caused by the omission of THS hours from the official payroll statistics (Section 8). After adjusting for THS hours, labor productivity in manufacturing at the end of 1997 was about 3 percent lower than the "reported" level. This correction, while noticeable, explains only a small part of the observed gap in the time trends of labor productivity growth between manufacturing and nonfarm nonmanufacturing industries. Furthermore, because changes in manufacturing THS hours are positively correlated to changes in output, we show that the exclusion of THS hours yields an upward bias in econometric estimates of the elasticity of output with respect to labor input. Brief conclusions close the paper.

2 The Temporary Help Supply Industry

What exactly do firms in the THS industry do? Firms in the THS industry are essentially offering a "business service": they recruit and screen candidates for limited-term jobs and administer their payroll, write the contracts, and assume the legal responsibilities of hiring and firing. However, obviously, the employees are under the direct or general supervision of the business to which the help is furnished.

What types of workers are used? The March demographic files of the Current Population Survey (CPS) shed some light on the characteristics of workers in the SIC 736, the

Personnel Supply Services (PSS) industry, the industry that contains THS firms (SIC 7363). The notion that a "temp" is a woman working part-time in a clerical position, with little job security and lower-than-average wages and benefits, does not seem to be as accurate in the 1990s as it was in the 1970s. Segal and Sullivan (1995, 1997) report an increase in the proportion of men and blue-collar workers at the end of the 1980s and beginning of the 1990s. Estevão and Lach (1999) showed that this trend has continued well into the 1990s.[2] Segal and Sullivan also reported that PSS workers are less attached to the labor force than other workers are.[3] Yet, a large fraction of them shift into permanent jobs within a year. Finally, PSS workers earn lower wages than workers with similar demographic and educational characteristics do. This wage differential varies widely by occupational group, being largest for blue-collar workers and almost non-existent for managerial and professional workers.[4]

3 The Basic Measurement Problem

Because THS employees are hired and paid by the THS firm, they are not in the payroll of the firm actually *using* their labor. As a consequence, THS workers are *not* included in the employment measures generated by the BLS in its establishment-based surveys. To define this problem more formally, let $y_t = 1$ denote the event that an individual is a THS worker in period t. Hereafter the time subscript is omitted for notational convenience. The parameter of interest is the proportion of workers in industry i (e.g., in manufacturing) that are THS employees, that is, the probability that an individual working in industry i is a THS worker, $\theta_i \equiv P(y=1|i)$.

Our approach to estimating θ is quite simple. Note that this conditional probability can be written as

$$\theta_i \equiv P(y=1|i) = P(i \mid y=1)\frac{P(y=1)}{P(i)} \tag{1}$$

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[2] In 1988, men made up 25 percent of all workers in the PSS industry, but in 1997 they reached 37 percent. The fraction of PSS employees working in blue-collar occupations grew from about 10 percent in 1979 to about 25 percent in 1997.

[3] PSS workers are more than twice as likely to be out of the labor force one year later than other permanent workers, and are also much more likely to be unemployed one year later.

[4] However, the average wage *change* of those workers who remain temporaries does not differ significantly from that of workers who remain permanent employees.

In order to estimate θ we need to estimate $P(y=1)$, $P(i)$, and $P(i|y=1)$. The first two probabilities are readily estimated from available data in every year by the observed proportions of THS and industry *i* workers. The last probability, however, is problematic because there is no information on the distribution of THS workers by industry of use on a *systematic* basis. We call $P(i|y=1)$ the *assignment probability*. Nevertheless, under certain assumptions, estimates of the assignment probability can be extracted from selected data sources for particular years.

Note that the number of workers in industry *i*—the denominator in the estimate of θ_i—should be the *true* number of workers, that is, the reported number plus the THS employees working in the industry. Under these considerations, the probability of finding a THS worker in industry *i* is estimated by

$$\hat{\theta}_i = \hat{P}(y=1/i) = \frac{\overbrace{\hat{P}(i/y=1)N_{y=1}}^{N_{y=1,i}}}{N_{y=0,i} + \underbrace{\hat{P}(i/y=1)N_{y=1}}_{N_{y=1,i}}} \tag{2}$$

$\hat{P}(i \mid y=1)$ is some estimate of the assignment probability—the probability that a THS worker works in industry *i*—and $N_{y=1}$ and $N_{y=0,i}$ are the observed number of THS and industry *i* workers, respectively. The numerator in (2) is the number of THS workers in industry *i* while the denominator is the total number of workers in industry *i* including THS workers.[5]

4 Data Sources on the THS Industry

Several data sets provide direct or indirect information on the assignment probability of THS workers. Table 1 summarizes the available data sources on the temporary help supply industry. The National Association of Temporary and Staffing Services (NATSS) collects data on THS employment that is consistent with the methodology employed by the Bureau of Labor Statistics (BLS) in its Current Employment Survey (CES), an establishment-based survey. The BLS provides information on the number of workers and hours on the payroll of firms belonging

[5] We use the average number of employees and hours in manufacturing and THS payroll data for each year even though some estimates of $P(i|y=1)$ use only information for a particular month of the year. The results presented in this paper do not change qualitatively if we use monthly information for employment and hours whenever the estimate for $P(i|y=1)$ is based on monthly information. We will also be interested in the proportion of manufacturing *hours* worked by THS workers. To do this, we let the *Ns* in equation (2) be the

to SIC 7363—Help Supply Services. This is a slightly broader category than purely THS firms, but the residual category that explains the difference between the NATSS series for THS employment and the CES series of employment in SIC 7363 is of trivial size (Figure 2).[6] Anyway, the number of THS workers (hours), $N_{y=1}$, appearing in equation (2) is from the NATSS.[7] The number of manufacturing workers (hours), $N_{y=0,\,i}$, appearing in equation (2) is from the CES.

The Current Population Survey (CPS) is a household-based survey providing information on households' and individuals' characteristics. It assigns each individual to an industry of employment, broadly equivalent to a 3-digit SIC industry. The CPS, therefore, does not identify individuals working in the Temporary Help Supply industry, but in the 3-digit industry SIC 736 that contains THS, i.e., the Personnel Supply Services (PSS) industry. However, non-THS establishments within the PSS industry do not provide workers in their payroll to manufacturers since they act mostly as "matchmakers". Therefore, it is safe to say that the flow of PSS hours to manufacturing is about equal to the flow of THS hours.[8]

The Contingent Worker Supplements to the CPS—surveyed in February 1995 and February 1997--are another source of data on the THS industry. In these supplements, respondents are asked directly if they are paid by a Temporary Help Supply agency. Furthermore, the supplement also records their industry of assignment. Thus, these surveys constitute the only *direct* evidence on the distribution of THS workers by industry of use.

Finally, input-output tables provide, under certain assumptions, estimates of the distribution of PSS workers and hours among different industries. When wages of PSS workers and other fees are independent of their industry of assignment, the proportion of the PSS

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number of hours of the different groups and $P(i|y=1)$ to be the proportion of hours of THS work assigned to industry i.

[6] Prior to the 1987 revision of the Standard Industrial Classification (SIC) scheme, THS firms were classified as SIC 7362 and were part of SIC 736 which also included Employment Agencies (7361) and a residual category. The 1987 revision combined the THS firms and the residual category (excluding facilities and continuing maintenance services) into a single category named "Help Supply Services" classified as SIC 7363.

[7] When calculating the proportion of THS *hours* in manufacturing, we multiply NATSS employment data by average weekly hours for SIC 7363 from the BLS-CES database. Average weekly hours for SIC 7363 are available only after 1982. Therefore, we do not have estimates of the flow of THS hours to manufacturing during 1972-1981.

[8] Non-THS establishments (SIC 7361) within the PSS industry are: chauffeur registries, maid registries, model registries, nurses' registries, ship crew registries, teachers' registries and employment agencies. The share of non-THS establishments in total PSS employment was less than 10 percent in 1997 and, as shown in the lower chart of Figure 2, non-THS employment does not contribute much to variations in PSS employment.

industry's output that goes to manufacturing— the input–output coefficient— estimates the proportion of PSS hours used by the manufacturing sector.[9] Input-output tables with the relevant information on the PSS industry are available for 1977, 1982, 1987 and 1992.

These four data sets generate snapshots of the THS industry from essentially independent sources (e.g., from individuals and from establishments). In the next sections we will extract whatever information they provide on the use of THS workers in manufacturing firms. Using methodologies tailored to each data set, we find that the information gained from them is fundamentally the same: the use of THS workers by manufacturing picked up considerably in the early 1990s.

5 Estimating *P(i|y=1)* using the Contingent Worker Supplement to the CPS

Our first set of estimates is derived from a simple and straightforward use of data from the Contingent Worker Supplement to the CPS of February 1995 and February 1997 to estimate the assignment probability, $P(i|y=1)$. Given the assignment probability, we estimate θ for manufacturing and elsewhere (Table 2) using equation (2). The probability of finding a THS worker in manufacturing in 1995 and in 1997 was about 3.7 percent. The probability of finding an hour of THS work in the manufacturing sector was about 3.0 percent in 1995 and a bit more in 1997.

Using the available data on THS workers' characteristics and information on where they are actually working we can estimate the determinants of the assignment probability, $P(i|y=1)$. We then use the estimated coefficients for the years 1995 and 1997 to predict $P(i|y=1)$ for the

[9] The output of the PSS sector can be written as $Y = w_m H_m N_m + w_r H_r N_r$, where the subscript *i* indicates the industry of assignment (*m* = manufacturing and *r* = non-manufacturing), w_i = hourly wage plus hourly overhead fees, H_i =average hours of work and N_i =number of workers assigned to industry *i*. If $w_m = w_r = w$, then the proportion of PSS output going to manufacturing (the input-output coefficient) is the share of total hours of work going to manufacturing. We do not have information on the evolution of the gap between w_m and w_r but assuming that it can be approximated by the gap between manufacturing average hourly earnings and average hourly earnings in other nonfarm industries, the input-output coefficient would overestimate α_m a bit: Manufacturing average hourly earnings in 1982 and 1987 was about 10 percent larger than elsewhere. In 1992, the gap declined to about 9 percent. If $H_m = H_r = H$, then the input-output coefficient is also the employment share directed to manufacturing.

whole sample period based on available data on the characteristics of PSS workers from the March tapes of the CPS.[10]

Table 3 reports the result of a logit regression where the (assignment) probability that a THS employee works in manufacturing depends on her occupation, educational level, race, gender, age, part-time status, region of residence and whether she lives in a metropolitan area. In order to increase the sample size, the estimation procedure pools the 1995 and 1997 data, and includes a dummy variable for 1997.

The base group for the independent variables consists of young blue-collar non-white female individuals with no high school education living in the West and working full-time. The simple logit estimates show that well educated blue-collar THS workers have a higher probability of working in manufacturing. In addition, the probability of working in manufacturing increases for THS workers between 35 and 50 years of age, for those living in the Midwest and for those living outside metropolitan areas. Finally, the probability of being a THS worker in manufacturing declines if the individual works part-time.

The coefficient estimates reported in Table 3 are used to forecast the probability that a THS employee works in manufacturing using data on PSS workers' characteristics from the March CPS tapes in each year between 1972 and 1997. The estimate of $P(i|y=1)$ is the weighted average of the individual predicted probabilities using CPS population weights.[11] We plug the estimates of $P(i|y=1)$ into equation (2) to generate the predicted $\hat{\theta}_i = \hat{P}(y=1|i)$ in every year. Figure 3 shows the predicted proportions of employees and hours of THS workers in manufacturing. The dots in the graph are the observed proportion of THS workers and hours in manufacturing based on the sample analog of the assignment probability in the Supplement (from Table 2).

Clearly, the series exhibits an upward trend. However, even though the results of this forecasting exercise seem plausible, there are at least two potential reasons why they may not be all that reliable. First, our placement of THS workers into manufacturing depends critically on the worker characteristics we included in the regressions. Second, even if we knew the correct regressors—and have data on them—we still need to make the crucial assumption that the parameters remain unchanged over time. And this may be a strong assumption in view of the

[10] Recall that the CPS does not identify workers in SIC 7363, only in SIC 736 (PSS). However, as discussed before, most PSS workers are THS workers (Figure 2).
[11] The assignment probability for hours is estimated by multiplying the population weights by the average number of hours worked by the individual during the week before the survey was conducted.

dramatic changes experienced by the THS industry at the beginning of this decade. In the next section we present an alternative, and complementary, approach that overcomes these problems.

6 Bounds on the Assignment Probability

6.1 The basic method

The methodological contribution of this paper is to develop a procedure that estimates a time series for the number of THS workers by industry of use. The procedure is non-parametric and can be readily applied to any year for which data on characteristics of THS individuals are available. In principle, it can also be applied to any level of aggregation even though in this paper we limit ourselves to the manufacturing sector. Furthermore, the methodology developed here applies to the more general problem of identifying conditional probabilities from observed marginal probabilities.[12]

To recollect, we want to estimate $\theta_i \equiv P(y=1|i)$ using (2) but do not have data that identifies this conditional probability because the assignment probability $P(i|y=1)$ is usually unobserved. A naïve way to proceed is to assume that THS status and industry affiliation are independent. In this case θ_i does not vary across industries and the estimator of θ_i is the proportion of THS workers in the whole economy, $\hat{\theta}_i \equiv \hat{P}(y=1)$.

Clearly, independence is too strict an assumption to make. But it can be relaxed a bit. Given a vector X of discrete variables such as education, location, occupation, gender, etc., the assignment probability can be written as

(3) $$P(i \mid y=1) = \sum_x P(i \mid y=1, x) P(x \mid y=1)$$

where the sum is over all possible values of X. Plugging (3) into (1) we obtain

(4) $$\theta_i \equiv P(y=1/i) = \sum_x P(i / y=1, x) P(x \mid y=1) \frac{P(y=1)}{P(i)}$$

[12] In this sense, our methodology is closely related to the discussion in Manski (1995).

