Working Paper Series

Wage Differentials for Temporary Services Work: Evidence from Administrative Data

Lewis M. Segal and Daniel G. Sullivan

Working Papers Series
Research Department
(WP-98-23)

Federal Reserve Bank of Chicago

Wage Differentials for Temporary Services Work:

Evidence from Administrative Data

Lewis M. Segal

Infometrics

Daniel G. Sullivan

Federal Reserve Bank of Chicago

December, 1998

The views expressed in this paper are solely those of the authors and are not official positions of the Federal Reserve Bank of Chicago or the Federal Reserve System. Thanks are owed to Ken Housinger for very capable assistance and to seminar participants at the Federal Reserve System Regional System Committee and the American Economics Association meetings, especially Daniel Hammermesh.

Abstract

We use administrative data from the unemployment insurance system of the Sate of Washington to study the magnitude of the wage differential associated with work in the temporary services industry. We find that temp wage rates are 15% to 20% below the levels that might have been expected based on trends during other periods in workers' careers even after controlling for differences between temps and other workers. Comparing temp wages to wages immediately before and after temp work or to the wages on non-temp jobs begun during the same period as workers were in the temp industry yields estimates of the temp work penalty as low as 10%.

I. Introduction

Employment in the temporary services industry has grown very rapidly over the last quarter century. Indeed, according to the Bureau of Labor Statistics' (BLS) Current Employment Survey (CES), the industry's employment has increased at an annual rate of over 11 percent since 1972, bringing its share of total U.S. employment from essentially zero to over two percent. This rapid growth has raised concerns because many view temporary service positions as "bad jobs." For instance, CES data show that average hourly earnings for production and nonsupervisory workers in the industry are 25% or more below national averages.[1] However, such simple comparisons fail to account for what may be substantial differences in skill levels and other factors between temporary services workers and those employed in other industries, a defect that we attempt to remedy in this paper.

From at least one perspective, a wage penalty for temporary services work would be surprising. Temporary services workers – hereafter "temps"– bear more risk of unemployment than other workers and one might reasonably expect that risk to be compensated by *higher* wages. The industry's workers, who overwhelmingly work under the direction of client firms on what are often short assignments, usually have no guarantee that they will be offered further work when those assignments are complete. As a result, temps are more likely than other workers to face unemployment or fewer than desired hours of work. For instance, in previous work (Segal and Sullivan (1997)) using matched data from Current Population Surveys, we found that temps were more than twice as likely (6.5% versus 2.6%) as other workers to be unemployment a year later and that in a given week they were four times as likely (20% versus 5%) to find themselves involuntarily working part time. As observers since Adam Smith have noted, workers, such as those in the construction trades, facing similar risks often earn compensating differentials.[2]

Of course, temps differ from construction and other workers who may receive compensating differentials for unemployment risk in a number of dimensions. In particular, unionization is virtually nonexistent in the temporary services industry. More generally, the typically very short job

1. Moreover, in previous work using the BLS's Current Population Survey (CPS) (Segal and Sullivan (1997)), we have shown that temps are much less likely to receive benefits such as health insurance from their employers.

2. For Smith's analysis see Book I, Chapter 10 of *The Wealth of Nations* (New York: Modern Library, 1937). For some evidence on compensating differentials for unemployment risk see, for example, Abowd and Ashenfelter (1981) and Topel (1984).

tenures of temps preclude the formation of groups of “insiders” along the lines of Lindbeck and Snower (1988). Without the kind of bargaining power unionization or the existence of entrenched insiders brings, temps may not be able to capture compensation for unemployment risk. Of course, this would run counter to the standard theory of compensating differentials which assumes a competitive labor market.

If temps do suffer a wage penalty, one explanation may be that it is compensated for by a positive and more salient job amenity – increased acquisition of human capital. Though, many critics of the temporary services industry claim that temp work not only is undesirable in the short term because of low current wages, but even more undesirable in the long term because its short job spells are inconducive to on-the-job training, industry advocates maintain that temps receive a good deal of training.[3] This latter view is supported by some survey evidence reported in Krueger (1993) and by Bureau of Labor Statistics data analyzed in Autor (1998). A large portion of the training provided by temporary services firms is in *general* skills, for instance in the use of computer software.[4] In addition to technical skills, temp workers may be able to acquire useful information about how well suited they are to a particular field, knowledge that is harder to obtain in conventional jobs. It is thus entirely possible that *per unit of time worked*, temps acquire more human capital that most other workers, a long-term advantage that may offset the short-term disadvantage of lower wages and benefits. From this perspective, whether temps earn positive or negative wage differentials depends on the importance of two partially offsetting job amenities: increased risk of unemployment versus more rapid accumulation of general human capital.

