The Cyclicality of the Stepping-Stone Effect of Temporary Agency Employment

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Abstract: We investigate whether the stepping-stone effect of temporary agency work varies over the business cycle. Using administrative data for 1985-2012 and the timing-of-events model, we estimate in- and post-treatment effects and their relationship to the unemployment rate. Findings show a strong lock-in effect of agency employment, particularly in tight labor markets, suggesting that firms do not use agency work for screening. The positive post-treatment effect is larger when unemployment is high, indicating that workers are activating networks they established while treated. The matching quality improves for those finding a job directly after treatment, with a higher gain when unemployment is low.

Keywords: temporary agency employment, stepping-stone effects, cyclicality, Germany

JEL-Codes: C41, J40, J64

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1. Introduction

A quarter of a century ago, most Western countries relaxed regulations on temporary agency work (hereafter, agency work) to increase labor market flexibility and thus overall employment (Boeri, 2011; Jahn et al., 2012). Agency work is characterized by a tripartite contractual relationship. The workers are employed by the agency, which is the legal employer. Based on a contract between the agency and the client firm, the client firm temporarily assigns tasks to the worker. The central idea underlying agency work is to lower hiring and firing costs for flexible jobs and thus allow firms to adjust the size of their workforce to the volatility of the business cycle. Indeed, that the demand for agency work has a strong procyclical component is well documented (de Graaf-Zijl and Berkhout, 2007; Jahn and Bentzen 2012). At the same time, agency work is meant to act as a bridge to regular employment, especially for individuals with difficulties finding a job. Due to the high volatility of agency work over the business cycle, paired with the poor working conditions that prevail in this sector, the existence of a "stepping-stone effect" of agency employment—that is, the ability of agency work to pave the way to permanent employment—has become a central part of the debate on two-tier labor markets (Boeri, 2011; Jahn et al., 2012; OECD, 2013).

While a growing body of literature has investigated whether agency work leads to stable jobs, there remains a dearth of evidence on whether the stepping-stone effect depends on the business cycle. Given that policy makers, when deciding how best to regulate agency work, need to know when agency work is a springboard to regular jobs, the lack of evidence on the cyclicality of the stepping-stone effect represents an important gap in the literature. This study provides systematic evidence on whether and, if so, to what extent the stepping-stone effect of agency work depends on macroeconomic conditions.

The results of the empirical literature investigating whether agency work is a bridge into regular jobs are mixed. For example, Lane (2003), Heinrich et al. (2009), and Jahn and Rosholm (2014) find evidence of agency work acting as a springboard into regular jobs. In contrast, Autor and Houseman (2010), De Graaf-Zijl et al. (2011), and Hveem (2013) find the opposite. Compared to workers employed on a direct-hire fixed-term contract, agency workers are less likely to end up in regular jobs (e.g., Amuedo-Dorantes et al., 2008; Givord and Wilner, 2015). One possible reason is that most firms hiring workers on a fixed-term basis aim at screening workers for permanent jobs or prolonging short probationary periods. Thus one would expect that fixed-term contracts might be an *a priori* pathway to regular jobs. In contrast, for firms hiring an agency worker, the screening function rarely plays an important role. The main motive for client firms is to adjust to unexpected changes in output demand over the business cycle (CIETT, 2002).

What the literature has largely overlooked thus far is that the pro-cyclical demand for agency workers likely also affects the transition from agency jobs to regular employment. The buffer function of agency work leaves open the question of when agency work provides a bridge to regular jobs. If the stepping-stone effect of agency work varies with the business cycle, such a finding might explain the mixed results in the empirical literature. The reason is that previous studies use different periods and thus measure the stepping-stone effect at different points in the business cycle.

So far, only Jahn and Rosholm (2014) investigate the cyclical behavior of the stepping-stone effect of agency work, with Danish data for 1997-2006. They found no systematic evidence that the stepping-stone effect depends on the business cycle. As to the effectiveness of active labor market programs over the business cycle, the evidence is sparse. Using country variation in metadata sets, Kluve (2010) and Card et al. (2015) show that active labor market programs are most effective in slack labor markets. These results are in line with those of the only two other studies on this subject, both of which use administrative data sets. First, Lechner and Wunsch (2009) investigate the cyclicality of training programs in Germany for unemployed people who entered a training program over a 10-year period (1986-1995). They show that negative lock-in effects are largest when training programs start during an economic upturn, while the positive long-run effects are largest in a downturn. Second, using Swedish administrative data, Forslund et al. (2011) compare the effectiveness of work practice and training programs for a six-year period (1999-2005), finding a clear counter-cyclical pattern for both.

This study investigates the cyclical behavior of the stepping-stone effect of agency employment using administrative employer-employee data from 1985-2012 for West Germany, which has a long tradition of agency employment. This long period allows us to contribute to the literature on the stepping-stone effect of agency employment in two ways. First, the time frame of the three most relevant studies span roughly only one business cycle. To obtain enough variation for this short observation period, they rely on variants of the local annual unemployment rate during the observation period. However, the use of the regional unemployment rate mixes cyclical movements of unemployment over time with structural differences in unemployment across regions. In contrast, given the long time span and high frequency of our data, we are able to access the cyclicality of the stepping-stone effect over 28 years, covering roughly three full business cycles.

Second, despite some empirical evidence on the quality of the jobs found in terms of post-unemployment earnings (see e.g., Andersson et al., 2009; Heinrich et al., 2009), we contribute to the literature on the stepping-stone effect of agency employment by investigating whether the quality of jobs found after leaving unemployment depends on the state of the economy itself.

Furthermore, to investigate the mechanism through which agency work provides a bridge into regular employment, we investigate the cyclicality of the in- and post-treatment effect of accepting an agency job during an unemployment phase. The in-treatment effect is the transition rate directly from agency work into regular employment, relative to the transition rate from open unemployment into regular employment. In contrast, the post-treatment effect investigates whether an agency job might have had a positive effect on the subsequent transition rate out of unemployment even had the worker fallen back into open unemployment after holding the agency job. Methodologically, we build on Abbring and van den Berg (2003a) and apply their timing-of-events model to an inflow sample into unemployment, controlling for time-invariant unobserved characteristics affecting selection into agency work and the transition out of unemployment.

The literature on the stepping-stone effect of agency work stresses three mechanisms through which agency work may provide a pathway to a regular job. First, human capital acquisition while on assignment at a client firm may give agency workers skills that lead to regular jobs (e.g., Abraham, 1990, Autor, 2001). However, if the skills requirement of the agency job falls below the workers' qualification levels, they might not be able to gain much human capital (e.g., Segal and Sullivan, 1997). Second, search theory argues that agency workers might receive more and faster information on vacancies. This information advantage may facilitate rapid entry into stable jobs and might be more pronounced if client firms use temporary staffing arrangements to screen workers for filling vacancies (e.g., Houseman et al., 2003). If client firms use agency work primarily as a buffer in an upturn, agency jobs crowd out direct job search and should thus have a strong lock-in effect (e.g., Autor and Houseman, 2010; Booth et al., 2002; Boeri and Garibaldi, 2009).

Third, signaling theory predicts that job seekers can overcome negative stigma effects or signal high productivity by accepting an agency job (Autor, 2001). However, the acceptance of an agency job might also stigmatize job seekers and could even signal low productivity, by suggesting that the job seeker is not productive enough to be hired as a regular worker. Which of these three mechanisms dominates likely depends on the state of the economy.

The question is how one should expect the in- and post-treatment effects to vary over the business cycle. We expect the lock-in effect of agency employment to be more pronounced in an upturn, given abundant job openings and less time for job search. We thus expect the in-treatment effect to be (more) negative in an upturn. The lock-in effect might be smaller in a downturn, when the job-finding rate is already low. However, if agency work acts as a screening device, we expect the in-treatment effect to become (more) positive in an upturn, when firms might face a shortage of qualified workers. Therefore, the cyclicality of the in-treatment effect is an empirical question.

In a recession, networks might play an important role for the post-treatment effect, that is, job-finding after having held an agency job, as the few open vacancies might be filled by referrals from former coworkers (Glitz, 2017). The same holds for the human capital effect: During a downturn, the expected unemployment duration is longer, and agency work might be a means of maintaining or even increasing human capital, as opposed to searching for a permanent job from open unemployment. In such a case, we would expect a counter-cyclical post-treatment effect.

We find that agency work does not serve as a bridge into regular employment while workers are in treatment, that is, the in-treatment effect is negative. However, we find a large positive post-treatment effect. In addition, we provide evidence that the in- and post-treatment effects are highly cyclical, with in-treatment effect tending to be less negative and the post-treatment effect more positive during downturns. The post-treatment effect is less volatile over the business cycle than the in-treatment effect. Taking these results together, we show that having had at least some agency experience during an unemployment period might reduce unemployment duration. This effect is more pronounced in downturns. In upturns, however, long treatment durations harm workers.

As for the quality of jobs found, we provide evidence that wages considerably improve for workers finding a regular job while working at an agency job. This effect is slightly more pronounced in an upturn. In contrast, wages for workers finding jobs from open unemployment after having had an agency job do not differ from those of workers without any agency experience.

The paper is organized as follows. Section 2 describes the temporary help sector and the unemployment insurance system in Germany. Section 3 explains our estimation strategy. Section 4 presents the data and main descriptive statistics. Section 5 discusses the results, and Section 6 concludes.

2. Institutional setting

In Germany, all agency workers are eligible for social benefits—including health insurance, vacation leave, and statutory pension plans—and are covered by Germany's relatively strict employment protection legislation after six months of employment. Like all other wage and salary workers, agency workers are eligible for unemployment benefits if they were employed for at least 12 months during the preceding two years. The maximum entitlement duration is 12 months for workers below age 55, the group of interest in this paper.[1] If a job seeker does not fulfill the eligibility criteria, he or she can claim unemployment assistance, which is means-tested.

Agency work has been regulated by national legal statute since 1972. While this law has been amended several times, employment protection legislation for regular workers has remained largely unchanged. Most reforms of agency work in the 1980s and 1990s aimed at increasing the flexibility of

[1] Further details about the unemployment insurance system in Germany and the changes in the system from the Hartz reforms can be found, e.g., in Lechner and Wunsch (2009) for the pre-2004 period and in Dlugosz et al. (2014) for the post-2004 period.

the client firms by prolonging the maximum period of assignment. The major purpose of the post-2000 reforms was to decrease the sizable wage gap between agency workers and workers employed outside the agency sector (for an overview of the regulations, see Burda and Kvasnicka, 2006). However, the effects of these reforms were small. Although Antoni and Jahn (2009) find that the prolongation of the maximum period of assignment slightly increased the employment duration of agency workers, Jahn (2010) found no impact on the size of the pay gap. Moreover, the reforms did not significantly affect the growth of the agency work sector (Jahn and Bentzen, 2012).

