Help or Hindrance: Temporary Help Agencies and the United States Transitory Workforce

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Abstract

The impact of a Temporary Help Agency (THA) job placement on an employee's future employment status and labour market income is examined using NLSY79 data for the late 1990s. Several matching estimators provide gender-specific estimates of the effects of temporary agency employment on future employment outcomes. Compared to direct-hire temps, women's earnings increase two years after THA employment, while men's do not. Four years after THA employment, women continue to benefit from THA jobs, while men experience lower earnings and probability of employment. We find THA work does not help men with future income or employability.

Keywords: Temporary Help Agencies Temporary Workers Gender Wage Labour Income Employment Status

JEL codes: J31 J21 J22 J16 J63

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1 Introduction

Across the United States job seekers find the number of temporary help agency (THA) jobs have increased dramatically in the last few decades. In response to a changing labour market, increased demand for flexible work arrangements has presented opportunity for private industry. In contrast to direct-hire temporary work arrangements, THA agencies are third-party human resources firms who match and place employees into temporary contracts with employers for a fee.[1] The THA firm offers employers flexibility in their staffing, while providing job search assistance for employees; a THA firm may have several employer clients to which a resume could be forwarded. THA firms are thus well positioned to affect the welfare of workers when placed in charge of an employee's job placement possibilities.

With 11 million individuals employed yearly by THA firms in the United States (American Staffing Association, 2009), investigating the impact of these third-party employment facilitators is important. Europe has regulated these labour market intermediaries in the past; THA firms were illegal in Italy until 1997, and Spain has found it necessary to implement specific training provision requirements for all workers, (Amuedo-Dorantes, Malo, and Muno-Bulln, 2008). With approximately one third of its labour force employed in THA positions where firing costs are lowest, Spain now faces the highest unemployment rate in the E.U., (Economist, 2009). Similar concerns about the well-being of THA employees have arisen in America where the median THA worker earns \$200 less per week than a regular worker, (Lane, Sharkey, and Wissoker, 2003).

In the relatively unregulated labour market of the U.S., the THA industry has grown rapidly since the 1970s, (Peck and Theodore, 2007), raising concerns for affected workers. In the absence of tight regulation, we might expect that past employees of THA firms would suffer lower wages and fewer job prospects than a comparable direct-hire temp worker who may capture some of the salary rents which would otherwise finance the THA firm.[2] This paper examines the medium and long-term effect of THA employment on future employment status and future earnings of former THA workers.

The analysis of THA effects on future employment status and future earnings, is performed across two time frames. First, THA employees are compared direct-hire temps in the medium-term illustrating the causal effect

[1] The fee is typically a portion of the hourly wage based on the difference between what the employer is willing to pay and the worker is willing to accept.

[2] THA regulations, as well as many other labour market rules, are widely accepted to be lax in North America when compared to most European countries.

of the THA firm two years after the THA job is reported. Secondly, THA hires are compared to direct-hire temporary workers four years after the THA job to help illustrate the longer-term outcomes. Because of long-standing priors on labour market elasticity differences (Lloyd and Niemi, 1978), men and women are examined separately within these two categories.

Empirical results for THA workers reveal a gender differential in labour market outcomes across both medium and long-term time frames. In the medium-term THA positions will have a positive impact on earnings growth for women only. In the long-term, this positive effect on women's earnings persists while men experience negative impacts on both employment probability and earnings. Because women often have more labour market interruptions for childbirth and childcare in the home, these women are likely utilizing the THA firm to help obtain a suitable job when they return to the labour market. Table 1 suggests the women have a higher aptitude than men and are able to benefit from the THA firm because of it.[3] The men of this study, with a more limited set of skills, do not achieve the same success from THA assisted job matching. It is likely that the men are working THA jobs out of necessity. Men and women appear to self-select into THA employment for different reasons, which may also include some unobservable differences.

Table 1: Backgrounds of Temp Workers

	Years of Schooling	AFQT Score
Men	12.237	25.877
Women	12.581	28.923
Difference	0.344*	3.048

Years of schooling based on highest grade completed from NLSY 79 data. AFQT scores are percentile scores. Sample restricted to temp workers in non-farm occupations.

1.1 Literature

Temporary employment in general is often considered inferior to a permanent work arrangement. Booth, Francesconi, and Frank (2002) and Ichino, Mealli, and Nannicini (2008) find that temp jobs offer transitional assistance, while Lane, Sharkey, and Wissoker (2003) and McGrath and Keister (2008), support the idea that temp jobs are an inferior arrangement. As

[3]Table 1, depicts summary statistics by gender on AFQT and years of schooling.

a subset of temp jobs, THA positions share many of these characteristics. Literature on THA specific workers is sensibly separated by geography

The European empirical literature on general temporary workers finds in favor of THA employment. Ichino, Mealli, and Nannicini (2008) study two specific regions of Italy using data from Manpower Italia, a prominent THA firm. Their results suggest that past THA employment has a favorable effect, through signaling of skills to future employers for the attainment of a permanent position. King, Burke, and Pemberton (2005) present a case study on an Information Technology focused THA firm in the U.K.; they discover that those with prior THA experience are more likely to be short-listed for permanent employment.[4]

Current literature in the U.S. diverges from the European literature; impacts from THA employment across studies are inconsistent, and analysis is mainly focused on disadvantaged workers. Lane, Sharkey, and Wissoker (2003) find that THA work may alleviate some burden on the welfare system by helping the unemployed obtain jobs, although most THA workers are "slightly worse off" than other employed workers.[5] Autor and Houseman (2005a,b) look at welfare-to-work data, examining whether THA employment can lift income levels above the welfare threshold. Initially both THA and direct-hire positions are found to be beneficial for the marginal worker, however, the impact drops off before the 12-month mark. Finally, Autor (2001), models how THA firms who offer training, do so to exploit the private info from employees, resulting in lower wage offers.

