Does the Sector Experience Affect the Pay Gap for Temporary Agency Workers?*

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Abstract

Usually temporary agency workers have to accept considerable wage penalties. However, remarkably little is known about the remuneration of workers who are employed in this sector for a considerable length of time or accept temp jobs frequently. Based on a rich administrative data set, we estimate the effects of the intensity of agency employment on the temp wage gap and post-temp earnings in Germany. Using a two-stage selection-corrected method in a dynamic panel data framework, this article shows that the wage gap decreases with the time a workers spend in the sector be it at the same job or at different employers. This may be an indication that workers are able to accumulate human capital in the sector which pays off in terms of remuneration. On the other hand, workers who switch temp jobs on a frequent basis have to accept an even higher wage penalty, which might be explained by stigma effects. Finally, temps who move to permanent jobs do not fully catch up to those who start in regular jobs in terms of remuneration.

Key words: Temporary Agency Employment, Treatment Intensity, Dose Response Function Approach, Wages, Germany.

JEL Classification: J30, J31, J42, J41.

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1 Introduction

This paper provides a comprehensive analysis of the remuneration of temporary agency workers. Using a two-stage selection-corrected method in a dynamic panel data framework, we explicitly take selection based on observable and unobservable characteristics into account when estimating the pay gap of temporary agency employment. Moreover, the literature so far concentrates on estimating the temp wage gap omitting that some workers spend considerable time in agency employment. We show that the earnings gap of agency workers depends on the experience in this sector or the 'treatment dose'. Finally, we analyze whether the temp experience and its dose affects the earnings of workers who move to a job outside the sector.

Investigating the working conditions and particularly the remuneration of agency workers has become increasingly important as temporary agency employment has turned out to be a significant employment form in most OECD countries during the past decades. This trend has been particularly observed in Western Europe (Belgium, France, Italy, The Netherlands, Spain, UK, Germany) and Japan. Germany, together with the US and the UK, has become one of the largest markets in the world (CIETT, 2010). As temporary agency jobs are often regarded as "bad jobs", the expansion of agency work raises concerns about labor market segmentation and dualism that trap particular low-skilled workers in jobs providing little career prospect and poor pay.

The empirical evidence for continental European countries indicates indeed that the average wage of temporary agency workers lags those of permanent workers by between 2 percent, in Portugal (Böheim and Cardoso, 2009) and 15 percent, in Germany (Jahn, 2010), after controlling for both observable and unobservable worker's characteristics. However, the temp wage gap is not only a continental European phenomenon. The results provided by Segal and Sullivan (1998) and Addison et al. (2009) for the US, Booth et al. (2002), Forde and Slater (2005) for the UK and Cohen and Haberfeld (1993) for Israel confirm that temps have to accept a considerable pay penalty there as well.[1]

As a consequence of the low wages in this sector not only most European governments but also the European commission feels the need to intervene. For example, the European Parliament approved a Directive which stipulates equal pay of permanent and agency workers in 2008. Member states can only derogate from the principle of equal treatment if the workers are paid either by a collective agreement or by an agreement between the national social partners (Eurofound, 2008).

However, agency employment might also have beneficial effects for the workers in this sector which might compensate them for the lower pay. It is often argued that some individuals may prefer to be employed in temp jobs rather than permanent jobs as a career choice, to obtain or maintain eligibility for unemployment benefits or to combine work with other activities or family responsibilities. Other individuals may value temp jobs as a means of entering the labor market, securing an immediate source of income while gaining work experience and human capital that can help them to move up the job ladder or may even serve as a bridge into employment outside the sector (e.g. Houseman et al. 2003). According to this hypothesis, the wage penalty

[1]To ease readability, we use the terms temp job or agency work interchangeably with temporary agency employment and temp or agency worker instead of temporary agency worker.

temps experience is compensated for by the increased acquisition of human capital and the development of productive job search networks (e.g. Autor, 2001).

Critics of this view claim that temporary agency work is unlikely to be conducive to on-the-job training or networks, given its short job duration and low-skilled content (Segal and Sullivan, 1997). Until today, the empirical evidence is rather mixed. While some studies find that the experience of temporary agency employment improve subsequent employment or wage outcomes (Ichino et al., 2008; Lane et al., 2003; Jahn and Rosholm, 2010) others find no strong evidence for the stepping stone function of temporary agency work (Amuedo-Dorantes et al., 2008; Autor and Houseman, 2011; García-Pérez and Muñoz-Bullón, 2005; Kvasnicka, 2009; Malo and Muñoz-Bullón, 2008). Andersson et al.(2009), Hamersma and Heinrich (2008) and Heinrich et al. (2009) show that temps are likely to have long-run earnings that are substantially below those who transition to work in other sectors.

However, agency employment is rather heterogeneous. While some workers accept only once an agency job during their employment career, for others it might be a career choice as they are employed in this sector for a considerable length of time or accept temp jobs on a frequent basis. If, as Autor (2001) argues, agencies provide workers with free general skills training or if agency workers are able to improve their human capital while being on assignment at different employers, one might suspect that the pay gap for workers with an employment career inside the sector might be lower or even dissipate. In this case concerns about the quality of agency jobs may be at least for one part of the flexible staff unfounded.

Moreover, a longer employment experience in the agency sector might be valued equivalently to an employment career outside the sector. The reason is that due to their training within the sector and various assignments agency workers might be able to acquire more human capital than workers being employed in other branches for a given period of time (Autor, 2001). This may result in an increase of wages in post-temp employment. Alternatively, a temp experience may stigmatize the worker in the sense that future employers may perceive a previous temporary help job as an indicator of lower ability and motivation. This negative signal may result in fewer job offers and job opportunities with lower wages than other workers would receive (Blanchard and Diamond 1994).

To shed more light on these competing hypotheses, this article gathers new evidence for Germany, by estimating not only the wage differentials between temps and non-temp workers as in the previous literature (Jahn, 2010), but also the effects on wages of the "intensity" or "dose" of agency employment. The latter is measured either as the cumulative number or the duration of past agency jobs. Conceiving temp employment as a multi-valued treatment, allows us to directly test whether workers experiencing higher exposures to temporary agency employment can indeed acquire more skills or establish more productive job search networks which may result in an increase of wages in the sector or in post-temp employment.

One of the most difficult issues in this literature is to take into account the self-selection of workers into temporary agency employment (Autor 2009). Therefore the observed market wages for different doses may still be the result of selection, even after controlling for individual worker and job characteristics. To address the issue of self-selection this paper applies a two-stage selection-corrected method in a dynamic panel data framework, using a random sample drawn from the Integrated Employment Biography (IEB) of the Institute for the Employment Research (IAB) for the period 2000-2008.

The worker's assignment decision is examined first by either a dichotomous or a polychotomous ordered probit model, depending on whether the binary or the multi-value treatment is considered, in a reduced-form quarter by quarter setting. Over-time variation, afforded by regional shares of temporary agency workers during our observation window, is exploited to identify an exogenous increase in the dose of temporary agency employment which is unrelated to wages. The wage equations of different treatment levels are then estimated by incorporating the possible selection bias terms obtained in the ordered probit estimation. The treatment effects for different doses of agency employment are than calculated from the estimation results. To investigate the dose effect on wages further, we calculate the predicted wage path associated with each treatment level for workers who move from temp to regular employment. As a robustness check, we calculate the same effects implementing a matching estimator, which allows for continuous treatment effect evaluation (Hirano and Imbens, 2004).

This study adds to the literature in this field in several respects. To the best of our knowledge, this is the first time a dose-response function approach is applied to a dynamic panel data setting. In this respect, we provide an extension of the Chamberlain's (1992) proposal in the spirit of the approach developed by Jiménez-

Martin (2006). Second, combined with a suitable IV-type identification strategy, our econometric model allows us to fill a gap in the literature providing new evidence about the causal impact of temporary agency employment intensity on wages and post-temp wages. Third, by implementing an extension of the propensity-score matching estimator in a setting with a continuous treatment, we are able to evaluate the effects of intensity of agency employment over all possible values of the treatment levels.

This article shows that the wage gap decreases with the time a worker spend in the sector be it at the same job or at different employers. Moreover, temps who move to permanent jobs considerably reduce their gap with those who start in regular jobs in terms of remuneration if they have spend more time in the agency sector. Both results may be an indication that workers are able to accumulate human capital in the agency sector which pays off in terms remuneration. However, workers who switch temp jobs on a frequent basis have to accept a higher wage penalty and considerably lower post-temp wages, which might reflect lower specific human capital investment or might be explained by stigma effects.

The paper is organized as follows. Section 2 highlights key facts about the temporary help sector in Germany. Section 3 introduces the data set and presents main descriptive statistics. Section 4 provides details on the empirical strategy. Section 5 explains the results of our empirical analysis and section 6 offers some concluding remarks.

2 Institutional background

Generally, temporary agency employment is characterized by a tripartite relationship, whereby a temp worker is employed by a temp agency which then hires the worker out under a commercial contract to perform a work assignment at a user firm. The agency is considered to be the employer, determining issues such as wages and terms of employment.