Germany is one of the largest markets in Europe for agency work. In 2012, when our observation period ends, about 900,000 workers, or 2.2% of the entire workforce, were employed by a temporary work agency. At the same time, the percentage of agency workers of the total European working population was approximately 1.2% (CIETT, 2017). Despite the relatively small size of the sector, agency work is an important pathway out of unemployment. In 2012, roughly 54% of the agency workers were previously unemployed, and 10% were previously out of the labor force (Federal Employment Agency, 2016).

Nevertheless, agency jobs are spot-market jobs that tend to be short, with a median duration of about 12 weeks. The high percentage of agency workers coming from unemployment, the concentration of low-skilled workers, and the poor working conditions in this sector have made the stepping-stone effect of agency work a central topic of policy debates on agency work in Germany.

Agency work clearly acts as a buffer over the business cycle. The 2008 economic crisis saw a substantial drop in the number of agency workers, from about 800,000 employed workers in 2008 to only about 600,0000 in 2009. The Federal Employment Agency estimates that around 70% of the total job loss during the 2008 financial crisis was due to layoffs in the temporary help sector (Federal Employment Agency, 2012). After the crisis, the temporary help sector began to recover rapidly, and by 2010 it had recovered completely. The number of agency workers reached its historic peak in 2017, at about one million workers.

The dynamic nature of agency work is also reflected in its volatility over the business cycle. The first differences of the log of the stock of agency workers and unemployed persons are shown in Figure 1, confirming a clear pro-cyclical pattern.[2]

[Figure 1 about here]

Likely reasons for agency work in Germany being important are, first, the matching efficiency of the temporary help sector is much higher relative to that of public employment services (Neugart and Storrie, 2006). Second, firms gain considerable productivity when complementing their permanent workforce with agency workers (Hirsch and Müller, 2012). Third, the extensive regulation of fixed-term contracts in Germany, coupled with the country's strict employment protection legislation, makes it attractive for client firms to use agency workers to adapt their workforce to changing economic conditions (Mitlacher, 2007; Venn, 2009). In contrast to the situation in the southern European countries, fixed-term contracts play only a minor role in the flexibility of German firms (Bentolila et al., 2012). The percentage of workers in Germany with fixed-term contracts has increased only slightly since 1985 (Destatis, 2017), and about 56% of these jobs are usually converted to permanent jobs (IAB, 2012).

3. Modelling the cyclicality of the treatment effects

3.1 Baseline Model

Our aim is to analyze the effect of taking an agency job during an unemployment period on job search duration before finding a regular one. As accepting an agency job while unemployed is not an exogenous, random event, the econometric model needs to exploit sources of variation, to distinguish the causal effects of agency work from the selection effects. We use the timing-of-events approach, formalized by Abbring and van den Berg (2003a). This strategy exploits random variation in the timing of the agency job to separate the causal effect of accepting an agency job from time-invariant selection

[2] As high-frequency data contain some short-run noise, we applied a centered, 12-period moving-average filter to the time series before differencing the data.

effects. The agency job is thus considered a part of the unemployment period. The counterfactual situation is one of continued unemployment until regular employment.

T_u is a continuous random variable measuring the time from inflow to unemployment until a regular job is found. T_u is censored for those who remain unemployed until the end of the observation period and for those making transitions into states other than employment. The transition rate into a regular job is specified as a Mixed Proportional Hazard (MPH):

$$h_u(t|x, in(t), post(t), v_u) =$$
$$\lambda_u(t)\exp[x\beta_u + in(t)\gamma_1 + u * in(t)\gamma_2 + post(t)\delta_1 + u * post(t)\delta_2 + v_u\ ] \quad (1)$$

The hazard function is the product of a baseline hazard, $\lambda_u(t)$, a scaling function depending on observed variables, x, an unobserved factor, v_u, and two time-varying indicators, one for being employed by an agency at time t, $in(t) = 1$, and one for having been an agency worker during the current unemployment period before t but not an agency worker at t, $post(t) = 1$. The coefficients γ_1 and δ_1 thus capture the in- and post-treatment effects of agency jobs on the hazard rate into regular employment, respectively. u is the quarterly unemployment rate centered around its sample mean. $u * in(t)$ and $u * post(t)$ are its interaction with the in- and post-treatment effect, and γ_2 and δ_2 measure the effect of the business cycle and are the coefficients of primary interest in this study.

The baseline hazard is specified as a flexible, piecewise-constant transition rate:

$$\lambda_u(t) = \exp\left[\sum_l \left(\lambda_{u,l} I_l(t)\right)\right],$$

where $l = 0, \dots, 11$ is a subscript for the time intervals measured in days, and $I_l(t)$ are time-varying indicator variables for elapsed duration t. We split the analysis period during the first six months into monthly intervals. From the seventh month on, we split the time axis into quarterly intervals up to two years, after which the transition rate is assumed constant.

We correct for potential endogeneity by modelling the time until an agency job is found, T_p. If T_p is observed, it is always shorter than T_u. Specifying once again a MPH function, the transition rate into agency jobs is:

$$h_p(t|x, v_p) = \lambda_p(t)\exp[x\beta_p + v_p] \tag{2}$$

As we have multiple unemployment periods for some job seekers, we assume the values of each unobserved heterogeneity term to be individual-specific, that is, constant across all unemployment periods experienced by the same individual.

An additional potential source of endogeneity is the duration of the agency job. To deal with this possibility, we explicitly model the treatment duration, that is, the duration of the agency job, T_d. The agency job may end with a transition directly into regular employment. However, as the agency job is considered part of the unemployment period, this transition is already modeled in equation (1). Thus, if the agency worker exits to regular employment, T_d is censored. T_d measures the time from the beginning of an agency job to a transition back into open unemployment. The treatment duration is modeled in the following way:

$$h_d(t|x, t_p, z, v_d) = \lambda_d(t)\exp[x\beta_d + f(t_p) + z\delta + v_d], \tag{3}$$

where $f(t_p)$ is a flexible function of the elapsed unemployment duration at the time when the agency job begins. It is specified as a step function, using essentially the same intervals as those used for the baseline hazard function. As extra control variables, z, we include the daily wage in the agency job and indicator variables for the occupation.

C_i indicates if the unemployment period i was completed with a transition into a regular job. The likelihood function for individual j with N unemployment periods is now

$$L(v_u, v_p, v_d) = \prod_{i=1}^{N} L_i(v_u, v_p, v_d), \tag{4}$$

where

$$\begin{aligned} L_i(v_u, v_p, v_d) \\ &= h_p[t_{pi}|x_i, v_p]^{I[t_{pi}<t_{ui}]} h_d[t_{di}|x_i, t_p, z, v_d]^{I[t_{pi}+t_{di}<t_{ui}]} h_u[t_{ui}|x_i, in(t_{ui}), out(t_{ui}), v_u,]^{C_i} \\ &\exp\left\{-\int_0^{t_{pi}} h_p\,[s|x_i, v_p]ds - \int_0^{t_{di}} h_d\,[t|x_i, t_p, z, v_d]dt - \int_0^{t_{ui}} h_u\,[r|x_i, in(t), out(t), v_u]dr\right\} \end{aligned}$$

As we use a 2% random sample of all agency job participants and only 0.5% of the nonparticipants (see next section), the likelihood contributions are weighted with the weighted exogenous sampling maximum likelihood estimation method (Manski and Lerman 1977) as in van den Berg and Vikström (2013).[3]

The distribution of unobserved variables is approximated non-parametrically by a trivariate discrete distribution with M mass points (Heckman and Singer 1984; Gaure et al. 2007). If the Akaike information criterion is satisfied, we proceed by adding another support point, and we continue to do so until the likelihood does not improve enough to satisfy the Akaike information criterion. This procedure allows for unrestricted correlation between the different unobserved variables and typically ends with six support points in the final estimation.

We subsequently simulate the expected remaining unemployment duration, measured from t_p, see Kyyrä et al. (2013):

$$\Delta(t_p, t_d) = E[T_u - t_p | T_p = t_p, t_d, T_u > t_p] - E[T_u - t_p | T_p = \infty, T_u > t_p] \tag{5}$$

$\Delta(t_p, t_d)$ measures the effect on the expected remaining unemployment duration of entering an agency job at t_p and holding it for (at most) t_d weeks.

[Figure 2 about here]

3.2 Key identifying assumptions

Three main assumptions underlie the timing-of-events model. The first is the MPH assumption, which is fairly standard but which might still be a threat for our identification strategy. However, given that we have access to repeated periods of unemployment for the same individual—on average we observe each individual in 3.4 unemployment periods—our results do not solely depend on the MPH functional form assumption. Therefore, the MPH assumption is not as critical as it would otherwise be. Observing multiple unemployment periods also implies that the distribution of unobserved variables

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[3] This sampling method is frequently used in economics. It provides a consistent but not fully efficient estimator. Ideally, we should have used the sandwich estimator for the covariance matrix. However, due to problems in calculating the numerical Hessian matrix, we use the inverse of the cross-products of the score vector.

is well identified. Thus identification does not rely entirely on the MPH assumption (e.g., Abbring and van den Berg 2003a, b; Brinch 2007; Gaure et al. 2007).

Second, under the assumption that unobserved characteristics are time-invariant and that there is no anticipation of treatment, random variation in the timing of the first agency job during the unemployment period identifies the causal effect. The non-anticipation assumption implies that the individual is assumed not to know more about when the agency job will start than is captured by the distribution of the duration. Anticipation in our model, and thus the risk of a change in behavior before the treatment starts would occur only if the job seeker knew too far in advance precisely when he would start an agency job.

We argue that there are four sources of random variation in the timing of the treatment. First, the job seeker needs to know how to contact an agency and whether the agency has an open position requiring his qualifications. Differences in information about how to approach the right agency and whether there are available job openings are sources of randomness. Second, agencies often advertise positions even when they do not have a current job offer from a client firm. Their aim is to screen workers and list them in their pool of available candidates. Given that client firms need workers at short notice and usually contact several agencies simultaneously, agencies need a worker availability databank so as to be able to react swiftly. As the job seeker does not know whether he or she is applying for a real opening or is merely being screened for the pool of available workers, there is random variation in the time from applying at the agency to possibly entering the pool of agency workers.

