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Identifying the Substitution Effect of Temporary Agency Employment

Elke J. Jahn
Enzo Weber

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of Labor

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Elke J. Jahn
IAB Nuremberg,
Aarhus University and IZA

Enzo Weber
IAB Nuremberg,
University of Regensburg and OEI

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IZA

P.O. Box 7240
53072 Bonn
Germany

Phone: +49-228-3894-0
Fax: +49-228-3894-180
E-mail: iza@iza.org

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ABSTRACT

Identifying the Substitution Effect of Temporary Agency Employment*

This paper fills a gap in the literature by investigating whether temporary agency employment substitutes regular employment. To take into account the interaction between the two employment forms, we identify a SVAR model with correlated innovations by volatility regimes. We show that a positive shock to temporary agency employment increases overall employment, but also leads to substitution of regular jobs.

JEL Classification: C32, J21, J41

Keywords: temporary agency employment, substitution effect, Germany

Corresponding author:

Elke J. Jahn
Institute for Employment Research (IAB)
Regensburger Strasse 104
90478 Nuremberg
Germany
E-mail: elke.jahn@iab.de

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1 Introduction

During the past two decades most European countries have witnessed an impressive growth of the temporary help service sector. The widespread surge in temporary agency employment (TAE) has been driven by the deregulation of the sector in the 1980s and early 1990s, while provisions for regular contracts (non-temporary agency employment: NTAE) were left essentially unaltered. The aim of these reforms was to increase overall employment by decreasing dismissal costs giving firms incentives to create temporary jobs which might be ultimately transformed into regular jobs. However, the incidence of TAE seems not to be correlated with the strictness of regulation of the sector but is positively correlated with the overall strictness of employment protection legislation (e.g. Boeri 2011). Latter fact has fueled the fear that TAE might substitute NTAE and, consequently, that two-tier labour markets might evolve.

While numerous microeconomic studies have shown that working conditions in the agency sector are poor (e.g. Antoni and Jahn 2009) and that these jobs are rarely stepping stones into permanent jobs (e.g. Autor and Houseman 2011), much less is known about the employment effects of TAE. Recently, Kahn (2010) analysed the impact of reforms of employment protection systems on the incidence of employment and fixed-term jobs in nine European countries. He finds no evidence that these reforms raised employment but might have increased the probability that workers start their career in fixed-term jobs.

However, so far it is an open question whether temporary agency employment substitutes permanent jobs. This paper fills this gap by analysing the interaction of two monthly time series for Germany, TAE and NTAE. Germany is an interesting country to look at as it is one of the biggest markets for TAE in the world (Jahn 2010). Moreover, we develop an identification method dealing with two critical points, predictive power of TAE and common factors.

2 Identification Problem

TAE is known to react quickly to the business cycle, usually before the labour market as a whole is affected. This implies that TAE should have forecasting power for NTAE – but such a linkage would be only predictive, not causal. Indeed, the cross-correlogram in Figure 1 shows a positive link of contemporaneous and lagged TAE with NTAE growth. Logically, mere descriptive statistics are not suitable to give any hint at possible substi-

tution effects. In our model we filter out purely predictive effects using a set of relevant leading indicators as control variables.

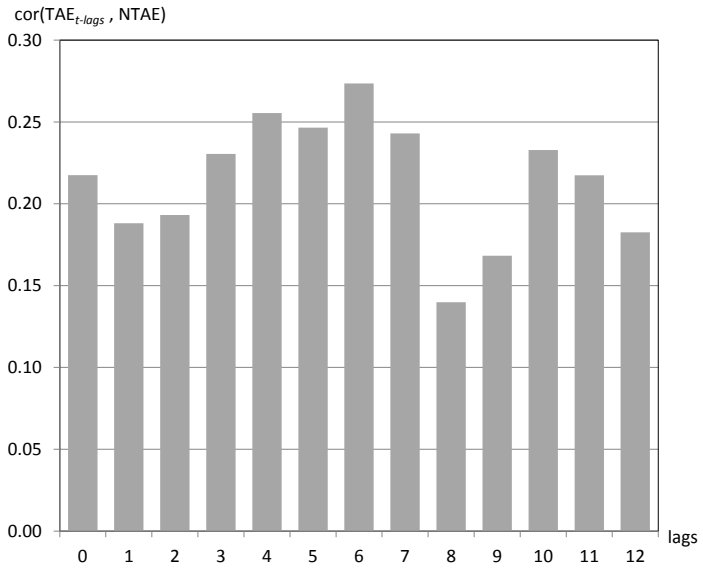

Figure 1: Cross-correlogram of TAE and NTAE growth

A second problem lies in the identification of the contemporaneous structure. There are two potential contemporaneous impacts: First, a spillover from TAE to NTAE, which is negative in case of substitution, and second, correlation of the structural shocks to the two employment forms. The latter, arising from latent common factors, is likely to be substantial since the two segments are interacted. Consequently, there are two potential sources of one contemporaneous residual cross-correlation in a reduced-form model of TAE and NTAE. Importantly, it is possible that a negative spillover occurs even if the reduced-form residuals are positively correlated (as in our data, see lag 0 in Figure 1). In this case the spillover effect would be overcompensated by a positive correlation of the structural shocks.