In Germany, agency employment is regulated by national legal statutes which apply only to temporary help agencies. Compared to international standards temporary agency employment was highly regulated until the end of 2003. The main regulations were: first, the maximum period of assignment, which determines how long a temp may be assigned to a user firm without interruption, was 12 months. After this period the agency had to provide the user firm with a different worker for the same task. Second, although temporary help agencies were allowed to conclude fixed-term contracts, a fixed-term contract could only be prolonged three times until total employment duration added up to 24 months. Third, the agency was only allowed to conclude the first employment contract for the duration of the first assignment. A second (or prolonged) employment contract with the same temp had to exceed the length of the next assignment by at least 25 percent.[2]

The most recent reform, which came into effect in 2004 was intended to strengthen the rights of temporary help workers by applying the principle of equal pay from the

[2]In 2002 the maximum period of assignment was extended to 24 months. Moreover, the principle of equal treatment from the 13th month of an assignment on was introduced. As workers are rarely employed more than six month at an agency, the reform did not have any practical effect (e.g. Antoni and Jahn, 2009).

first day of an assignment on. The new law allows deviation from the principle of equal treatment if the agency applies the conditions stipulated in a sectoral collective agreement to all its temp workers. As a consequence, wage gaps between temps and the permanent staff of a user firm are permissible if the wages established in the user firms collective agreement are higher than those in the temp industrys collective agreement. In addition, by signing a collective agreement, the agency can free itself from all other regulations. As a consequence, numerous collective agreements were concluded in anticipation of this legal reform. By the end of 2003, nearly 97 percent of all temporary help agencies paid their temps according to a sectoral collective agreement. Consequently, the principle of equal treatment and all other regulations have lost any practical meaning for the temporary help industry.

In contrast to many other countries where temps are exempted from mandated social benefits, in Germany all workers have access to health insurance, sick, leave, holiday leave, pension plans and work councils and are protected by statutory employment protection legislation.

About 70 percent of all temps are male. As 90 percent of the temp jobs are full time jobs, temps rarely are parallel employed in a non-temp job. Blue-collar occupations such as production jobs, security service, laborers and other low-skilled jobs are dominant in this sector (Jahn 2010). The concentration of workers in this sector who are at risk of marginalization in combination with evidence that the German metal industry (e.g., automobile and aircraft industry) uses temps to circumvent the high wages agreed upon in collective bargaining is one main reason while the remuneration of agency workers is of key interest in the German policy debate about temporary agency employment.

During our observation period the number of agency workers increased tremendously from 277 thousand in January 2000 to 823 thousand in July 2008 and dropped to 674 thousand by the end of 2008. Temporary agency employment constituted three percent of the total dependent workforce and two percent of the overall workforce in 2008. The labor market flows suggest that the temporary help industry is even larger than any stock figure or the industrys share would suggest. In 2008 about about 1,050 thousand new temporary agency jobs were concluded and, due to the crisis, 1,170 thousand were terminated. In addition, the temporary help industry played an important role in job creation in Germany: one out of four new jobs in 2007 was created in this sector.

3 Data

3.1 Data description

Our empirical analysis is based on a 5 percent random sample of temporary agency workers and a 0.5 percent sample of remaining workers drawn from the Integrated Employment Biography (IEB) of the Institute for the Employment Research (IAB) which covers the period 1975-2008. The IEB combines data from five different administrative sources (see Dorner et al. 2010 for details). This merged administrative data set contains daily information about employment periods subject to social security contributions, job seeking periods, participation in active labor market programs, and periods during which the worker was eligible for unemployment assistance and benefit. The IEB provides information on socio-economic and job characteristics at the individual level. Being of an administrative nature, the IEB also provides longitudinal information on the employment and unemployment history of employees. The IEB is especially useful for analysis that take wages into account since the wage information is used to calculate social security contributions and is therefore highly reliable.

Nevertheless, the IEB has some minor drawbacks. First, employment spells in temporary help agencies are identified by an industry classification code. Consequently, temporary agency workers cannot be distinguished from agencies permanent administrative staff which accounted for about five to seven percent of agency employees in 2003 depending on the size of the agency (Antoni and Jahn, 2009). Note also, as the legal employer is the agency, we do not observe how often and in which sectors a worker has been on assignment. Second, wages above the social security contribution ceiling are top-coded. To address this problem we imputed wages above the social security contribution ceiling using a heteroscedastic single imputation approach developed by Büttner and Rässler (2008).[3]

Third, the IEB reports gross daily wages and does not provide information on hours worked. We therefore exclude part-time employees, interns, and at-home workers from the sample since the wage information is not comparable for these groups. For the same

[3]The regression is run separately by each year, gender and Eastern and Western German employees. In addition, we included the following control variables: age, age squared, nationality, six educational groups, industry codes, four variables for the occupational status, and eleven occupational variables, classifying the current position held by the worker, duration at the current job, duration of the current job squared, firm size and type of the region (metropolitan, urban, rural).

reason we exclude workers with wages below the social security contribution threshold. Fourth, trainees are excluded as they belong to the agency staff and are not assigned to user firms.

Fifth, the information on education is provided by employers. This means that information on educational levels is missing for about 19 percent of the individuals. We therefore imputed the missing information on education by employing a procedure developed by Fitzenberger et al. (2005), which allows inconsistent education information to be corrected over time as well. After applying this imputation procedure, we had to drop about 4 percent of the individuals in the final data set due to missing or inconsistent information on education.

The analysis is restricted to the period 1995 to 2008 and to non-agricultural employees between the ages of 18 and 60. We use the information for the period 1995 to 1999 to control for the employment career of the workers of the previous five years. This allows estimating the wage equations for the period 2000 to 2008. To estimate the wage differentials, we constructed a quarterly panel data set and included all workers who were employed on June 30 of the respective year, but we took advantage of the daily spell structure to construct the workers employment history.

3.2 Variables and Descriptive Statistics

The dependent variable is the log gross daily wage of the worker, which has been deflated to 2005 levels using the CPI deflator. The binary treatment variable is an indicator which is equal to one if a worker is employed at a temporary help service agency and zero otherwise. The multi-valued treatment is instead measured either as the cumulative number of weeks in temporary agency employment or the number of agency jobs over the past 5 years. In a third specification, we also look at the number of weeks spent in the current temp job.

As socio-demographic controls the following variables are included: gender, age, age squared, citizenship, and education.[4] The employment history is controlled for by the previous labor force status (unemployed, long-term unemployed, not in the labor force, employed as a temp and regular employed), whether the worker received previously unemployment benefits, unemployment assistance or no benefits, the employment experience in weeks during the past five years, the number of regular and temp jobs during the past 5 years and the uninterrupted previous employment duration in weeks.

As far as the current job is concerned, we differentiate between six occupational groups: technical occupations with highly skilled workers, service occupations, clerical occupations, manufacturing metal occupations, laborer and manufacturing other (see Jahn 2010, for more details).

To account for the heterogeneity among the agencies, we include the age of the firm, the firm size (5 classes), the share of female workers in the agency, the percentage of temp agency employees with a university degree and with no vocational training. Finally, as macroeconomic variables, we consider the real annual growth rate of GDP, the regional unemployment rate (based on 413 districts which form a local administrative

[4]Ethnic Germans are coded as foreigners because their human capital and employment history may be closer to that of foreigners (Brücker and Jahn, 2011). Education has been classified using the following groups: Secondary degree without vocational training, secondary degree with vocational training, high school degree without vocational training, high school degree with vocational training (base category), college, and university degree.

unit), a dummy indication whether the worker is employed in east or west Germany, and three variables indicating whether a worker is employed in a metropolitan, urban, or rural area.

Table 1 presents the means of basic socio-economic characteristics for temp and non-temp workers which allows us to control for possible selection effects. In our analysis we are able to include 5.1 million spells, among them 659 thousand temp work spells, and 278 thousand workers. About 20 percent of the temps and 19 percent of the non-temp workers are employed in East Germany. On average temporary help workers earn less than regular workers. The average daily real gross wage of temp workers is 53 Euros during the observation period, the average wage for regular workers is 90 Euros.

Most temps are male. Compared to the share of foreigners in overall employment, which on average amounts to 12 percent, foreigners are overrepresented in temps at 22 percent. The average age of temp workers (36 years) is lower than in the comparison group (39 years). Workers with secondary degree and no vocational training are overrepresented in temp employment (17 percent), compared to their share in regular employment (9 percent). In contrast to most European countries, service jobs and clerical occupations do not play an important role. About two thirds of all temps are employed in manufacturing or as laborers. While about 54 percent of the temps were previously unemployed, this is only true for 18 percent of the non-temps. More than 62 percent of the regular employed workers had been regularly employed before their current job, which only holds for about 21 percent of the temp workers.

Table 1 also reveals that the employment career of temp workers is much more fragmented. On average they changed the job about four times and accepted two temp job five years prior to the present temp job. In contrast, workers which are currently employed outside the temporary help sector switched their job twice on average and barely have any temp experience.

In order to get a first idea for the differences in mean wages between temps and non-temp workers, we run OLS regressions separately for each year by gender and region, which include only a dummy for being a temp worker as a control.

[Figure 1 about here]

The first striking result is that all wage differentials exhibits a downward trend between 2000 and 2006. This result confirms earlier findings by Jahn (2010) who found a widening earnings gap for the period 1997-2004 as well. Afterwards, the wage gap decreases slightly for all groups, which might be a consequence of a tightening labor market due to the upturn between 2007 and mid 2008. Figure 1 also reveals that the wage differential for Eastern Germany is considerably lower than for Western Germany and the wage gap for women is smaller than for man.