In order to estimate θ_i we need to estimate all the components appearing on the right hand side of (3) or (4). Recall that $P(y=1)$ and $P(i)$ are estimated from NATSS and CES data, while the CPS provides estimates of the distribution of characteristics among *TH*S (actually PSS) workers, $P(x|y=1)$. The problematic term is, of course, $P(i \mid y=1, x)$, the probability of working in industry i conditional on the individual being a THS worker and on having $X = x$, which, in general, is not identified from the data. Assigning, say, all blue-collar THS workers to manufacturing, as in Segal and Sullivan (1995), overcomes this problem because identification of θ is obtained by assuming $P(i|y=1, x=\textit{blue collar}) = 1$ and $P(i|y=1, x=\textit{other occupation}) = 0$ so that (4) equals $\dfrac{P(y=1, x=bluecollar)}{P(i)}$ which is straightforward to compute.

If we now assume that y and industry affiliation i are independent *conditional on x* (e.g., the probability of working in manufacturing among, say, all females electrical engineers in Louisiana is the same irrespective of their THS status), then θ_i simplifies to

(4')
$$\theta_i = \sum_x P(i \mid x) P(x \mid y=1) \frac{P(y=1)}{P(i)}.$$

The parameter described in (4') can be estimated consistently by the sample proportions corresponding to the probabilities in the right hand side of (4'). The estimated θ varies across industries only because of differences in the distribution of characteristics, $P(x|i)$, across them.[13] Equation (4') reflects what is perhaps the most intuitive way of tackling the problem: estimate the distribution of some characteristic X among THS workers, $P(x|y=1)$, and then combine it with, the distribution of such characteristic in industry i, $P(i|x)$.

We will show here that in order to learn something about the time series behavior of $P(i \mid y=1, x)$,or θ_i, we do not need to resort to drastic independence assumptions. In fact, we will show how to bound these probabilities in a non-trivial manner without making further assumptions on the relationship between industry affiliation and THS status.

We start by noting that for any value x of X, the conditional assignment probability can be written as,

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[13] Note that $\dfrac{P(i \mid x)}{P(i)} = \dfrac{P(x \mid i)}{P(x)}$.

(5) $$P(i \mid y=1, x) = \frac{P(i, y=1 \mid x)}{P(y=1 \mid x)}.$$

We first provide bounds for the numerator of (5). Conditional on *X = x*, the probability of the joint event "the individual works in industry i" and "*y = 1*" is lower than the marginal probability of each single event, i.e.,

$$P(i, y=1 \mid X = x) \le Min\{P(i \mid X = x), P(y=1 \mid X = x)\}$$

which, from (5), implies the following upper bound for the conditional assignment probability

(6) $$P(i \mid y=1, x) \le Min\left\{\frac{P(i \mid x)}{P(y=1 \mid x)}, 1\right\}$$

In addition, $P(i \cup y=1 \mid x) = P(i \mid x) + P(y=1 \mid x) - P(i, y=1 \mid x) \le 1$ implies,

$$P(i, y=1 \mid x) \ge Max\{0, P(y=1 \mid x) + P(i \mid x) - 1\}.$$

so that this inequality implies the following lower bound for the conditional assignment probability

(7) $$P(i \mid y=1, x) \ge Max\left\{0, \frac{P(y=1 \mid x) + P(i \mid x) - 1}{P(y=1 \mid x)}\right\}$$

These bounds, together with (4), prove the following proposition,

Proposition 1:

$$\sum_x \alpha_l(x) P(x \mid y=1) \frac{P(y=1)}{P(i)} \le \theta_i \le \sum_x \alpha_u(x) P(x \mid y=1) \frac{P(y=1)}{P(i)}$$

where $\alpha_l(x) = Max\left\{0, \frac{P(y=1|x)+P(i|x)-1}{P(y=1|x)}\right\}$ and $\alpha_u(x) = \text{Min}\left\{\frac{P(i|x)}{P(y=1|x)}, 1\right\}$ and the sum is over all possible values of X.

It should be emphasized that the intervals generated by these bounds are not confidence intervals in the statistical sense. Rather, the interval covers the true parameter θ with probability one.

The $\alpha(x)s$ are the bounds on the assignment probabilities. Are these bounds informative? The answer depends on the choice of the conditioning vector *X*. For a given value $X = x$, the lower bound on the (conditional) assignment probability is strictly positive when

(*Condition L*) $\qquad P(y=1|x)+P(i|x)>1$

while the upper bound is strictly less than one when

(Condition U) $\qquad P(y=1|x) > P(i|x)$

These conditions are more likely to be satisfied the larger $P(y=1|x)$ is. In fact, when these two conditions are satisfied the lower and upper bounds for the conditional assignment probabilities at that given value of *X* are

$$\left[\frac{P(i|x)-[1-P(y=1|x)]}{P(y=1|x)}\right] \text{ and } \frac{P(i|x)}{P(y=1|x)}$$

respectively. Note that the distance between the bounds decreases with $P(y=1|x)$, so that the closer $P(y=1|x)$ gets to one, the tighter the interval containing the assignment probability.

The intuition behind the requirement that $P(y=1|x)$ be large is that *X* is a "good" discriminant (or classifier) between *THS* and non-*THS* status in the sense that given $X = x$ there is a "high" probability that the individual is a *THS* worker. At the limit, when $P(y=1|x)=1$ all individuals with $X=x$ are THS workers so that, conditional on $X=x$, the proportion of THS workers assigned to industry *i* equals the porportion of individuals with $X=x$ assigned to industry *i*. That is, $P(i|y=1,x)=P(i|x)$ when $P(y=1|x)=1$. In the preceding expression, the interval between the upper and lower bounds of the conditional assignment probability collapses to the point $P(i \mid x)$. Thus, when $P(y=1 \mid x)=1$ the data identify the conditional assignment probability at that particular value of *X*.[14]

There is, of course, no guarantee that such an *X* exists. In fact, it is hard to think of individual characteristics that perfectly discriminate among THS and non-THS workers. In the usual case, when such an *X* does not exist, we can still extract some information on the assignment probability $P(i \mid y=1, x)$ and, therefore, on θ_i without resorting to additional assumptions. This information is in the form of bounds on $P(i \mid y=1)$ which in turn induce bounds on θ_i. This is a clear example of the tradeoff between the strength of the assumptions we make on the processes generating the observed data and the nature of the information on θ that can be extracted from them: a point estimate versus an interval estimate.

What is the advantage of using a vector-valued *X* as opposed to, say, using each component of the *X* vector sequentially? More precisely, how sensitive is the width of the interval containing θ to the manner in which the information in the data is processed? Assuming that conditions analogous to *L* and *U* are satisfied for the vector and for each component individually, the width of the interval depends upon how close $P(y=1|x)$ is to one for the values of *X*. Intuitively, the more information is contained in *X*, the better one can predict the *THS* status of the individual. Thus, one would expect $P(y=1|X)$ to be higher when *X* is a vector than when it is a scalar.

What Proposition 1 is telling us is that we can choose any *X* (a scalar or a vector of any dimension, with as many discrete values as one wishes) and construct the bounds according to the formula in Proposition 1. In principle, one could systematically search the entire database for all combinations of conditioning variables, compute the bounds and associated intervals containing θ_i for each such vector and then take as the final interval for θ_i the intersection of all such intervals.

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[14] For example, suppose *X* represents location, and let THS City be one such location. If it is known that *all* individuals in THS City are THS workers then, among all THS City individuals, conditioning on the individual's THS status *and* location is the same as conditioning only on the individual's location. In other words, knowing that the individual lives in THS City is sufficient to guarantee that the individual is a THS worker, i.e., $P(y=1|\text{THS } City)=1$. This implies $P(i|y=1, \text{THS } City) = P(i|\text{ THS } City)$.

6.2 Further issues on estimation

Before estimating the bounds described in proposition 1, we need to deal with three issues. First, consistent estimation of the bounds requires that sample proportions be consistent estimators of the corresponding probabilities appearing in the bounds. This is possible when individuals in each cell defined by the values of X have the same underlying probabilistic model of choice. In other words, X should capture as much as possible of the heterogeneity across individuals when making their decision to be a THS worker. Thus there are good reasons for *jointly* conditioning on all available information.

A statistical reason, however, for *not* using a large vector X is that the cells defined by it will, almost certainly, have a lower number of observations than those defined by, let us say, a scalar X. Thus, there is a possible tradeoff between the *precision* of the estimated probabilities and the *bias* that results from not controlling for potential heterogeneity across individuals. The balance between precision and bias in the estimation procedure is an empirical issue to be decided on a case by case basis.

The second issue is more fundamental. The bounds suggested in proposition 1 are supposed to be estimated from CPS data by their empirical analogs —the proportion of individuals with $X = x$ that are a THS worker (actually PSS), and the proportion of individuals working in industry i. The latter proportion, however, underestimates $P(i|x) = P(i, y=0|x) + P(i, y=1|x)$ because we do not observe the number of THS workers in i; the data can identify only $P(i, y = 0|x)$. In order to correct for this "omission bias" we need to know the assignment probability, which is precisely what we wish to estimate.[15] Not correcting for this bias underestimates both bounds on the assignment probability. We used an iterative approach to estimate the bounds that takes into consideration the omission bias explicitly. The final results, however, were nearly identical to estimates obtained assuming the absence of such bias.[16]

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[15] $P(i|x) = P(i, y=0|x) + P(i, y=1|x) = P(i, y=0|x) + P(i|y=1, x)P(y=1|x)$.

[16] At the initial stage the bounds for the assignment probability were estimated using the sample proportions, $\frac{N_{i,y=0,x}}{N_x}$, to estimate $P(i|x)$ for each x. Then the bounds for the assignment probability, $\alpha_l^{(1)}$ and $\alpha_u^{(1)}$, were calculated using Proposition 3. We then used the mid-point of the estimated interval at each realization of X, $\bar{\alpha}^{(1)}(x) = \frac{\hat{\alpha}_u^{(1)}(x) - \hat{\alpha}_l^{(1)}(x)}{2}$ to reestimate $P(i|x)$ using $\frac{N_{i,y=0,x}}{N_x} + \bar{\alpha}^{(1)}(x)\frac{N_{y=1,x}}{N_x}$ and derived new bounds for the assignment probability, $\alpha_l^{(2)}$ and $\alpha_u^{(2)}$, according to Proposition 3. If the mid-point of the new bounds was significantly different from its previous value we recalculated $P(i|x)$ for all

The third issue arises when individuals actually employed by a THS agency report industry *i* as their employer, i.e. they misreport. Then the count of THS individuals underestimates the true number of THS workers and, consequently, the sample proportion of THS workers is a downward biased estimate of $P(y=1|x)$. This source of bias, however, can be corrected.

Specifically, among all individuals in the CPS with $y = 0$, some of them probably are THS workers that did not answer the question correctly because of some confusion about who was their actual employer: The industry that uses their labor (e.g., manufacturing) or the industry that paid their wages (the PSS industry). On the other hand, it is reasonable to assume that those individuals answering $y = 1$ (PSS individuals) do not make any mistakes. Let y^* represent the *true* PSS status. The (observed, true) possibilities are illustrated in the following table:

Observed state y	*True state* y^*
1	1
0	1
0	0

The event {y = 0, y^* = 1} is interpreted as "misreporting" and $P(y^* = 1 | y = 0)$ is the probability of misreporting. The event {y = 1, y^* = 0} does not appear in the table because we assume that those individuals reporting PSS are not making a mistake; hence the probability of this event is zero.

Calculation of the bounds requires estimates of $P(y^* = 1|x)$ and $P(x| y^* = 1)$.[17] Note that the event $\{y^* = 1\} = \{y^* = 1, y = 1\} \cup \{y^* = 1, y = 0\}$, and that these two events are mutually exclusive. Therefore $P(y^* = 1)$ equals the sum of the probability of each event,

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realizations of X and obtained new bounds on the assignment probability. This process was iterated until the discrepancy between the mid-point of the new bound and the previous one was negligible.

[17] Recall that $P(y = 1)$ is estimated from CES (payroll) data so it is not biased by misreporting.

$$P(y^* = 1 \mid x) = P(y^* = 1, y = 1 \mid x) + P(y^* = 1, y = 0 \mid x)$$

(12)

$$= \underbrace{P(y = 1 \mid x)}_{\text{observed}} + \underbrace{P(y^* = 1 \mid y = 0, x)}_{\text{misreporting rate}} P(y = 0 \mid x)$$

using the assumption that individuals reporting THS status are indeed THS workers (i.e., do *not* make a mistake) so that $P(y^* = 1 \mid y = 1, x) = 1$. That is, conditional on $X = x$, the true proportion of THS workers equals the observed proportion of THS workers plus a percentage (probability of misreporting) of the observed proportion of non-THS.

The second estimated proportion affected by misreporting, $P(x \mid y^* = 1)$, can be rewritten as

$$P(x \mid y^* = 1) = P(y^* = 1 \mid x) \frac{P(x)}{P(y^* = 1)} \tag{13}$$

where $P(y^* = 1) = \sum_x P(y^* = 1 \mid x) P(x)$.

In order to deal with this problem, we need an estimate of the probability of misreporting, i.e., the probability that an individual reporting non-THS status is in fact a THS worker, $P(y^* = 1 \mid y = 0, x)$. Fortunately, this probability can be estimated from the Contingent Worker Supplements to the CPS of February 1995 and February 1997. The supplement asks each worker in the main CPS whether he was hired by a temporary help supply firm or not. By comparing the worker's answers in the supplement to the answers in the main CPS, we can estimate $P(y^* = 1 \mid y = 0, x)$.

Assuming that the probability of misreporting in every year is equal to the average of the misreporting probability in 1995 and in 1997, the observed probability of being a THS can be adjusted every year according to the last expression in (12). Having estimated $P(y^* = 1|x)$ for every value of X, we average them using CPS population weights to estimate $P(y^* = 1)$ and, using (13), $P(x| y^* = 1)$.