As we noted above, simple comparisons of temp worker wages to those of workers in other industries may not be indicative of true wage differentials associated with temp work. Temp workers differ from the norm in a number of dimensions. For instance, they are typically younger, more likely to be women, and are less likely to have a college degree, factors associated with lower wage rates.[5] In previous papers (Segal and Sullivan (1995, 1997)) we presented evidence suggesting that a significant part of the wage gap between temps and other workers was due to differences

3. See, for example, NATSS (1994, 1996a, and 1996b).

4. Autor (1998) notes that the fact that much of the general training is provided upfront, before temps go on assignments for their employers, presents a challenge for some versions of the theory of human capital because workers could choose to take the training without ultimately accepting any assignments, leaving the temporary services firm without anyway to recoup its training expenses.

5. See, for example, Segal and Sullivan (1995, 1997).

in various observable worker characteristics, as well as to other characteristics of jobs such as part-time status and coverage by a collective bargaining agreement. Moreover, we found that when we controlled for worker-specific fixed effects that the estimated wage penalty associated with temp work dropped to around 3%.

However, the above results relied on a matched CPS outgoing rotation group sample in which the identification of temp status was problematic because of the frequency with which temp workers misreport their industry. This problem of measurement error in the temp indicator was likely exacerbated in the fixed effect specifications since the fact that workers are only observed twice, one year apart, implies that the effects of measurement error are amplified relative to both levels regressions and fixed effects specifications with more than two time periods. We argued that the relatively high frequency of transitions between temp and perm work reduced the possible magnitude of this bias. Nevertheless, the issue of how much of the temp-perm wage gap is explained by worker characteristics is worth revisiting.

In this paper, we use a new data source, administrative files from the Unemployment Insurance (UI) system of the state of Washington, to study the effect of temporary services employment on workers' wages and earnings. As we discuss further below, administrative data has a number of important advantages for studying these issues. These include large sample sizes and long and complete records of workers' career histories. There are also disadvantages. Most importantly, we have no demographic or occupational information about the workers we study, which means that we cannot study how results differ according to workers' occupation, a factor we found to be important in our previous work.

We find that temp wage rates are 15% to 20% below the levels that might have been expected based on trends during other periods in workers' careers even after controlling for differences between temps and other workers. However, we also find that the periods in which workers take jobs in the temporary services industry tend to be ones in which their wages likely would have been lower in non-temp jobs as well. Comparing temp wages to wages immediately before and after temp work or to the wages on non-temp jobs begun during the same period as workers were in the temp industry yields lower estimates of the temp work differential. In the latter case the differential is approximately -10%.

II. Data

The primary data source for this paper is a 10% sample of quarterly wage records from Washington State covering the years 1984 to 1994. This sample was created as part of the Continuous Wage and Benefit History (CWBH) program that collected Unemployment Insurance (UI) data from several states for late 1970s and early 1980s.[6] Of the states that participated in the original CWBH program, Washington is one of the few to have continued to create data samples for use by researchers. Moreover, to our knowledge, Washington is the only state that provides administrative data on hours of work.

Each quarter, employers covered by the state's UI system are required to report total earnings and hours worked for each of their employees. The main categories of workers not covered are the self-employed and federal government workers. Our 10% sample of these records is based on the last two digits of workers' Social Security Numbers (SSN). This file, which includes worker and firm IDs, the four digit SIC code of the employer, and worker earnings and hours, contains nearly 100 million records. Large sample sizes are very helpful because temporary service workers are still only a small fraction of the labor force. Using the SIC code on the UI administrative data, we are able to identify about 1,400 temporary services workers in the first quarter of 1984, a figure that rises to over 6,000 by the last quarter of 1994.[7]

Using the UI data allows us to follow workers' careers at a quarterly frequency over an eleven year span from 1984 to 1994. Thus we are able to observe workers' wages for significant periods before and after their period of temporary services employment. We also get a nearly complete record of workers' employment relationships. This is important because temporary services jobs are frequently second jobs and thus would be missed in data sources that only record workers' primary jobs. Finally, because the records are used to compute benefit eligibility and levels, measurement errors are likely to be fewer than in survey data sources in which inaccuracies have no consequences for those reporting the data.

6. See, for example, Anderson and Meyer (1994).

7. Temporary services firms are those with SIC code 7362 up until 1986. In 1987 and after they are in SIC 7363 along with employee leasing firms also known as Professional Employer Organizations, or PEOs. As we discuss below, the mismeasurement caused by the possible confusion of leased and temporary workers is likely to be minimal in Washington State.