Third, before entering an agency's pool, the job seeker will be interviewed by an agency employee, who will evaluate his or her qualifications. The agency might also reject an applicant for (possibly) not being sufficiently qualified to meet the flexibility needs of client firms. Fourth, there is also some random variation in the timing of final assignment to a client firm, because the timing of assignment depends on the demand side and is random from the job seeker's viewpoint. Typically, if there is a job offer from a client firm responding to an unexpected increase in demand for its services, both the agency and the job seeker have to react quickly, for an agency job that usually starts within a few days.

This process implies considerable variation in the timing of the first agency job, as Figure 2—displaying the transition rate from open unemployment to an agency job—shows.

3.3 Measuring the quality of the stepping-stone effect

To assess the quality of the job found after leaving unemployment, we investigate whether holding an agency job affects the daily earnings in the subsequent job. We follow Arni et al. (2013) by explicitly modeling the post-treatment wage. However, in contrast to their approach, we specify a log-normal distribution for the post-unemployment wage, that is,

$$f(w|x, v_w) = \frac{1}{\sigma}\varphi\left(\frac{lnw - x\beta_w - in\gamma_{1,w} - u * in\gamma_{2,w} - post\delta_{1,w} - u * post\delta_{2,w} - v_w}{\sigma}\right), \quad (6)$$

where $\varphi(.)$ denotes the pdf of the standard normal distribution, σ is the standard deviation of the wage distribution, and *in*- and *post*- indicate whether the transition into the regular job took place directly from an agency job or from open unemployment after having held an agency job. As in equation (1), $u * in$ and $u * post$ are the interaction terms with the unemployment rate. The parameters of this model are then estimated jointly with those of the model specified in (1), again extending the distribution of unobservables. The advantage of this specification is that we are also able to present estimates of the size of the wage advantage or disadvantage relative to the control group. To identify the impact of the treatment on post-wages, we use the same assumptions as in Subsection 3.2.

4. Data and descriptive statistics

To investigate the cyclicality of the stepping-stone effect of agency employment, we need detailed high-frequency data on unemployment durations and subsequent jobs over a period encompassing several business cycles. We combine two administrative data sets for the period 1980-2012: the Integrated Employment Biographies (IEB) and the Establishment History Panel (BHP) provided by the Institute for Employment Research (IAB).

The IEB comprises all wage and salary employees and all individuals registered as unemployed in the German social security system (for details, see Ganzer et al., 2017). This data set contains daily information on unemployment, job durations, and transitions. Moreover, it contains a rich set of worker characteristics and wages. As the information of the IEB is used for calculating social security contributions and unemployment benefits, the data set is highly reliable and especially useful for the analysis of unemployment duration. We merge this data set with the BHP, which also stems from the German social insurance system and provides information on firms and industries (for details, see Schmucker et al., 2016). We focus here on individuals entering unemployment in West Germany (excluding Berlin) during the period 1985-2012. Furthermore, we restrict the data to males aged 20-55 years, to circumvent selectivity issues regarding female employment and early retirement.[4]

We excluded East Germany to avoid confounding business cycle effects. This decision also allows us to exploit the full period of data available, as the dataset contains information on East German workers only from 1992.

Using an industry classification code, we identify employment periods in temporary help agencies. For the analysis, we use a 2% random sample of all individuals who were employed by a temporary work agency at least once during their unemployment career, and a 0.5% random sample of all other individuals from 1980-2012. To construct the previous employment history of the job seekers, we use information from 1980 to 1984.

The dependent variable is unemployment duration measured in days. An unemployment period is defined as a sequence of days during which a person receives either unemployment benefits or unemployment assistance or is employed at an agency. Unemployment periods continuing through the sample period are treated as independently right-censored observations (3.4% of all periods).[5]

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[4] During our observation period, the share of male agency workers is 77 percent, and about 70 percent of the agency jobs are in the manufacturing sector.

[5] Sanctions or longer sickness periods might lead to gaps between two unemployment periods without any further notification, as workers do not receive unemployment benefits during these periods. If notification gaps exceed 31 days, we treat the next unemployment notification as a new unemployment period. We apply the same rule for transitions out of unemployment to regular employment.

Regular employment is defined as being employed subject to social security contributions outside the temporary help sector.[6]

To concentrate on workers accepting an agency job due to a lack of alternatives outside the sector, we made the following selection decisions First, to insure that workers have at least some attachment to the labor market and to exclude students who are "temping" while completing their education, we require the job seeker to have been employed for at least six months during the past five years.

Second, due to identification of the agency workers by industry classifications, agency workers cannot be distinguished from the administrative staff of temporary work agencies. We do not expect this problem to affect our estimations, because our analysis focuses on agency workers who were unemployed before accepting an agency job. Nevertheless, we exclude individuals who hold management positions at temporary work agencies, as they are likely to belong to the agency staff. For the same reason, we exclude agency workers with an agency spell lasting more than two years.[7] After this sample selection, the sample consists of 78,973 individuals experiencing a total of 264,420 unemployment spells. Thus we observe on average about 3.4 unemployment spells per person.

We use the following socio-demographic variables: age (three dummies), married, not having German citizenship, having a child in the household, and education (two dummies). In addition, we have information on whether the worker receives unemployment benefits or unemployment assistance. As a proxy for the human capital and employability of the worker, we use the employment history over the previous five years: previously employed (two dummies, in the agency sector or as an apprentice), or outside the labor force. "Regularly employed" is the reference category. Moreover, we control for the fraction of time spent in agency and regular employment during the previous five years, the number of regular jobs held (three dummies, 2-3, 4-6, and 7 or more), and the number of agency

6 The data does not allow us to distinguish between employment on a direct fixed-term contract and employment on an open-ended contract. However, as outlined in Section 2, the majority of fixed-term contracts are converted into regular contracts.

7 Since 2012, the data set also contains information on whether the worker is an agency worker or belongs to the agency staff. This information allows us to investigate how many unemployment periods of the treatment group were falsely classified as treatments even though the worker was actually working as a placement officer. It turns out that, in 2012, roughly 0.8 percent of all ongoing periods involving at least one treatment were classified as treatments even though the worker was employed at least once during his unemployment period as a placement officer. Typically, the worker stayed in the position until the end of the unemployment spell. Thus our results for the in-treatment effect might be, if at all, slightly downward biased (becoming more negative).

jobs during the previous five years. In the endogenous treatment duration, we also include five dummies for the occupation of the agency job and the log of the deflated daily earnings to control for the type of agency job, which might vary over the business cycle.

Moreover, we include dummies for the year and quarter, as well as the aggregate centered unemployment rate for West Germany.[8] All controls—except the two treatment indicators, the occupation dummies, the log wage during treatment, the year and quarter dummies, and the unemployment rate—are measured at the beginning of the unemployment period. However, the time-invariant regressors may still vary over different unemployment periods for the same person.

Information on job durations and daily gross wages included in the data are highly reliable. However, as the agency is the legal employer, we do not know to which client firms workers are assigned or whether an agency worker has transitioned to a former client firm. Moreover, the data provides only information on whether a worker is employed full-time or part-time but contain no information on the number of hours worked. Consequently, the post-earnings refer to daily earnings. The lack of information on the number of hours worked might further justify restricting the sample to male workers, given that most male unemployed exit unemployment to full-time jobs (see Table A2 in the Appendix).

[Table 1 about here]

Table1 presents key descriptive statistics for the treatment and the control groups in upturns (i.e., for unemployment rates below the sample mean), and in downturns (i.e., for unemployment rates above the sample mean) measured at the beginning of an unemployment period. Unemployed people from the treatment group are about two years younger, and non-Germans are clearly overrepresented in the treatment group. While about 30% of the treatment group received unemployment assistance at the beginning of the unemployment period, only about 22% of the control group did so. During upturns, the percentage of workers receiving unemployment assistance is slightly larger.

8 Using the regional unemployment rate would confound cyclical movements of unemployment over time and structural differences in unemployment across regions. We also experimented with including regional dummies to the estimations, but they do not affect the results. To lower the computational burden, we dropped these dummies from the final estimations.

As to previous labor force status, only minor differences appear. About half of the unemployed people in the treatment group were employed before registering for unemployment benefits or assistance, while 64% of the control group were previously employed. However, unemployed people from the treatment group more often held an agency job before becoming unemployed, that is, they went from regular employment or out of the labor force into agency work and then into open unemployment. As the timing-of-events model does not allow for selection at time zero, inflow into unemployment always begins with an open unemployment period.[9] Moreover, Table 1 shows that roughly 50% (60%) of the treated (control) group ultimately ended up in regular employment.

The median time until first accepting an agency job is about 4.7 months when the unemployment period started in a downturn, and 3.1 months when unemployment started in an upturn. The median duration of an agency spell is about 2.7 months during a recession and 3.0 months during a boom. The average number of separate agency work spells during an unemployment period (given that there is at least one) is 1.2.

Figure 2 shows the raw daily transition rate to agency employment. The hazard rate to agency work starts at about 0.08% per day and decreases over the first year of unemployment to a level of around 0.03%, and decreases only slightly thereafter. The large variation in the timing of entry to agency work shows that a great deal of variation in the time until treatment is likely to be exogenous.

[Figure 2 about here]

The transition rate into regular employment for the non-treated starts at a level of 0.45%, then gradually decreases. The transition rate jumps after one year likely because unemployment benefits run out for most workers after a year. The hazard rate for the transition to regular employment for the treated starts much lower, as they have been treated before leaving unemployment. After 18 months, the exit rate for the treated lies slightly above the exit rate for the non-treated. This pattern suggests that the dynamics of the job search and selection processes are important.

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9 As a robustness check, we also estimated our baseline model but excluding those unemployment periods. The results are robust to these changes.

Finally, Table A2 in the Appendix investigates post-wages for the control and the treatment groups. For the treatment group, we divide the post-wages by those who left unemployment directly from treatment and those who left after falling back into open unemployment at least once. The table shows that post-wages are always higher for the treatment group leaving unemployment directly from treatment and lowest for the treatment group leaving treatment from open unemployment.