The most recent empirical literature on THA employment is recognizing the importance of control-group selection for meaningful results. Using data on temp work and employer subsidies, Hamersma and Heinrich (2008) discover that THA employees are likely to suffer from comparatively lower future earnings. The authors caution against the use of regular workers for comparison because of stark differences in characteristics between the two groups. Amuedo-Dorantes, Malo, and Muno-Bulln (2008) also prefer a different comparison group for THA employees: direct-hire temps. The authors examine the likelihood of being hired on to a permanent position after holding a THA position. They find that these jobs do not facilitate "temp-to-perm" transitions as well as direct-hire temp positions and refer to the choice of control group as a reason why their results differ from Ichino, Mealli, and Nannicini (2008).

[4]THA experience with the same firm: prior knowledge of employee's ability is the most beneficial to the employee.

[5]These THA jobs are less likely than other jobs to offer health care benefits, which is implicit of a lower real wage.

In order to isolate the effect of THA firms from the effect of being a temporary worker in general, this paper adopts the direct-hire comparison group.[6] Comparing THA workers to other temp workers in the United States, we identify causal relationships between THA employment and future employment opportunities. A variety of estimation techniques are applied to ensure robustness of results. We are unaware of any other published works examining the impact of a THA job on the working population of the United States.

2 Data

The data used in this paper are from the National Longitudinal Survey of Youth 1979 (NLSY79) cohort, available from the Bureau of Labor Statistics. Created from a survey of the population of the United States aged 14-22 in 1979, the same 12,686 individuals are surveyed yearly until 1994 at which point the data were collected bi-annually. From the publicly available NLSY79 data, THA job-status information is available for the years 1994-1998.

The NLSY79 is a preferred data source for economists, not only because of its scope, but also due to the information it presents on otherwise unobserved measures of ability. The AFQT ability measure, a key variable for labour economists, is not well replicated in other data sources. The availability of high quality micro-data helps to position this paper in the body of current literature, which often makes use of private data collected by THA firms or regional THA associations, and case studies.

Created from job status questions in the years 1994-98, a respondent's participation in a THA job is indicated by the binary variable "Agency". Although the NLSY79 reports on several jobs, the Current Population Survey (CPS) job alone is considered in this paper. The estimation is restricted to those who "considered [themselves] a temp worker, sent by a temporary agency," or a "temp worker, hired directly by the company," Further cleaning of the data removed those employed in farm and those in military service.

Because THA employees represent the minority of the U.S. population at less than 3 percent (Peck and Theodore, 2002), with 168 of 313 THA

[6] Impacts were also calculated for comparisons of THA to permanent employees. Estimated impacts were dominated, however, by the difference between temporary work in general and permanent work. These estimates are excluded because of the lack of insight into the effect of a THA agency.

observations found in the race oversamples it is important to include these respondents. Sample weights are employed in the propensity score calculation for matching and other regressions to maintain representativeness while allowing use of the full sample.[7]

The effect of THA employment is measured on labour market outcomes two and four years after the respondent reported THA employment.[8] The first observable is employment status, indicating whether or not the individual was employed during the year of response.[9] The second measured outcome is the natural log of total labour income in dollars, approximating the percentage change in overall earnings. The future total labour income of an individual is suggestive of the labour market opportunities presented to a former THA employee.

For most THA workers, because job tenure in the years 1994 to 1998 is between 10 and 12 weeks (American Staffing Association, 2009), we define the medium-term as a two year time frame and the long-term as a four year gap between reported THA employment and the examined earnings. For medium-term workers, the THA job should be the most recent experience to appear on a resume. The medium-term is therefore illustrative of how recent THA work experience may impact these individuals. The four year time frame permits analysis of the persistence of medium-term effects, as well capturing long-term effects once the THA work no longer represents recent employment.

Preliminary examination of the data (presented in Table 2) shows two distinct effects and justifies the segregation of the data by time frame and gender. While the long-term data reveals THA men are slightly worse off, for women we find a significant positive relationship between THA employment and earnings in both the medium and long-term. The only caveat of the NLSY79 dataset is the absence of younger workers in the sample; all NLSY79 participants were born before 1970.[10] During observation at a THA job, ages

[7]Participants in the 2009 NLSY79 general workshop learned that the yearly (probability) weights were calculated based on parental income, age, race, and sex. Results are robust to the exclusion of these weights.

[8]Outcomes are measured on years 1996-2002.

[9]Unfortunately the employment status recode generated by NLS staff from complex weekly job histories is unavailable for the years 2000-2004. The employed dummy is therefore created by selecting those workers who reported total earnings, including tips and bonuses, greater than $1000 per year. Those earning less than this threshold do not constitute employed individuals for the purpose of this study. We will be unable to distinguish OLF from unemployed until these missing years are released in the future.

[10]Unfortunately, the NLSY 79 survey has no data prior to 1994 about THA employment, and therefore no observations for the 12686 respondents at younger ages.

range from 29-40.

Table 2: t-Test for Equality of Means: Agency vs. Direct-hire Temps

		Medium-Term: 2 Years after THA		Long-Term: 4 Years after THA	
		Males	Females	Males	Females
Ln(labour Income)	Direct	9.44	8.92	9.23	8.60
	Agency	9.35	9.30	9.19	9.07
	P-value	0.550	0.008	0.759	0.004
Pr(Employed)	Direct	0.63	0.61	0.98	0.93
	Agency	0.68	0.69	0.96	0.95
	P-value	0.330	0.141	0.493	0.338

3 Estimation

3.1 Framework

In order to determine the causal effect of past THA employment on future labour market outcomes, THA workers are compared to direct-hire temp workers. The main matching framework stems from Rubin (1974), Rosenbaum and Rubin (1983), and later Dehejia and Wahba (2002); mixed matching and OLS are also employed. Matching estimation provides the next-best option to a true natural experiment because it can identify causal effects without concerns of functional form or weak instruments present in alternative methodologies.