There are, of course, also drawbacks to using administrative data. As already mentioned, a major one is the lack of any demographic or occupational information on workers. We compensate for the lack of the typical human capital controls in our wage equations by relying on the longitudinal nature of our data to estimate models with fixed effects and individual-specific time trends. Such strategies should eliminate most sources of bias in our estimates of wage differentials. However, lack of demographic and occupational data does prevent us from determining whether our results for temporary services wage gaps differ according to workers' age, race, sex, or occupation, the latter being a factor we found in previous work to make a significant difference to estimated wage differentials and mobility patterns.[8]

Another difficulty associated with the use of administrative data is the lack of any direct means of distinguishing between cases in which workers are unemployed for a full quarter, are working in the uncovered sector, are working under another social security number, or have moved out of state. All of these possibilities result in there being no record for the worker's SSN in a particular quarter. For our analysis of average wage rates, this inability to distinguish missing data from truly zero earnings does not represent a major problem. However, we also present some evidence on total earnings levels associated with temp work whose interpretation depends on how we treat the lack of a wage record.

Yet another difficulty is that although firms are required to report hours, in practice they sometimes do not. In fact, about 8% of quarterly wage records do not report positive hours. Unfortunately, temporary services firms fail to report hours information about three times more often than this overall rate. Without valid information on hours we are unable to compute an average wage rate and thus cannot use such observations in wage comparison models. If the true wage rates associated with these missing observations were very different from the norm, our results would be potentially misleading. We know of no reason to think that these missing wage rates would be unusual. Missing hours data, however, is more common when earnings levels are low, probably indicating that job tenure was very short.

---

8. Segal and Sullivan (1995, 1997) found significant differences between white-collar, pink-collar and blue-collar temps. For example, for white collar workers, the wage penalty associated with temp work was less and temps were more likely to remain temps one year later. For blue-collar workers, the wage penalty was larger and temps were less likely top remain temps a year later. Results for pink-collar temps were generally in between those for white- and blue-collar temps.

Finally, despite the fact that these data are used for administrative purposes, what appear to be keypunch or other errors do occur. For instance, very high or very low implied wage rates are sometimes observed as are cases in which earnings rise then fall by a factor of ten or more over a three quarter period, suggesting that a decimal place was shifted. We excluded from our analyses cases that appear to be measurement errors.

Table 1 shows the growth of temporary services employment levels and employment shares in Washington State and nationally. The rate of growth of temporary services employment in Washington has been slightly faster than that of the nation as a whole, but the pattern over time is fairly similar. The shares of employment accounted for by the industry in Washington State, which are shown in Figure 1, are also reasonably similar to those for the nation.[9] This is reassuring since it suggests that our findings for Washington State may generalize to the nation as a whole. More evidence in this regard comes from Washington State Department of Employment Security (1997) which compares the occupational shares in temporary help supply in the Seattle metropolitan area to those for the nation as a whole using the BLS's Occupational Compensation Survey: Temporary Help Supply Services for 1989 and 1994. They find that employment shares for most occupations in Seattle are similar to those of the nation. In particular, shares in executive, administrative and managerial; sales and marketing; and clerical and administrative support are very similar, though shares for professional specialty and technical and related support are somewhat higher than nationally, while those for blue-collar occupations are somewhat lower.

A final difference between Washington State and the rest of the nation is the lower fraction of leased workers in SIC 7363. The SIC 7363 category contains both temporary services firms and employee leasing firms, also known as professional employer organizations (PEOs). This latter group of firms assume the existing work forces of other firms, performing all the administrative work associated with employing workers, such as writing pay checks and paying taxes, but have no role in recruiting or training workers. Their employees are typically long-term workers tied to the firms they are leased to. Since our interest is in temporary services employment, we view it as

9. The somewhat higher fractions shown for Washington State may be partially due to the fact that the rates are for work some time in a quarter while those for the nation are for work some time in a month. Because turnover in the industry is especially high, fractions of workers employed in the industry rise relatively rapidly with the length of time interval. For instance, in other work (Segal and Sullivan 1997), we have found that the fraction of workers employed some time during a two year interval is approximately 5% in Washington State.

a plus that the 1992 Census of Services Industries reported that only about 3% of SIC 7363 workers in Washington are leased, compared to about 23% nationally.[10]

III. Effects of Temp Work on Wages

In this section we present our evidence on the magnitude of temp wage differentials using the Washington State administrative data. As noted above, aberrant data values occasionally occur that would tend to obscure the main message in the data. So we eliminated observations that seemed likely to be mistakes.[11] In particular, we eliminated observations with quarterly hours above 1,040 (= 13 times 80), quarterly earnings above $50,000, average hourly wages below $1 or above $100, or which implied an hourly wage that is a factor of ten or more away from a worker's average over the whole 1984-1994 period. In order to keep the computations manageable we also limited the data on workers who were never temps to a 10% sample. The resulting data set, in which dollar figures were converted to real 1990 levels using the standard CPI-U, had about 8.9 million observations.