5. Results

5.1 Selection into agency work and back into open unemployment

Full results from estimating the selection equation, the treatment duration equation, and the unemployment duration equation appear in Table A1 in the Appendix. Duration dependence in the selection equation is negative. Workers below age 25 (the reference group) have much higher transition rates into agency jobs than older workers. Being married is associated with a higher transition rate into agency jobs, but having children in the household lowers the probability of treatment. The transition rate of workers without German citizenship is considerably higher than for German citizens. Moreover, we find that high-skilled workers are less likely to take agency jobs than low- and medium-skilled workers, likely due to the low-skilled nature of most agency jobs. Workers receiving unemployment assistance have a lower probability of taking an agency job than those receiving unemployment benefits. The transition probability to agency work decreases in a downturn, due to lower demand for agency workers in a slump.

The treatment duration equation measures the time from the start of an agency job until the worker enters open unemployment again. The duration dependence is negative. The transition rate back into open unemployment is highest for workers aged 45-55, high-skilled workers, non-German workers, and workers with children in the household. A higher wage during treatment lowers the transition rate to open unemployment. The probability of transitioning back into open unemployment is highest for agency workers who accept manufacturing jobs (the reference category). This finding is expected, as the manufacturing sector (automobile and aircraft) is one of the major users of agency workers, adjusting its workforce to the highly volatile product demand over the business cycle.

5.2 Cyclicality of in-treatment and post-treatment effects

Table 2 shows the results for the treatment effects. First, we estimate a basic duration model with a flexible baseline.

[Table 2 about here]

In Model 1, we include only the two main explanatory variables (the in- and post-treatment indicators) but do not control for observable or unobservable heterogeneity, or take into account selection out of the treatment into open unemployment. Model 1 in Table 2 suggests a significant negative in-treatment effect. Working for an agency significantly lowers the transition rate out of unemployment compared to seeking a regular job from open unemployment. The post-treatment effect is positive and significant, indicating that having worked for an agency at least once during an unemployment spell increases the transition rate into regular jobs. The interaction terms between treatment indicators and the unemployment rate are not significant.

Second, we estimate the same basic duration model but add the covariates described in Section 4. After we control for observed heterogeneity, the in-treatment effect slightly decreases in absolute terms, and the post-treatment effect increases by roughly 10 percentage points. Moreover, the interaction terms between the treatment indicators and the unemployment rate become positive and significant. An increase in the unemployment rate by one percentage point above the mean increases the transition rate into regular employment by 6% while in treatment and by roughly 2% after having received treatment at least once. The positive signs of both interaction terms thus confirm our theoretical expectations that the lock-in effect is less negative and that the post-treatment effect is larger in a downturn.

Third, we estimate the timing-of-events model and take into account time-invariant unobserved heterogeneity. The results after adding six mass points appear in Model 3, Table 2. In contrast to Model 2, the negative in-treatment effect in Model 3 decreases considerably, by 9 percentage points. If the unemployment rate increases one percentage point above the mean, the in-treatment effect increases by about 6 percentage points (i.e., becomes less negative), the post-treatment effect decreases by 7 percentage points, and the interaction term with the unemployment rate increases slightly. After we control for time-invariant unobserved characteristics, the considerable change in the in- and post-treatment coefficients makes clear that controlling for selection is crucial when investigating the stepping-stone effect of agency employment.

Fourth, Model 4 presents the results when we add the equation for the treatment duration. As we argue in Section 3.1, by adding the treatment duration equation to the timing-of-events model, we also control for selection from agency work back into open unemployment, which might be important, as selection could vary over the business cycle. In the treatment equation, to take into account the type of agency jobs that might vary according to the state of the economy, we also control for the occupations and the log of the daily wage. The treatment effects and their interactions with the unemployment rate do not react strongly to the inclusion of the treatment duration equation. Consequently, the endogeneity of the treatment duration is not very important, presumably because it is often exogenously determined by the client firm.

The negative in-treatment effect points to the presence of a lock-in effect. Taking an agency job during an unemployment period lowers the transition rate out of unemployment by roughly 26%, i.e., a fairly strong lock-in effect. This result is in line with the findings of Kvasnicka (2009), who investigated the stepping-stone effect of agency work for Germany based on a matching approach for an inflow sample for 1994-1996. However, our findings contradict Jahn and Rosholm's (2014) results, which show a large positive in-treatment effect in Denmark using a similar methodological framework.

The negative in-treatment effect in Germany suggests that, in contrast to Denmark, German client firms use agency work to buffer their workforce. Indeed, given that German firms rarely appear to use agency work as a screening device, taking an agency job reduces the transition rate to a regular job. A comparison of employment protection legislation in the two countries supports this explanation. While dismissing workers in Germany typically involves long-lasting legal procedures, redundant workers in Denmark (especially those employed for short periods) can be laid off with barely any costs.

Consequently, German firms have a much higher incentive to adjust their workforce over the business cycle by hiring agency workers, who can easily be dismissed when product demand declines. Moreover, the large lock-in effect might also be a consequence of the comparably long median duration of agency jobs in Germany, which is about three months. In contrast, agency jobs in Denmark last only about six weeks (Jahn and Rosholm, 2014).

For the counter-cyclical lock-in effect, our results are in line with the findings of Lechner and Wunsch (2009), who investigate the effectiveness of training programs over the business cycle. They also report that the lock-in effect is largest when unemployment is high. Our finding of a more negative lock-in effect during an upturn might be attributable to lower job search efforts during agency work. As a result, agency workers receive job offers less regularly—thus lowering their transition rate to regular jobs—than unemployed people seeking regular jobs from open unemployment. In contrast, in a downturn, taking an agency job during unemployment might harm the unemployed less, because job openings are scarce.

Having worked for an agency earlier at least once in the same unemployment period leads to a large positive post-treatment effect. The transition rate to regular employment increases by about 35%. As with the in-treatment effect, we find a cyclical pattern. The post-treatment effect is larger in a downturn. The positive post-treatment effect suggests that agency workers might be able either to accumulate human capital or to gain job-search networks while employed at the agency. If the unemployment rate increases by 1 percentage point, the post-treatment effect increases by 3%. Thus the cyclicality of the post-treatment effect is less pronounced than that of the in-treatment effect. That the post-treatment effect increases in a downturn might be attributable to the expansion of search networks during an agency job—networks that are potentially more important when jobs are scarce. Indeed, in a different German context, Glitz (2017) has recently shown that coworker networks play an important role in finding a new job.

In a next step we use the data to construct a quarterly time series of the in- and post-treatment effects by combining quarterly information on the centered unemployment rate, the treatment effects, and the interaction terms between the two. Table 3 summarizes our estimates for 1985-2012 and shows that the aggregate unemployment rate varies considerably, from 5.8 to 11.8%, during our observation period.

[Table 3 about here]

In Table 3 treatment effects also vary markedly over our observation period, with estimates for the in-treatment effect ranging from -43% to -5%, and thus remaining negative. The post-treatment effect ranges over the business cycle, between 26% and 46%, and is always positive. A plot of the time series of the treatment effects and the centered unemployment rate in Figure 3 illustrates this substantial cyclicality.

[Figure 3 about here]

5.3 Cyclicality of the treatment effects and the level of unemployment

Thus far, under the assumption that the impact of the unemployment rate on the treatment effects is linear, we have found evidence that both the in- and post-treatment effects are cyclical. However, if unemployment is already high, the effect of the unemployment rate on the treatment effects might be less pronounced.

To test this possibility, we rerun the analysis, adding dummy variables for the unemployment rate and their interaction with the treatment effects as covariates to the model.

[Table 4 about here]

As Table 4 makes clear when presenting the main results from the modified model, the coefficients of the interaction of the unemployment rate and the in-treatment effect are always statistically significant. Indeed, if unemployment is low, the unemployment rate has the most adverse impact on the in-treatment effect. This negative impact again points to the irrelevance of the screening hypothesis and confirms the importance of the lock-in effect and buffer function hypotheses. While the reduction of the in-treatment effect in absolute terms is moderate when the unemployment rate lies between 7% and 10%, once the unemployment rate reaches levels over 10%, the in-treatment effect becomes only slightly negative.

The post-treatment effect remains constant at low unemployment rates, staying close to 30%. At unemployment rates above 9%, the already high and positive post-treatment effect becomes even more pronounced. This result supports our expectation that either network effects or the acquisition of human capital plays a role in the transition to a regular job.

Finally, we investigated the in- and post-treatment effects by subgroups.[10] Non-German citizens have a significantly higher post-treatment effect than German citizens; unemployed people with university degrees have a significantly lower negative in-treatment effect; and medium-skilled unemployed workers have a significantly higher negative in-treatment effect than low-skilled unemployed workers. The post-treatment effect for recipients of unemployment assistance is positive but smaller than that for the reference group receiving unemployment benefits. Nonetheless, for all groups, we find no significant differences in the cyclicality of the treatment effect, relative to the overall pattern.

5.4 Expected remaining unemployment duration

To obtain an impression of the economic relevance of the treatment effect, in a post-estimation step we calculate and compare the expected remaining unemployment durations for unemployed people both with and without treatment. To do so, we follow the approach outlined in Section 3.1. For different combinations of t_p and t_d, we calculate the effect of the treatment for all treated individuals in the sample and then take sample averages. We do this calculation for low unemployment rates (5-7%), median unemployment rates (8-9%) and high unemployment rates (>10%). To interpret the results more easily, we display the treatment effects in days in absolute terms.

[Figure 4 about here]

In Figure 4, Panel A, the treatment duration varies in intervals of 15 days for the median time until entry into the first agency job (111 days). In a recession with unemployment rates above 10%, the treatment effect on the expected remaining unemployment duration is largest. Taking an agency job

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10 Results are available from the authors upon request.

of two weeks during unemployment reduces the expected remaining unemployment duration for the treatment group by 154 days. If the duration of the agency job increases, the gain from treatment is less pronounced. However, even if an agency job lasts about one year, the effect remains positive, that is, the expected remaining unemployment duration for the treated is about 58 days shorter.

Once business conditions improve, the gains from having received treatment become less pronounced. At unemployment rates between 8% and 9%, the gains are 109 days if the agency job lasts 15 days. For a treatment duration of one year, this gain turns into an approximately three-day-longer unemployment duration. In tight labor markets, the treatment harms workers with treatment durations lasting longer than 240 days. The negative correlation between treatment effect and treatment duration again confirms our argument that reduced search intensity is likely the reason for the negative in-treatment effect.