Note that the probability of misreporting is conditional on $X=x$. To the extent that the mix of characteristics varies across years, we may get significant variation in the degree of misreporting in each year. Figure 4 plots the total number of PSS workers (SIC 736) in the

March CPS tapes from 1972 to 1997 with and without the correction for misreporting. The adjustment for misreporting increases the level of PSS employment in the CPS by about 40 percent, on average. However, it does not explain the discrepancy between the reported levels of employment in the CPS and the reported levels of employment in the CES—a payroll survey that better captures the level of employment in the PSS industry.[18] We assume that this discrepancy does not bias our estimates of the assignment probability.[19]

7 Estimates of Manufacturers' Use of THS Workers

We estimated the bounds for the proportion of THS workers (and hours) in manufacturing using data from the March CPS tapes for the 1972-1997 period.[20]

After some experimentation with different conditioning variables we decided on a conditioning vector that includes occupation (2-digit), state of residence, educational achievement, gender, age and a dummy variable for whether the individual works part-time or not.[21] In general, the unconditional probabilities appearing in Proposition 3 are estimated from large samples, while probabilities conditional on X are generally based on samples with a small number of observations. For this reason, we computed asymptotic confidence intervals around the bounds. The formal derivation of the confidence intervals can be found in the Appendix. In order to guarantee the feasibility of the computation of the confidence intervals, we did not use the cells—realizations of the vector X—in which there was only one observation (individual). This left us with 8,000-13,000 cells, depending on the year.

[18] Besides misreporting, another reason for such difference may be that the CPS is constructed from a monthly survey of individuals asked about their *primary* jobs while the establishment survey records number of jobs. This could potentially explain some of the difference since many PSS workers hold more than one job.

[19] This is a good assumption if the reasons for the discrepancy between the two measures of PSS employment are unrelated to the industry of assignment

[20] The universe is defined as employed workers who, at the time of the survey, are not self-employed and do not work in farms, fishing or forestry. Each individual observation is weighted by its sample population weight.

[21] Excluding any of these variables makes the bounds slightly wider and including of extra variables affects the bounds just marginally. The variables that contributed most to the narrowing of the distance between both bounds were, in order of importance, occupation, educational achievement and state of residence. We avoided using more finely defined variables, such as occupation at the 3-digit level of aggregation, because this reduces considerably the number of observations in some cells. We also experimented with coarser breakdowns of the occupation and education variables—12 and 5 categories in 1985, respectively—while keeping the remaining variables untouched. As expected, the bounds tend to be tighter once finer breakdowns of each variable are allowed.

Note also that, unlike the logit estimates discussed earlier, $P(y=1|i, X=1)$ is estimated independently for every year. Therefore, the underlying function relating individual characteristics to the probabilities of assignment is allowed to change over time, as suggested by the description of the THS industry in Section 2.[22]

7.1 Bounds

Table 4 shows the estimated bounds, and the mid-point of the interval for θ. A number of interesting points are worth emphasizing. First, the bounds are quite informative.

Second, both bounds exhibit an upward trend over time as would have been expected from the anecdotal evidence on the increasing use of temporary help supply arrangements discussed in the introductory section. While in the first years of our sample the lower bound for the probability of finding a THS worker (or an hour of THS work) in manufacturing was negligibly different from zero, after the late 1980s the lower bound gets close to ¾ percent. The upper bound also presents a clear upward trend, going from about ½ percent in the first half of the 1970s to about 4-¾ percent, on average, in the last three years of our sample. In fact, the average lower bound for θ in the 1995-97 period is larger than the upper bound at the end of the 1970s strongly suggesting a regime shift in manufacturers' hiring patterns in the 1980s and 1990s. This trend can be seen more clearly in Figure 5 where the bounds and the midpoint of the interval between the lower and upper bounds are plotted. Asymptotic 95 percent confidence intervals are shown to be quite tight and cannot even be noticed in the lower panel of Figure 5.

Third, the bounds exhibit a cyclical pattern that is consistent with the idea that manufacturers use this form of employment as an adjustment margin for sudden economic shocks. For instance, as a response to the economic slowdown at the end of the 1980s and beginning of the 1990s the use of THS workers decreased significantly. Subsequently, in 1992 manufacturers hired a large number of THS workers while leaving payroll employment relatively flat. We observe the same pattern during the recession at the beginning of the 1980s. The use of THS workers dropped during the 1980-82 recession and rebounded during the subsequent recovery. Finally, note that the direct estimates of θ derived from the assignment probabilities in

[22] We also present equivalent results for the proportion of PSS hours in manufacturing hours. The methodology is identical to the one described below. The basic difference is that each observation used to build the theoretical bounds is weighted by the average hours the individual worked the week before the survey was taken. So, $P(y=1|i)$ should be interpreted as the probability of finding one hour of PSS work in the manufacturing sector.

the Contingent Worker Supplements (Table 2) are indeed contained in the interval created by the estimated bounds.

7.2 Point estimates

The reported bounds give us already a substantial amount of information: θ_i seems to have increased over time, and THS hiring and firing by manufacturing firms seems to be cyclical. However, we can also use the framework presented here to generate point estimates for θ_i. In addition, the bounds derived in the previous subsection can be used to evaluate the plausibility of independent point estimates. Furthermore, in the absence of any further information, the mid-point between the bounds can be a reasonable choice for a point estimate.[23]

A second point estimate may be derived from the identifying assumption that $P(y=1|x,i)=P(y=1|x)$, i.e., the events "being a PSS worker" and "working in manufacturing" are independent once we control for a vector of worker characteristics (as per equation (4')). We call this estimator the "conditional independence" estimator. Figure 6 reports estimates of θ under this assumption. These estimates mimic the behavior of the mid-point estimates pretty well, except that they are shifted downward. As mentioned before, their movements over time are consistent with the hypothesis that manufacturers have been using THS workers as an adjustment margin to economic shocks.

A third point estimate is obtained by making the identifying assumption that a particular realization of *X* is sufficient to perfectly discriminate among the industries of assignment. As mentioned in Section 6, assuming that all blue-collar THS workers are employed by manufacturers, ($P(i|y=1,x=\textit{blue collar}) = 1$, and that other type of THS workers are not

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[23] We can offer two justifications for using the midpoint of the interval as a point estimate of θ. First, the midpoint $\frac{\theta_U+\theta_L}{2}=\theta_L+\frac{\theta_U-\theta_L}{2}$ is the value of θ that minimizes the maximal error; i.e., it satisfies a min-max criterion. More precisely, if we choose any point *x* in the interval, the maximal error is $Max\{x-\theta_L,\theta_U-x\}$. The value of *x* that minimizes this maximal error is the midpoint. In addition, suppose $\hat{\theta}$ is an unbiased estimator of θ (such as the one obtained from the 1995 CPS February Supplement), but θ is itself also a random variable. The expected value of $\hat{\theta}$ conditional on a realized value of θ is $E[\hat{\theta}\mid\theta]=\theta$, while the unconditional expectation is $E[\hat{\theta}]=\int_{\theta_L}^{\theta_U}\theta f(\theta)d\theta$, $f(\theta)$ is the density function of θ. It is straightforward to prove that if $f(\theta)$ is symmetric in the interval $[\theta_L,\theta_U]$ then $E[\hat{\theta}]=\frac{\theta_U+\theta_L}{2}$.

employed by manufacturers, $P(i|y=1, x=other\ occupation) = 0$, implies

$\theta_i = \frac{P(y=1, x=bluecollar)}{P(i)}$. We call this estimator the "blue collar" estimator. Figure 7 plots the blue-collar estimates for θ_i. This estimator suggests that manufacturers were not using nearly as much THS workers in the 1970s and in the 1980s as implied by the previous point estimates and logit forecasts. This prompts a more dramatic increase in manufacturers' use of THS workers in the 1990s. It should be pointed out, however, that some of the annual estimates in the 1980s fall below the theoretical lower bound casting serious doubts on the validity of this particular identifying assumption.

The identifying assumptions discussed above are useful for data analysis when there are no other sources of information on the parameter under study. Indeed the methodological framework developed here allows the researcher to interpret the sensitivity of each point estimate to different identifying assumptions. We think, however, that the wedge between the direct estimates from the Contingent Worker Supplement for 1995 and 1997 and the point estimates presented so far is somewhat uncomfortable.

This uneasiness motivates our last attempt at estimating $P(i|y=1)$ by combining the information from the Contingent Supplement of the 1995 and 1997 February CPS, the bounds derived above, and the information provided by the input-output tables for 1977, 1982, 1987 and 1992—the only years where there is direct information on the PSS industry.

Figure 8 displays the predicted $\hat{\theta}_i = \hat{P}(y=1 | i)$ based on the input-output estimates for the assignment probability, $P(i|y=1)$, and equation (2). According to these estimates the proportion of PSS workers in manufacturing rose from 0.3 percent in 1977 to 1.1 percent in 1992. Specifically, note the jump in the series after 1987. This is consistent with the anecdotal evidence about the increased pace at which manufacturing firms started to use PSS workers in the late 1980s. Also, the estimates based on the input-output tables fall within the bounds estimated using the March CPS data.

Combining the estimated bounds for $P(i|y=1)$ —$\hat{\alpha}_{lb}$ and $\hat{\alpha}_{ub}$— and the direct estimates for α in 1977, 1982, 1987, 1992, 1995 and 1997—$\hat{\alpha}_t$—we construct an alternative time series for α. First, we calculated a parameter β_t, $0 \le \beta_t \le 1$, for these six years that satisfies

$$(14) \qquad \hat{\alpha}_t = \beta_t\, \hat{\alpha}_{ub,t} + (1-\beta_t)\, \hat{\alpha}_{lb,t}$$

for each of the six years with direct estimates for α.

We then use an interpolation of the six computed β's to generate point estimates of α in the remaining years using the right-hand side of (14).[24] Using equation (2) we got estimates of θ. We call this estimator the “interpolated” estimator. Figure 8 also shows the results of this exercise. The final estimates preserve the cyclicality observed in the bounds and suggest a large increase in the use of THS workers by manufacturers in the 1990s.

Figure 9 presents the point estimates discussed here as well as the estimated bounds. All estimates suggest an upward trend in the hiring of THS workers by manufacturers. The interpolated estimates show the largest increases in THS hiring in the 1990s. In contrast, the smooth trend in the “mid-point ” and the logit estimates contradicts the existence of a trend break at the beginning of the 1990s. Recall, however, that the latter estimates are based on stronger ad hoc assumptions than the other estimates plotted in Figure 9. In short, our preferred point estimator is the interpolated estimator because by using a combination of the theoretical bounds and the survey evidence it does not throw away good direct data on the industry of assignment (at least for 1995 and 1997). Moreover, these point-estimates are always within the theoretical bounds.

8 Implications for Employment and Labor Productivity in Manufacturing

With the estimated θ in hand we can provide quantitative answers to several interesting questions.

1. What is the true number of manufacturing employment and hours?

Writing $N^{true} = N + \theta N^{true}$, the true number of workers in manufacturing is $\frac{N}{1-\hat{\theta}}$, where N is the observed number of manufacturing workers in the CES (BLS payroll survey). A similar formula was used for hours. Figure 10 plots the reported (raw) series of manufacturing employment and hours from the CES and the respective series adjusted for the use of THS employment and hours using the estimates described above. Table 5 reports the underlying data for Figure 10, and Table 6 displays the time series of THS workers in manufacturing.

The adjustments are based on the different point estimates for θ discussed previously. All of the corrections to manufacturing payroll employment suggest a significant increase in the number of THS workers in manufacturing between 1991 and 1997, but the interpolated

[24] We also assumed that the β's from 1972 to 1976 are identical to the β in 1977.

adjustment implies a more dramatic increase (about 34.0 percent at an annual rate). As a consequence, manufacturing employment adjusted for THS workers grew about ¾ percent at an annual rate whereas reported employment grew only about ¼ percent at an annual rate during the same period. Hours worked exhibit a similar pattern.

Finally, while a simple analysis of the reported manufacturing payroll employment data would suggest that the expansionary period between 1992 and 1997 generated only about 550,000 manufacturing jobs, the inclusion of THS workers in our calculations elevates this figure to between 890,000 and 1,060,000. Moreover, the decline in manufacturing hours between the local peak in 1989 and 1997—about 1-½ percent—disappears once THS workers are taken into account. Depending on the point estimates used, manufacturing hours increased as much as 1-¼ percent between 1989 and 1997.

These findings are consistent with the view that, recently, the THS industry facilitated rapid changes in the level of employment in firms that otherwise would be more reluctant to change their permanent labor force in the face of what may be temporary changes in demand conditions. Furthermore, the level of THS employment in manufacturing at the end of our sample is significantly high by historical standards, suggesting that, in the event of a downturn, much of the adjustment in labor input can be accomplished with small effects on the reported manufacturing payroll employment series.

2. How variable, and cyclical, is THS *employment in manufacturing?*

The year-to-year variation in THS employment and hours is of an order of magnitude larger than for non-THS. The coefficient of variation of the non-THS manufacturing employment series is about 0.1; the coefficient of variation for the manufacturing THS employment series ranges from 0.6 (logit adjustment) to 1.1 (interpolated adjustment).

The three estimates of THS workers suggest a noticeable degree of cyclicality in manufacturers' use of THS hours and employment. The wedges between each adjusted and the unadjusted series are smaller during the downturn of the beginning of the 1990s and widen during the subsequent expansion. However, the interpolated estimator generates a larger degree of cyclicality in THS employment and hours in manufacturing. These estimates are also more consistent with the anecdotal evidence pointing to a large increase in manufacturing THS employment at the end of the 1980s.

3. How does the use of THS *workers affect the measurement of labor productivity?*

The differences in the levels and growth rates between the reported data and the data adjusted for the use of THS workers imply that reported labor productivity is overstated in the manufacturing sector and understated in the service sector.