The treated group in this paper is THA workers while the un-treated are the direct-hire temps. W is the treatment indicator variable and X is a vector of individual characteristics. The empirical model presents the effects of treatment, given by Delta, as follows:

$$\Delta = E(Y_1 - Y_0|X)$$

where Y_1 represents the outcome when treated and Y_0 represents the outcome when untreated. In other words, Y_1 can represent the earnings of an agent who has worked a THA job in the past while Y_0 will represent the earnings of an agent who has not. Because we can only observe one of these outcomes for each agent in a given period, Δ is never observed for a single individual. We therefore rely on matching to give us the counterfactual:

$$\Delta = E(Y_1|X, W = 0)$$

Matching takes a treated case and finds an observation in the untreated state that is as similar as possible across the X characteristics. Due to the fact that these observations should have significant variation only in the treatment status, the causal effect of treatment can be considered a random variable (Wooldridge, 2002).

3.2 Assumptions

The CIA, or conditional independence assumption

$$Y_i \perp W|X, \quad i \in 0, 1$$

states that the "treatment status is random, conditional on X". This assumption requires that one controls for all possible X which might affect the treatment status W and outcome Y_i, so that the selection of the treated observation is effectively randomized.

To address selection into THA work this paper conditions on past labour market status.[11] Ashenfelter (1978), shows that prior to participation in treatment groups such as a training program, workers experienced a dip in their earnings. Past and current income comparisons may therefore lead to false-positive conclusions about program participation.[12] Heckman and Smith (1999), find that "Unemployment dynamics and not earnings or employment dynamics, drive participation in training programmes", and condition on past labour force status to avoid bias from economy-wide effects.

Because we cannot test the CIA directly, we turn to the data; a very broad set of covariates, chosen to control for all characteristics expected to influence THA participation, will permit this independence. The validity of the matches performed in this paper should be clear because of the ability to match at the individual level across a plethora of characteristics, inclusive of the AFQT score. The personal characteristics contained within X are: dummies on past labour force status, marital status, highest completed

[11] Because the employment status recode variable is available up to 1998, we are able to utilize the true employment status variable here which includes separate distinction for those unemployed and those out of the labour force.

[12] This effect is commonly referenced as "Ashenfelter's Dip".

education from elementary to college, race, geography, U.S.-born, a health limitation, and measures of age, AFQT, family size, lagged weekly hours at work, and total number of jobs. Occupational categories are also present within X and include managers, sales workers, clerical workers, craftsmen, operative workers, service workers and labourers.

3.3 Impacts

The first outcome measured by matching is the average effect of treatment on the treated (ATT).

$$ATT = E(Y_1|X, W = 1) - E(Y_0|X, W = 1)$$
$$ATT = E(Y_1 - Y_0|X, W = 1)$$

Under the CIA assumption, ATT is a measurement of the causal effect of temp agency employment (or treatment) on observations flagged as treatment participants W = 1. Data from the treated group is used to compute the unobserved outcome from matching on the control observations: direct-hire temps.

Beyond the ATT, matching also computes the average effect of treatment on the untreated (ATU).

$$ATU = E(Y_1 - Y_0|X, W = 0)$$

ATU shows the effect of treatment which would have occurred if the untreated had been treated. In other words, ATU measures impacts that would have occurred if those in direct-hire temp jobs had accepted an agency temp job instead.

Finally, matching estimates can be used to compute the average treatment effect (ATE) on the entire population.

$$ATE = E(Y_1 - Y_0|X)$$

ATE gives the effect of THA employment on a randomly drawn member of the population, Wooldridge (2002), and corresponds to the impact given by regression models.

3.4 The Propensity Score

Despite the benefits of non-parametric techniques, dimensionality can arise as a problem.[13] The common remedy for this issue, implemented in this

[13]The matching technique employs kernel estimation, which often generates a poor fit at the boundary of any dataset as the moving average reaches this boundary. As dimension increases, so does the proportion of observations at any boundary.

paper, is the use of a propensity score. The propensity score, $\Pr(W = 1|X)$, is the probability that any observation is treated, a THA employee, based on the covariates X.

Matching on the propensity score instead of all the covariates eliminates the dimensionality issue, and has been found to be consistent wherever matching on all covariates is consistent, provided the CIA holds (Rosenbaum and Rubin, 1983). Where the outcomes are independent of treatment status conditional on the covariates, the outcomes are also independent of treatment status conditional on the propensity score (Smith and Todd, 2005). It is not trivial that any estimation error from the propensity score regression will contaminate the standard errors of the matching process.[14]

Using a logit framework with THA participation as the dependent variable, regression is performed on the covariates, returning the propensity score as the fitted value. Since the propensity score is produced from the parametric model, it is of a single dimension and alleviates the dimensionality problems listed above. The validity of results also relies on the assumption that all observations are "on support"; matches are computed from the region where propensity score distributions for W=1 and W=0 overlap.

$$0 < \Pr(W = 1|X) < 1$$

Similarities between THA and direct-hire temp workers, across personal characteristics X, permit this common support region, illustrating that direct-hire temps are a suitable matching framework comparison group for THA workers.

3.5 Estimators

A distinct advantage of the matching framework in this paper is the non-parametric nature of the estimation. Davidson and MacKinnon (2004) describe the Epanechnikov kernel estimator,

$$\hat{f}(x) = \frac{1}{nh}\sum_{t=1}^{n} K\left(\frac{x - x_t}{h}\right), \qquad where \quad K(z) = \frac{3\left(1 - \frac{z^2}{5}\right)}{4\sqrt{5}}, \qquad for \quad |z| < \sqrt{5}, 0$$

[14]Heckman, Ichimura, and Todd (1999) recommend bootstrapping as a best effort to correct standard errors. As suggested in Davidson and MacKinnon (2002), 1499 repetitions are used to compute bootstrapped values. Although it is computationally expensive to have so many iterations, in the interest of preserving the power of the test (0.01) the sacrifice is made.

that is used to select the control observations on which the treated observation is to be matched.[15] The choice of the kernel estimator means that the match for the treated observation is computed out of a weighted distribution of similar untreated observations. The non-parametric kernel estimation has advantages over other parametric regression methods because it does not impose a specific functional form on the estimation and, therefore, may be consistent when standard regressions are not. In the absence of a natural experiment, this is a preferred method for identifying robust causal effects.