As noted above, our empirical strategy is to control for differences between temps and other workers by estimating models containing individual-specific constants and time trends. However, to facilitate comparisons to unadjusted differences in means we begin by presenting estimates of the following simple statistical model:

$$(1) \qquad y_{ijt} = \beta_t + \gamma D_{ijt} + \varepsilon_{ijt}$$

where y_{ijt} is the log of the wage for worker i in job j in quarter t, the β_t are fixed effects for calendar quarters, D_{ijt} is a dummy variable that is one when the worker is employed by a temporary services firm and zero otherwise, γ is the impact of temp work, and ε_{ijt} is an error term with the usual ideal properties. The β_t control for the tendency of wages to grow over time as well as seasonal patterns and recessions. Otherwise, however, model (1) is equivalent to a cross-sectional difference in mean wages between temps and other workers.

10. Washington State Department of Employment Security (1997).

11. Though outliers appear in administrative data, one advantage is that they tend to be extremely wild outliers that are easy to distinguish from valid data and thus outlier bounds can be set quite wide.

The estimate of γ in model (1) (shown in the top-left of Table 2) is -0.391 (with a standard error of 0.002).[12] This difference, which in terms of simple percentages translates into a 47.8% wage differential, is significantly larger than those found in national CES data for production workers. One reason may be the inclusion of non-production workers. Almost all temps count as production workers in the CES, but in other industries, 20% or more of the highest paid workers are eliminated from the CES. However, it seems likely that the true, cross-sectional difference is at least somewhat higher in Washington State than nationally.

As we have noted, temps differ from other workers in numerous dimensions, so estimates of model (1) are unlikely to capture the true wage differential associated with temp work. Any permanent differences in the characteristics of temp and other workers can be controlled for by estimating a standard fixed-effect specification:

$$(2) \qquad y_{ijt} = \alpha_i + \beta_t + \gamma D_{ijt} + \varepsilon_{ijt}$$

which differs from (1) by the inclusion of separate constants for each worker. The effects of any variables which, for a given worker, do not change over time, would be absorbed into these worker-specific constants. The estimate of γ in model (2) (shown in the middle row of Table 2) of -0.167 (standard error 0.002) is considerably smaller than that for model (1). This must reflect the fact that workers who hold temp jobs typically have lower earnings even when they are employed in other industries.

By holding constant any unchanging, individual-specific differences between temps and other workers, model (2) comes closer to capturing the true wage differential associated with temp work. However, it may not go far enough. There may be other unobserved differences between temps and other workers that are not constant over time. If these differences are changing at a nearly constant rate over time, however, they may be accounted for by a model containing individual-specific time trends in addition to individual-specific constants:

12. The standard errors shown in Table 2 are probably somewhat optimistic. In particular, if in contrast to the ideal assumption made about the error term in model (1), there are error components that are common to all jobs in a quarter of a given type – i.e. temp and other – then the estimated standard errors in Table 2 are too small. However, when we limit ourselves to a data set in which all temp jobs are averaged together to form a single observation and all perm jobs are averaged together to form another observation, and re-estimate the analogue of model (1), we obtain very similar point estimates and estimated standard errors that are only about 25% higher than those in Table 2 (though the 0.002s do change to 0.003s after rounding). We prefer to work with the data set in which observations correspond to jobs because it facilitates the estimation of somewhat richer models below.

(3) $$y_{ijt} = \alpha_i + \omega_i t + \beta_t + \gamma D_{ijt} + \varepsilon_{ijt}$$

which differs from (2) by the inclusion of individual-specific time slopes.

Because of our lack of the standard human capital controls, it may be especially important to employ model (3). For instance, the standard human capital specification would include a quadratic in experience and experience squared, or equivalently (in this context) age and age squared:

(4) $$y_{ijt} = \alpha_i + \beta_t + \theta_1 A_{it} + \theta_2 A_{it}^2 + \ldots + \varepsilon_{ijt}$$

where A_{it} is worker i's age at time t. However, if the worker's birth date is b_i then $A_{it} = t - b_i$. Substituting this relation into (4) introduces worker-specific time trends:

(5) $$y_{ijt} = \alpha_i' + \beta_t' - 2\theta_2 b_i t + \ldots + \varepsilon_{ijt}$$

Model (3) has been found by Heckman and Hotz (1989) to yield improved nonexperimental estimates of training programs and by Jacobson, LaLonde, and Sullivan (1993a) to be useful in the analysis of data similar to that employed here.

The estimate of γ based on model (3) (shown in the bottom row of Table 2) – -0.152 (standard error 0.002) – is slightly lower in magnitude than that based on fixed effects alone. Since workers are more likely to have spells of temp work later in the sample period, this evidently reflects the fact that those who work as temps tend to have lower wage time slopes in addition to lower wage levels.