4 Empirical strategy

In this section we describe a consistent estimation procedure for the generalized dynamic sample selection model with panel data. Our point of departure is the following two equation model[5]

[5]In our empirical analysis, we also consider the single equation version of the model discussed in

$$
\begin{cases}
w_{it}^0 = \alpha_0^0 + X_{it}'\alpha_1^0 + \tau_t + \mu_i^0 + e_{it}^0 \;\; for \;\; t_i^0 \;\; s.t. \;\; D_{it} = 0 \\
w_{it}^1 = \alpha_0^1 + X_{it}'\alpha_1^1 + \tau_t + \mu_i^1 + e_{it}^1 \;\; for \;\; t_i^1 \;\; s.t. \;\; D_{it} = 1
\end{cases}
\tag{1}
$$

where w_{it} is the log of the real daily wage for worker i in year t, X is a vector of the observed worker and job characteristics described in the previous section, μ are the time invariant individual specific effects and τ includes the GDP growth rate, the unemployment rate and time dummies.[6] The binary indicator D is the endogenous treatment variable and determines whether the temps wage or the non-temps wage is observed. The switching regime is driven by the model for D, which is given by:

$$
D_{it}^* = \beta_0 + Z_{it}'\beta_2 + v_{it} \tag{2}
$$

where the vector Z includes both a set of worker characteristics, i.e. gender, age, citizenship, education, the employment history, whether the worker is living in East Germany, and all the lags and the leads of the shares of temporary agency workers at district level, which constitute our exclusion restrictions. The districts are clusters of municipalities, which are grouped based on commuting patterns that can be interpreted as self-containing labor markets. In total 413 local labor markets are identified. In our opinion, they represent a more appropriate territorial configuration with respect to larger administrative areas, like regions, to examine the interaction between workers

this section, which is given by: $w_{it} = \alpha_0 + X_{it}'\alpha_1 + \tau_t + \delta_d D_{it} + \mu_i + e_{it}; \quad i = 1, ..., N$

[6]Time dummies include the starting quarter of the job spell and a full set of quarter and year dummies.

and potential externalities. The share of temporary agency workers at the commuting area level presents a suitable supply driven instrument for the individual decision to be a temporary agency worker herself which is not correlated with earnings.

In the equations of interest we should take into account that when $cov(e_{it}^k, v_{it}) \neq 0$, then neither $E(e_{it}^0|s_{it}^* \leq 0)$ or $E(e_{it}^1|s_{it}^* > 0)$ is expected to be zero. In order to control for the endogenous selection problem, we estimate the parameters of the indicator equation (2) and then, under the assumption of normality, which is not a crucial assumption for the results to hold, we correct the equations of interest with corresponding inverse Mill's ratios.[7] Adding consistent estimates of the inverse Mill's ratios, $\hat{\lambda}_i^0$ and $\hat{\lambda}_i^1$ to equation (1), we obtain:

$$\begin{cases} w_{it}^0 = \alpha_0^0 + X_{it}'\alpha_1^0 + \tau_t + \sigma_0\hat{\lambda}_i^0 + \mu_i^0 + e_{it}^0 \;\; for \;\; t_i^0 \;\; s.t. \;\; D_{it} = 0 \\ w_{it}^1 = \alpha_0^1 + X_{it}'\alpha_1^1 + \tau_t + \sigma_1\hat{\lambda}_i^1 + \mu_i^1 + e_{it}^1 \;\; for \;\; t_i^1 \;\; s.t. \;\; D_{it} = 1 \end{cases} \tag{3}$$

It is interesting to observe that under the structure imposed on the model, the estimated coefficients of the inverse Mill's ratios are informative on the presence and direction of the selection process (σ_0 for selection on unobserved ability or productivity and σ_1 for the selection on the basis of their unobserved gain or of an unobserved component in the treatment effect). Specifically, in the presence of an exclusion restriction, like in our case, then the null of no selection on the unobservables can be tested directly. In the framework above, this simply amounts to a test of the null hypothesis

[7]Following Jiménez-Martin's (2006) we estimate a reduced-form quarter by quarter probit model for the agency employment decision.

that σ_0 and σ_1 are zero.

We consistently estimate equations (3) using the fixed effect estimator. Obviously, the variance and covariance matrix of the two-step estimator needs to be adjusted for the replacement of λ_i^0 and λ_i^1 with $\hat{\lambda}_i^0$ and $\hat{\lambda}_i^1$ by bootstrapping the sequential two-step estimator.

We then extend the previous model by considering a multi-value treatment setting. We measure the treatment intensity or dose either as the cumulative number or the duration of past temp jobs over the last 5 years. In an alternative specification, we also look at the number of weeks spent in the current temp job. The wage equations for each level of treatment j are:

$$w_{it}^j = \alpha_0^j + X_{it}'\alpha_1^j + \tau_t + \mu_i^j + e_{it}^j \ \ for \ \ t_i^j \ \ s.t. \ \ D_{ijt} = 1; j = 0, 1, 2....m \tag{4}$$

To cope with endogeneity issues, a quarter by quarter ordered probit model is adopted to estimate the treatment choice equation. The dose-response function of the optimal level of treatment can be expressed as:

$$DR_{ijt}^* = \gamma_0^j + Z_{it}'\gamma_1^j + u_{ijt} \tag{5}$$

The observed treatment dose is represented by a dummy variable D_{ijt} and $\delta_1, ..., \delta_m$ are cut-off points for the different treatment levels. Hence the probability of having treatment level j becomes:

$$prob(D_{ijt}=1)=\Phi(\delta_j-\gamma_0^j-Z_{it}'\gamma_1^j)-\Phi(\delta_{j-1}-\gamma_0^{j-1}-Z_{it}'\gamma_1^{j-1}) \tag{6}$$

where Φ is a standard normal cumulative density function. Let $\psi_{ij}=\frac{\sigma_{ve}}{\sigma_v}$ be the covariance matrix of error terms between treatment dose choice and wage equations and

$$\begin{aligned}\lambda_{ijt} &= E\left(\frac{u}{\sigma_u}|\frac{\delta_{j-1}-\gamma_0^{j-1}-Z_{it}'\gamma_1^{j-1}}{\sigma_u}<\frac{u}{\sigma_u}<\frac{\delta_j-\gamma_0^j-Z_{it}'\gamma_1^j}{\sigma_u}\right)\\ &= \frac{\phi(\frac{\delta_{j-1}-\gamma_0^{j-1}-Z_{it}'\gamma_1^{j-1}}{\sigma_u})-\phi(\frac{\delta_{j-1}-\gamma_0^{j-1}-Z_{it}'\gamma_1^{j-1}}{\sigma_u})}{\Phi(\frac{\delta_{j-1}-\gamma_0^{j-1}-Z_{it}'\gamma_1^{j-1}}{\sigma_u})-\Phi(\frac{\delta_{j-1}-Z_{it}'\gamma_1^{j-1}}{\sigma_u})},\ 1<j<m\end{aligned} \tag{7}$$

be the expected value of the correction term. Then equation (4) can be rewritten as:

$$w_{it}^j=\alpha_0^j+X_{it}'\alpha_1^j+\tau_t+\psi_{ij}\lambda_{ijt}+\mu_i^j+e_{it}^j\ \ for\ \ t_i^j\ \ s.t.\ \ D_{ijt}=1;\ \ j=0,1,2....m \tag{8}$$

As before we estimate equation (7) using a two-stage estimator.

The estimation results obtained from the previous selection-corrected wage equations are used to calculate the implicit wage differential between different doses of agency employment. The corrected differentials can generally be expressed as:

$$cd_j=\frac{1}{N}\sum_{i=1}^{N}\sum_{t=1}^{T}\left[E(\hat{w}_{it}^j|D_{ijt}=1)-E(\hat{w}_{it}^{j-1}|D_{ij-1t}=1)\right] \tag{9}$$

where N is the number of individuals, $\hat{w}_{it}^j$ and $\hat{w}_{it}^{j-1}$ are predictions from the wage equation (7), including the selection terms.

5 Results

5.1 Main Results

This section reports findings for each of the treatment dimensions we look at both binary and multi-valued. Implementing both the single equation and the endogenous switching approach helps in understanding the strength of our results.

Table 2 report results for the binary treatment from the single equation approach. Whether the first row does not control for the selection into temporary agency employment, the second does. In line with the previous studies and with the descriptive evidence, a negative effect of temporary agency employment is estimated. Interestingly, the earnings gap slightly decreases from 19.6 to 18.8 percent, once the selection on unobservables is taken into account. Separate estimates according to gender, to whether the individual works in East or West Germany and to whether the period before or after the 2003 reform is considered, indicate that women and workers in East Germany suffer from a slightly lower wage penalties. Wage penalties are also reduced after the 2003 reform.[8] Table A1 in the Appendix shows that the selection adjustment term or the standard inverse Mills ratio is statistically significant and suggests a negative selection bias.[9] This implies that the estimated wage penalty is biased upward if the sample selection bias is not controlled for. For this reason, we proceed presenting only

[8]The full set of regression coefficients for each group are available on request from the authors.

[9]The control function approach requires an exclusion restriction. As mentioned before, all the lags and the leads of the shares of temps at the district level where individuals works is used as instruments. Besides the economic motivation for the instruments presented above, their statistical validity is largely confirmed by the F-statistics reported in the footnotes below tables 2,3 and 4. The F-statistics are always above 70, which allow us to clearly reject the null of weak instrument (Stock and Yogo, 2005).

the results obtained from the control function approach.