Panel B in Figure 4 shows whether the treatment effect varies with the time elapsing before entering the first agency job, evaluated at constant treatment durations of 91 days (median). Panel B shows that workers at the median treatment duration always benefit from having received treatment. The expected remaining unemployment duration decreases most when unemployment is high. The gain is largest for those who entered treatment after having been unemployed for more than two years. In line with the results in Table 4, we find no differences for unemployment rates between 5.8% and 9%.

Taken together, these results point to the robustness of our main finding that both the in- and post-treatment effects move counter-cyclically. In other words, the treatment effect is more favorable in slack labor markets with high unemployment rates than in tight labor markets, where lock-in effects impede workers' search for regular jobs.

5.5 The quality of the stepping-stone effect over the business cycle

Another concern in the debate on the stepping-stone effect of agency work is the quality of the job found after treatment. Job search theory predicts, for three reasons, that the match quality, and thus the wage of the first regular job, should improve if an unemployed person leaves agency work directly after treatment: First, in contrast to job seekers in the control group, at least some agency workers might have received training from the client firm or agency. The agency's incentive to invest in training lies not only in assigning its staff to more tasks and responsibilities but also in providing an incentive for client firms to rehire the agency worker after he or she completes the temporary job assignment. If the client firm hires the agency worker, agencies typically charge that firm a premium. Thus it is plausible that the treatment group should be able to accumulate more human capital in a given time interval than the control group seeking a regular job while unemployed (Autor, 2001).

Second, if the client firm continues to employ the worker, it is already informed about his or her productivity, thereby resulting in a higher match quality. Moreover, having an agency job may give the worker access to an additional network (e.g., via coworkers) that they could use in the job search. Third, accepting an agency job during an unemployment period might prolong eligibility for unemployment benefits. Consequently, the treatment group might have higher reservation wages than workers at risk of receiving only unemployment assistance, which is considerably lower than unemployment benefits. Thus we expect a higher post-wage for the treatment group exiting agency work directly to a regular job. Moreover, in contrast to the transition rate to regular employment, we expect that the post-wages should react pro-cyclically, given that the bargaining position of the worker is stronger during upturns.

For post-wages for an agency worker falling back at least once from treatment into unemployment, the theoretical prediction is not as clear: First, workers might have gained some human capital when assigned to a client firm. However, given the depreciation of human capital, the human capital effect should be much lower than for those who left directly after treatment. Second, as workers have likely never before worked for the new employer, reductions of information asymmetries for future employers do not play a role in job-finding. Finally, falling back into open unemployment might negatively stigmatize the worker. We therefore expect a slightly positive effect, if any, on post-wages, an effect considerably below that after exiting to a regular job immediately after treatment. Moreover, given that—from the perspective of prospective employers—workers falling back into open unemployment are as equally productive as the control group, our expectation also holds for the cyclicality of post-wages.

[Table 5 about here]

Table 5 presents the results dividing the post-wages into in- and post-treatment effects. As we do not expect the effect to be linear, we interact the in- and post-treatment indicators with unemployment rate dummies. The interpretation of the in-treatment effect is the effect on post-wages of going from an agency job directly to a regular job. To investigate the long-run effect on the match quality, we restricted our sample to the inflow to unemployment during 1985-2010, which allows us to follow the worker up to 18 months.[11] The results show that the match quality, and thus the post-wages of workers leaving while in treatment, are considerably higher than for workers searching for a job from open unemployment. The wage gains for agency workers exiting directly to a regular job is about 18 log points directly after transitioning to a regular job. Wage gains decrease only moderately over time. After 18 months they are still about 13 log points. The lower post-earnings after 18 months might be explained by some workers becoming unemployed again.

One possible explanation for the higher post-earnings is that workers are more often employed full-time. Although our data set does not provide information about the exact number of hours that the worker is employed, our data provides information on whether the worker holds a full-time or part-time job. Table A2 in the Appendix shows that the percentage of workers who found a full-time job always lies well above 90%, a plausible finding given that we are investigating only male job seekers. To further investigate whether the number of hours might play a role, we ran a competing risk model investigating whether the treatment effects vary by transition to full-time and part-time employment. The pattern is qualitatively the same.[12]

As for the cyclicality of the post-wages after leaving unemployment for a regular job, we find that post-wages are 5 log points lower at unemployment rates above 10% than the post-wages in an upturn.

[11] The treatment effects for the slightly shorter observation period are almost identical. Results are available from the authors upon request.

[12] Results are available from the authors upon request.

Nonetheless, the gain remains considerable, at about 13 log points. One possible explanation for the pro-cyclicality of the post-wages is that the bargaining power of the worker deteriorates as soon as the economy enters a downturn.[13] Table 5 also shows that the pro-cyclical pattern of post-wages disappears with the time that elapses after leaving unemployment.

Finally, in line with search theory, we find that post-wages are not affected for workers falling back at least once into open unemployment, nor do we find any cyclical effect. As discussed in Section 4, we are not able to observe whether an agency worker is hired by a former client, thereby causing the higher post-wages for the in-treatment group. However, we observe the occupation of the worker while in treatment and his first regular job after leaving unemployment. To check whether a reduction in information asymmetries is a plausible explanation for the higher post-wages of workers exiting directly from the agency job to a regular job, we run a linear probability model using the sample of all treated job seekers. The dependent variable is a binary indicator taking the value one if the occupation of the agency job equals the occupation in the first regular job, and zero otherwise. As explanatory variables we used the in-treatment indicator (which is one if the worker is employed at an agency before leaving to a regular job) and zero otherwise, and the controls used in our preferred specification. The regression shows that the probability of finding a regular job in the same occupation as the last agency job is significantly higher (coef. 0.141, se 0.010) than for the treatment group exiting to a regular job from unemployment. This result supports the expectation that these workers indeed found a job at a former client firm, which is already aware of the worker's productivity and thus pays a higher wage.

6. Conclusion

The results of the empirical literature investigating whether temporary agency work is a bridge into regular employment are mixed. While some studies find that agency work paves the way to better jobs, others show that agency work is not a springboard into regular employment. However, as the

[13] Indeed, that entry wages are lower in a downturn has been recently documented for Germany by Stüber (2017).

demand for agency work is strongly cyclical, we expect the springboard effect to be cyclical as well. Such a finding could explain the lack of consensus thus far in the literature on the stepping-stone effect.

We find that the stepping-stone effect is indeed strongly counter-cyclical. The lock-in effect (in-treatment) is strongest during economic upturns, when many outside offers are available. While employed at an agency, workers search less for regular jobs and thus receive fewer job offers. In a downturn, with fewer jobs available, reduced job search might not harm workers. Moreover, taking an agency job during "good" times might negatively stigmatize a job seeker, whereas taking such a job during "bad" times might signal high productivity.

We also find a large positive post-treatment effect, which moves counter-cyclically as well. Having had at least some employment experience during unemployment might benefit workers in periods with slack labor demands. Workers in agency jobs apparently build networks of coworkers at the client firm. These networks might be particularly useful in economic downturns, when the unemployed have more difficulties finding a job.

As to the matching quality after workers leaving unemployment, those who left unemployment directly from an agency job (in-treatment) have a considerable earnings advantage over those who found a job after open unemployment. Reductions of information asymmetries and firm- or industry-specific human capital effects are potential explanations for these results. Post-earnings after treatment show a pro-cyclical pattern, indicating better job matches in times of low unemployment.

During the past two decades, policy makers throughout Europe have been promoting agency work by lowering restrictions on its use. However, given the short-term nature of agency work and the poor working conditions in this sector, policy makers have become increasingly reluctant to further support this form of employment if it does not return the unemployed to regular jobs. Our study contributes to this discussion by showing that promoting agency work for unemployed people in tight labor markets—when demand for agency workers is high—will not pave the way to better jobs. In contrast, during downturns—when demand is low—encouraging the unemployed to accept such jobs may open up opportunities that will lead to stable employment in the future.

References

Abbring, J.; van den Berg, G. (2003a), "The Nonparametric Identification of Treatment Effects in Duration Models," *Econometrica* 71 (5), 1491–1517.

Abbring, J.; van den Berg, G. (2003b), "The identifiability of the mixed proportional hazards competing risks model," *Journal of the Royal Statistical Society* Series B 65 (3), 701–710.

Abraham, K. (1990), "Restructuring the Employment Relationship: The Growth of Market-Mediated Work Arrangements." In Katharine G. Abraham and Robert B. McKersie, eds., *New developments in the labour market: Toward a new institutional Paradigm*, Cambridge: MA, MIT Press, pp. 85–119.

Amuedo-Dorantes, C.; Malo, M.; Muñoz-Bullón, F. (2008), "The Role of Temporary Help Agency work on Temp-to-Perm Transitions," *Journal of Labor Research* 29 (2), 138–161.

Andersson, F.; Holzer, H.; Lane, J. (2009), "Temporary Help Agencies and the Advancement Prospects of Low Earners." In David Autor, ed., *Studies in Labor Market Intermediation*, Chicago: The University of Chicago Press, 373–398.

Antoni, M.; Jahn, E. (2009), "Do Changes in Regulation Affect Employment Duration in Temporary Work Agencies?" *Industrial and Labor Relations Review* 62 (2), 226–251.

Arni, P.; Lalive, R.; van Ours, J. (2013), "How Effective Are Unemployment Benefit Sanctions? Looking Beyond Unemployment Exit", *Journal of Applied Econometrics* 28, 1153–1178.

Autor, D. (2001), "Why Do Temporary Help Firms Provide Free General Skills Training?". *The Quarterly Journal of Economics* 116 (4): 1409–1448.

Autor, D.; Houseman, S. (2010), "Do Temporary-Help Jobs Improve Labor Market Outcomes for Low-Skilled Workers? Evidence from "Work First"," *American Economic Journal: Applied Economics* 2 (3), 96–128.

Bentolila, S., Cahuc, P., Dolado, J.J., and Barbanchon, T.L. (2012), "Two-Tier Labour Markets in the Great Recession: France Versus Spain," *The Economic Journal* 122 (562), F155-F187.

Boeri, T. (2011), "Institutional Reforms and Dualism in European Labor Markets," in (O. Ashenfelter and D. Card, eds.), *Handbook of Labor Economics*, Volume 4B, pp. 1173-1236, Amsterdam: Elsevier.B.V.

Boeri, T.; Garibaldi, P. (2009), "Beyond Eurosclerosis," *Economic Policy* 24 (59), 409–461.