Columns 3 and 8 in Table 7 show the official (BLS) statistics for labor productivity growth. The bottom part of the table illustrates the puzzle that has been voiced by policy makers, academics and the popular press. The trend growth in manufacturing labor productivity is significantly larger than the trend productivity growth in the whole non-farm business sector. For instance, during the period 1982 to 1997, reported manufacturing labor productivity grew at an annual rate of 3.2 percent while labor productivity in the non-farm business sector grew at an annual rate of 1.3 percent. Furthermore, while aggregate productivity growth has decelerated since the 1980s, manufacturing labor productivity has accelerated substantially. How much of this wedge can be accounted for by the mismeasurement of the labor input?[25]

Column 4 reports all persons hours adjusted for hired THS hours in manufacturing using the point estimates for the probability of finding THS workers in manufacturing (using the interpolated point-estimate). Comparing columns 3 and 5 gauges the effect on measured productivity growth of adjusting for PSS hours in manufacturing. As expected, the effect is strongest during the 1990s when the use of THS workers picked up. On this account, between 1991 and 1997 the average growth rate of labor productivity in the manufacturing sector was biased upward by ½ percentage point per year. In other words, adjusting for the increase in the use of THS workers lowers the measured growth rate of productivity during this period from about 3.8 percent per year to 3.3 percent per year.

The small differences in the growth rates accumulate over time. Assuming that θ was zero before 1982 and thereafter θ is given by the interpolated point estimates implies that the productivity level in 1997 was about 3.0 percent lower than the reported one. Nevertheless, THS-adjusted productivity still accelerates in the 1990s and the full explanation for the divergence between manufacturing and non-farm business productivity growth lies elsewhere. [26]

[25] Using value-added instead of output measures reduces to some extent the impact of mismeasuring labor.
[26] Most economists would single out the mismeasurement of output outside the manufacturing sector as the most likely explanation for productivity gap. At the core of this argument lies the suspicion that the price deflators used by the Commerce Department to get real output data from nominal output series overstates the actual inflation in the service sector and thus understates real output growth outside manufacturing.

4. *Does accounting for* THS *workers reduce measured procyclicality of labor productivity?*

Procyclical movement in labor productivity (and total factor productivity) is a well-known feature of aggregate fluctuations. Some researchers argue that this empirical fact is evidence of (external or internal) increasing returns to scale in production or of market. Others argue that procyclical productivity is due to cyclical variations in the rate of utilization of labor or capital. As shown earlier, use of THS workers is cyclical. In good times, increasing THS workers raises output but not *measured* employment. In bad times, "firing" of THS workers decreases output but not *measured* employment. Hence, on this account, *measured* labor productivity is procyclical. If this explanation has any empirical relevance, then adjusting the hours figures to include THS hours should decrease the procyclicality of labor productivity in manufacturing.

Direct estimates of the manufacturing production function corroborate this point. A simple regression of the annual percent changes in manufacturing output on the annual percent change in manufacturing all employee-hours and kilowatt-hours—a proxy for capital utilization—generates a coefficient of about 1.2 for employee-hours. This result supports the claim that changes in manufacturing labor input affect output more than proportionately. Once we correct the labor input measure by including temporary help supply worker-hours in manufacturing, this coefficient declines to 1—suggesting constant returns to changes in labor input.[27]

9 Conclusions

The goal of this paper was to estimate the extent to which the manufacturing sector is outsourcing labor from the service sector via the hiring of THS workers. We reviewed the

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Others, e.g., David (1990), suggest that the gains from the new information technologies are yet to come: while manufacturers have appropriated some of these gains, its diffusion to the rest of the economy is slow.

[27] The first regression we run was

$$\underset{(0.01)}{\Delta IP = 0.04} + \underset{(0.37)}{1.20\,\Delta HRS} + \underset{(0.52)}{0.14\,\Delta KWH}$$

All variables were defined as difference of logarithms. IP = Annual manufacturing production (Source: Federal Reserve Board). HRS = All employee hours (source: Survey of Current Business, BEA, B.10 table). KWH = kilowatt-hours consumed in manufacturing (source: Federal Reserve Board). Standard deviations are shown in parentheses. Sample: 1991 to 1997. $R^2 = 0.84$. These results are nearly identical to the estimates obtained using data from 1972 to 1997.

The second regression was

$$\underset{(0.01)}{\Delta IP = 0.03} + \underset{(0.36)}{1.01\,\Delta HRS\_ADJ} + \underset{(0.58)}{0.19\,\Delta KWH}$$

HRS_ADJ = All employee hours including THS hours in manufacturing. We used the interpolated point-estimates presented in previous sections. Sample: 1991 to 1997. $R^2 = 0.81$. We limit ourselves to the 1990s when manufacturers' use of THS workers became a relevant phenomenon.

available sources of data and the methodological issues involved in extracting the desired information. Using the February 1995 and 1997 Contingent Workers Supplements to the CPS and the input-output tables we found an upward trend in manufacturers' use of PSS workers which appears to pick up somewhat in the late 1980s. These estimates, however, rely on strong assumptions and/or are hampered by the lack of frequent (annual) data. We therefore suggest an alternative approach that overcomes these problems.

Our approach uses minimal assumptions and is non-parametric. It consists of establishing bounds for the probability that a THS worker does indeed work in a manufacturing industry. We develop conditions under which these bounds are tight and estimate them using readily available data from the March tapes of the CPS.

The estimated bounds are informative and confirm that manufacturing firms have increased the use of temporary help supply workers during the 1990s. Furthermore, the time series behavior of the estimated series of THS employees (hours) in manufacturing is consistent with the hypothesis that manufacturers have been using this type of work as a buffer to economic shocks. However, accounting for THS employment explains only a small part of the divergence between labor productivity growth in manufacturing and elsewhere in the 1990s.

Another contribution of this paper is to have made available an estimated time series of the number and hours of THS workers employed by manufacturing firms (Table 6). In addition, our methodology can be applied to lower levels of aggregation (e.g., 3 digit SICs). Once these series are generated they can be correlated with industry characteristics in order to test different models of the demand for such workers.

Finally, besides addressing a specific economic issue, the paper also provides a methodological framework to bound conditional probabilities that are not directly observed by the researcher. The development of these bounds follows the general spirit in Manski's work (1995). These bounds are not just useful by themselves but also provide a powerful tool to assess the reliability of point estimates for the parameter under study.

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Appendix

In this appendix we show how to construct confidence intervals for the bounds on θ appearing in Proposition 3. Denote these theoretical bounds by θ_i^l and θ_i^u, and the theoretical bounds on the assignment probabilities by α_i^l and α_i^u,

Because the number of observations in the CES is very large we treat the sample proportions of individuals working in manufacturing, $\hat{P}(i, y=0)$, as a consistent estimator of $P(i, y=0)$. The same holds for the NATSS estimate $\hat{P}(y=1)$. The number of observations of individuals working in the PSS sector in the CPS is also sufficiently high to treat $\hat{P}(x \mid y=1)$ as the true probability $P(x \mid y=1)$.[28] However, the cells defined by the different realizations of the vector *X* do not have that many observations. Even though we excluded from computation of the bounds those cells that have a single observation, we still have many cells with 2, 3, etc. individuals. Thus, the estimates of $P(y=1 \mid x)$ and $P(i \mid x)$ may not be very precise.

Here we show how to build confidence intervals for $P(y=1 \mid x)$ and $P(i \mid x)$ and how to use them to construct asymptotic 95% confidence intervals for θ_i^l and θ_i^u.

Note that y_j—the binary variable telling whether individual *j* having characteristic *x* is a THS worker or not—is a Bernoulli variable with probability $P(y=1/x)=\pi(x)$,

$$y_j = \begin{cases} 1 \text{ with probability } \pi(x) \\ 0 \text{ with probability } 1-\pi(x) \end{cases}.$$

Similarly, i_j is the binary variable telling whether individual *j* works in industry *i* or not. Let $\xi(x)=P(i \mid x)$. An easy way to construct a confidence interval for these probabilities is to rely on the asymptotic distribution of the statistic. It is straightforward to show that 95% confidence intervals for $\pi(x)$ and $\xi(x)$ are given by

$$\left[\hat{\pi}(x)-1.96\sqrt{\frac{\hat{\pi}(x)(1-\hat{\pi}(x))}{n(x)}}, \hat{\pi}(x)+1.96\sqrt{\frac{\hat{\pi}(x)(1-\hat{\pi}(x))}{n(x)}}\right]$$

[28] For instance, the March CPS tapes have between 275 and 400 observations for the PSS industry in every year after 1985.

$$\left[\hat{\xi}(x)-1.96\sqrt{\frac{\hat{\xi}(x)(1-\hat{\xi}(x))}{n(x)}}\ ,\ \hat{\xi}(x)+1.96\sqrt{\frac{\hat{\xi}(x)(1-\hat{\xi}(x))}{n(x)}}\right]$$

Let these lower and upper values of the confidence interval for $\pi(x)$ and $\xi(x)$ be denoted by $\hat{\pi}^l(x)$ and $\hat{\pi}^u(x)$, and $\hat{\xi}^l(x)$ and $\hat{\xi}^u(x)$, respectively. A 95% confidence interval for θ_i^u is then

$$CI(\theta_i^u)\equiv\left[\begin{array}{l}\dfrac{\hat{P}(y=1)}{\hat{P}(i,y=0)+\hat{\alpha}_i^l\hat{P}(y=1)}\sum_x \mathrm{Min}\left\{\dfrac{\hat{\xi}^l(x)}{\hat{\pi}^u(x)},1\right\}\hat{P}(x/y=1)\,, \\ \\ \dfrac{\hat{P}(y=1)}{\hat{P}(i,y=0)+\hat{\alpha}_i^l\hat{P}(y=1)}\sum_x \mathrm{Min}\left\{\dfrac{\hat{\xi}^u(x)}{\hat{\pi}^l(x)},1\right\}\hat{P}(x/y=1)\end{array}\right]$$

And a 95% confidence interval for θ_i^l is

$$CI(\theta_i^l)\equiv\left[\begin{array}{l}\dfrac{\hat{P}(y=1)}{\hat{P}(i,y=0)+\hat{\alpha}_i^u\hat{P}(y=1)}\sum_x Max\left\{0,\dfrac{\hat{\pi}^l(x)+\hat{\xi}^l(x)-1}{\hat{\pi}^u(x)}\right\}\hat{P}(x/y=1), \\ \\ \dfrac{\hat{P}(y=1)}{\hat{P}(i,y=0)+\hat{\alpha}_i^u\hat{P}(y=1)}\sum_x Max\left\{0,\dfrac{\hat{\pi}^u(x)+\hat{\xi}^u(x)-1}{\hat{\pi}^l(x)}\right\}\hat{P}(x/y=1)\end{array}\right]$$

Table 1

Data Sources for Temporary Help Supply Employment and Hours

	Level of aggregation	**Periods Covered**	**Frequency of Data**	**Information about workers' characteristics**	**Information about industry of use**
National Association of Temporary Staffing Services (NATSS)	Employment in THS firms (NATSS uses the BLS-CES series for before 1987)	1972-97	Quarterly	Aggregate proportions by major occupations	No
Current Employment Survey (CES)[1]	Employment in THS firms (SIC 7362) during1972-82; Employment and hours in SIC 7363 (THS firms plus residual category) from 1982 onwards	1972-97	Monthly	No	No
Current Population Survey (CPS)[1] March tapes	Employment and hours in SIC 736	1972-97	Annual	Yes	No
Contingent Worker Supplement[1] February tapes	Employment and hours in THS firms	1995 and 1997	Two data points	Yes	Yes
Input-output tables[2]	Flow of output from SIC 736 to other industries	1977, 1982, 1987, 1992	Every 5 years	No	Estimated

Sources: [1] Bureau of Labor Statistics
[2] Bureau of Economic Analysis

Table 2
Estimates (%) of P(i|y=1) and P(y=1|i) using
the February CPS-Contingent Worker Supplements

		Workers		Hours	
		1995	1997	1995	1997
P(i|y=1)	Non-Manufacturing	67.30	72.11	65.30	69.38
	Manufacturing	32.70	27.89	34.70	30.62
P(y=1|i)	Non-manufacturing	1.85	2.18	1.71	2.02
	Manufacturing	3.68	3.65	3.00	3.11

Note: P(i/y=1) was estimated directly from the Contingent Worker Supplement to the 1995 and 1997 February CPS. P(y=1|i) was obtained using the direct estimates of the assignment probability, and information from the NATSS and the CES payroll survey according to equation (2).

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Table 3
Forecasting equation for P(i|y=1)
Logit regression

	Coefficients
Constant	-0.52
	(0.396)
Professional	-0.85
	(0.235)
White Collar	-1.32
	(0.213)
Completed high school	0.21
	(0.249)
Some college education	0.23
	(0.263)
Bachelors' degree or more	0.52
	(0.303)
White	0.39
	(0.193)
Male	0.20
	(0.166)
Age: 25-35	0.04
	(0.202)
Age: 35-50	0.13
	(0.208)
Age: More than 50	-0.20
	(0.208)
Northwest	0.04
	(0.244)
Midwest	0.75
	(0.213)
South	-0.04
	(0.220)
Metropolitan area	-0.47
	(0.205)
Part-time	-0.46
	(0.163)
Dummy for 1997	-0.20
	(0.152)
Log-likelihood	-523.40
number of obs.	956.00

Standard errors in parentheses.
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Table 4
Bounds for the Proportion (%) of THS Employment (Hours) in Manufacturing

	Employees			Hours		
	Lower	Mid	Upper	Lower	Mid	Upper
1972	0.02	0.26	0.49	--	--	--
1973	0.06	0.29	0.53	--	--	--
1974	0.08	0.37	0.66	--	--	--
1975	0.03	0.28	0.54	--	--	--
1976	0.04	0.33	0.63	--	--	--
1977	0.05	0.38	0.71	--	--	--
1978	0.05	0.43	0.81	--	--	--
1979	0.06	0.55	1.03	--	--	--
1980	0.06	0.56	1.06	--	--	--
1981	0.07	0.49	0.92	--	--	--
1982	0.10	0.60	1.10	0.09	0.46	0.83
1983	0.24	0.73	1.21	0.19	0.53	0.88
1984	0.31	0.82	1.33	0.26	0.65	1.04
1985	0.23	0.85	1.46	0.21	0.71	1.20
1986	0.31	1.03	1.76	0.27	0.86	1.46
1987	0.27	1.25	2.24	0.24	1.00	1.76
1988	0.19	1.25	2.31	0.15	1.04	1.93
1989	0.57	1.42	2.26	0.50	1.17	1.84
1990	0.56	1.58	2.60	0.47	1.32	2.16
1991	0.37	1.43	2.49	0.30	1.16	2.02
1992	0.66	2.00	3.34	0.56	1.67	2.78
1993	0.72	2.48	4.23	0.68	2.12	3.57
1994	0.66	2.35	4.04	0.56	2.00	3.44
1995	0.76	2.92	5.08	0.61	2.42	4.22
1996	0.95	2.68	4.41	0.84	2.30	3.76
1997	0.84	2.86	4.89	0.73	2.47	4.21

Note: The bounds were computed using the formula in Proposition 3 including corrections for misreporting and omission biases. The conditioning variables are:occupation (2 digits), state, education, gender, race, age (<= 25, 26-35,35- 50, >= 50) and a part-time work dummy (equal 1 if employee worked less than 35 hours in the previous week, 0 otherwise). Average weekly hours data for SIC 7363 begin only in 1982.