Tables 2 also summarizes the estimated effects of the multi-value treatments when a single equation approach is implemented.[10] If the treatment is measured in terms of the number of weeks spent in temporary agency employment in the current job or over the last 5 years, we find evidence that the estimated earning gaps are decreasing with the treatment intensity. A temp worker who accumulates more than 52 weeks of temporary agency employment in the current job (over the last 5 years) has a negative wage gap of about 12 (14) percent with respect to a regular worker. The wage penalty raises to about -20 (-18) percent if a temp worker with less than 8 weeks of agency employment is considered. [11] Slightly lower temp wage differentials are estimated in East Germany, after the 2003 reform is implemented and for women. These results are in line with the hypothesis that temporary agency employment can be viewed as a means of gaining work experience, human capital and labor market contacts that lead to better wages. In this sense, we don't find any evidence that spending more weeks as a temp worker is interpreted as a negative signal or stigma in the labor market. When we look at the number of temp jobs as treatment, however, lower and negligible differences in the wage penalties are found across different number of treatments. To sum up, it seems that the accumulated duration of temporary agency employment is more relevant than the number of temp jobs in terms of the human capital that can be accumulated in temporary agency employment. That the number of previous agency

[10] The full estimation results can be found in Table A2-A4.

[11] Given that the single equation model is estimated exploiting the within variation through the Fixed Effects method, the obtained effects are interpreted as the average effect of treatment on the treated (ATT).

jobs has no effect in terms of remuneration might be an indication that accumulated human capital can not be transfered between jobs. One possible explanation might be that the human capital is firm or industry specific.

The results presented so far may be still questioned in terms of the assumptions imposed. The single equation model assumes in fact that the effects of temporary agency employment do not vary across individuals. The endogenous switching model relaxes the former assumption and allows the effect to be heterogeneous in both observable and unobservable characteristics. To this end, we also estimate the wage equation for each treatment regime separately and we augment it with the Mills ratios obtained from the selection model, as described in the methodological section.

Table 3 reports the estimated wage equations for the treated and the non-treated separately. The coefficients on most of the observable characteristics differ considerably across temp and non-temp workers. If we look at the education variable, for example, it is immediately apparent that its regression coefficients implies very different magnitudes according to the employment regime. These findings warn against uncritical aggregation by sector and indicate the presence of observable heterogeneity, we need to take into consideration when the relevant treatment effects are estimated. More importantly, the coefficient of the Mills ratio in the temporary agency wage equation remains significant, indicating there is unobserved heterogeneity in the treatment effect left, even after controlling for observed heterogeneity. As in the single equation approach, the coefficient of the Mills ratio in the temp sector indicates negative selection in the same way we argued before. The results of Table 3 stress the need to allow for observable heterogeneous returns in addition to selection on unobservables in our application.[12]

The estimated ATTs from the endogenous switching model for both the binary and multi-value treatments are summarized in Table 4. The calculated effects generally involves greater magnitudes compared to the single equation model. Thus, for example, a temp worker who accumulates more than 52 weeks of temporary agency employment in the current job (over the last 5 years) has a negative wage gap of approximately 13 (17) percent with respect to a regular worker. The same wage gap increases to -40 (-35) percent for a temp with less than 8 weeks of agency employment. On the other hand, the higher is the number of temp jobs, the larger the estimated wage gap with respect to being in regular employment: having more than 3 distinct temporary agency jobs over the last 5 years implies a significant negative wage gap of approximately 20 percent with respect to having just one temporary agency job. This again reinforces the idea that human capital or the professional network can only be accumulated or transfered if the worker is employed for longer period of time and probably in the same firm or sector. Qualitatively similar results are obtained when the dose effects are calculated separately by the relevant groups described before.

To describe the dose effect on wages further, we simulate alternative predicted wage path for workers who move to regular employment with different levels of exposure to the temp sector, either in terms of number or duration of past temp jobs. The patterns involving workers with different number (duration) of past temp jobs are reported in

[12] Note, that Table A7 to A9 confirm the presence of observable heterogeneity also when multi-value treatment definitions are used.

figure 2 (3). Having always had a regular job is the pattern that delivers the highest real wage profile. Workers with more than 2 agency jobs display much lower wage profiles over the first 5 years after leaving the temp sector. They also have a decreasing wage growth, implying that they never catch up the wage profile of the regular workers. However, having just one temp job does not entirely damage the wage profile. We interpret the results obtained from these simulations as a sign of stigma effects for those workers who switched often temp jobs. On the other hand, workers with higher temp agency experience are able to considerably reduce their wage gap 15 quarters after leaving the temporary agency sector. Indeed, having accumulated less than 8 weeks of temp employment in the past does not considerably improve the wage profile. This confirms that higher temp employment durations allows workers to accumulate human capital which pays off in terms remuneration.

5.2 Sensitivity Analysis

In order to investigate further the potential causal effect of the intensity of temporary agency employment on wages, a matching analysis has been conducted. Following recent developments in the treatment evaluation literature (Hirano and Imbens, 2004), the wages of individuals exposed to temporary agency employment are compared to matched less exposed individuals.[13] This approach interprets the cumulative duration of past agency jobs as treatment and evaluates its effect on wages. Specifically, the focus is here on the estimation of the dose-response function and treatment effect be-

[13]The approach allows to estimate the effects between units at different treatment levels, by comparing the values of the estimated potential outcome for different levels but not an estimation of the effects between treated and non-treated units.

havior. The implementation of such an analysis is also particularly important since it may provide useful policy suggestions: it allows us to evaluate the impact of temporary agency employment on wages for different level of exposure. The outcome variable (log of wages) is taken in levels, the treatment is obviously the temporary agency employment experience over the last 5 years, measured in weeks. The matching variables include all the observed worker and job characteristics used in equation (1). We also add a set of time and quarter dummies to control for common aggregated demand and supply shocks. Given the number of observations and available counterfactuals, it has not been possible to estimate the effects for each quarter, so the latter are evaluated in a pooled regression. To assess the balancing property, we divide the treatment variable into terciles and test whether the GPS adjusted mean differs in one tercile compared to the others.[14]

Figure 2 shows that the average dose-response functions increase with respect to the level of treatment, confirming therefore the positive contribution of temporary agency experience on wages. Doses of treatment produce significant responses when the treatment reaches given levels in its distribution. Therefore, the experience effect is increasing and statistically significant and it turns even stronger for high doses of treatment. The average treatment effects are here defined respectively as the variation in the estimated response function due to a 10 weeks increase (delta) in the treatment

[14]This is equivalent to testing that the conditional mean and treatment indicator are independent (CIA) where r(d;X) is evaluated at the median value of the treatment within the tercile d*. Following Hirano and Imbens (2004), we test this hypothesis by blocking. For each tercile we define three blocks and compute the mean difference in X for observations (D=d) and (D>d). Then, we combine these three mean differences, weighted by the relative number of observations in each block, and compute the associated t-statistic value.

variable. For treatment level below 100 weeks, the former increase enhances individual wage on average by 0.1 percentage point every additional 10 weeks. The same effect doubles when treatment levels above 100 weeks are considered. All in all, these results implies that a 20-25 percent wage differential is observed between workers with the lowest and the highest temporary agency experience. These findings are qualitatively in line with the previous results, especially with those obtained from the endogenous switching regression approach.[15]

6 Conclusion

Until today remarkably little was known about the remuneration of temporary agency workers and the empirical evidence failed to treat the temporary agency employment as a rather heterogeneous phenomenon. While some workers are only employed there for a short period during their employment career others spend a considerable length of time in this sector or accept temp jobs on a frequent basis. Using a comprehensive longitudinal data set, this paper investigates the effects of temporary agency employment on wages in Germany. Contrary to the majority of previous empirical works, which focused on binary definitions of treatment and neglected any selection issue, this article gathers new evidence, by estimating not only the wage differentials between temps and non-temp workers but also the effects on wages of the ”intensity” or ”dose” of temporary employment. The latter is measured either as the cumulative number of temp

[15]Estimates according to gender, to whether the individual works in East or West Germany and to whether the period before or after the 2003 reform is considered, provide similar results. The latter are available on request from the authors.

jobs or the duration of current or past temp jobs. Conceiving temporary employment as a multi-valued treatment, allows us to directly test whether workers experiencing higher exposures to temporary employment can indeed acquire more skills or establish larger job search networks which may result in an increase of wages. As workers self-select into different levels of treatment, the observed market wages for different doses may still be the result of selection, even after controlling for individual worker and job characteristics. For our analysis, we use a two-stage selection-corrected method in a dynamic panel data framework. Over-time variation, afforded by regional shares of temporary agency workers during our observation window, is exploited to identify an exogenous increase in the dose of temporary agency employment which is unrelated to wages.

In line with the previous study in this fields, the results show that agency workers have to accept considerable lower wages. Interestingly, the earnings gap slightly decreases, once the selection on unobservables is taken into account. Our findings imply that the estimated wage penalty is biased upward if the sample selection bias is not controlled for.

When the treatment is measured in terms of the number of weeks spent in temporary agency employment in the current job or over the last 5 years, we find evidence that the estimated earning gaps are decreasing with the treatment intensity. Moreover, temps who move to permanent jobs considerably reduce their gap with those who start in regular jobs in terms of remuneration in case they have spend more time in the agency sector. Both results may be an indication that workers are able to accumulate human capital in the agency sector which pays off in terms remuneration. These results are in line with the hypothesis that temporary agency employment can be viewed as a means of gaining work experience or improving human capital that lead to better paid jobs. This empirical evidence may also suggest that it may be inefficient for temporary agency workers to invest in firm specific human capital, or for the employers to provide this training unless the job has a longer term perspective.