We solve the identification problem by exploiting distributional properties. Our data turn out to be highly non-normal with substantial excess kurtosis (1.2 and 4.9 for residuals from AR(3) processes of TAE and NTAE growth). This represents a typical outcome if the data result from a mixture of normal distributions, see e.g. Lanne and Lütkepohl (2010). One plausible reason is that there are several regimes operating within the sample period, which differ regarding the shock variances. Examples would be different phases of high or low volatility or outliers that may be generated from a different distribution than the other observations. Therefore, we will take into account heteroscedasticity in the structural shocks to TAE and NTAE. This has the potential to identify simultaneous systems, as

discussed by Sentana and Fiorentini (2001), Rigobon (2003) or Weber (2010). The idea is that variation in the structural variances provides additional identifying information through rotation of the reduced-form covariance matrix: For example, in the bivariate case, a new regime introduces two additional unknowns (i.e., the structural variances, $\Sigma_{11,i}$ and $\Sigma_{22,i}$ below), but in the reduced form a whole new covariance matrix (Ω_i below) with three moments (i.e., two variances and the covariance) is obtained. No conventional instruments or identifying parameter restrictions are required.

Lanne and Lütkepohl (2010) model the heteroscedasticity through a mixture of normal distributions. However, their approach does not take into account correlation of the structural shocks, which is indispensable in our case. Allowing for unrestricted covariances would lead to the unfavourable situation that each shift in variance introduces as many structural parameters (variances and covariances) as additional equations from the reduced-form covariance matrix, so that nothing would be gained from heteroscedasticity. Weber (2010) solves this problem by specifying constant conditional correlations for the structural disturbances ("SCCC model"): Once the constant correlation coefficient is taken into account, shifts in volatility introduce no additional unknowns from covariances. As Weber analyses financial market data, he models the heteroscedasticity in GARCH-form. Instead, as a methodological contribution, we combine the SCCC approach with the mixture of distributions specification of Lanne and Lütkepohl (2010), which is more appropriate for labour market data.

3 Methodology

We model NTAE and TAE in y_t (dimension $n = 2$) by the first-differenced[1] structural vector autoregression (SVAR) with lag length q

$$A\Delta y_t = C + \sum_{j=1}^{q} (B_j \Delta y_{t-j} + D_j \Delta x_{t-j}) + D_0 \Delta x_t + \varepsilon_t \ , \tag{1}$$

where the B_j represent $n \times n$ coefficient matrices of lagged effects, ε_t is an n-dimensional serially uncorrelated vector of structural shocks and C a vector of constants. The contemporaneous impact of TAE on NTAE is included as the upper right element in the triangular matrix A with diagonal elements normalised to one. The vector x contains the control variables with coefficient matrices D_j.

[1] Cointegration test revealed no evidence for a robust relationship in levels.

The error term ε_t is a mixture of k normally distributed random variables: $\varepsilon_t = e_{it} \sim N(0, \Sigma_i)$ with probability γ_i, $i = 1, \ldots, k$. Following Weber (2010), we specify the covariances of the shocks in the e_{it} as $\Sigma_{12,i} = \rho\sqrt{\Sigma_{11,i}\Sigma_{22,i}}$, where ρ is the constant correlation.

We estimate the parameters from the stochastic model part, i.e. the γ_i and Σ_i, along with the coefficients from the mean equation (1) by Maximum Likelihood using numerical methods. The reactions of NTAE to TAE are distributed over time. We are interested in the total effect Ξ, which is obtained in a first-differenced equation by summing over all single impacts, i.e. $\Xi = (\sum_{j=1}^{q} B_{12,j} - A_{12})/(1 - \sum_{j=1}^{q} B_{11,j})$. Significance of this expression can be checked by likelihood ratio tests, where under the null the numerator is restricted to zero.