Booth, A.; Francesconi, M.; Frank, J. (2002), "Temporary Jobs: Stepping Stones or Dead Ends?" *The Economic Journal*, 112 (480), F189–F213.

Burda, M.; Kvasnicka, M. (2006), "Temporary Help Work in Germany: Trends and Perspectives " Perspektiven der Wirtschaftspolitik 7, 195-225.

Brinch, C. (2007), "Nonparametric Identification of the Mixed Hazards Model with Time-Varying Covariates," Econometric Theory 23 (2), 349–354.

Card, D., Kluve, J. and Weber, A. (2015), What Works? A Meta Analysis of Recent Active Labor Market Program Evaluations, IZA Discussion Paper No. 9236, Bonn.

CIETT (2002), Rationale for Agency Work – European labour suppliers and demanders' motives to engage in agency work, Rotterdam.

CIETT (2017), Annual Economic Report, http://www.wecglobal.org.

De Graaf-Zijl, M. and Berkhout, E.E. (2007), "Temporary agency work and the business cycle", *International Journal of Manpower* 28 (7), 539-556.

De Graaf-Zijl, M.; van den Berg, G.; Hemya, A. (2011), "Stepping Stones for the Unemployed: The Effect of Temporary Jobs on the Duration until (Regular) Work," *Journal of Population Economics* 24 (1), 107–139.

Destatis (2017), Fixed-term employment, Wiesbaden: Federal Office of Statistics.

Dlugosz, S.; Stephan, G.; Wilke, R. (2014), "Fixing the leak: Unemployment incidence before and after the 2006 reform of unemployment benefits in Germany." *German Economic Review* 15 (3), 329–352.

Federal Employment Agency (2012), Der Arbeitsmarkt in Deutschland, Zeitarbeit – Aktuelle Entwicklungen, Nuremberg.

Federal Employment Agency (2016), Der Arbeitsmarkt in Deutschland, Zeitarbeit – Aktuelle Entwicklungen, Nuremberg.

Forslund, A., Fredriksson, P., and Vikstrom, J. (2011). „What Active Labor Market Policy Works In a Recession?" *Nordic Economic Policy Review* 1, 171-207.

Gaure, S.; Røed, K.; Zhang, T. (2007), “Time and Causality: A Monte Carlo assessment of the Timing-Of-Events Approach,” *Journal of Econometrics* 141(2), 1159–1195.

Ganzer, A.; Schmucker, A.; von Berge, P.;Wurdach, A. (2017). Sample of the Integrated Labour Market Biographies – regional file 1975-2014 (SIAB-R 7514), IAB Datenreport Series, 01/2017 Nuremberg.

Givord, P.; Wilner, L. (2015), “When Does the Stepping-Stone Work? Fixed-Term Contracts Versus Temporary Agency Work in Changing Economic Conditions,” *Journal of Applied Econometrics* 30 (5), 787-805.

Glitz, A. (2017), “Coworker Networks in the Labour Market”, *Labour Economics* 44 (1), 218-230.

Heckman, J.; Singer, B. (1984), “A Method for Minimizing the Impact of Distributional Assumptions in Econometric Models for Duration Data,” *Econometrica*, 52 (2), 271–320.

Hveem, J. (2013), “Are temporary work agencies stepping-stones into regular employment?” *IZA Journal of Migration* 2013, 2:21.

Heinrich, C.; Mueser, P.; Troske, K. (2005), “Welfare to Temporary Work: Implications for Labor Market Outcomes,” *The Review of Economics and Statistics* 87 (1), 154–173.

______________ (2009), “The Role of Temporary Help Employment in Low-wage Worker Advancement.” in David Autor, ed., *Studies of Labor Market Intermediation*, Chicago: The University of Chicago Press, 399–436.

Hirsch, B.; Mueller, S. (2012), “The Productivity Effect of Temporary Agency Work: Evidence from German Panel Data,” *The Economic Journal 122 (562)*, F216-F235.

Houseman, S.; Kalleberg, A.; Erickcek, G. (2003), “The role of temporary agency work in tight labor markets,” *Industrial and Labor Relations Review* 57 (1), 105–127.

IAB (2012), IAB-Aktuell: „Befristete Neueinstellungen,“ Nuremberg: Institute for Employment Research (IAB). Online available: http://doku.iab.de/aktuell/2012/befristete_beschaeftigung_uebernahme.pdf

Ichino, A.; Mealli, F; Nannicini, T. (2008), “From temporary help jobs to permanent employment: what can we learn from matching estimators and their sensitivity?” *Journal of Applied Econometrics*, 23 (3), 305–327.

Jahn, E.; Rosholm, M. (2013), ”Is Temporary Agency work a Stepping Stone for Immigrants?” *Economics Letters*, 118 (1), 225-228.

Jahn, E.; Rosholm, M. (2014), ”Looking Beyond the Bridge: How Temporary Agency work Affects Labor Market Outcomes,” *European Economic Review*, 65, 108-125.

Jahn, E.; Schnabel, C.; Riphahn, R. (2012), “Feature: Flexible Forms of Employment: Boon and Bane” *The Economic Journal*, Vol. 122 (562), 2012, F115–F124.

Jahn, E.J. (2010), “Reassessing the pay gap for temps in Germany”, *Journal of Economics and Statistics*, 230 (2): 208-233.

Jahn, E.J. and Bentzen, J. (2012), “What Drives the Demand for Temporary Agency Workers,” Labour 26 (3), 341-355.

Kluve, J. (2010), “The Effectiveness of European Active Labor Market Programs”, *Labour Economics* 17, 904-918.

Kvasnicka, M. (2009), “Does Temporary Agency Work Provide a Stepping Stone to Regular Employment?” in David Autor, ed., *Studies of Labor Market Intermediation*, Chicago: The University of Chicago Press, 335–372.

Kyyrä T.; Parrotta, P.; Rosholm, M. (2013), “The effect of receiving supplementary UI benefits on unemployment duration,” *Labour Economics,* 21, 122-133.

Lane, J.; Mikelson, K.; Sharkey, P.; Wissoker, D. (2003), “Pathways to Work for Low-Income Workers: The Effect of Work in the Temporary Help Industry,” *Journal of Policy Analysis and Management* 22 (4), 581–598.

Lechner, M.; Wunsch, C. (2009), “Are Training Programs More Effective When Unemployment Is High?” Journal of Labor Economics 27 (4), 653–691.

Malo, M.; Muñoz-Bullón, F. (2008), “Temporary help agencies and participation histories in the labour market: a sequence-oriented approach,” *Estadística Española* 50 (167), 25–65.

Manski, C.; Lerman S. (1977), “The Estimation of Choice Probabilities from Choice Based Samples,” *Econometrica* 45 (8), 1977–1988.

Mitlacher, L.W. (2007), “The Role of Temporary Agency Work in Different Industrial Relations Systems – a Comparison between Germany and the USA,” *British Journal of Industrial Relations* 45 (3), 581-606.

Neugart, M. and Storrie, D. (2006), “The emergence of temporary work agencies,” Oxford Economic Papers, 58 (1): 137-156.

OECD (2013), *Employment Outlook 2013*. Paris: OECD Publishing.

Schmucker, A.; Seth, S.; Ludsteck, J.; Eberle, J.; Ganzer, A. (2016), Establishment History Panel 1975-2014, IAB Datenreport Series, 03/2016 Nuremberg.

Segal, L.; Sullivan, D. (1997), "The Growth of Temporary Services Work," *Journal of Economic Perspectives* 11 (2), 117–136.

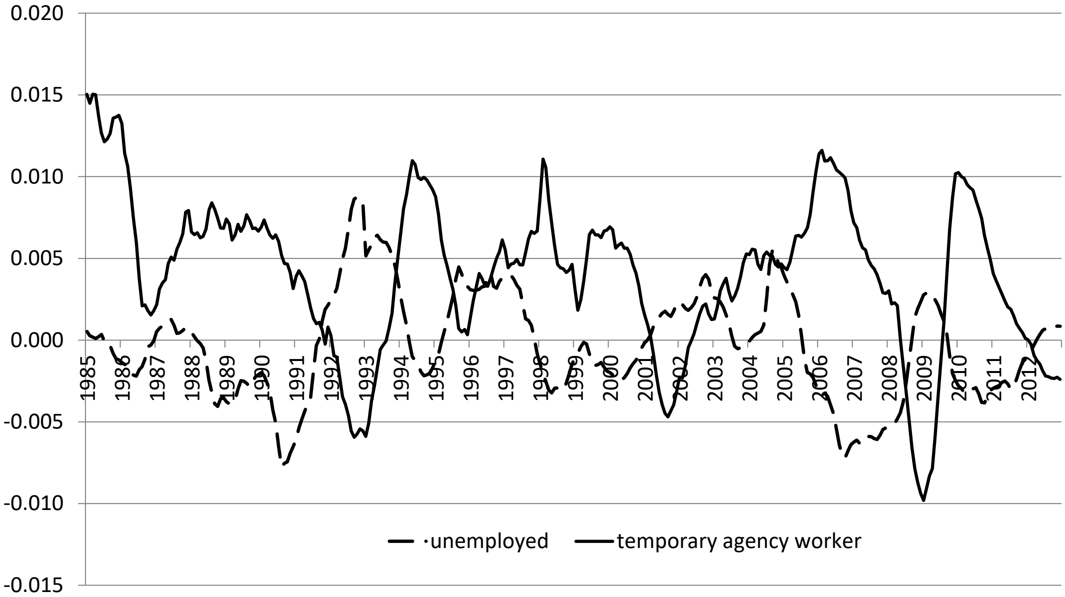
Stüber, H. (2017), "The Real Wage Cyclicality of Newly Hired and In-cumbent Workers in Germany", *The Economic Journal*, 127(600), 522-546.

Van den Berg, G.; Vikström, J. (2013), "Monitoring Job Offer Decisions, Punishments, Exit to Work and Job Quality," *The Scandinavian Journal of Economics* 116 (2), 284-334.

Venn, D. (2009), "Legislation, collective bargaining and enforcement: Updating the OECD employment protection indicators," OECD Social, Employment and Migration Working Papers No. 89, OECD.

Tables and Figures

Figure 1: Cyclicality of agency employment



Notes: Labor Placement Statistics and Unemployment Statsistics, Federal Employment Service: The level values of the variables are smoothed by an 12-period centered moving average; first differences of log values are displayed at the vertcal axis.