This surmise is confirmed, when we look at the number of distinct temp jobs as treatment. In this case the wage gap increases considerably with the number of treatments, especially in the endogenous switching model. This may be again a consequence of lower firm specific investment or training. Moreover, workers who frequently switch between jobs might signal a lower productivity or that they are not wishing to remain at the firm. Changing jobs too often might therefore be interpreted as a negative signal that stigmatizes workers. Alternatively, agencies may pay these workers wages below the productivity as they might lack an outside option. In this case, they are able to exercise monopsony control over the wages of workers filling the bottom tier of a two-tier pay structure.

To sum up, this study confirms the popular perception that temporary agency jobs are generally not desirable when compared to permanent employment, at least in term of remuneration. This holds also for workers who are employed at the sector for a considerable length of time, as the wage gap for these workers is still of an alarming size. In light of the fact that agency employment in Germany is only rarely a pathway into regular jobs (Kvasnicka 2009), these costs are not transitory. Consequently, the boost of temporary agency employment in Germany during the last decade might not only have increased labor market flexibility in Germany but has also created a two tier labor market where a small part of the work force move regularly between unstable jobs and are not financially compensated for taking that higher risk.

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Tables and Figures

Table 1: Descriptive statistics

	Temp		**Non-temp**	
	mean	sd	mean	sd
Average real gross wage	53	29	90	46
Personal Characteristics				
Age	36	11	39	10
Male	0.751	0.432	0.663	0.473
Foreign	0.216	0.411	0.120	0.325
East	0.203	0.402	0.191	0.393
Education				
Secondary degree no vt	0.170	0.376	0.089	0.285
Secondary degree with vt	0.688	0.463	0.702	0.458
High school degree no vt	0.008	0.091	0.007	0.086
High school degree with vt	0.071	0.257	0.081	0.273
Politechnics	0.029	0.168	0.046	0.209
University	0.033	0.178	0.075	0.263
Previous labor force status				
Unemployed	0.536	0.499	0.183	0.386
Long-term unemployed	0.084	0.278	0.025	0.156
Not in the labor force	0.113	0.317	0.124	0.330
Temporary employed	0.142	0.349	0.069	0.253
Regular employed	0.210	0.407	0.624	0.484
Previous benefits				
Unemployment benefits	0.254	0.435	0.111	0.314
Unemployment assistance	0.156	0.363	0.036	0.185
Prev. empl. characteristis				
Current uninterrupted job tenure	82.900	85.800	184.000	95.200
No temp jobs (5 years)	1.930	1.460	0.221	0.673
No all jobs (5 years)	3.930	2.540	2.490	2.080
Weeks in temp jobs (5 years)	85.900	79.800	6.830	24.100
Weeks in non-temp jobs (5 years)	82.700	74.300	219.000	64.100
Occupation				
Technical occupation	0.032	0.176	0.078	0.269
Manufacturing other	0.074	0.262	0.166	0.372
Manufacturing metal sector	0.267	0.442	0.178	0.382
Laborer	0.318	0.466	0.022	0.146
Clerical occupation	0.148	0.355	0.352	0.478
Service occupation	0.160	0.367	0.205	0.403
Firm characteristics				
Firmsize 0-10	0.020	0.140	0.153	0.360
Firmsize 11-50	0.196	0.397	0.242	0.428
Firmsize 51-200	0.519	0.500	0.247	0.431
Firmsize 201-500	0.188	0.391	0.147	0.354
Firmsize > 501	0.078	0.267	0.212	0.408
Age of the firm (years)	10	7	18	11
Share low skilled workers	26	27	9	15
Agglomeration				
Metropolitan	0.567	0.495	0.546	0.498
Urban	0.337	0.473	0.342	0.474
Rural	0.096	0.295	0.112	0.316
Regional unempl. rate (quarter)	11.500	4.650	11.000	4.980
Observations	659,082		4,416,529	

Table 2: Single equation approach, binary and multi-value treatments

	Binary treatment						
	All	**Men**	**Women**	**West**	**East**	**Before 2004**	**After 2004**
FE	–0.196***	–0.198***	–0.185***	–0.209***	–0.196***	–0.198***	–0.188***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Control function approach	–0.188***	–0.193***	–0.165***	–0.206***	–0.188***	–0.202***	–0.174***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
	Multi value treatment						
	All	**Men**	**Women**	**West**	**East**	**Before 2004**	**After 2004**
Dose response function approach (1)							
Current temp job < 8 weeks	–0.204***	–0.206***	–0.185***	–0.219***	–0.204***	–0.205***	–0.182***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Current temp job 8-26	–0.180***	–0.183***	–0.159***	–0.194***	–0.180***	–0.184***	–0.161***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Current temp job 26-52	–0.158***	–0.165***	–0.129***	–0.171***	–0.158***	–0.177***	–0.139***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Current temp job > 52	–0.119***	–0.135***	–0.071***	–0.135***	–0.119***	–0.159***	–0.107***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
Dose response function approach (2)							
Temp experience < 8 weeks	–0.214***	–0.212***	–0.210***	–0.231***	–0.214***	–0.205***	–0.190***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
Temp experience 8-26	–0.194***	–0.193***	–0.190***	–0.211***	–0.194***	–0.193***	–0.174***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
Temp experience 26-52	–0.176***	–0.179***	–0.162***	–0.192***	–0.176***	–0.187***	–0.158***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
Temp experience > 52	–0.136***	–0.150***	–0.094***	–0.153***	–0.136***	–0.173***	–0.130***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
Dose response function approach (3)							
No of temp jobs=1	–0.179***	–0.184***	–0.159***	–0.195***	–0.179***	–0.190***	–0.166***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
No of temp jobs=2	–0.179***	–0.187***	–0.144***	–0.196***	–0.179***	–0.202***	–0.168***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
No of temp jobs=3	–0.170***	–0.180***	–0.125***	–0.187***	–0.170***	–0.205***	–0.159***
	(0.001)	(0.001)	(0.003)	(0.001)	(0.001)	(0.002)	(0.001)
No of temp jobs > 3	–0.169***	–0.184***	–0.099***	–0.189***	–0.169***	–0.221***	–0.153***
	(0.001)	(0.001)	(0.003)	(0.002)	(0.001)	(0.002)	(0.002)

Notes: The reported coefficients are in relative terms and indicate the average treatment on the treated effects. For the multi-value treatments, the first (second) column shows the effects with respect to the treatment intensity equal to 0 (the lowest level).

Table 3: Wage equations by treatment status, binary treatment

	Temp employment	**Regular employment**
Age	0.031***	0.038***
	(0.001)	(0.000)
Age squared/1000	–0.381***	–0.446***
	(0.007)	(0.002)
Secondary degree with vt	0.012***	0.033***
	(0.003)	(0.001)
High school degree no vt	–0.027***	–0.094***
	(0.009)	(0.003)
High school degree with vt	0.015***	0.053***
	(0.005)	(0.002)
College degree	0.070***	0.107***
	(0.007)	(0.002)
University degree	0.076***	0.166***
	(0.008)	(0.002)
East	–0.086***	–0.147***
	(0.003)	(0.001)
Employment duration	0.001***	0.000*
	(0.000)	(0.000)
Employment duration squared/1000	–0.001***	0.000***
	(0.000)	(0.000)
Number of regular jobs over the last 5 years	–0.001***	0.000
	(0.000)	(0.000)
Work experience	0.000**	0.000***
	(0.000)	(0.000)
Work experience squared/1000	–0.000***	0.000*
	(0.000)	(0.000)
Previously unemployed	–0.039***	–0.038***
	(0.001)	(0.001)
Previously long term unemployed	–0.008***	–0.023***
	(0.002)	(0.001)
Previously regular employed	–0.035***	–0.006***
	(0.002)	(0.000)
Previously out of the labor force	0.067***	0.049***
	(0.003)	(0.001)
Previously temporary employed	–0.020***	0.020***
	(0.002)	(0.001)
Unemployment benefits/assistance	–0.008***	–0.030***
	(0.001)	(0.001)
Mills ratio	–0.020***	0.013***
	(0.001)	(0.001)
N	659,082	4,416,529

Notes: The dependent variable in all estimations is the log gross daily wage. All regressions are estimated with the FE approach and include in addition and among others occupation dummies, firm characteristics, regional unemployment and GDP growth rate, agglomeration and time dummies. Significance levels: ***1%, **5%, *10%. Standard errors are bootstrapped using a sequential two step bootstrapping procedure with 200 replications.