4 Data

The dataset provided by the Federal Employment Agency's "Labour Placement Statistics" is unique in the sense that it provides monthly information on the total number of temporary agency workers. During our observation period, 1991:01 to 2010:12, TAE increased from 105,000 to 824,000; see Figure 2. On average, agency employment has grown by nine percent per year. Although TAE still accounts for a relatively small share of paid employment (three percent in 2010), it plays an important role in job creation: one out of two new jobs in 2010 was created in this sector. Since more than 90 percent of the TAE work full-time, we can exclude that they hold multiple jobs to a great extent.

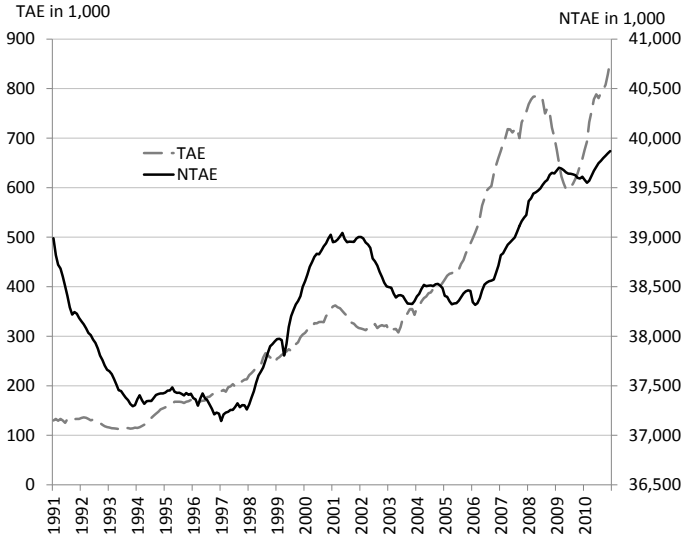

Figure 2: TAE and NTAE (seasonally adjusted)

Despite the rather strict regulation of the German TAE sector, agency jobs are spot-market jobs that provide barely any employment protection (see Antoni and Jahn 2009 for details). Moreover, about 60 percent of the TAE were non-employed before accepting an agency job and the average wage differential is about –20 percent (Jahn 2010).

Our second main statistical source is the labour force survey provided by the Federal Statistical Office. For our estimations we use the monthly stock of all employees which include civil servants and self-employed workers. Compared to the number of wage and salary workers this may be a more adequate measure for our purpose, since we cannot exclude that there are interactions between self-employment and TAE. From the monthly stock of employed workers we subtract TAE to receive the number of workers employed outside the sector (NTAE).

As controls we use economic activity (industrial production) as the major determinant of labour demand, order inflow and the DAX as standard predictors of economic growth, and registered vacancies as a leading indicator of the labour market. We include all endogenous and control variables in logs.

5 Results and Conclusions

We choose $q = 3$ lags for the VAR according to AIC and autocorrelation tests. We set the number of regimes $k = 3$, since both the second and the third regime increase the likelihood substantially, while further regimes bring no significant improvement. The presence of regimes is confirmed by the differences between the estimated variances: Table 1 shows that both variances increase considerably in the second regime. The third regime bears an additional increase of the TAE variance, while the NTAE variance is reduced below the level in the first regime. The estimated probabilities imply that beyond a base regime, we have two relevant regimes with varying volatility.

Regime	Var NTAE*	Var TAE*	Prob.
1	0.57 (0.24)	0.71 (0.21)	0.57 (0.10)
2	3.64 (1.76)	2.11 (0.84)	0.19 (0.07)
3	−4.15 (1.85)	3.96 (1.42)	0.24 (−)

*In regime 2 and 3 variance *differences* between regimes (2–1 and 3–2)

Table 1: Regime Variances and Probabilities

The hypothesis $\Xi = 0$ is rejected in a LR test with a p-value of 0.006. In particular, a positive TAE shock significantly reduces NTAE. As was supposed above, despite the positive reduced-form correlation (Figure 1), a negative effect could be estimated from the data due to the fact that it is overcompensated by a large correlation of the shocks, $\rho = 0.59$. Thus, we can state that TAE does substitute NTAE.

For estimating the size of the substitution effect, we deem a model using changes in numbers of employees more appropriate than the estimation based on growth rates. Therefore, we estimate (1) using non-logged levels of NTAE and TAE in y, where identification is ensured by imposing the correlation of the shocks in ε_t as obtained in the log model.[2] We receive $\Xi = -0.50$, indicating that a positive shock to TAE reduces NTAE, but increases *overall* employment (NTAE+TAE). For instance, a TAE rise of 200,000, as observed in boom years like 2006 or 2010, would substitute 100,000 regular jobs, but also leave a net gain of 100,000 jobs.

To sum up, enhancing labour market flexibility creates jobs in total as claimed by the proponents of two-tier labour market reforms. Yet deregulation comes at a price: Regular jobs are substantially substituted by temporary jobs.

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