Controlling for individual-specific constants and time trends greatly reduces the magnitude of the estimated wage differential associated with temp work. However, a log wage penalty of over 15% would, in the context of the standard competitive model of compensating differences, imply a significant positive amenity related to faster human capital acquisition or some other factor. The estimated wage differential is also considerably higher than those we obtained using CPS data in our previous work (Segal and Sullivan (1997)). This would be consistent with major biases due to measurement error in our previous work. In addition, some of the difference may be due to differences between Washington State and the rest of the nation, a factor hinted at by the high unadjusted differential obtained from model (1).

Estimates based on model (3) show that temp wage rates are considerably lower than might have been expected based on trends observed earlier and later in workers' careers. However, anecdotal and other evidence suggests that workers frequently turn to temp work after having suffering some career setback such as loss of a job due to a layoff or plant closing.[13] Such events may be associated with substantial reductions in wages and earnings that would not reflect temp work *per se*, but the circumstances that led them to accept temp work.[14] In this case, the trends observed at times significantly removed from the dates at which workers take temp jobs may not yield a valid comparison.

One way to begin to this issue is to allow for "effects" of temp work in periods immediately before and after their spells of temp work.To keep things relatively simple, we eliminated from our sample workers who had more than one spell of temp work, where a temp spell is defined as a sequence of consecutive quarters in which a worker held at least one temp job. The right hand column of Table 2 shows the effect of this sample restriction on the estimates of the models we have already discussed. For the individual-specific trends specification, the estimate – -0.160 (with a standard error of 0.003) – is just slightly higher in magnitude when we limit the sample to workers with at most one spell of temp employment.

We then created a series of dummy variables representing the number of quarters before or after the temp spell, $D^k{}_{ijt} = 1$ if the quarter t is k quarters after the temp spell. If k is negative then $D^k{}_{ijt} = 1$ that many quarters before the temp spell starts. In particular, the dummy D_{ijt} in previous specifications is denoted by $D^0{}_{ijt}$. We then estimated models of the form

$$(6) \qquad y_{ijt} = \alpha_i + \omega_i t + \beta_t + \sum_{k \geq -8}^{8} D^k{}_{ijt}\gamma_k + \varepsilon_{ijt}.$$

The parameters γ_k now measure the effect of temp work k quarters after the temp spell. The model is identified by the assumption that $\gamma_k = 0$ in period more than eight quarters removed from the temp work spell.

13. For example, Farber (1998) finds that workers reporting displacement in the 1994 Displaced Worker Supplement to the CPS are somewhat more likely to report being temps in a matched extract from the 1995 Contingent Worker CPS Supplement.

14. Evidence on the adverse consequences of job displacement can be found in, for example, Topel (1990), Ruhm (1991), Jacobson, LaLonde, and Sullivan (1993a, 1993b, 1993c) and is surveyed in Fallick(1996) and Kletzer (1998).

Estimates of the γ_k for $k = -8$ to $k = 8$ are plotted in Figure 2. Several features of the plot are notable. First, the estimates of the wage differential associated with periods immediately before and after temp work are negative. This indicates that these periods are associated with events leading to workers' having lower wages even when they are not working as temps. These effects tend to zero as the period is further removed from the time of the temp spell.[15] This suggests that the choice of an eight quarter "window" in model (6) is not particularly restrictive. Indeed we obtain very similar results with windows of six or ten quarters. Second, the estimate associated with temp quarters themselves (shown in the top left of Table 3) is slightly larger in magnitude than that based on model (3) – -0.161 (.004) versus -0.160 (.003). This is because the quarters of non-temp work that are inside the eight quarter window, during which wages tend to be lower, are removed from the effective comparison group. However, when we compare the temp work indicator coefficients to the coefficients for the quarter before and the quarter after temp work, the difference is smaller than the simple estimate based on model (3).

A simple, upper bound estimate of the true wage differential associated with temp work taking account the special circumstances in which workers accept temp jobs is $\tilde{\gamma}_{01} = \gamma_0 - (\gamma_{-1} + \gamma_1)/2$, the difference between the coefficients on the temp work indicator and the average of the quarters right around the temp work spell. This quantity is an upper bound for the magnitude of the temp work effect because the γ_k coefficients become more negative as k approaches zero. Thus using $|k| = 1$ rather than the theoretically preferable, but unobservable, $k = 0$, understates the size of the drop in non-temp wages that would have occurred in the quarters workers accept temp jobs. The estimate of $\tilde{\gamma}_{01}$ based on model (6) is -0.140 (.005).

Model (6) assumes that the temp work wage differential is constant over time. This assumption is relaxed in the model whose estimates are shown in the second column of Table 3 (labeled Model (6a)). In this specification a time trend is interacted with the temp job indicator so that the indicator coefficient measures the differential in the first quarter of temp work and the coefficient on the time trend interaction shows by how much the differential changes each additional quarter the temp spell lasts. The estimates indicate that the differential tends to be larger at the beginning of temp spells, shrinking about 1.4 percentage points each quarter the job lasts. At such a rate it

15. This effect is clearer in Figure 3, which as we discuss below is based on a richer specification that more satisfactorily represents the data.

would still take several years of temp work before the differential shrunk to zero. The fact that the temp work wage differential shrinks as temp spells last longer is also consistent with the fact that the differential increased when we limited the sample to workers with at most one temp work spell.