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Table 5
Manufacturing Payroll Employment and Hours

	Payroll Employment (thousands)				Payroll Hours (millions)			
	Reported	logit	blue collar	interp	Reported	logit	blue collar	interp
1972	19152.50	19211.83	19164.33	19186.30	40407.50	--	--	--
1973	20153.17	20214.95	20166.76	20196.30	42618.33	--	--	--
1974	20080.75	20163.04	20104.42	20135.42	41840.42	--	--	--
1975	18320.67	18380.69	18335.65	18357.02	37691.33	--	--	--
1976	18996.50	19073.95	19045.83	19040.83	39567.17	--	--	--
1977	19687.33	19760.56	19728.88	19740.49	41249.50	--	--	--
1978	20511.00	20597.62	20577.54	20566.55	43050.08	--	--	--
1979	21043.83	21145.94	21131.10	21106.42	43918.42	--	--	--
1980	20287.58	20399.60	20364.50	20339.50	41881.42	--	--	--
1981	20172.42	20271.51	20221.26	20211.47	41703.67	--	--	--
1982	18782.67	18887.99	18845.91	18820.08	38268.92	38427.05	38347.76	38321.74
1983	18433.42	18561.38	18475.46	18494.03	38402.58	38610.60	38465.13	38489.72
1984	19374.67	19553.94	19427.70	19449.24	40892.92	41188.10	40972.42	41013.86
1985	19249.67	19449.83	19291.98	19309.82	40568.75	40906.20	40633.89	40669.85
1986	18948.08	19171.86	19031.16	19020.75	40098.42	40490.55	40241.65	40217.61
1987	18998.25	19268.23	19138.98	19063.69	40511.58	40965.03	40713.11	40616.65
1988	19315.08	19614.99	19433.97	19378.34	41153.83	41673.05	41332.50	41242.15
1989	19390.92	19658.48	19493.01	19532.38	41242.25	41692.66	41416.93	41481.55
1990	19074.92	19400.00	19219.78	19227.42	40403.50	40951.02	40641.02	40649.62
1991	18404.92	18734.90	18599.40	18528.00	38920.75	39485.62	39239.45	39108.82
1992	18105.92	18503.90	18358.40	18308.12	38657.58	39336.65	39064.60	38984.23
1993	18076.08	18572.68	18416.72	18428.10	38969.75	39814.56	39525.03	39588.20
1994	18323.33	18891.08	18724.18	18769.14	39890.92	40882.38	40561.89	40683.81
1995	18525.08	19166.82	19066.87	19231.95	40057.67	41157.46	40908.32	41296.74
1996	18494.67	19259.33	19121.40	19128.36	39967.58	41285.77	40977.36	41118.90
1997	18675.92	19413.72	19292.75	19382.96	40720.42	42032.49	41764.59	42027.12

Note: The 'Reported' column is from the Current Employment Survey (CES). The 'logit', 'blue collar' and 'interp' columns refer to each adjusted series, where the probability of finding a THS worker (hour) in manufacturing corresponds to the logit, P(i|y=1,x=blue collar)=1 or interpolated estimates. Average weekly hours data for SIC 7363 begin only in 1982.

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Table 6
THS in Manufacturing

	Employment			Hours		
	logit	blue collar	interp	logit	blue collar	interp
1972	59.33	11.83	33.80	--	--	--
1973	61.78	13.59	43.13	--	--	--
1974	82.29	23.67	54.67	--	--	--
1975	60.03	14.98	36.36	--	--	--
1976	77.45	49.33	44.33	--	--	--
1977	73.23	41.55	53.16	--	--	--
1978	86.62	66.54	55.55	--	--	--
1979	102.11	87.27	62.58	--	--	--
1980	112.02	76.92	51.92	--	--	--
1981	99.09	48.84	39.05	--	--	--
1982	105.32	63.24	37.42	158.14	78.84	52.82
1983	127.96	42.04	60.61	208.02	62.55	87.13
1984	179.27	53.04	74.57	295.19	79.51	120.94
1985	200.17	42.31	60.15	337.45	65.14	101.10
1986	223.78	83.08	72.66	392.14	143.23	119.19
1987	269.98	140.73	65.44	453.45	201.53	105.06
1988	299.91	118.88	63.26	519.22	178.66	88.31
1989	267.56	102.10	141.46	450.41	174.68	239.30
1990	325.08	144.86	152.50	547.52	237.52	246.12
1991	329.98	194.48	123.08	564.87	318.70	188.07
1992	397.98	252.48	202.20	679.06	407.02	326.65
1993	496.60	340.64	352.01	844.81	555.28	618.45
1994	567.75	400.85	445.80	991.47	670.98	792.90
1995	641.73	541.78	706.87	1099.79	850.66	1239.08
1996	764.66	626.73	633.69	1318.18	1009.78	1151.32
1997	737.81	616.83	707.05	1312.07	1044.17	1306.70

Note: The 'logit', 'blue collar' and 'interp' columns correspond to the number of THS workers (thousands) and hours (millions) in manufacturing obtained when using the logit, P(i|y=1,x=blue collar)=1 or interpolated estimate of the probability of finding a THS worker (hour) in manufacturing. Average weekly hours data for SIC 7363 begin only in 1982.

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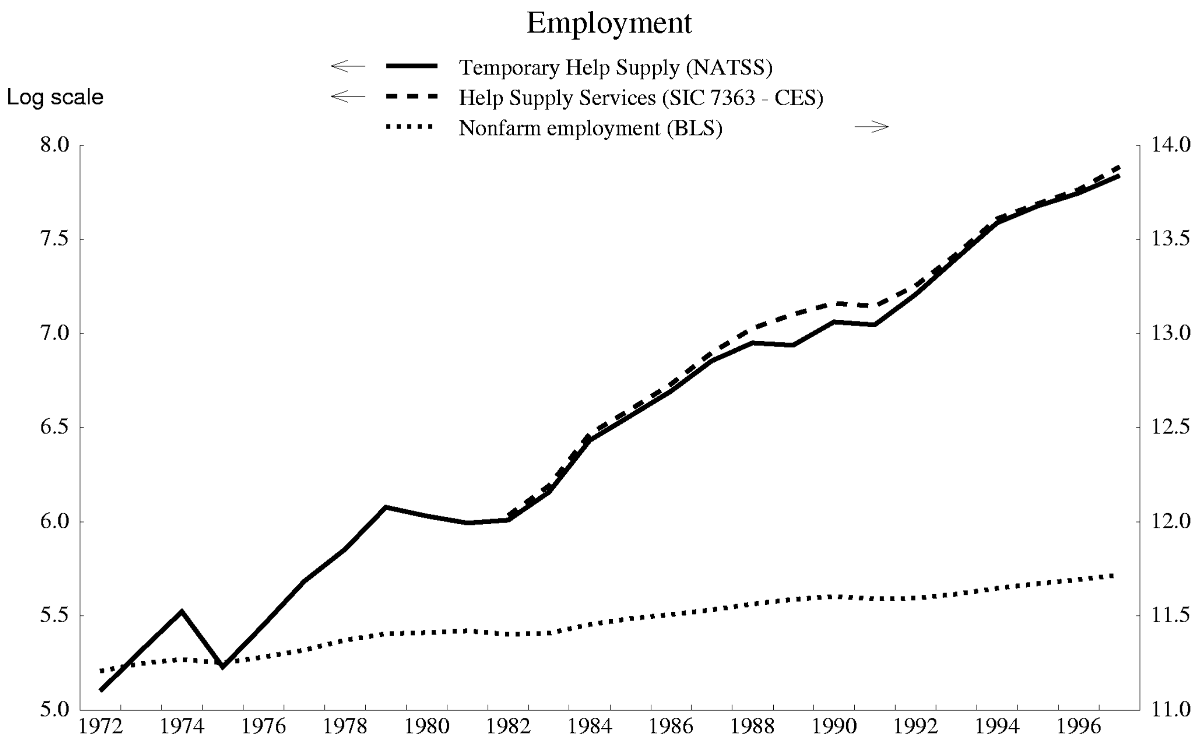
Table 7
Productivity accounting
(Using data from the BLS-Productivity & Costs release)
1982=100

	Manufacturing					Non Farm Business		
	Output	Hours	Productivity	Adjusted Hours	Adjusted Productivity	Output	Hours	Productivity
1982	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
1983	104.31	100.99	103.28	101.09	103.19	106.11	101.85	104.19
1984	114.87	107.52	106.84	107.70	106.66	114.44	107.99	105.97
1985	118.39	106.76	110.90	106.88	110.77	118.55	110.76	107.03
1986	121.85	105.18	115.84	105.36	115.64	122.56	111.65	109.76
1987	125.98	105.95	118.91	106.09	118.75	126.22	115.20	109.56
1988	131.90	108.79	121.24	108.88	121.14	131.40	118.93	110.49
1989	132.82	109.29	121.54	109.80	120.97	135.54	122.06	111.05
1990	133.26	106.99	124.56	107.52	123.94	136.55	122.38	111.57
1991	130.63	102.52	127.42	102.90	126.95	134.16	119.40	112.36
1992	136.75	102.08	133.96	102.86	132.96	138.17	119.23	115.89
1993	141.68	103.49	136.90	105.09	134.82	142.28	122.68	115.97
1994	149.16	105.73	141.08	107.82	138.34	147.84	126.74	116.65
1995	155.66	106.20	146.57	109.55	142.08	152.30	129.78	117.35
1996	161.37	105.82	152.49	108.93	148.14	158.58	131.98	120.16
1997	171.93	107.68	159.66	111.23	154.58	165.63	136.24	121.57
	Average annual rate of growth over the period indicated							
82-90	3.65	0.85	2.78	0.91	2.72	3.97	2.56	1.38
91-97	4.68	0.82	3.83	1.31	3.34	3.57	2.22	1.32
82-97	3.68	0.49	3.17	0.71	2.95	3.42	2.08	1.31

Hours adjustment using the interpolated estimates depicted by the dotted line in Figure 8. Average weekly hours data for SIC 7363 begin only in 1982.
September 22, 1999 at 15:53:52

Figure 1


Employment
Temporary Help Supply (NATSS)
Help Supply Services (SIC 7363 - CES)
Nonfarm employment (BLS)
Log scale
8.0
7.5
7.0
6.5
6.0
5.5
5.0
14.0
13.5
13.0
12.5
12.0
11.5
11.0
1972
1974
1976
1978
1980
1982
1984
1986
1988
1990
1992
1994
1996

