Estimating the Macroeconomic Effects of Active Labour Market Policies using Spatial Econometric Methods

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Abstract

Most evaluation studies of active labour market policy focus on the microeconometric treatment effect using individual data and therefore ignore indirect effect like substitution or deadweight effects. In our paper, we investigate the macroeconomic effects of various active labour market programmes in West Germany on a regional level from January 2003 to December 2004. We use a dynamic specification of the augmented matching function and account for spatial interactions. Furthermore, in contrast to other evaluation studies on the regional level we are able to use detailed information on the duration of employment spells. Thus, we provide evidence on the sustainability of the measures. To obtain consistent estimates in presence of a dynamic panel data model with spatially correlated errors, a GM estimator is applied, which was recently developed by Mutl (2005). The broad conclusion that we draw from our analysis is that we find no evidence of positive effects of the programmes under consideration on the matching process in West Germany. These findings are robust with respect to several modelling strategies.

Keywords:
Matching Function, Active Labour Market Policy, Dynamic Panel Data Model, Spatial Dependence

JEL Classification: C21, C23, J64, J68

1 Introduction

Many countries spend a huge amount of funding on active labour market policy (ALMP). In the case of Germany the budget reached about 1.2% of GDP in 2002. In spite of these efforts, unemployment remains at high levels. Due to this disappointing situation, there is a growing interest in empirical studies evaluating the causal effects of active labour market programmes. Whereas some countries have a long-lasting experience in the evaluation of policy measures, Germany has developed an "evaluation culture" only recently. Nowadays, however, the scientific evaluation of programmes is often mandatory.

Most of the empirical studies on the effects of ALMP for Germany and for other countries are microeconometric in nature. They draw on individual data in order to evaluate whether participation in a programme increases the individual probability of finding a job and leaving unemployment. For identification of the causal effects of participation it would be necessary to observe an individual in two mutually exclusive states - participation and non-participation - and to compare the two outcomes. Unfortunately, the counterfactual situation "what would have happened" is not observable. In the literature this is known as the "fundamental problem of evaluation". There are, however, several strategies to identify the unknown treatment effect even when the design is non-experimental - which is typically the case. The most common ones are nonparametric methods like matching approaches or the difference-in-difference method.[1]

Macroeconomic evaluation studies are relatively scarce, but their number has risen over recent years. Instead of looking at individuals they focus on regional labour markets. As Calmfors (1994) notes, active labour market policy affects not only participants but also non-participants due to indirect effects. At the regional level, unintended negative effects like displacement, deadweight and substitution effects, should be taken into account. In microeconometric studies these negative side effects, which increase with the scale of the programme, are ignored or even excluded by assumption.[2] Because for some measures, like wage subsidies, this assumption is unrealistic, we aim at providing evidence on the aggregate effects of active labour market programmes. We also take into account positive side effects of the programmes. These include multiplier effects or external effects of human capital.

At the regional level, the counterfactual question changes: "What would have happened to an outcome if the regional ALMP had been different?" The regional variation in ALMP can be used estimating the regional effect by means of a regression model. Macroeconomic studies for Germany differ in their design as there are several options for the adequate outcome measure at the regional level. Büttner and Prey (1998) as well as Hujer et al. (2006) choose the regional unemployment rate and estimate an augmented version of the Beveridge curve. Hagen and Steiner (2001) and Fertig et al. (2006) take labour market flows as the outcome variable. Finally, Hagen (2003) employs three different dependent variables - labour market flows, regional unemployment and regional employment.

Following the work of Boeri and Burda (1996), and Bellmann and Jackman (1996) we start from the well-known matching function, which explains the number of outflows from unemployment within a period by the number of job seekers and vacancies. Like Hujer and Zeiss (2005), we estimate a dynamic panel data model to control for unobserved time invariant regional effects and for adjustment processes. However, our work differs from the existing literature in a number of respects. First, rather than looking only at the stock of programme participants, we also consider outflows from programmes in order to shed more light on lock-in effects. Second, we are able to use the information on the duration of employment spells. Thus, we can assess the sustainability of ALMP success. Finally, we explicitly allow for spatial correlation in the error term within a dynamic panel framework. This is done as the assumption of independence among the observation units (employment agencies) is hardly fulfilled. Spatial interactions have also been taken into account by Fertig et al. (2006), but only with cross-sectional data. To estimate

[1] Each of them has to consider several identification assumptions. For further methodological details see Heckman, LaLonde, and Smith (1999) or Rubin (1986). A good overview of the conceptual framework of ALMP evaluation is provided by Fertig and Kluve (2004).