Recent literature (Abadie and Imbens, 2002), has identified mixed regression and matching techniques as the most robust method of obtaining ATE results. Mixed matching techniques and OLS results are calculated for comparison to kernel ATE estimates. Similar to the Abadie-Imbens technique, our mixed matching method is a two step process where Nearest neighbour (NN) matching is employed to select a sample on which regression is then performed. The NN matching without replacement minimizes the distance between the treated and most similar control observation across propensity scores, giving rise to some bias which is typically linear in form.[16] Once this match is complete, OLS regression is used to correct for the bias and give the impact of treatment, Δ. This method is "preferred" (Imbens and Wooldridge, 2009), for robustness and exhibits a "double robustness property": When either the propensity score estimation for the NN match or the second stage regression are misspecified, the correct specification of the other will ensure estimates are still valid. When the CIA holds for the NN match, the results are consistent. The linear regression performed on this new sub-sample is now robust to misspecification of the regression function and gives the ATE result (Robins and Ritov, 1997).

For verification of robustness, traditional OLS estimates as well as the mixed matching estimates are provided in the appendix (Table A6). Results are sufficiently similar to kernel matching ATE results.

3.6 Sensitivity Analysis

Because of the importance of the bandwidth selection to kernel estimates, sensitivity analysis is performed on the bandwidth. Bandwidths of 0.005 and 0.8 are tested, representing upper and lower extremes. Results are available

[15]The Epanechnikov kernel is favored to the Gaussian kernel because of its relative compactness; support is (-1,+1).

[16]No replacement forces the matching process to select a new nearest neighbour control observation for each match. Unlike kernel estimation, NN matching takes the closest single neighbour as a match.

in the Appendix (Tables A2 & A5) and show robustness to bandwidth fluctuations. The Gaussian kernel density matches were also estimated but excluded because of similarity to the Epanechnikov matches.

Careful bandwidth choice is important for two reasons. Choice of a large bandwidth results in an increased bias; over-smoothing across control observations. Very small bandwidth selections, unless the distribution is unusually narrow, result in an unnecessary large variance. Post-estimation, matches with small bandwidth may be out of balance, indicating that some control observations were used multiple times to match certain characteristics which were scarce in the small sample size.[17] A widely accepted device, the Silverman Rule, selects the bandwidth to minimize the expected mean standard error,

$$h = 0.9 \min(s, \hat{q}_{0.75} - \hat{q}_{0.25}) n^{-\frac{1}{5}}$$

where s is the standard deviation of the kernel function's parameters (Davidson and MacKinnon, 2004). Results are reported for the Silverman optimal bandwidth range.

4 Results

Two sets of estimation results are presented in this section, as well as a discussion of the determinants affecting selection into THA employment. Results comparing THA to their direct-hire counterparts in the medium-term show causal effects of THA employment in the period after reporting a THA job. Following these results, the findings from a long-term examination of THA impacts are presented.

4.1 Selection into THA

It is informative to examine selection into THA positions, because such analysis provides us with an understanding of the composition of the treated group and their propensity scores. The propensity score regressions predict the probability of being a THA worker, given the covariates X (see Appendix Table A1). For men, selection into THA work is influenced by race as well as certain job categories, including operatives, clerical and labour, many of which are popular occupations for THA firms to target (see Appendix Figure A10). These are also lower skilled jobs, which supports the observation

[17] A test for inequality of means between matched and control group is accepted for almost all variables including AFQT scores, work history variables, and other important control variables.

that lower THA males have a lower skill level than the women. Having a health limitation leads to selection away from THA work, likely because these workers have an increased need for health insurance which is typically not available to THA workers.

For women, several of the same job categories increase the probability of being a THA worker. Figure A11 in the Appendix details THA occupations by gender. Having only completed secondary school or middle school also increases the propensity to be a THA worker. Being single has a stronger impact than being married, although both seem to play a role. When the data are restricted to isolate mainly single parents, however, selection into temping is shown to be correlated with past labour market interruptions in women.[18] Table 3 presents summary statistics supporting the findings of this paper; women who have left the labour market due to children select into THA positions when they return. In contrast to men at only 14 percent, 33 percent of women who reported THA work were out of the labour force in the 2 years prior. Also, THA women are 8 percent more likely to have been out of the labour force in the past two years than the Direct-Hire women.

Table 3: Past L.F. Status of Single Parents by Temp Job

		Employed	Unemployed	OLF
Women	Agency	62%	5%	33%
	Direct-Hire	58%	17%	25%
Men	Agency	57%	29%	14%
	Direct-Hire	66%	13%	21%

Data restricted to those with a family size greater than two, and reporting un-married. LF status collected 2 years prior to THA work.

4.2 Medium-Term

Table 4 presents the results from medium-term matches; the effect of THA employment 2 years afterward.

The lack of significance for any of the matches on men suggests that men are not advantageously choosing THA jobs for the same reasons as women. This is likely reflecting that fewer labour market choices are available to the male temps, which is not surprising given that the men in this sample,

[18]Data are restricted to family size ≥ 3 and unmarried. This picks up mainly single parents, but may also select some agents living with siblings and parents. Because of the age of respondents (29-40) these un-desired observations will be the minority.