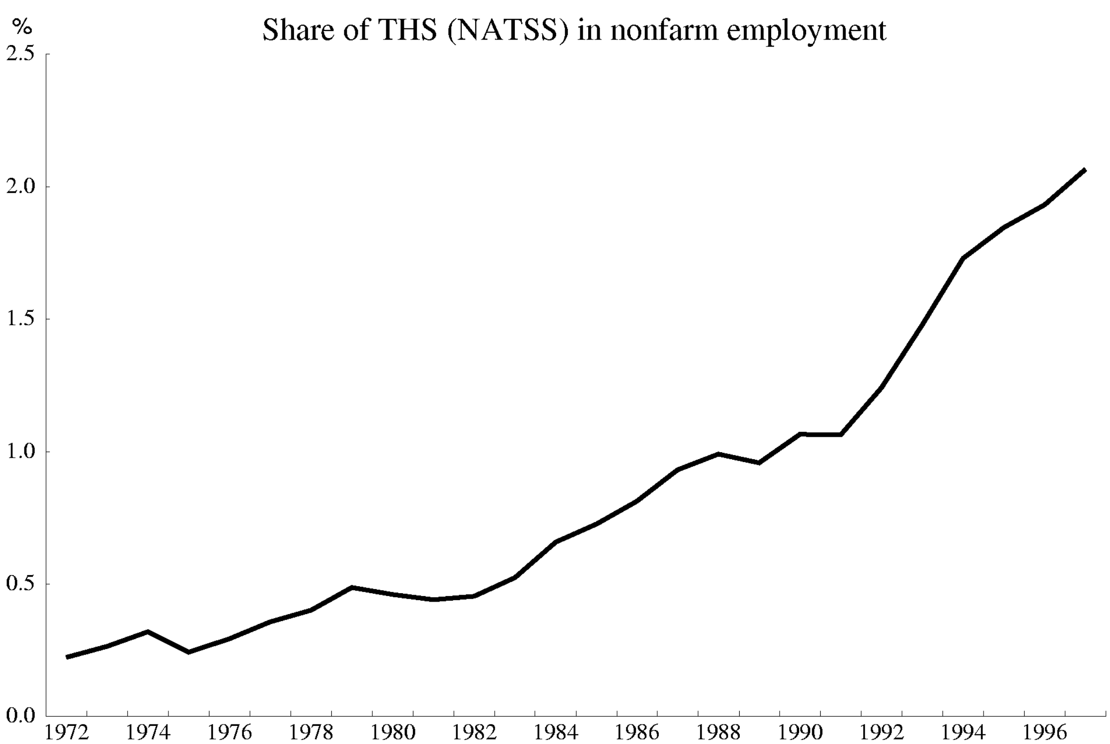
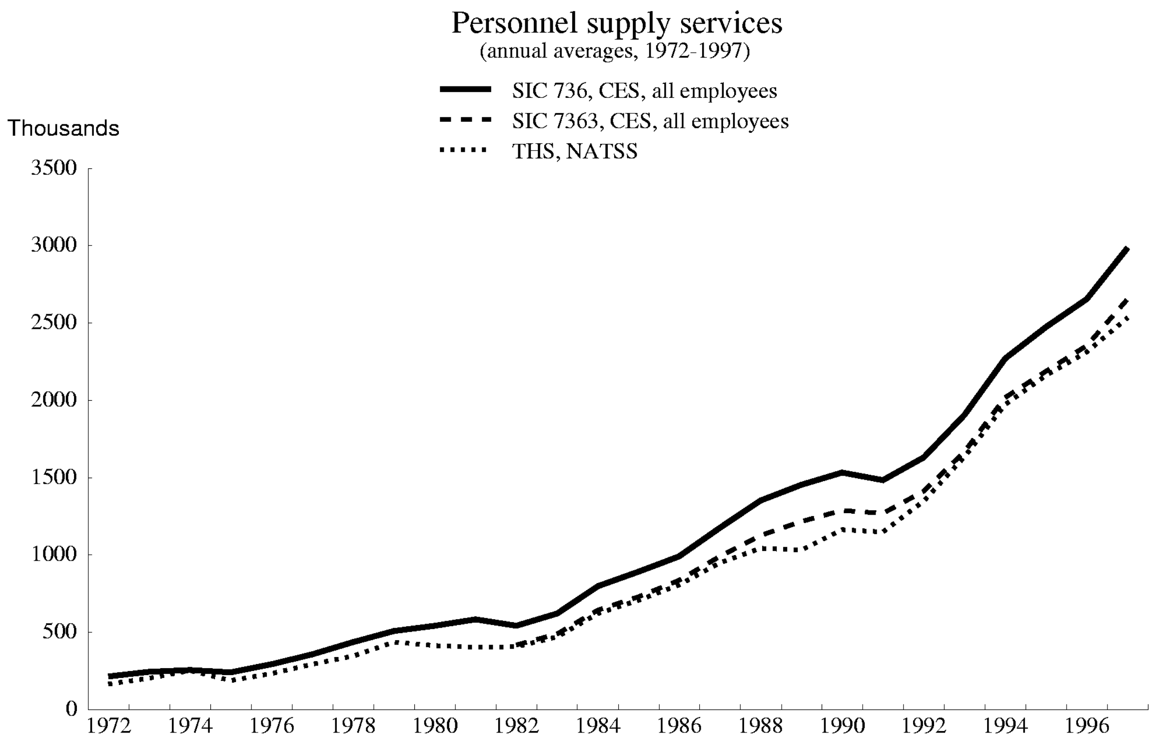

Share of THS (NATSS) in nonfarm employment
%
2.5
2.0
1.5
1.0
0.5
0.0
1972
1974
1976
1978
1980
1982
1984
1986
1988
1990
1992
1994
1996

Figure 2


Personnel supply services
(annual averages, 1972-1997)
SIC 736, CES, all employees
SIC 7363, CES, all employees
THS, NATSS
Thousands
3500
3000
2500
2000
1500
1000
500
0
1972
1974
1976
1978
1980
1982
1984
1986
1988
1990
1992
1994
1996

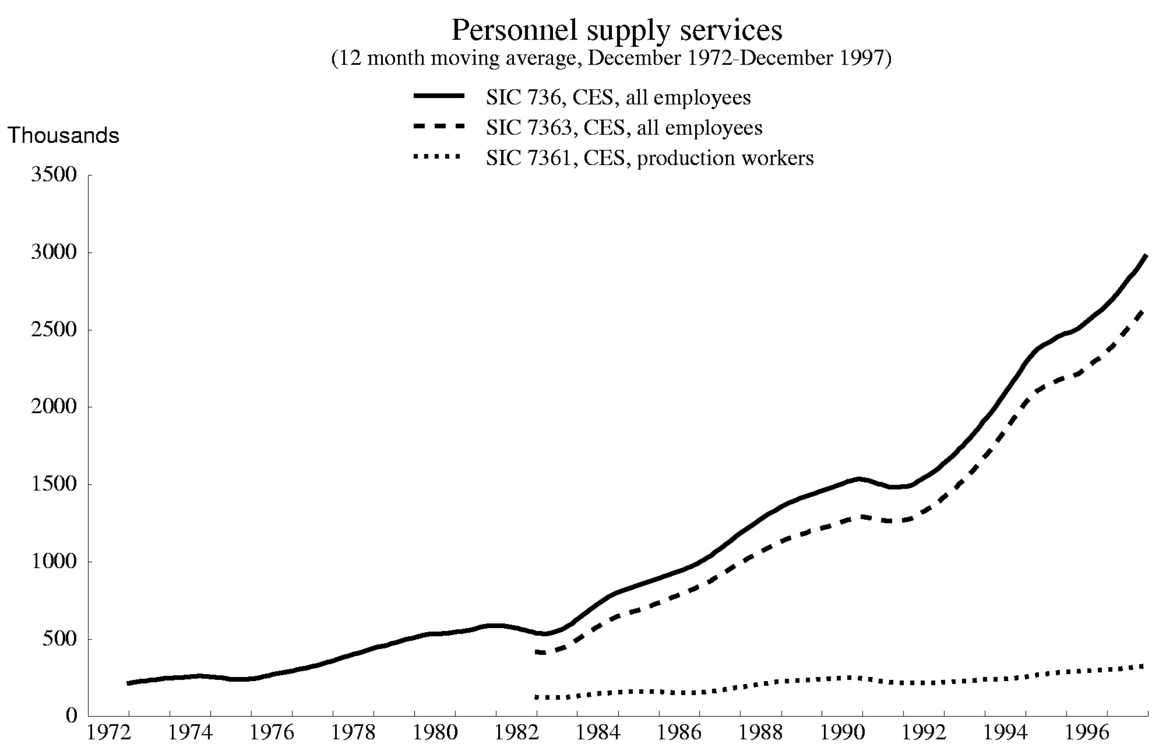
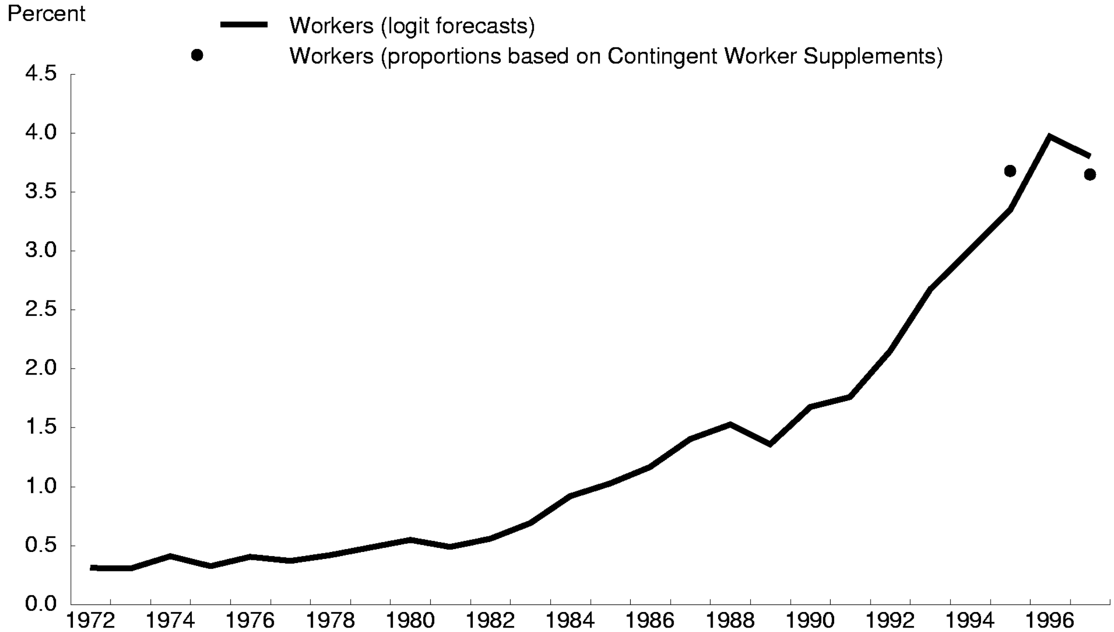

Personnel supply services
(12 month moving average, December 1972-December 1997)
SIC 736, CES, all employees
SIC 7363, CES, all employees
SIC 7361, CES, production workers
Thousands
3500
3000
2500
2000
1500
1000
500
0
1972
1974
1976
1978
1980
1982
1984
1986
1988
1990
1992
1994
1996

Figure 3

Proportion of THS workers in manufacturing
Predictions based on CPS surveys
(Sample: 1972-97)



Proportion of THS hours in manufacturing
Predictions based on CPS surveys
(Sample: 1982-97)