Table 4: Endogenous switching approach, binary and multi-value treatments

	Binary treatment						
	All	**Men**	**Women**	**West**	**East**	**Before 2004**	**After 2004**
Control function approach	–0.286***	–0.328***	-0.207***	-0.303***	-0.254***	-0.262***	-0.267***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	Multi value treatment						
	All	**Men**	**Women**	**West**	**East**	**Before 2004**	**After 2004**
Dose response function approach (1)							
Current temp job < 8 weeks	–0.403***	–0.442***	–0.369***	–0.372***	–0.353***	–0.268***	–0.323***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Current temp job 8-26	–0.352***	–0.390***	–0.273***	–0.379***	–0.325***	–0.233***	–0.328***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Current temp job 26-52	–0.299***	–0.322***	–0.230***	–0.306***	–0.297***	–0.250***	–0.252***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Current temp job > 52	–0.209***	–0.256***	–0.134***	–0.219***	–0.180***	–0.213***	–0.236***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Dose response function approach (2)							
Temp experience < 8 weeks	–0.354***	–0.446***	(*)	–0.367***	(*)	(*)	–0.298***
	(0.001)	(0.001)	(*)	(0.001)	(*)	(*)	(0.001)
Temp experience 8-26	–0.332***	–0.385***	–0.259***	–0.369***	–0.289***	(*)	–0.305***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(*)	(0.001)
Temp experience 26-52	–0.324***	–0.377***	–0.228***	–0.337***	–0.340***	(*)	–0.258***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(*)	(0.001)
Temp experience > 52	–0.254***	–0.296***	–0.170***	–0.265***	–0.226***	–0.231***	–0.263***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Dose response function approach (3)							
No of temp jobs=1	–0.252***	–0.291***	–0.194***	–0.269***	–0.223***	–0.232***	–0.217***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
No of temp jobs=2	–0.320***	–0.357***	–0.186***	–0.342***	–0.277***	–0.291***	–0.312***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
No of temp jobs=3	–0.328***	–0.389***	–0.269***	–0.330***	–0.341***	–0.298***	–0.296***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
No of temp jobs > 3	–0.392***	–0.435***	–0.355***	–0.409***	–0.334***	–0.428***	–0.372***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

Notes: The reported coefficients are in relative terms and indicates the average treatment on the treated effects. For the multi-value treatments, the first(second) column shows the effects with respect to the treatment intensity equal to 0 (the lowest level). (*) the corresponding coefficient is not available due to data availability.

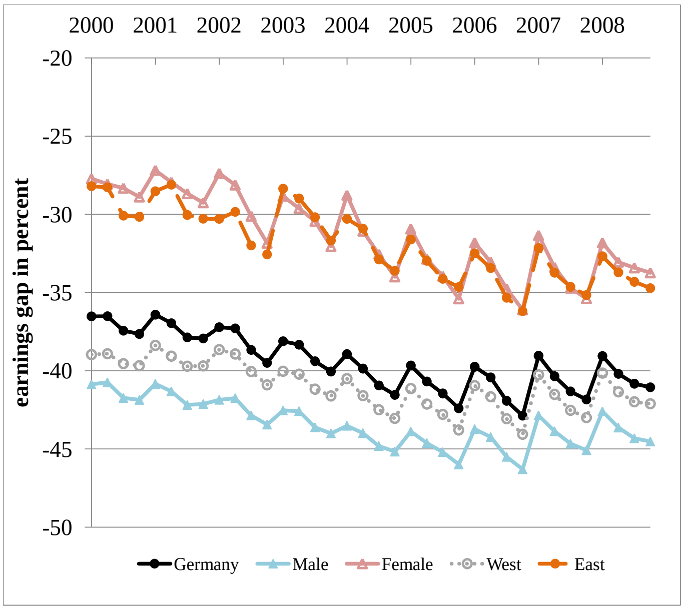

Figure 1: Raw temp earnings gap (2000-2008)

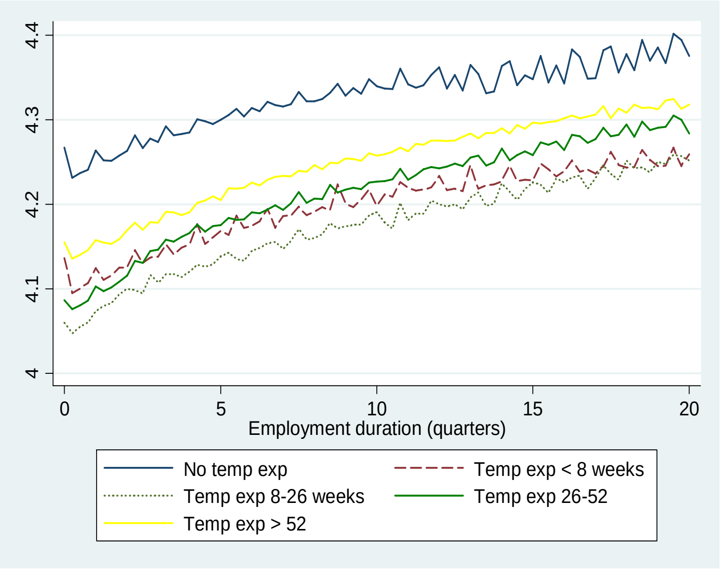

Figure 2: Wage predictions of temps moving to regular employment with different treatment levels. Temp experience as treatment.

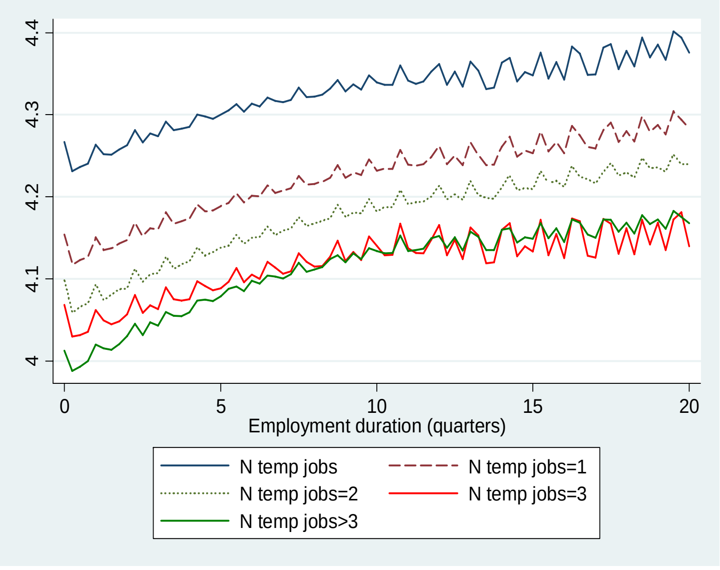

Figure 3: Wage predictions of temps moving to regular employment with different treatment levels. No of temp jobs as treatment.

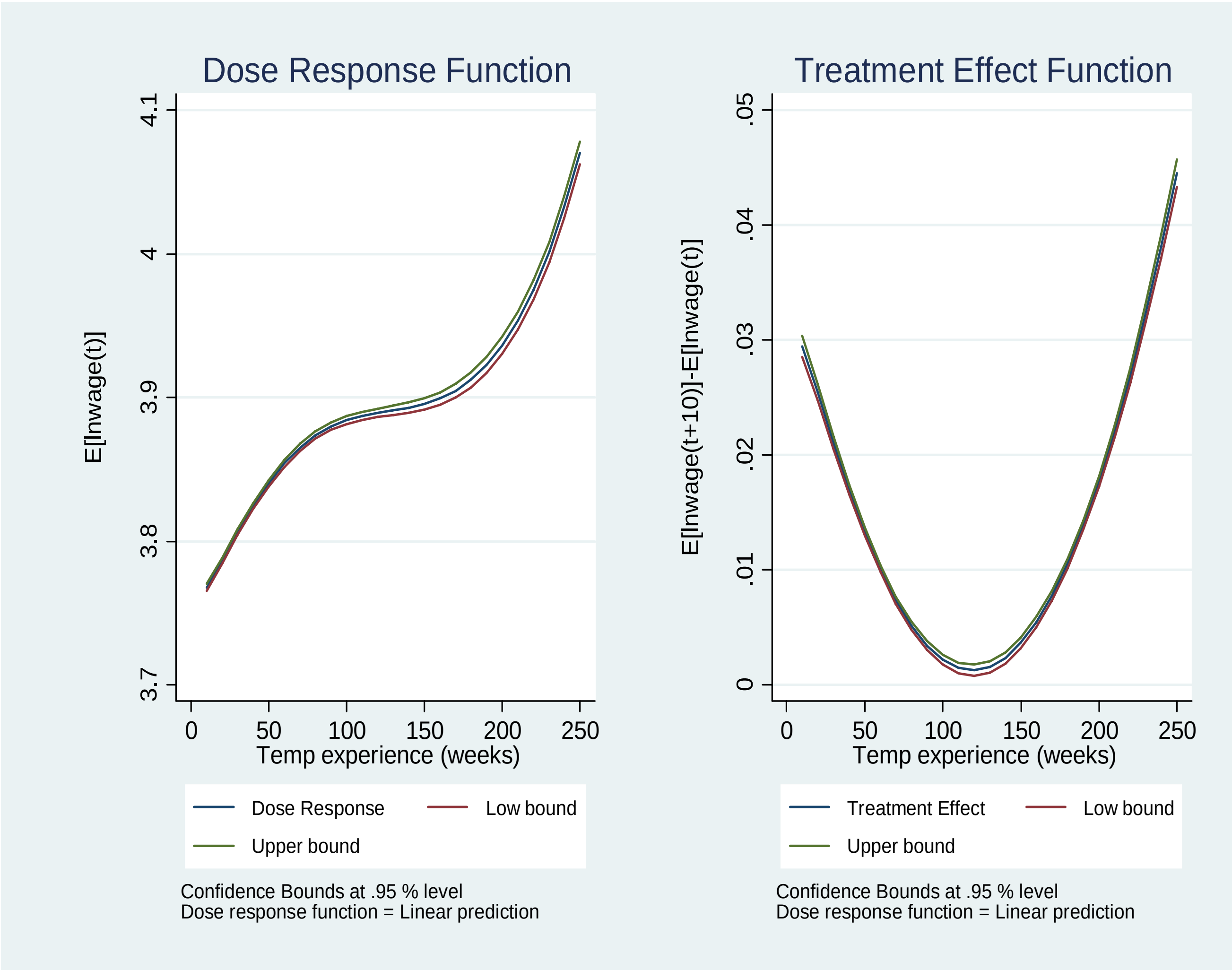

Figure 4: The effects of temporary agency employment experience over the last 5 years on wages, matching approach.