We argued that $\tilde{\gamma}_{01} = \gamma_0 - (\gamma_{-1} + \gamma_1) / 2$ was likely an over estimate of the temp wage differential after taking into account the circumstances that lead to workers accepting temp jobs because the temp wage effect in non-temp work period was increasing as the quarter approached the temp period. To get an estimate of where workers wages in other jobs were headed in the temp period, we added an indicator for a job being a "new perm job" – that is, for the job being outside the temporary services industry and having begun during the period the worker was a temp. We excluded continuing perm jobs because they likely would have included many jobs temps would have recently been forced to leave and thus would not be indicative of the kind of jobs temp workers would have been able to get.

Results of adding this indicator are shown in the third column of Table 3; in the fourth column the interactions of time trends with the temp and new perm indicators are included. For the latter, Figure 3 also plots the new estimates of the γ_k coefficients, adding the level of the new perm coefficient to the plot. As can be seen, when the new perm indicator is added to the model, the estimates of the temp indicator increase in magnitude. This is because the perm jobs that are taken out of the comparison group – those beginning during the quarters of the temp spell – are ones of abnormally low wages. Indeed, the coefficient on the new perm indicator in the last column is -0.111 (.006), indicating that perm jobs begun in the same quarters workers were employed in the temporary services industry were about 11% below expectations based on trends in the periods before and after temp work.

The difference between the temp work indicator and the new perm indicator – -0.107 (.006) would seem to be a reasonable estimate of the true temp wage differential once account is taken of the special circumstances likely surrounding the period of workers' employment in the temporary services industry. The coefficients on the time trend interactions indicate that the differentials between both temp jobs and new perm jobs and what would have been expected on the basis of period outside the eight quarter window shrink over time. The differential closes very slightly more slowly – 0.134 (.0017) versus 0.139 (.0045) for temp jobs than new perm jobs, a difference that is marginally statistically significant.

IV. Conclusion

We found that there is a definite negative wage differential associated with temp work. This is true even after we control for worker-specific fixed effects and time trends. Comparing temp wages to what would have been expected on the basis of wages trends at other times in workers' careers suggests a differential of 15% to 20%. But, up to half of this effect appears to be due to factors associated with temp work rather than to temp work *per se*. When we compare temp wages to more reasonable indicators of the non-temp opportunities temp workers might have had, the differential is only around 10%.

Of course, even a wage penalty of 10% is quite significant. Interpreted in terms of the competitive theory of compensating differentials, it would indicate that temps significantly value the increased opportunity to acquire human capital or some other non-wage aspect of temp work, especially given the increased risk of unemployment that it entails. Alternatively, the wage penalty may be a manifestation of temp workers' lack of bargaining power.

References

Abowd, John M. and Orley Ashenfelter, "Anticipated Unemployment, Temporary Layoffs, and Compensating Differentials," in *Studies in Labor Markets*, ed. Sherwin Rosen, Chicago: University of Chicago Press, 1981, pp. 141-170.

Anderson, Patricia and Bruce Meyer (1994), "The extent and Consequences of Job Turnover," *Brookings Papers on Economic Activity, Microeconomics*, 1994, pp. 177-236.

Autor, David H., "Why to Temporary Help Firms Provide Free general Skills Training?," unpublished manuscript, Kennedy School of Government, 1998.

Fallick, Bruce C (1996), "A Review of the Recent Literature on Displaced Workers," *Industrial and Labor Relations Review* 50(1), October, pp. 5-16.

Farber, Henry, "Job Displacement and Contingent Work," unpublished manuscript, Princeton University, 1998.

Heckman, James J. and V. Joseph Hotz, "Choosing among Alternative Nonexperimental Methods for Estimating the Effect of Social Programs: The Case of Manpower Training," Journal of the American Statistical Association, 84 (408), December 1989, pp. 862-874.

Jacobson, Louis, Robert LaLonde, and Daniel Sullivan (1993), "Earnings Losses of Displaced Workers," *American Economic Review* 72 (September), pp. 685-709.

Jacobson, Louis, Robert LaLonde, and Daniel Sullivan (1993b), *The Costs of Worker Dislocation Kalamazoo*, MI: Upjohn Institute Press.

Jacobson, Louis, Robert LaLonde, and Daniel Sullivan (1993c), "Earnings Losses of High Seniority Displaced Workers," *Economic Perspectives, a Review from the Federal Reserve Bank of Chicago*, pp. 2-22.