Figure 2: Smoothed Kaplan Meier hazard rates out of unemployment to employment and agency jobs

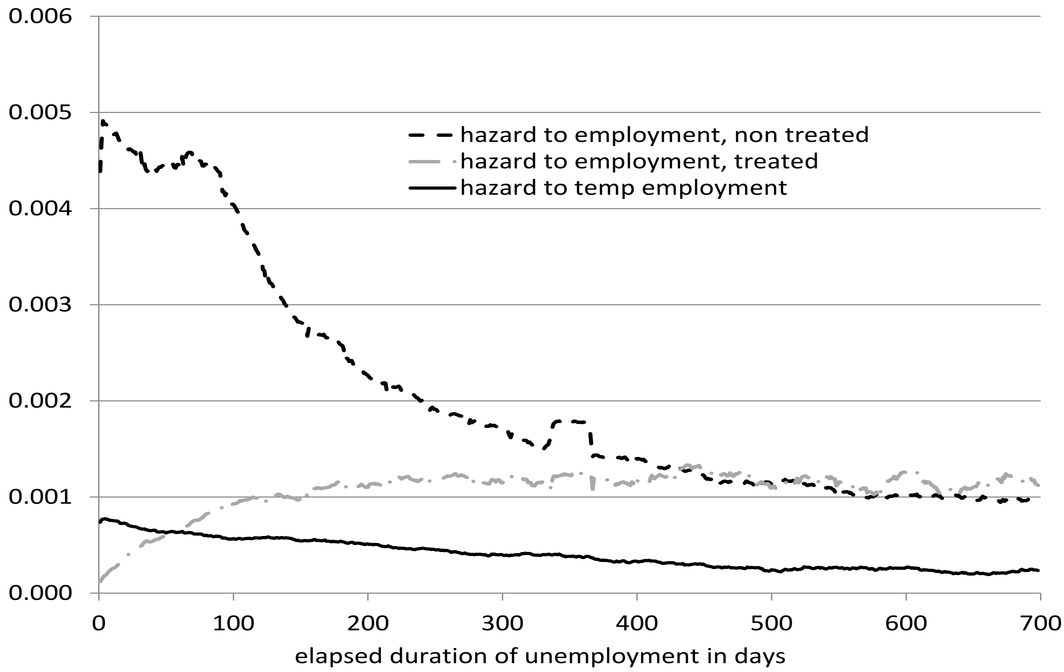


Figure 3: Cyclicality of the treatment effect

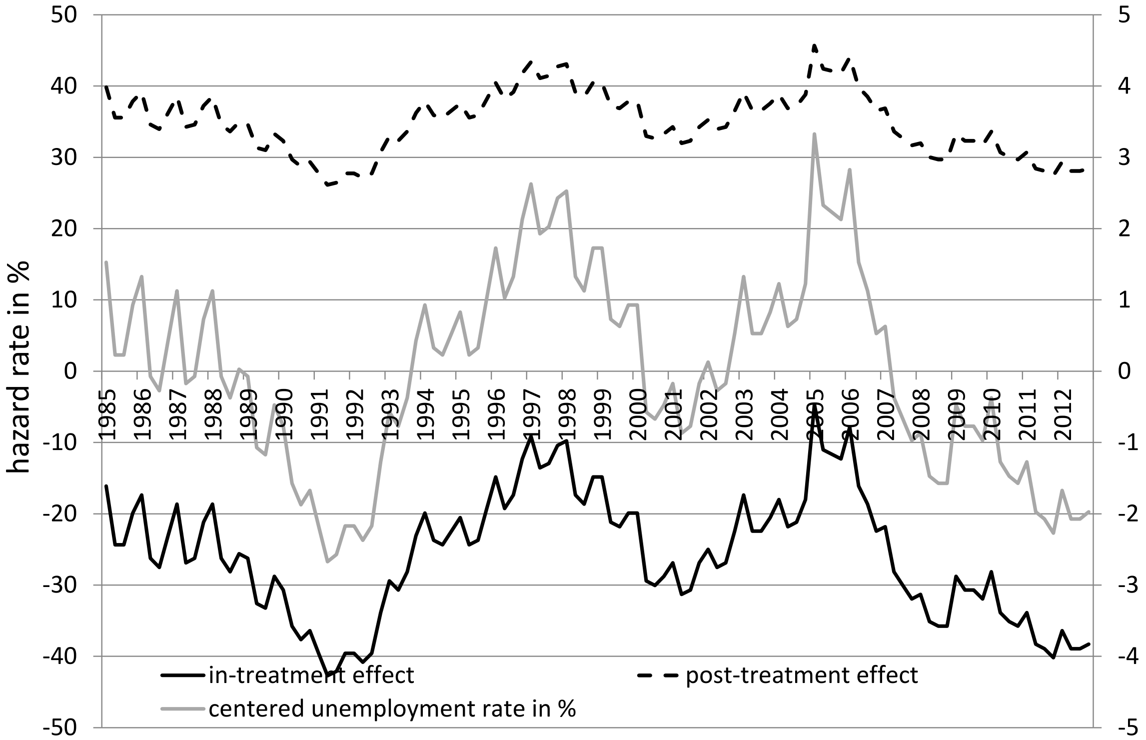


Figure 4: Average treatment effect on the treated in days

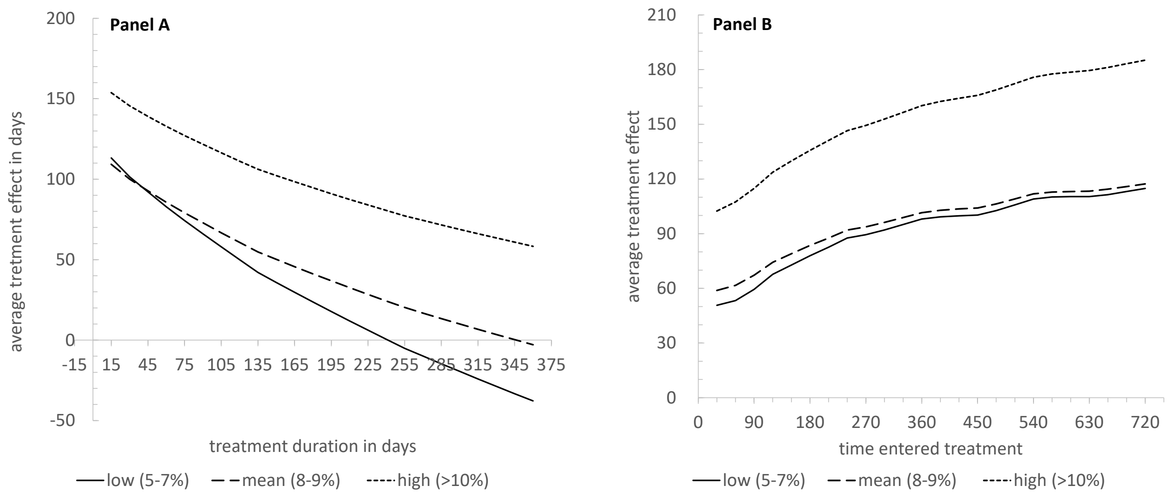


Table 1: Selected sample statistics

	Control				Treatment			
	Downturn		Upturn		Downturn		Upturn	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Average age	34.047	9.250	34.439	9.565	32.498	8.609	33.399	9.286
Married	0.421	0.494	0.386	0.487	0.358	0.479	0.309	0.462
Child in household	0.371	0.483	0.347	0.476	0.335	0.472	0.307	0.461
Foreign	0.236	0.425	0.224	0.417	0.308	0.462	0.285	0.452
Low qualified	0.189	0.391	0.190	0.392	0.216	0.411	0.218	0.413
Medium qualified	0.767	0.423	0.764	0.425	0.757	0.429	0.752	0.432
High qualified	0.044	0.205	0.046	0.210	0.028	0.164	0.030	0.171
Unemployment assistance	0.217	0.412	0.235	0.424	0.293	0.455	0.318	0.466
Previous regular employed	0.639	0.480	0.648	0.478	0.548	0.498	0.541	0.498
Previous temp	0.023	0.150	0.039	0.194	0.093	0.291	0.149	0.356
Previous apprentice	0.006	0.078	0.005	0.073	0.007	0.084	0.009	0.095
Previously out of labor force	0.332	0.471	0.308	0.462	0.352	0.478	0.301	0.459
Spells ending in regular employment (%)	61.767		61.570		51.690		47.514	
Median duration of agency spell (months)					2.727		2.990	
Median time until first accepting an agency job (months)					4.699		3.055	
Mean number of agency spells					1.226		1.228	
No. of unemployment spells	124,842		110,964		12,461		15,973	
No. of persons [a)]		58,222				20,751		
No. of unemployment spells per person [a)]		2.885				4.640		
Share right-censored spells		2.801				9.099		

Notes: IEB V11.0, 1980-2012. [a)] The numbers of persons and unemployment spells per person refer to persons who have been treated at least once during the observation period. All events refer to the unemployment rate centered around its mean at the beginning of the unemployment spell. Further control variables are the fraction of time spent in regular and agency work during the past five years, the number of agency jobs during the past five years, dummies for the number of regular jobs (2-3, 4-6, 7 or more) during the past five years, the time-varying centered quarterly unemployment rate for Western Germany, and year and quarter dummies.

Table 2: In-treatment and post-treatment effects

	Model 1			Model 2			Model 3			Model 4		
In-treatment	-0.164	**	(0.012)	-0.154	**	(0.012)	-0.247	**	(0.013)	-0.258	**	(0.014)
In-treatment x unemployment rate	0.011		(0.008)	0.064	**	(0.012)	0.061	**	(0.009)	0.063	**	(0.009)
Post-treatment	0.291	**	(0.014)	0.387	**	(0.014)	0.316	**	(0.014)	0.348	**	(0.015)
Post-treatment x unemployment rate	-0.016		(0.009)	0.024	**	(0.009)	0.033	**	(0.009)	0.033	**	(0.009)
Control variables	N			Y			Y			Y		
Unobserved heterogeneity	N			N			Y			Y		
Treatment duration	N			N			N			Y		

Notes: IEB V11.0, 1980-2012. Standard errors in parentheses. **/* denotes statistical significance at the 1/5 % level. The distribution of the unobservables is approximated non-parametrically by a bivariate discrete distribution with six mass points. The unemployment rate for West Germany is centered around its sample mean. In addition, Models 2 to 4 include three age dummies, two education dummies, a dummy for being married and having children, a dummy for having no German citizenship, the fraction of time spent in regular and agency work during the past five years, the number of agency jobs during the past five years, dummies for the number of regular jobs (2-3, 4-6, 7 or more) during the past five years, dummy variables indicating whether the workers was previously an agency worker, an apprentice, or out of the labor force, year and quarter dummies, and parameters for the distribution of the unobserved characteristics. In Model 4, the endogenous treatment equation in addition controls for the type of occupation during the agency job (5 dummies) and the log of the daily wage during the agency job.