Table 4: Medium-Term Results - Agency vs. Direct-Hire Temps 2 years post-THA

Gender	Outcome Two Years Post THA	Measure	Coef.	z-Stat	S.E.	Optimal Bandwidth
Men	Ln(labour Income)	ATT	-0.165	-0.89	0.185	0.156
		ATU	-0.056	-0.33	0.171	
		ATE	-0.114	-0.75	0.152	
	Pr(employed)	ATT	0.072	0.95	0.075	
		ATU	0.063	0.96	0.065	
		ATE	0.068	1.02	0.066	
Women	Ln(labour Income)	ATT	0.312*	1.85	0.169	0.167
		ATU	0.420**	2.10	0.200	
		ATE	0.368**	2.28	0.161	
	Pr(employed)	ATT	0.013	0.22	0.062	
		ATU	0.085	1.21	0.071	
		ATE	0.052	0.90	0.058	

Propensity score matching results with Epanechnikov Kernel estimator. Data are from NLSY79 years 1994-1998. Results are robust to inclusion of past current labour income in the propensity score. Bootstrapped test statistics and standard errors are reported.

have less education and score lower in ability than the women on average (see Table 1). We may therefore expect these men to be less desirable to employers than their female counterparts. Even conditional on AFQT and education, male temps have worse job prospects than those who are not temp workers.

For the analysis of women, the kernel match of interest identifies the positive causal effect of being an agency temp on future earnings. In the female match, the ATT (average effect of treatment on the treated) gives a value of 0.312. Those women who sought a THA job instead of a direct-hire temp job were earning 27 percent more two years after they were observed at the THA job.[19] The ATU (average effect of treatment on the untreated) was also positive with a value of 0.419. Those women who took direct-hire temp jobs would have earned 34 percent more on average if they had been in the treatment group (THA employed).

Economic theory would predict that women who have left the labour

[19]The Log form gives an approximation to percentage change. The true percentage is calculated by $1 - e^{\beta}$

force to have or to raise children will deliberately choose THA jobs when re-entering to gain work experience in a sector where they would like to gain permanent employment. These women would have an absence of recent labour market experience and be out of practice with job-hunting techniques and strategies, but not necessarily lacking skills. For this reason, it is not surprising to find that women are benefiting from THA employment. To find matches, THA firms compare the needs of employers and workers. In addition, these firms may offer some basic skills training or at least skills screening, in which case a better match between workers and jobs would likely result from a THA. For an agent with recent job hunting experience, however, we would not necessarily assume superior matching from a THA firm.[20] These results are consistent with Autor (2001), who postulates that THA training benefits the stronger candidates only.[21]

The ATU and ATE matches for women on future earnings are significant at the 5 percent level, while the ATT is significant at the 10 percent level. The coefficient is robust to bandwidths tested in range from 0.005 to 0.8 (see Appendix Table A2). Although there is some sensitivity of the t-statistic to extremely low bandwidths, this should not be a concern because significance is found at the optimal bandwidth. The match coefficients are also robust to estimator choice, including OLS estimation and mixed matching techniques as shown in Appendix Table A4.

In addition to standard sensitivity analysis, it is also important to take note of the balance statistics from the matching outcomes as these will indicate the quality of the results. Well balanced estimates show the ability of the propensity score matching to handle the bias-variance trade off when choosing comparison observations across the covariates. Of all the covariates used in matching for women's medium-term labour income, a majority are balanced. The superior balance of covariates for men is suggestive of a greater degree of heterogeneity amongst the women choosing THA jobs. Balance test statistics for this medium-term match are presented in Appendix Table A4.

[20] Depending on the structure of the THA firm, it is common to find the THA firm facing a trade off between speed of match (directly reflecting commission income) and the quality of the match between employee and employer. An experienced job hunter may be able to match themselves better to a job than a THA firm where commission to the THA employee affects the matching quality.

[21] Autor discusses how agents with low ability, as discovered through up-front THA training exercises, are not recommended to as many employers.

4.3 Long-Term

As with the findings for the medium-term, women are benefiting from THA positions four years after reporting THA work. The loss of significance on the ATU suggests that women are self-selecting efficiently into THA employment; those who have chosen direct-hire jobs would have had no long-term benefits from a THA job. At 35%, the positive impact on long-term earnings is considerable. This persistence in post-THA wage growth indicates the continued success of the THA women, further demonstrating their working aptitude. The significance of the ATE coefficient suggests that the ATT effect is strong enough to dominate the ATU for these women. Women's future propensity to be employed continues to be unaffected by THA employment, demonstrating that women's labour supply schedule is influenced by factors exogenous to the labour market like childbirth.

For men, a new story emerges in the long-term. The coefficients on ATT, ATU and ATE for both long-term earnings and employment prospects are negative. Holding a THA job appears to present men with a wage penalty as they age, which is not noticeable in the medium-term. This suggests that the inferior access to skill development available to a THA employee may catch up with men as time passes. Their limited skills should be relatively less valuable as the skill-sets of non THA men in their cohort increase. This penalty also extends into employment probability, suggesting that men experience harmful signaling effects from a resume listing THA employment. Employers may be more sympathetic to younger employees who have recent THA employment because they have comparatively limited labour market experience. These effects extend from the observed to the hypothetical situation (ATU); those men who did not chose THA employment would have been worse off if they did. Table 5 presents the long-term matching results, while Table A1 in the Appendix shows the propensity score calculations. These results are robust to bandwidth and estimation technique as depicted in the Appendix Tables A5 and A6.

The post-estimation balance from the long-term matches is also strong. Tables A7 and A8 in the Appendix show the long-term balance test results for men. For our match on women's long-term future earnings, Table A9 illustrates that most covariates are balanced after matching.

5 Conclusion

This paper examines the medium and long-term effects of THA employment on employment status and earnings for workers born in the years 1957-1969.