Appendix

Table A1: Binary treatment and single equation approach

	Model 1	**Model 2**
Temporary agency employed	–0.196***	–0.188***
	(0.000)	(0.001)
Age	0.039***	0.039***
	(0.000)	(0.000)
Age squared/1000	–0.454***	–0.454***
	(0.002)	(0.002)
Secondary degree with vt	0.028***	0.028***
	(0.001)	(0.001)
High school degree no vt	–0.079***	–0.079***
	(0.003)	(0.003)
High school degree with vt	0.044***	0.044***
	(0.002)	(0.002)
College degree	0.099***	0.099***
	(0.002)	(0.002)
University degree	0.156***	0.155***
	(0.002)	(0.002)
East	–0.130***	–0.129***
	(0.001)	(0.001)
Employment duration	0.000***	0.000***
	(0.000)	(0.000)
Employment duration squared/1000	–0.001***	–0.001***
	(0.000)	(0.000)
Number of regular jobs over the last 5 years	0.000***	0.000***
	(0.000)	(0.000)
Work experience	0.000***	0.000***
	(0.000)	(0.000)
Work experience squared/1000	0.001***	0.001***
	(0.000)	(0.000)
Previously unemployed	–0.036***	–0.037***
	(0.000)	(0.000)
Previously long term unemployed	–0.028***	–0.027***
	(0.001)	(0.001)
Previously regular employed	–0.008***	–0.008***
	(0.000)	(0.000)
Previously out of the labor force	0.050***	0.050***
	(0.001)	(0.001)
Previously temporary employed	0.018***	0.019***
	(0.001)	(0.001)
Unemployment benefits/assistance	–0.028***	–0.029***
	(0.001)	(0.001)
Mills ratio		–0.005***
		(0.000)
N	5,075,611	5,075,611

Notes: The dependent variable in all estimations is the log gross daily wage. Model 2 corrects for the selection equation. All regressions are estimated with the FE approach and include in addition and among others occupation dummies, firm characteristics, regional unemployment and GDP growth rate, agglomeration and time dummies. Column 2, F-stats (p-value) on excluded instruments: 1171.06 (0.000). Significance levels: ***1%, **5%, *10%. Standard errors clustered at the individual level.

Table A2: Duration of the current temp job, single equation approach

	Model 1	**Model 2**
Current temp job < 8 weeks	–0.204***	
	(0.001)	
Current temp job 8-26	–0.180***	0.016***
	(0.001)	(0.001)
Current temp job 26-52	–0.158***	0.031***
	(0.001)	(0.001)
Current temp job >52	–0.119***	0.057***
	(0.001)	(0.001)
Age	0.038***	0.029***
	(0.000)	(0.001)
Age squared/1000	–0.447***	–0.371***
	(0.002)	(0.007)
Secondary degree with vt	0.026***	0.011***
	(0.001)	(0.003)
High school degree no vt	–0.078***	–0.026***
	(0.003)	(0.009)
High school degree with vt	0.042***	0.015***
	(0.002)	(0.005)
College degree	0.097***	0.071***
	(0.002)	(0.007)
University degree	0.153***	0.077***
	(0.002)	(0.008)
East	–0.128***	–0.085***
	(0.001)	(0.003)
Employment duration	0.000***	0.000***
	(0.000)	(0.000)
Employment duration squared/1000	–0.000***	–0.000***
	(0.000)	(0.000)
Number of regular jobs over the last 5 years	–0.000***	–0.001***
	(0.000)	(0.000)
Work experience	0.000***	0.000
	(0.000)	(0.000)
Work experience squared/1000	0.000***	0.000**
	(0.000)	(0.000)
Previously unemployed	–0.040***	–0.042***
	(0.000)	(0.001)
Previously long term unemployed	–0.026***	–0.006***
	(0.001)	(0.002)
Previously regular employed	–0.007***	–0.031***
	(0.000)	(0.002)
Previously out of the labor force	0.051***	0.068***
	(0.001)	(0.003)
Previously temporary employed	0.027***	–0.010***
	(0.001)	(0.002)
Unemployment benefits/assistance	–0.027***	–0.006***
	(0.001)	(0.001)
Mills ratio	–0.019***	–0.013***
	(0.000)	(0.001)
N	5,075,611	659,082

Notes: The dependent variable in all estimations is the log gross daily wage. All regressions are estimated with the FE approach and include in addition and among others occupation dummies, firm characteristics, regional unemployment and GDP growth rate, agglomeration and time dummies. F-stats (p-value) on excluded instruments: 676.78 (0.000). Significance levels: ***1%, **5%, *10%. Standard errors clustered at the individual level.

Table A3: Temp experience over the last 5 years, single equation approach

	Model 1	**Model 2**
Temp experience < 8 weeks	–0.214***	
	(0.001)	
Temp experience 8-26	–0.194***	0.014***
	(0.001)	(0.001)
Temp experience 26-52	–0.176***	0.028***
	(0.001)	(0.001)
Temp experience >52	–0.136***	0.044***
	(0.001)	(0.001)
Age	0.038***	0.027***
	(0.000)	(0.001)
Age squared/1000	–0.448***	–0.354***
	(0.002)	(0.007)
Secondary degree with vt	0.027***	0.009***
	(0.001)	(0.003)
High school degree no vt	–0.077***	–0.027***
	(0.003)	(0.009)
High school degree with vt	0.043***	0.012**
	(0.002)	(0.005)
College degree	0.098***	0.068***
	(0.002)	(0.007)
University degree	0.155***	0.073***
	(0.002)	(0.008)
East	–0.128***	–0.086***
	(0.001)	(0.003)
Employment duration	0.000***	0.000***
	(0.000)	(0.000)
Employment duration squared/1000	–0.000***	–0.000***
	(0.000)	(0.000)
Number of regular jobs over the last 5 years	0.000***	–0.001***
	(0.000)	(0.000)
Number of temp jobs over the last 5 years	–0.005***	–0.002***
	(0.000)	(0.001)
Work experience	0.000***	–0.000***
	(0.000)	(0.000)
Work experience squared/1000	0.001***	0.000***
	(0.000)	(0.000)
Previously unemployed	–0.038***	–0.040***
	(0.000)	(0.001)
Previously long term unemployed	–0.025***	–0.003*
	(0.001)	(0.002)
Previously regular employed	–0.007***	–0.032***
	(0.000)	(0.002)
Previously out of the labor force	0.051***	0.069***
	(0.001)	(0.003)
Previously temporary employed	0.026***	–0.017***
	(0.001)	(0.002)
Unemployment benefits/assistance	–0.027***	–0.005***
	(0.001)	(0.001)
Mills ratio	–0.013***	–0.005***
	(0.000)	(0.001)
N	5,075,611	659,082

Notes: The dependent variable in all estimations is the log gross daily wage. All regressions are estimated with the FE approach and include in addition and among others occupation dummies, firm characteristics, regional unemployment and GDP growth rate, agglomeration and time dummies. Significance levels: ***1%, **5%, *10%. F-stats (p-value) on excluded instruments: 734.47 (0.000). Standard errors are bootstrapped using a sequential two step bootstrapping procedure with 200 replications.

Table A4: Number of temp jobs over the last 5 years, single equation approach

	Model 1	**Model 2**
No of temporary agency jobs=1	–0.179***	
	(0.001)	
No of temporary agency jobs=2	–0.179***	0.016***
	(0.001)	(0.001)
No of temporary agency jobs=3	–0.170***	0.021***
	(0.001)	(0.001)
No of temporary agency jobs > 3	–0.169***	0.021***
	(0.001)	(0.002)
Age	0.038***	0.030***
	(0.000)	(0.001)
Age squared/1000	–0.453***	–0.371***
	(0.002)	(0.007)
Secondary degree with vt	0.027***	0.009***
	(0.001)	(0.003)
High school degree no vt	–0.079***	–0.027***
	(0.003)	(0.009)
High school degree with vt	0.043***	0.012**
	(0.002)	(0.005)
College degree	0.098***	0.067***
	(0.002)	(0.007)
University degree	0.155***	0.072***
	(0.002)	(0.008)
East	–0.128***	–0.086***
	(0.001)	(0.003)
Employment duration	0.000***	0.001***
	(0.000)	(0.000)
Employment duration squared/1000	–0.001***	–0.001***
	(0.000)	(0.000)
Number of regular jobs over the last 5 years	0.000**	–0.002***
	(0.000)	(0.000)
Work experience	0.000***	0.000***
	(0.000)	(0.000)
Work experience squared/1000	0.001***	–0.000***
	(0.000)	(0.000)
Previously unemployed	–0.038***	–0.038***
	(0.000)	(0.001)
Previously long term unemployed	–0.026***	–0.003*
	(0.001)	(0.002)
Previously regular employed	–0.007***	–0.033***
	(0.000)	(0.002)
Previously out of the labor force	0.051***	0.067***
	(0.001)	(0.003)
Previously temporary employed	0.020***	–0.027***
	(0.001)	(0.002)
Unemployment benefits/assistance	–0.029***	–0.008***
	(0.001)	(0.001)
Mills ratio	–0.012***	–0.003***
	(0.000)	(0.001)
N	5,075,602	659,082

Notes: The dependent variable in all estimations is the log gross daily wage. All regressions are estimated with the FE approach and include in addition and among others occupation dummies, firm characteristics, regional unemployment and GDP growth rate, agglomeration and time dummies. Significance levels: ***1%, **5%, *10%. F-stats (p-value) on excluded instruments: 727.09 (0.000). Standard errors are bootstrapped using a sequential two step bootstrapping procedure with 200 replications.