Kletzer, Lori (1998), "Job Displacement," *Journal of Economic Perspectives* 12(1), Winter 1998, pp. 115-136.

Krueger, Alan B., "How Computers Have Changed the Wage Structure: Evidence from Microdata, 1984-1989," *Quarterly Journal of Economics*, February 1993, 108, pp. 33-60.

Lindbeck, Asser and Dennis Snower, *The Insider-Outsider Theory of Employment and Unemployment*, Cambridge MA and London: The MIT Press, 1988.

National Association of Temporary and Staffing Services, "1994 Profile of the Temporary Workforce," *Contemporary Times – A Publication of the National Association of Temporary and Staffing Services*, Alexandria, VA, Spring 1994.

National Association of Temporary and Staffing Services, "Temporary Help Services Continue to Create Employment Opportunities Despite Millions of Job Casualties" Alexandria, VA: News Release, March 25, 1996a.

National Association of Temporary and Staffing Services, "Temporary Help Employment Experiences Strong Growth in 2nd quarter; This emerging form of employment is 'Wave of the Future'," Alexandria, VA: News Release, September 24, 1996b.

Podursky, Michael and Paul Swaim (1987), "Job Displacement Earnings Loss: Evidence from the Displaced Worker Survey," *Industrial and Labor Relations Review* 41 (October), pp. 17-29.

Ruhm, Christopher J. (1991), "Are Workers Permanently Scarred by Job Displacement?," *American Economic Review 81(1)*, March, pp. 319-324.

Segal, Lewis and Daniel Sullivan (1995), "The Temporary Work Force," *Economic Perspectives, a Review from the Federal Reserve Bank of Chicago*, Vol 19, no. 2 (March/April), 2-19.

Segal, Lewis and Daniel Sullivan (1997), "The Growth of Temporary Services Work," *Journal of Economic Perspectives*, Vol. 11, No. 2 (Spring), pp. 117-136.

Segal, Lewis and Daniel Sullivan (1997), "Temporary Services Employment Durations: Evidence from State UI Data," Federal Reserve Bank of Chicago Working Paper 97-23.

Smith, Adam, *The Wealth of Nations*, New York: Modern Library, 1937 (originally published 1776, of course).

Topel, Robert (1984), "Equilibrium earnings, Turnover, and Unemployment: New Evidence," *Journal of Labor Economics* 2, 4 (October 1984): 500-522.

Topel, Robert (1990), "Specific Capital and Unemployment: Measuring the Costs and Consequences of Job Loss," *Carnegie Rochester Conference Series on Public Policy* 33, pp. 181-214.

Washington State Department of Employment Security (1997), "Temporary Help Supply Employment in Washington," Studies in Industry and Employment, April.

Table 1: Temporary services employment levels and shares, U.S. and Washington State

Period	Washington State		Total U.S.[a]	
	Employment[b]	Share[c]	Employment	Share
1984:Q4	17.04	0.95	674.00	0.70
1985:Q4	20.03	1.0913	773.67	0.79
1986:Q4	21.92	1.1422	880.33	0.88
1987:Q4	32.08	1.4898	1045.00	1.01
1988:Q4	34.32	1.5969	1137.33	1.09
1989:Q4	41.34	1.7345	1236.33	1.14
1990:Q4	43.67	1.7578	1279.33	1.17
1991:Q4	40.91	1.6334	1300.00	1.20
1992:Q4	44.59	1.7688	1494.33	1.37
1993:Q4	49.14	1.8855	1785.33	1.60
1994:Q4	60.14	2.24	2125.00	1.84
1984:Q4 to 1994:Q4	253%[d]	1.29[e]	215%	1.14

a. Average of October, November, and December.
b. In 1,000s
c. In percent of employment.
d. Percentage growth
e. Change in share