Table 5: Long-Term Results - Agency vs. Direct-Hire Temps 4 Years Post-THA

Gender	Outcome Two Years Post THA	Measure	Coef.	z-Stat	S.E.	Optimal Bandwidth
Men	Ln(labour Income)	ATT	-0.384*	-1.87	0.206	0.157
		ATU	-0.435**	-2.31	0.188	
		ATE	-0.408**	-2.26	0.180	
	Pr(employed)	ATT	-0.043***	-2.51	0.017	
		ATU	-0.056*	-1.89	0.030	
		ATE	-0.049**	-2.35	0.021	
Women	Ln(labour Income)	ATT	0.432**	1.92	0.225	0.155
		ATU	0.280	1.06	0.264	
		ATE	0.354*	1.65	0.214	
	Pr(employed)	ATT	0.047	1.17	0.040	
		ATU	0.028	0.80	0.035	
		ATE	0.037	1.09	0.034	

Propensity score matching results with Epanechnikov Kernel estimator. Data are from NLSY79 years 1994-1998. Results are robust to inclusion of past current labour income in the propensity score. Bootstrapped test statistics and standard errors are reported.

It brings together longitudinal data from the NLSY79, propensity score matching techniques and a THA to direct-hire comparison for the United States. Findings include different effects by gender from THA employment through the late 1990s.

We summarize the impacts of THA employment by gender. When choosing THA employment over direct-hire temp work, in the medium-term women benefit while men are unaffected. By contrast, in the long-term, it appears that women self-select correctly into THA positions because only those who did participate in a THA job are found to have increased earnings.[22] Men also differ in the long-term; negative impacts are found on both future earnings and employment probability. These results suggest women are using THA firms to help with labour market re-entry. Men, by comparison, appear to take THA jobs because their skills are not transparent or sufficient to prospective to end employers. Having a THA instead of a

[22]ATT is positive and significant, while the ATU is not. This means that those who did not chose a THA job, would not have been better off if they had participated in THA work.

permanent job leads to wage penalties and difficulties obtaining employment in the long-term as the men age. These results for men support Autor and Houseman (2005a,b), Lane, Sharkey, and Wissoker (2003) and Booth, Francesconi, and Frank (2002) who also find negative impacts from THA employment specifically on marginal workers.

Notwithstanding the relatively small size of the U.S. temp industry compared to some European countries, there are implications which may be drawn from these results. Assuming that the positive trend in women's earnings is indicative of good employer-employee matches, employers in industries where the labour force is dominated by men may not benefit from dealing with THA firms. Male workers may be poorly matched by THAs or hold and possess an inferior skill-set. On average, men in this position should not accept wage-skimming practices from THA firms if they are forward looking; in the long run a THA job will have a negative impact. Contrary to men, women, who may have interrupted labour supply schedules due to their children, may experience higher future earnings if they register with THA firms.

In addition to the private sector implications, public policy may benefit from these findings. Because THA work is not found to assist those who would otherwise choose regular employment, for men it would appear that partnership with THA firms to solve general issues with unemployment could discourage workers from self-matching into the more beneficial direct-hire jobs. Thus for government funded employment placement programs, the recommended focus would be women who seek temporary employment; women currently out of the labour force and trying to re-enter may benefit most from THA programs.

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APPENDIX

Table A1: Logit Regression Results (Propensity score calculation)

	Men			Women		
	n=265	R^2=0.226		n=341	R^2=0.233	
Agency	Coef.	S.E.	z-Stat	Coef.	S.E.	z-Stat
Raceb	1.1318**	0.5212	2.17	0.6324	0.3966	1.59
U.S. Born	-2.1746***	0.7571	-2.87	-0.3336	1.0017	-0.32
Manager	2.5221*	1.3216	1.91	0.8531	0.7647	1.12
Clerical	1.6040**	0.6467	2.48	1.0257**	0.4222	2.43
Craftsmen	1.2125*	0.7048	1.72	-1.2371	1.0521	-1.18
Operatives	2.7767***	0.5729	4.85	2.2423***	0.6375	3.52
Labor	1.2882**	0.5643	2.28	1.5007**	0.6801	2.21
Service	0.6032	0.7674	0.79	-1.6136***	0.6093	-2.65
Famsize	-0.0580	0.1122	-0.52	-0.4380***	0.1312	-3.34
Northc	1.1458***	0.5684	2.56	-0.2701	0.5125	-0.53
Single	0.2418	0.4601	0.53	0.9000*	0.5335	1.69
Married	0.2570	0.5016	0.51	0.7711*	0.4349	1.77
Highschool	0.1721	0.7138	0.24	1.2095**	0.5503	2.20
Middlesc	0.1418	0.9335	0.15	1.5664**	0.7745	2.02

Insignificant coefficients: Lagolf, Sales, Northeast, Elementary, Health are always negative; Age, South, Urban, AFQT, Hrslag, and Njobrep are always positive; Lagunemp and Local Urate are negative for women, Raceo is negative for men.

Table A2: Medium-Term sensitivity analysis results: Bandwidth variations

Gender	Outcome	ATT	ATU	ATE	Bwidth
Men	Ln(Labor Income)	-0.1625	-0.993	-0.1329	0.8
		(0.1452)	(0.146)	(0.1418)	
	Pr(Employed)	0.0218	0.0455	0.0332	
		(0.0579)	(0.0572)	(0.0583)	
	Ln(Labor Income)	-0.1943	-0.2026	-0.1985	0.005
		(0.2315)	(0.2558)	(0.2174)	
	Pr(Employed)	0.0213	0.0417	0.031	
		(0.0945)	(0.092)	(0.0781)	
Women	Ln(Labor Income)	0.3224**	0.3838**	0.3542**	0.8
		(0.1461)	(0.1536)	(0.1457)	
	Pr(Employed)	0.0423	0.063	0.0535	
		(0.052)	(0.0515)	(0.051)	
	Ln(Labor Income)	0.4515	0.3693	0.4067*	0.05
		(0.2869)	(0.2444)	(0.2358)	
	Pr(Employed)	0.0987	0.115	0.1075	
		(0.0891)	(0.087)	(0.0754)	

Bootstrapped standard errors are in parentheses. The coefficient on women's future earnings remains positive despite bandwidth fluctuation.