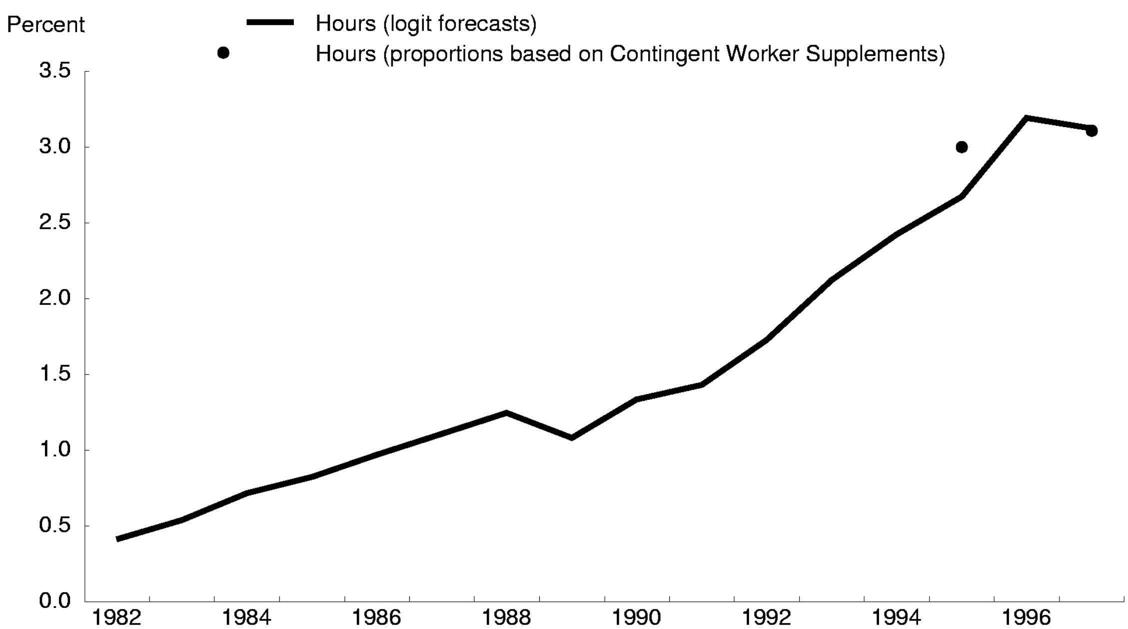


Figure 4

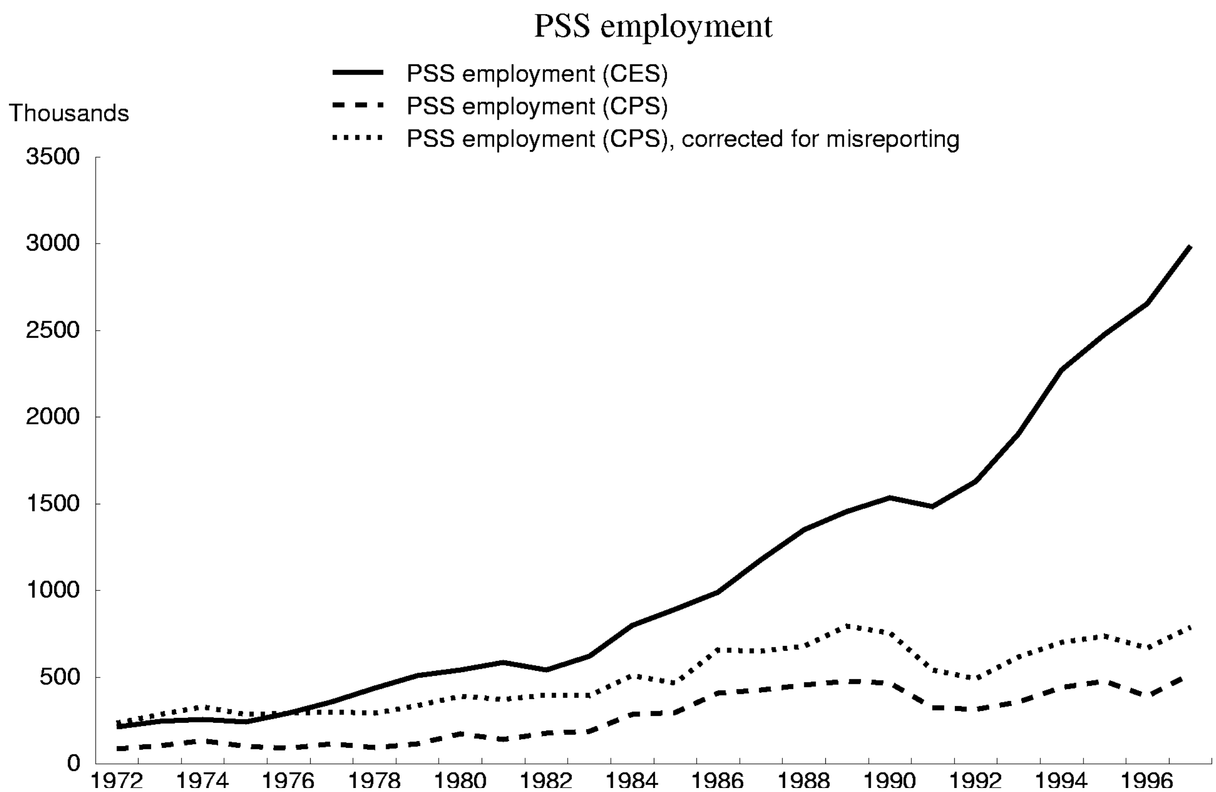
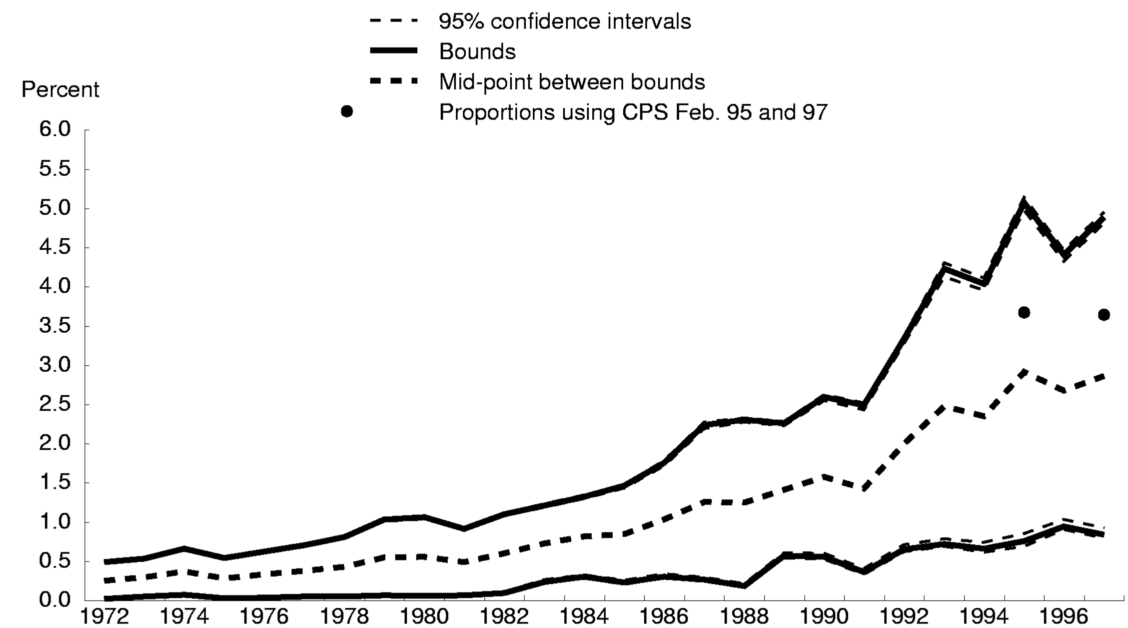

PSS employment
PSS employment (CES)
PSS employment (CPS)
PSS employment (CPS), corrected for misreporting
Thousands
3500
3000
2500
2000
1500
1000
500
0
1972
1974
1976
1978
1980
1982
1984
1986
1988
1990
1992
1994
1996

Figure 5

Proportion of THS workers and hours in manufacturing

Workers
(Sample: 1972-97)



Hours
(Sample: 1982-97)

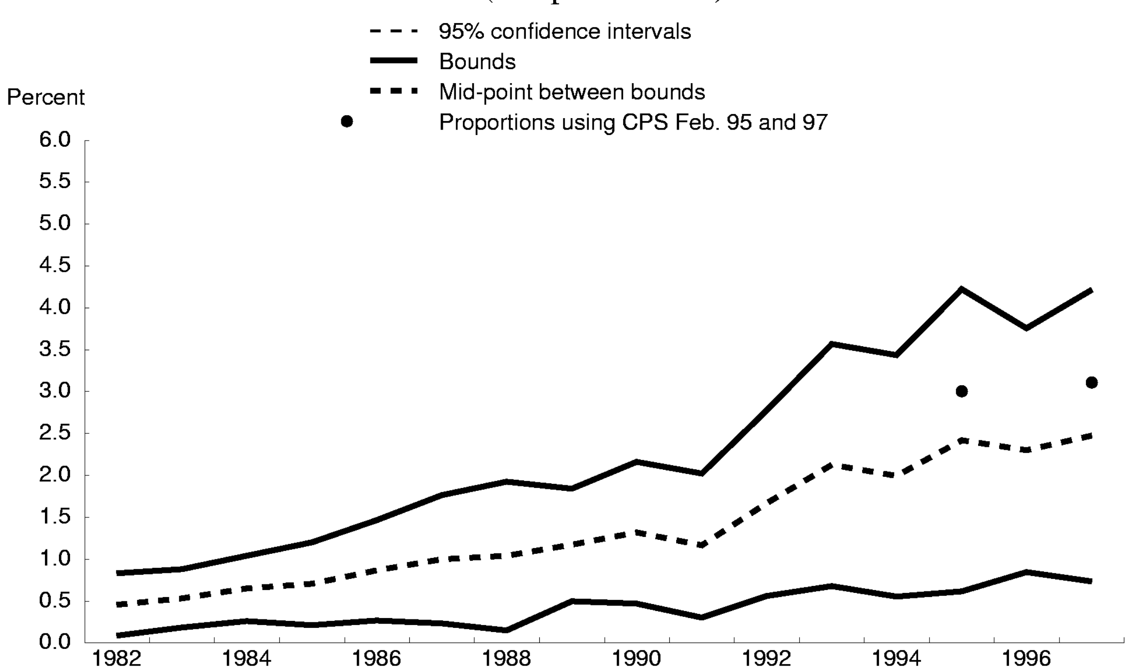
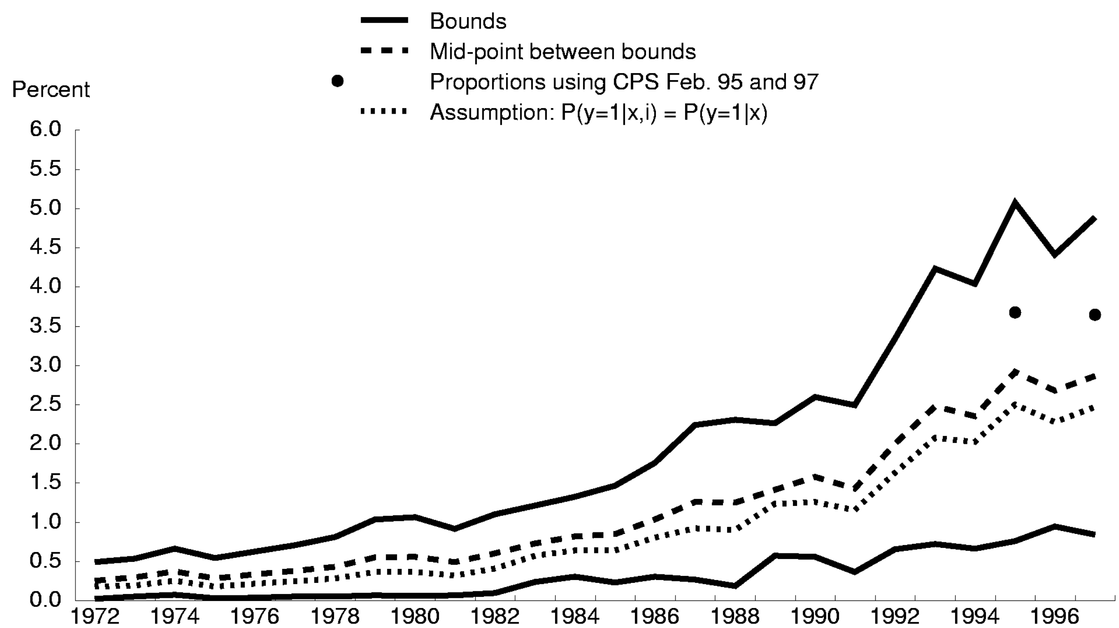


Figure 6

Proportion of THS workers and hours in manufacturing
Workers
(Sample: 1972-97)



Hours
(Sample: 1982-97)

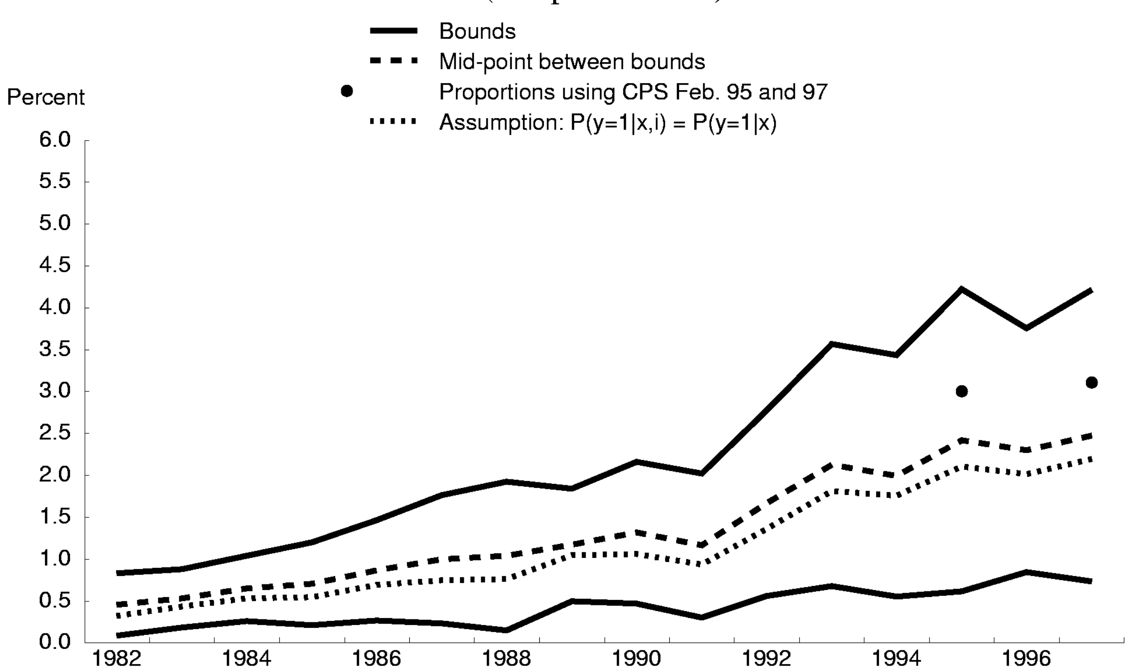
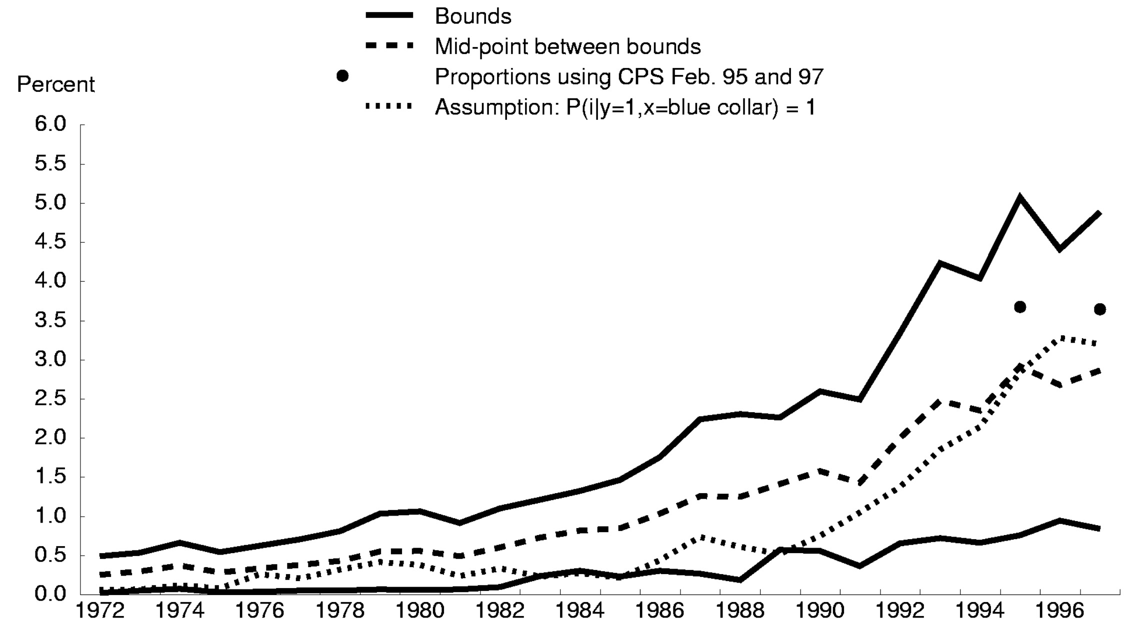


Figure 7

Proportion of THS workers and hours in manufacturing

Workers
(Sample: 1972-97)



Hours
(Sample: 1982-97)