Table 2: Estimates of the temp log wage differential – temp dummy only

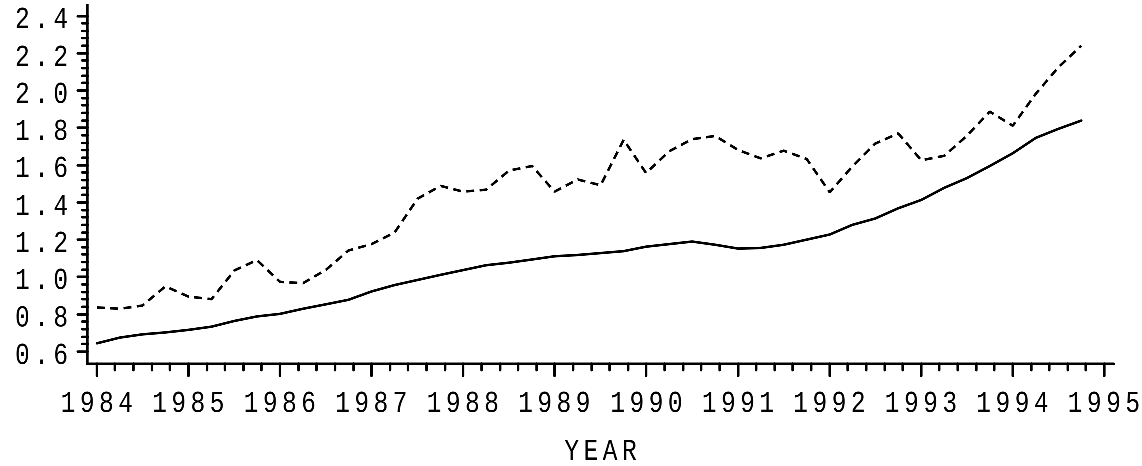
Control variables	Full sample	Workers with at most one temp spell
Quarter dummies	-0.391 (.002)	-0.390 (.002)
Quarter dummies and worker fixed effects	-0.167 (.002)	-0.180 (.002)
Quarter dummies, worker fixed effects, and worker-specific time trends	-0.152 (.002)	-0.160 (.003)

Table 3: Estimates of log wage effects[a]

Variable	Model (6)	Model (6a)	Model (6b)	Model (6c)
Temp job indicator	-0.161 (.004)	-0.186 (.004)	-0.195 (.004)	-0.218 (.004)
Indicator for one quarter before temp job	-0.025 (.005)	-0.025 (.005)	-0.050 (.005)	-0.050 (.005)
Indicator for one quarter after temp job	-0.017 (.005)	-0.017 (.005)	-0.047 (.005)	-0.048 (.005)
Temp job time slope		0.0139 (.0017)		0.0134 (.0017)
Indicator for new perm job			-0.093 (.004)	-0.111 (.006)
Perm job slope				0.0139 (.005)
Temp job indicator minus average of indicators for one quarter before and after.	-0.140 (.005)	-0.165 (.005)	-0.146 (.005)	-0.169 (.005)
temp job indicator minus new perm job indicator.			-0.102 (.005)	-0.107 (.006)

a. Sample restricted to workers with at most one temp spell. All model include quarter- specific fixed effects and worker-specific fixed effects and time trends.

Figure 1: Employment share of Temporary Services, monthly U.S. and quarterly Washington State



U.S.: solid   Washington: dashed

Figure 2: Estimates of temp effect in period before and after temp work

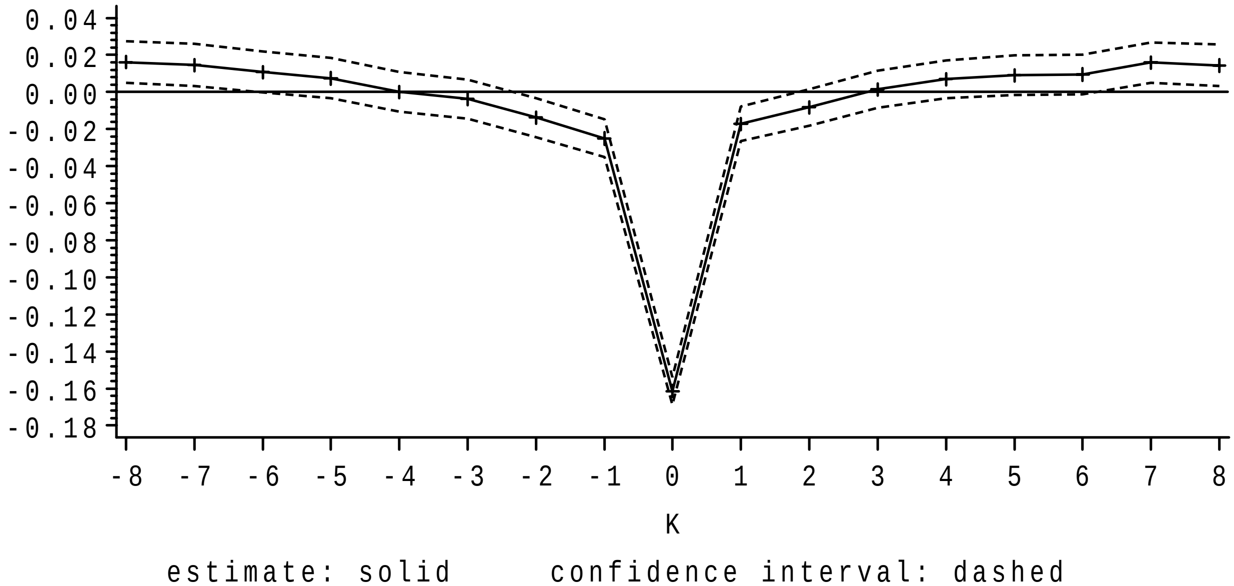


Figure 3: Estimates of temp effect in quarters before and after temp work