Table A3: Medium - Term ATE Estimates for Alternative Estimation Procedures

	Estimation	Outcome	Coef.	t-stat	S.E.
Men	OLS	Ln(Labor Income)	-0.0691	-0.39	0.17613
		Pr(Employed)	-0.0843	-1.14	0.07373
	Mixed Matching	Ln(Labor Income)	-0.1262	-0.76	0.16548
		Pr(Employed)	0.0335	0.54	0.06238
Women	OLS	Ln(Labor Income)	0.3877**	2.34	0.16537
		Pr(Employed)	0.0237	0.37	0.06488
	Mixed Matching	Ln(Labor Income)	0.4762***	2.83	0.16856
		Pr(Employed)	0.0127	0.18	0.06846

OLS estimates are computed with heteroskedasticity robust standard errors. The coefficient on women's future earnings remains positive despite alternative estimation techniques.

Table A4: Balance Test on Matched Means: Women's Medium-Term Labor Income

Variable	Treated	Control	t-stat		Variable	Treated	Control	t-stat
Lagunemp	0.1161	0.1453	-1.71*		Northeast	0.135	0.077	2.24**
Lagolf	0.2589	0.1974	3.01***		Northc	0.259	0.247	0.84
LocalUrate	2.339	2.610	0.13		South	0.446	0.466	-2.73***
Age	35.214	35.081	-0.06		Single	0.268	0.325	-1.39
Raceb	0.571	0.477	-0.88		Married	0.411	0.415	-0.41
Raceo	0.054	0.107	-0.63		Elementary	0	0	–
Manager	0.054	0.070	-1.40		Highschool	0.768	0.658	2.06**
Sales	0.018	0.007	2.97***		Middlesc	0.143	0.195	-2.00**
Clerical	0.402	0.418	-2.18**		Urban	0.830	0.871	-0.88
Craftsmen	0.009	0.002	-0.93		AFQT	30.161	26.169	2.16**
Operatives	0.250	0.236	-3.15***		Hrslag	22.143	22.061	-0.83
Labor	0.080	0.052	-0.15		Health	0.107	0.057	1.75*
Service	0.045	0.039	3.13***		Njobrep	12.018	11.077	-0.17
Famsize	3.250	3.367	2.04**					

Balance stats given by T-tests for equality of means in treated and non-treated groups after matching. T-tests are from regressing on Agency, weighted using the matching weights.

Table A5: Long-Term sensitivity analysis results: Bandwidth variations

Gender	Outcome	ATT	ATU	ATE	Bwidth
Men	Ln(Labor Income)	-0.3171**	-0.3072**	-0.3124**	0.8
		(0.1416)	(0.1494)	(0.1421)	
	Pr(Employed)	-0.0435**	-0.0442**	-0.0438**	
		(0.0183)	(0.0177)	(0.0174)	
	Ln(Labor Income)	-0.4198*	-0.3866*	-0.4039*	0.005
		(0.2484)	(0.2356)	(0.2208)	
	Pr(Employed)	-0.0538*	-0.033	-0.0439*	
		(0.0279)	(0.025)	(0.0244)	
Women	Ln(Labor Income)	0.3827**	0.3907**	0.3868**	0.8
		(0.1811)	(0.1775)	(0.1756)	
	Pr(Employed)	0.0314	0.0236	0.0285	
		(0.0281)	(0.0273)	(0.0281)	
	Ln(Labor Income)	0.4471	0.4198	0.4336	0.005
		(0.3547)	(0.3542)	(0.3218)	
	Pr(Employed)	0.0743	0.0243	0.0483	
		(0.0638)	(0.0478)	(0.0473)	

Results are bootstrapped to improve standard errors (in parentheses). Coefficients do not change from optimal bandwidth results for any significant outcomes.

Table A6: Long- Term ATE Estimates for Alternative Estimation Procedures

	Estimation	Outcome	Coef.	t-stat	S.E.
Men	OLS	Ln(Labor Income)	-0.3510**	-2.14	0.16385
		Pr(Employed)	-0.0409	-1.79	0.02289
	Mixed Matching	Ln(Labor Income)	-0.2868*	-1.89	0.15143
		Pr(Employed)	-0.0472**	-2.25	0.01902
Women	OLS	Ln(Labor Income)	0.3573*	1.87	0.19081
		Pr(Employed)	-0.0003	0.01	0.03639
	Mixed Matching	Ln(Labor Income)	0.2764	1.36	0.20308
		Pr(Employed)	0.0145	0.40	0.03659

OLS estimates are computed with heteroskedasticity robust standard errors. The coefficient on women's future earnings remains positive despite alternative estimation techniques, and the coefficient on men's future earnings and probability of employment remain negative.

Table A7: Balance Test on Matched Means: Men's Long-Term Labor Income

Variable	Treated	Control	t-stat		Variable	Treated	Control	t-stat
Lagunemp	0.152	0.308	-3.30***		Northeast	0.095	0.123	0.15
Lagolf	0.095	0.101	1.19		Northc	0.305	0.161	0.31
LocalUrate	2.571	2.711	0.13		South	0.409	0.537	-1.68*
Age	34.305	34.685	-1.23		Single	0.410	0.455	-0.52
Raceb	0.562	0.530	0.17		Married	0.286	0.239	0.19
Raceo	0.076	0.093	0.12		Elementary	0.010	0.016	-0.54
Manager	0.000	0.007	-0.80		Highschool	0.752	0.725	0.16
Sales	0.010	0.014	0.26		Middlesc	0.152	0.168	-0.33
Clerical	0.114	0.135	-1.24		Urban	0.848	0.816	0.18
Craftsmen	0.067	0.072	-0.20		AFQT	26.781	25.723	0.11
Operatives	0.314	0.186	-1.56		Hrslag	26.419	34.187	-3.44***
Labor	0.238	0.378	-1.13		Health	0.095	0.128	0.14
Service	0.076	0.062	1.56		Njobrep	13.800	15.384	-1.18
Famsize	2.629	2.456	1.06					

Balance stats given by T-tests for equality of means in treated and non-treated groups after matching. T-tests are from regressing on Agency, weighted using the matching weights. Two covariates are out of balance at 5%.