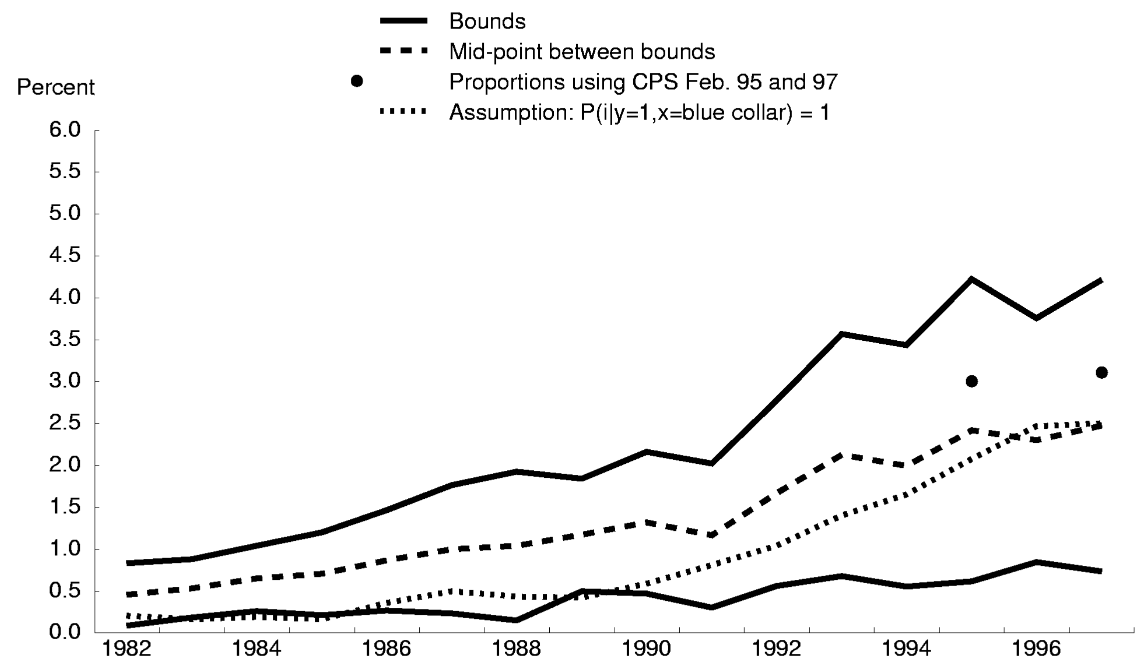
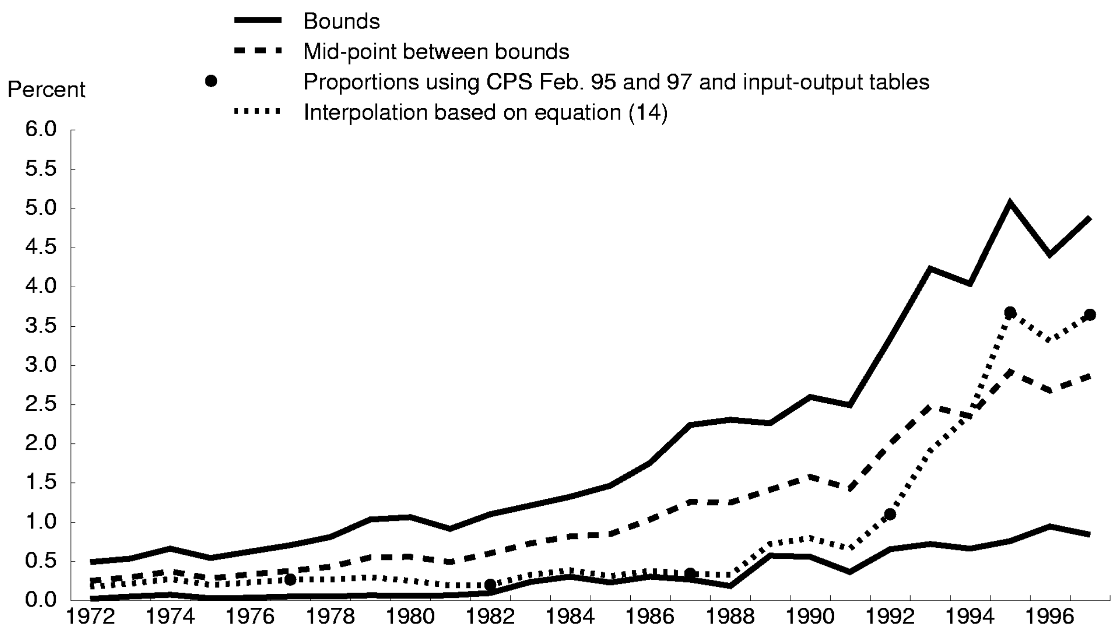


Figure 8

Proportion of THS workers and hours in manufacturing
Workers
(Sample: 1972-97)



Hours
(Sample: 1982-97)

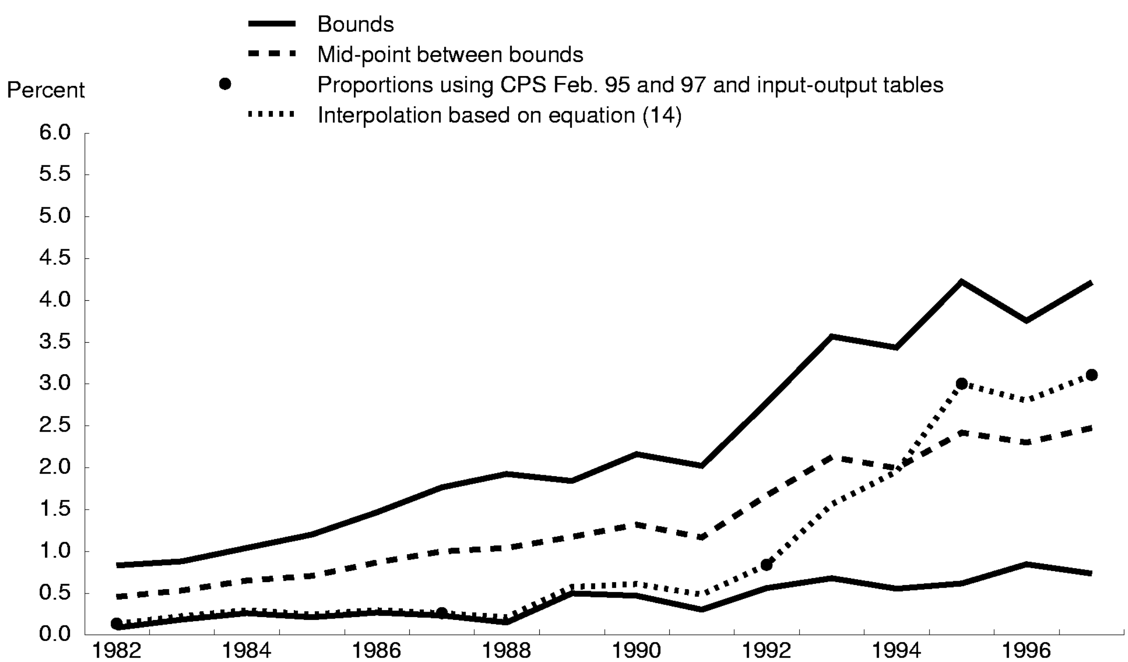
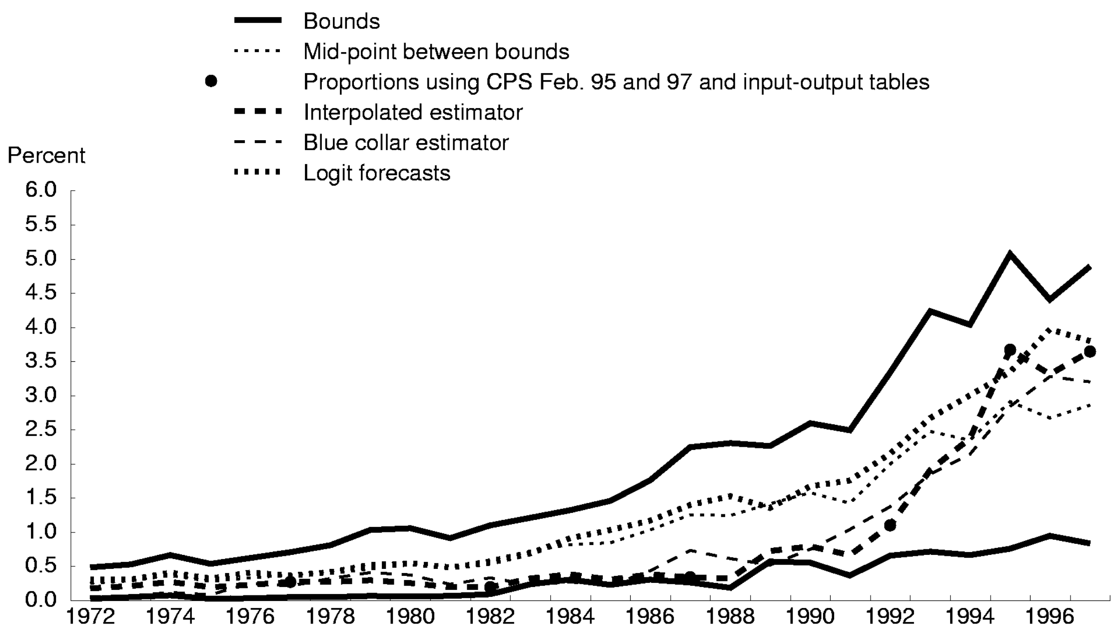


Figure 9

Proportion of THS workers and hours in manufacturing
Workers
(Sample: 1972-97)



Hours
(Sample: 1982-97)

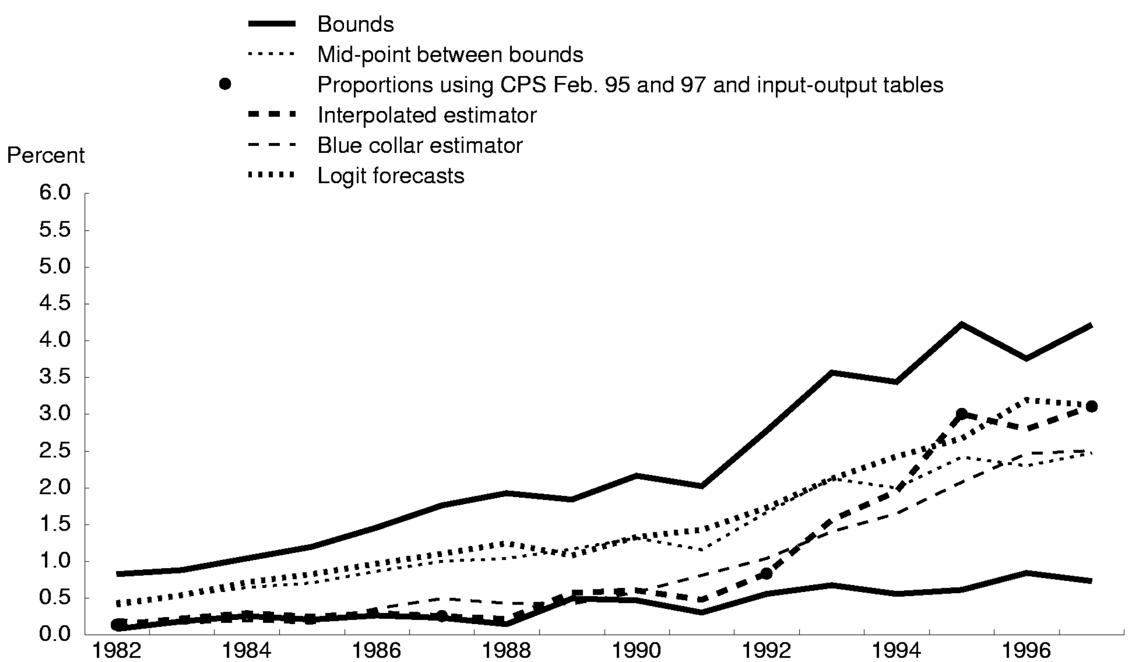
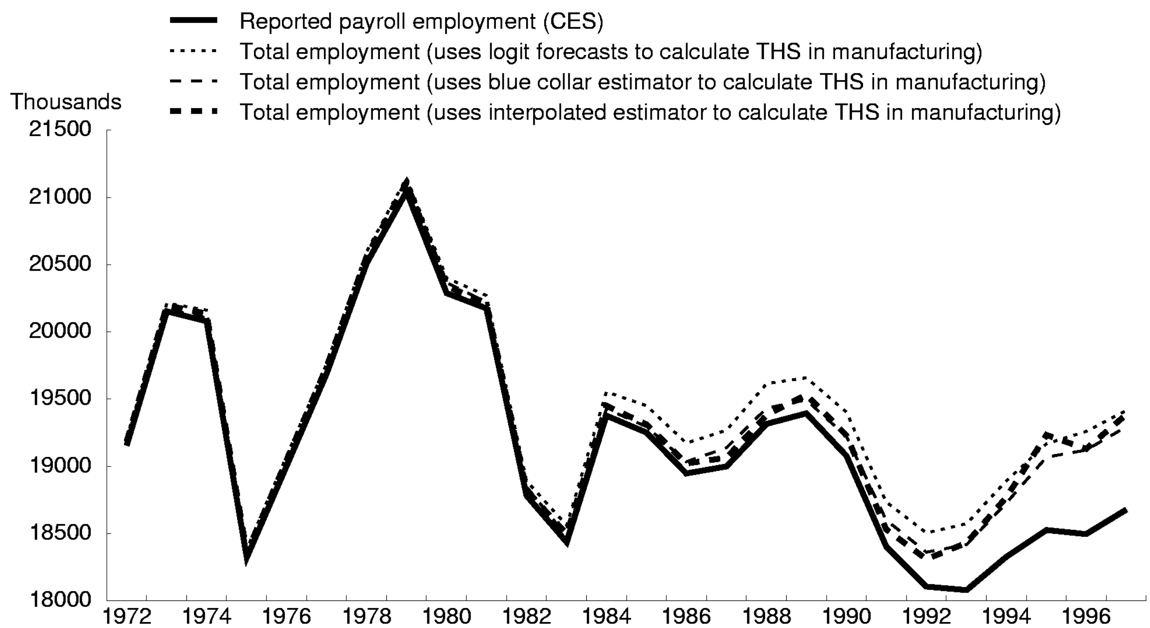


Figure 10

Manufacturing employment and hours
Employment
(Sample: 1972-97)



Hours
(Sample: 1982-97)