Table 3: Unemployment rate and treatment effects

	Mean	S.D.	Min	Max
Aggregate unemployment rate	8.5	1.4	5.8	11.8
In-treatment effect	-25.8	8.7	-42.7	-4.7
Post-treatment effect	34.8	4.5	26.1	45.7
Observations (quarters)		112		

Notes: IEB V11.0, 1980-2012. The in-treatment and post-treatment effects are estimated using the results from Table 3, Model 4.

Table 4: Treatment effects and the level of unemployment

In-treatment (ref: 5.8-7%)	-0.409	**	(0.024)
In-treatment x unemployment rate 7-8%	0.133	**	(0.033)
In-treatment x unemployment rate 8-9%	0.164	**	(0.038)
In-treatment x unemployment rate 9-10%	0.170	**	(0.034)
In-treatment x unemployment rate >10 %	0.310	**	(0.041)
Post-treatment (ref: 5.8-7%)	0.295	**	(0.027)
Post-treatment x unemployment rate 7-8%	0.037		(0.036)
Post-treatment x unemployment rate 8-9%	-0.014		(0.046)
Post-treatment x unemployment rate 9-10%	0.117	**	(0.038)
Post-treatment x unemployment rate >10 %	0.090	*	(0.046)

Notes: IEB V11.0, 1980-2012. Standard errors in parentheses. **/* denotes statistical significance at the 1/5 % level. The distribution of the unobservables is approximated non-parametrically by a bivariate discrete distribution with six mass points. The unemployment rate for West Germany is centered around its sample mean. The following controls are included in all estimations: three age dummies, two education dummies, a dummy for being married and having children, a dummy for having no German citizenship, the fraction of time spent in regular and agency work during the past five years, the number of agency jobs during the past five years, dummies for the number of regular jobs (2-3, 4-6, 7 or more) during the past five years, dummy variables indicating whether the workers was previously an agency worker, an apprentice, or out of the labor force, year and quarter dummies, and parameters for the distribution of the unobserved characteristics. The endogenous treatment equation in addition controls for the type of occupation during the agency job (5 dummies) and the log of the daily wage during the agency job.

Table 5: Cyclicality of post-wages, after …

	Exit	6 months	1 year	18 months
In-treatment (ref: 5.8-7%)	0.180 **	0.162 **	0.145 **	0.133 **
	(0.013)	(0.010)	0.0113	(0.010)
In-treatment x unemployment rate 7-8%	-0.012	-0.013	0.001	-0.003
	(0.015)	(0.012)	(0.013)	(0.012)
In-treatment x unemployment rate 8-9%	-0.044 **	-0.033 *	-0.027	-0.022
	(0.016)	(0.013)	(0.015)	(0.013)
In-treatment x unemployment rate 9-10%	-0.065 **	-0.038 **	-0.027 *	-0.011
	(0.015)	(0.012)	(0.014)	(0.012)
In-treatment x unemployment rate >10 %	-0.050 **	-0.046 **	-0.020	-0.012
	(0.017)	(0.013)	(0.015)	(0.013)
Post-treatment (ref: 5.8-7%)	-0.012	-0.005	-0.010	-0.015
	(0.012)	(0.012)	(0.014)	(0.013)
Post-treatment x unemployment rate 7-8%	-0.020	-0.034	-0.029	-0.004
	(0.015)	(0.014)	(0.016)	(0.015)
Post-treatment x unemployment rate 8-9%	-0.016	0.011	0.015	0.031
	(0.017)	(0.017)	(0.019)	(0.018)
Post-treatment x unemployment rate 9-10%	0.000	-0.020	-0.014	0.000
	(0.015)	(0.015)	(0.017)	(0.016)
Post-treatment x unemployment rate >10 %	-0.006	-0.008	-0.025	-0.008
	(0.017)	(0.016)	(0.018)	(0.017)

Notes: IEB V11.0, 1980-2012. Standard errors in parentheses. **/* denotes statistical significance at the 1/5 % level. In order to investigate the long-term outcomes, we have restricted the sample to the inflow for the years 1985-2010. The distribution of the unobservables is approximated non-parametrically by a bivariate discrete distribution with six mass points. The following controls are included in all estimations: three age dummies, two education dummies, a dummy for being married and having children, a dummy for having no German citizenship, the fraction of time spent in regular and agency work during the past five years, the number of agency jobs during the past five years, dummies for the number of regular jobs (2-3,4-6, 7 or more) during the past five years, dummy variables indicating whether the workers was previously an agency worker, an apprentice, or out of the labor force, year and quarter dummies, and parameters for the distribution of the unobserved characteristics.

Appendix

Table A1: Full estimation results

	Selection equation		Treatment equation		Hazard equation	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
0-28	-9.473	(0.362)	0.195	(0.562)	-3.245	(0.026)
28-56	-9.495	(0.362)	-0.179	(0.562)	-3.109	(0.026)
56-84	-9.548	(0.362)	-0.500	(0.562)	-3.082	(0.026)
84-112	-9.631	(0.362)	-0.743	(0.563)	-3.035	(0.027)
112-140	-9.683	(0.362)	-0.878	(0.563)	-3.167	(0.028)
140-175	-9.667	(0.362)	-0.897	(0.563)	-3.373	(0.028)
175-245	-9.719	(0.362)	-1.104	(0.563)	-3.451	(0.028)
245-364	-9.847	(0.362)	-1.124	(0.562)	-3.675	(0.028)
364-546	-10.091	(0.363)			-3.802	(0.028)
546-728	-10.349	(0.363)			-3.977	(0.030)
728-1092	-10.575	(0.364)			-4.089	(0.030)
1092-	-11.186	(0.364)			-4.727	(0.032)
Age 25-34	-0.452	(0.018)	0.051	(0.023)	-0.246	(0.008)
Age 35-44	-0.624	(0.021)	0.180	(0.026)	-0.438	(0.010)
Age 45-55	-0.955	(0.024)	0.251	(0.030)	-0.748	(0.011)
Married	0.030	(0.017)	-0.041	(0.021)	0.136	(0.007)
Child	-0.130	(0.016)	0.094	(0.020)	-0.009	(0.007)
Foreign	0.127	(0.015)	0.035	(0.019)	-0.112	(0.008)
Medium skilled	0.136	(0.017)	-0.037	(0.020)	0.214	(0.008)
High skilled	-0.332	(0.039)	0.041	(0.055)	0.065	(0.017)
Prev. agency employed	0.424	(0.021)	-0.025	(0.026)	-0.199	(0.016)
Prev. apprentice	0.307	(0.069)	-0.033	(0.088)	0.157	(0.034)
Prev. out of the labor force	-0.164	(0.015)	-0.078	(0.019)	-0.410	(0.006)
Fraction regular employed	-0.133	(0.028)	-0.185	(0.036)	0.156	(0.012)
Fraction agency employed	0.847	(0.052)	-0.563	(0.064)	0.168	(0.035)
Agency experience (dummy)	0.066	(0.015)	0.048	(0.019)	0.185	(0.008)
1 regular job	0.052	(0.019)	0.134	(0.024)	0.361	(0.009)
2-4 regular jobs	0.075	(0.032)	0.262	(0.043)	0.567	(0.011)
5+ regular jobs	0.124	(0.004)	0.070	(0.004)	-0.065	(0.004)
UA	-0.202	(0.015)	0.133	(0.019)	-0.173	(0.007)
Unemployment rate	-0.105	(0.019)	0.118	(0.023)	-0.135	(0.008)
Occ. personal services			-0.219	(0.056)		
Occ. commercial services			-0.252	(0.041)		
Occ. IT and natural sciences			-0.087	(0.093)		
Occ. other support services			-0.254	(0.024)		
Occ. Unknown			-0.142	(0.020)		
Daily wage (log)			-1.273	(0.023)		
In-treatment effect					-0.258	(0.014)
Post-treatment effect					0.348	(0.015)
In-treatment *unemployment rate					0.063	(0.009)
Po-treatment * unemployment rate					0.033	(0.009)
Points of support						
ln υ_1	1.292	(0.384)	-0.739	(0.546)	-1.465	0.065
ln υ_2	1.744	(0.350)	-0.598	(0.528)	-2.081	0.020
ln υ_3	0.810	(0.351)	-0.207	(0.528)	-2.741	0.019
ln υ_4	-0.819	(0.489)	1.871	(0.533)	-1.764	0.067
ln υ_5	-0.972	(0.551)	-0.999	(0.701)	-1.111	0.024
Prbability masses (log transform)						
λ_1					-2.540	(0.173)
λ_2					0.049	(0.250)
λ_3					2.073	(0.143)
λ_4					2.006	(0.142)
λ_5					-0.972	(0.290)

Source: IEB V11.0, 1980-2012. Standard errors in parenthesis. The distribution of the unobservables is approximated non-parametrically by a bivariate discrete distribution with six mass points. The unemployment rate for West Germany is centered around its sample mean. In addition, the model includes year and quarter dummies.

Table A2: Sample statistics – employment quality

	Control		In-treatment		Post-treatment	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Daily wage (log)						
After exit	4.095	0.405	4.153	0.337	3.941	0.422
After 6 months	3.028	1.882	3.575	1.532	2.768	1.887
After 12 months	2.669	2.027	3.488	1.623	2.664	1.933
After 18 months	2.800	2.001	3.305	1.772	2.547	1.981
Full-time						
After exit	0.927	0.260	0.961	0.193	0.907	0.291
After 6 months	0.958	0.201	0.972	0.166	0.934	0.248
After 12 months	0.959	0.199	0.975	0.158	0.935	0.247
After 18 months	0.962	0.191	0.974	0.160	0.933	0.250
Observations	136.639		6.976		5.125	

Notes: IEB V11.0, 1980-2012. The number of observations in the in-treatment and post-treatment group can overlap, if a jobseeker who received more than one treatment exits after his last treatment.