Table A5: Wage equations by treatment status, duration of the current agency job

	Current agency job in weeks			
	< 8	**8-26**	**26-52**	**> 52**
Age	0.019***	0.025***	0.030***	0.031***
	(0.004)	(0.002)	(0.002)	(0.001)
Age squared/1000	–0.326***	–0.395***	–0.403***	–0.355***
	(0.039)	(0.021)	(0.021)	(0.009)
Secondary degree with vt	0.030***	0.019***	–0.000	–0.010*
	(0.009)	(0.006)	(0.007)	(0.006)
High school degree no vt	–0.029	–0.057***	–0.022	0.048***
	(0.035)	(0.021)	(0.026)	(0.017)
High school degree with vt	0.040**	0.017	0.021*	–0.018**
	(0.019)	(0.011)	(0.013)	(0.009)
College degree	0.050*	0.062***	0.100***	0.099***
	(0.029)	(0.017)	(0.017)	(0.012)
University degree	0.053	0.047**	0.075***	0.115***
	(0.035)	(0.020)	(0.022)	(0.014)
East	–0.073***	–0.085***	–0.076***	–0.080***
	(0.011)	(0.006)	(0.007)	(0.005)
Employment duration	0.000*	0.001***	0.001***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Employment duration squared/1000	–0.000	–0.001***	–0.001***	–0.001***
	(0.001)	(0.000)	(0.000)	(0.000)
Number of regular jobs over the last 5 years	–0.001	–0.000	–0.000	0.001***
	(0.001)	(0.001)	(0.001)	(0.000)
Work experience	–0.000	0.000	0.000	–0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Work experience squared/1000	0.001	0.000	–0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Previously unemployed	–0.053***	–0.001	–0.010**	0.010***
	(0.006)	(0.004)	(0.004)	(0.002)
Previously long term unemployed	–0.005	–0.003	–0.016***	–0.008***
	(0.007)	(0.004)	(0.004)	(0.003)
Previously regular employed	–0.040***	0.000	0.000	0.009***
	(0.007)	(.)	(.)	(0.002)
Previously out of the labor force	0.090***	0.095***	0.073***	–0.001
	(0.013)	(0.008)	(0.009)	(0.004)
Previously temporary employed	–0.016**	0.033***	0.020***	0.015***
	(0.007)	(0.003)	(0.004)	(0.002)
Unemployment benefits/assistance	–0.002	–0.002	–0.008**	0.003
	(0.005)	(0.003)	(0.004)	(0.003)
Mills ratio	–0.016***	–0.018***	–0.013***	–0.004***
	(0.002)	(0.001)	(0.002)	(0.001)
N	126,761	169,322	125,180	237,819

Notes: The dependent variable in all estimations is the log gross daily wage. All regressions are estimated using the FE approach and include in addition firm characteristics, regional unemployment and GDP growth rate, agglomeration and year dummies. Significance levels: ***1%, **5%, *10%.Standard errors are bootstrapped using a sequential two step bootstrapping procedure with 200 replications.

Table A6: Wage equations by treatment status, temp experience over the last 5 years

	Temp experience in weeks			
	< 8	**8-26**	**26-52**	**> 52**
Age	0.048**	0.032***	0.032***	0.028***
	(0.021)	(0.004)	(0.003)	(0.001)
Age squared/1000	–0.557***	–0.481***	–0.466***	–0.331***
	(0.191)	(0.043)	(0.035)	(0.009)
Secondary degree with vt	0.028	0.032***	–0.006	0.005
	(0.050)	(0.011)	(0.009)	(0.004)
High school degree no vt	0.032	–0.002	–0.023	–0.004
	(0.167)	(0.034)	(0.036)	(0.015)
High school degree with vt	–0.009	0.059***	0.022	0.002
	(0.108)	(0.022)	(0.019)	(0.007)
College degree	0.059	0.159***	–0.001	0.077***
	(0.164)	(0.037)	(0.028)	(0.010)
University degree	–0.196	0.062*	0.046	0.066***
	(0.165)	(0.035)	(0.035)	(0.011)
East	–0.131	–0.110***	–0.081***	–0.083***
	(0.081)	(0.014)	(0.011)	(0.004)
Employment duration	–0.001	0.001***	0.001***	0.000***
	(0.001)	(0.000)	(0.000)	(0.000)
Employment duration squared/1000	0.004	–0.001**	–0.001**	–0.000***
	(0.005)	(0.001)	(0.000)	(0.000)
Number of regular jobs over the last 5 years	–0.009	0.000	–0.004***	0.001*
	(0.006)	(0.002)	(0.001)	(0.000)
Number of temp jobs over the last 5 years	0.045**	–0.011***	–0.000	–0.004***
	(0.018)	(0.003)	(0.002)	(0.001)
Work experience	0.000	0.000*	0.000***	–0.000***
	(0.001)	(0.000)	(0.000)	(0.000)
Work experience squared/1000	0.001	–0.000	–0.001***	0.000**
	(0.003)	(0.001)	(0.000)	(0.000)
Previously unemployed	–0.147	–0.034***	0.020***	–0.047***
	(0.090)	(0.007)	(0.006)	(0.002)
Previously long term unemployed	0.000	–0.003	–0.014**	–0.008***
	(0.037)	(0.007)	(0.006)	(0.003)
Previously regular employed	–0.062	–0.019**	0.000	–0.038***
	(0.090)	(0.009)	(.)	(0.002)
Previously out of the labor force	0.037	–0.023	0.066***	0.086***
	(0.076)	(0.016)	(0.013)	(0.004)
Previously temporary employed	0.000	0.028***	0.026***	–0.022***
	(.)	(0.009)	(0.006)	(0.002)
Unemployment benefits/assistance	–0.014	–0.003	0.004	–0.002
	(0.034)	(0.006)	(0.005)	(0.002)
Mills ratio	–0.025	–0.016***	–0.008***	–0.016***
	(0.024)	(0.004)	(0.002)	(0.001)
N	69,617	121,137	118,919	349,409

Notes: The dependent variable in all estimations is the log gross daily wage. All regressions are estimated with the FE approach and include in addition and among others occupation dummies, firm characteristics, regional unemployment and GDP growth rate, agglomeration and time dummies. Significance levels: ***1%, **5%, *10%. Standard errors are bootstrapped using a sequential two step bootstrapping procedure with 200 replications.

Table A7: Wage equations by treatment status, number of temp jobs over the last 5 years

	Number of temp jobs			
	1	**2**	**3**	**> 3**
Age	0.036***	0.030***	0.017***	0.019***
	(0.001)	(0.001)	(0.002)	(0.003)
Age squared/1000	–0.426***	–0.361***	–0.197***	–0.284***
	(0.009)	(0.016)	(0.025)	(0.029)
Secondary degree with vt	–0.005	0.016*	0.038***	0.017*
	(0.006)	(0.008)	(0.014)	(0.010)
High school degree no vt	0.003	0.041	0.239***	0.019
	(0.019)	(0.027)	(0.044)	(0.047)
High school degree with vt	–0.015	0.030**	0.022	0.026
	(0.011)	(0.013)	(0.021)	(0.016)
College degree	0.022*	0.223***	–0.140***	0.057**
	(0.013)	(0.018)	(0.040)	(0.029)
University degree	0.079***	0.229***	0.118***	0.030
	(0.014)	(0.019)	(0.042)	(0.036)
East	–0.115***	–0.092***	–0.116***	–0.062***
	(0.008)	(0.008)	(0.010)	(0.008)
Employment duration	0.001***	0.001***	0.000***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Employment duration squared/1000	–0.002***	–0.001***	–0.001***	–0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Number of regular jobs over the last 5 years	–0.002***	–0.004***	–0.004***	0.001**
	(0.000)	(0.001)	(0.001)	(0.001)
Work experience	0.000***	0.000***	0.000***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Work experience squared/1000	–0.001***	–0.001***	–0.002***	–0.001
	(0.000)	(0.000)	(0.000)	(0.000)
Previously unemployed	0.003	0.025***	–0.075***	–0.023***
	(0.003)	(0.005)	(0.006)	(0.005)
Previously long term unemployed	–0.007**	–0.030***	0.002	–0.018**
	(0.004)	(0.005)	(0.008)	(0.008)
Previously regular employed	–0.001	0.000	–0.042***	–0.022***
	(0.002)	(.)	(0.008)	(0.006)
Previously out of the labor force	–0.011**	–0.005	0.116***	0.162***
	(0.005)	(0.008)	(0.013)	(0.014)
Previously temporary employed	0.000	0.041***	–0.062***	–0.020***
	(.)	(0.005)	(0.006)	(0.005)
Unemployment benefits/assistance	–0.043***	–0.002	–0.004	–0.005
	(0.004)	(0.005)	(0.006)	(0.004)
Mills ratio	0.000	–0.004***	0.002	–0.002**
	(0.001)	(0.001)	(0.002)	(0.001)
N	353,764	157,340	74,440	73,538

Notes: The dependent variable in all estimations is the log gross daily wage. All regressions are estimated with the FE approach and include in addition and among others occupation dummies, firm characteristics, regional unemployment and GDP growth rate, agglomeration and time dummies. Significance levels: ***1%, **5%, *10%.Standard errors are bootstrapped using a sequential two step bootstrapping procedure with 200 replications.