Table A8: Balance Test on Matched Means: Men's Long-Term Employment Status

Variable	Treated	Control	t-stat		Variable	Treated	Control	t-stat
Lagunemp	0.203	0.232	-1.96*		Northeast	0.116	0.155	0.41
Lagolf	0.145	0.124	2.50**		Northc	0.275	0.187	-0.68
LocalUrate	2.623	2.737	0.21		South	0.420	0.486	-1.59
Age	34.514	34.716	-0.86		Single	0.427	0.447	-0.26
Raceb	0.609	0.601	-0.35		Married	0.261	0.275	-0.76
Raceo	0.072	0.078	0.85		Elementary	0.015	0.012	0.25
Manager	0.007	0.004	-0.47		Highschool	0.754	0.699	0.69
Sales	0.015	0.010	1.09		Middlesc	0.159	0.219	-1.18
Clerical	0.116	0.110	-0.06		Urban	0.870	0.841	0.37
Craftsmen	0.058	0.074	-0.58		AFQT	24.746	22.449	0.69
Operatives	0.319	0.172	-1.45		Hrslag	25.319	30.378	-3.74***
Labor	0.275	0.443	-2.05**		Health	0.094	0.155	0.73
Service	0.072	0.067	1.92*		Njobrep	12.913	15.058	-1.89*
Famsize	2.681	2.701	0.03					

Balance stats given by T-tests for equality of means in treated and non-treated groups after matching. T-tests are from regressing on Agency, weighted using the matching weights. Three covariates are out of balance at 5%.

Table A9: Balance Test on Matched Means: Women's Long Term Labor Income

Variable	Treated	Control	t-stat		Variable	Treated	Control	t-stat
Lagunemp	0.157	0.153	-1.28*		Northeast	0.127	0.143	-1.46
Lagolf	0.196	0.125	3.89***		Northc	0.226	0.216	0.60
LocalUrate	2.275	2.585	0.08		South	0.510	0.394	0.44
Age	34.843	35.086	0.08		Single	0.324	0.312	-0.86
Raceb	0.578	0.500	-1.29		Married	0.392	0.402	-0.66
Raceo	0.069	0.080	1.03		Elementary	0	0	–
Manager	0.049	0.101	-2.07**		Highschool	0.794	0.730	1.39
Sales	0.020	0.023	1.44		Middlesc	0.088	0.144	-2.64***
Clerical	0.441	0.460	-1.70*		Urban	0.794	0.860	-1.71*
Craftsmen	0.020	0.005	1.76*		AFQT	32.284	28.193	1.98**
Operatives	0.196	0.141	-1.71*		Hrslag	22.314	22.222	-1.68*
Labor	0.049	0.033	-0.17		Health	0.147	0.104	1.77*
Service	0.039	0.034	2.11**		Njobrep	12.784	11.543	-0.77
Famsize	3.029	3.027	2.76***					

Balance stats given by T-tests for equality of means in treated and non-treated groups after matching. T-tests are from regressing on Agency, weighted using the matching weights. Although six covariates are out of balance at 5% three at 1%,for categorical variables where only one dummy is out of balance (education & occupation), we may conclude with reasonable certainty that this dimension as a whole is balanced.

Figure A10

Temp Employees by Type

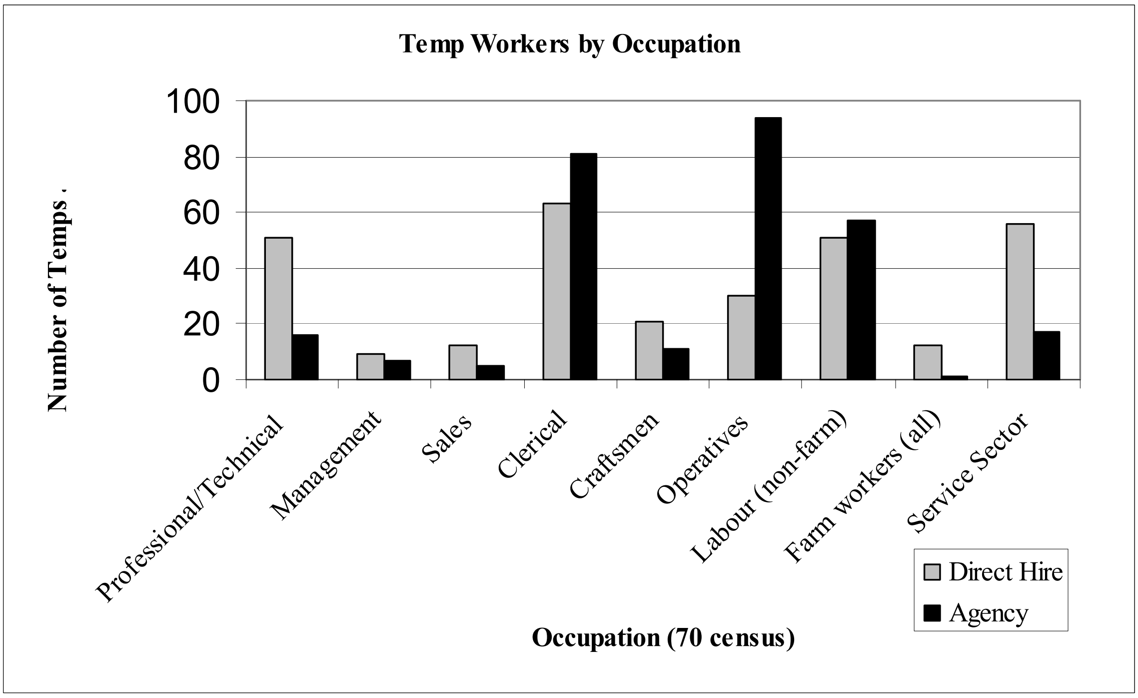

Figure A11

THA Employees by Gender