[2] Stable unit treatment value assumption (SUTVA), see Rubin (1986).

a dynamic panel data model with spatial correlation we apply a procedure recently developed by Mutl (2005). To our knowledge, this is the first empirical study in labor market economics that implement this new estimator.
The outline of the paper is as follows. The next section provides a brief overview of the institutional background of active labor market policy in Germany, and of the different programmes of ALMP in particular. In the third section we explain the theoretical background of the augmented matching function and the basic econometric specification. The spatial econometric techniques are discussed in Section 4. In Section 5 we describe the data and give some descriptive measures. This is followed by the presentation of our results (Section 6). Section 7 concludes.

2 Active Labor Market Programs under Consideration

2.1 Institutional Setup and Legal Basis

Active Labour Market Policy has a long tradition in Germany. The starting point was the Employment Promotion Act (Arbeitsförderungsgesetz) in 1969. Responsible for the implementation of labour market programmes in Germany is the Federal Employment Agency (Bundesagentur für Arbeit) and the affiliated 178 local employment agencies (LEA) at the regional level. Given the favorable economic situation at the end of the 1960s the Employment Promotion Act was aiming for full employment and for balancing out labour demand and supply. In fact, it dealt with raising labour supply qualitatively as well as quantitatively.
The Employment Promotion Act had to be adjusted several times during the seventies and eighties, as the economic situation detoriated. As a consequence of German reunification in 1990 and the subsequent sharp rise in unemployment - most notably in the Eastern part - there was the need for a completely new legal basis for ALMP. Thus, in 1998 the Employment Promotion Act was replaced by the Social Security Code III (Sozialgesetzbuch III).
Three of the changes are of particular interest in this context. Firstly, the main objective has changed - it is no longer a high employment ratio or the prevention of low-quality employment but a sustainable re-integration of unemployed individuals into regular employment. A particular focus is the integration of people with severe labour market problems such as elderly persons or long-term unemployed. Furthermore, the Social Security Code III establishes for the first time ever in Germany that ALMP measures have to be evaluated. Finally and for the present analysis most important, there was a shift of responsibility from the head office to the local employment agencies. A decentralization of ALMP took place. The Federal Employment Agency allocates funds for ALMP to every local employment agency in a pooled form (Eingliederungstitel). The allocation of the overall budget from the federal to the regional level is according to a labor market indicator, which considers several aspects of the regional labor market like unemployment or employment growth rate (for more details see Blien (2002)). The local employment agencies are more or less free in the decision on how to split the budget between different measures. This procedure is flexible enough to take local characteristics into account and to weight the measures differently according to local requirements. The variation in ALMP across regions enables us to evaluate the effect of ALMP on the regional level.
Until today the Social Security Code III has been the legal basis for ALMP in Germany and thus is also the basis for our study, which covers the period from January 2003 to December 2004. Between 2003 and 2005 the four so-called Hartz Reforms were implemented ("Gesetze für moderne Dienstleistungen am Arbeitsmarkt"). Each of these reforms has its own emphasis.[3] In particular, Hartz IV, which became effective on January 1th 2005, has lead to large changes to the social welfare system in Germany by merging unemployment assistance and social assistance into a new assistance for jobseekers, called "unemployment benefit II". Because of this structural break we focus on the period before 2005.

[3] For a comprehensive overview see Jacobi and Kluve (2006)

2.2 Active Labour Market Programmes

Labor market measures may be divided into two groups - passive and active measures. In 2004 the expenditures for passive measures were 49 billion euros - by far the largest part was spent on unemployment benefit payments. The expenditures for measures of active labour market policy add up to 19 billion euros. There exists a large number of various discretionary measures of employment promotion in Germany. According to the statistical classification employed by the Federal Employment Agency, five broad categories can be distinguished: Measures promoting the qualification of the unemployed, incentive schemes for employers and self-employed, direct provision of jobs, special programmes targeting youths and other measures. In our analysis we exclude programmes for youths as well as subsidies for self-employment and other measures. The remaining programmes - Labour Market Qualification, Wage Subsidies and Direct Employment Programmes - are described in the following.

2.2.1 Labour Market Qualification

The main objective of qualification programmes is to adjust the qualifications of the unemployed to the needs of labour demand and thus to improve the matching efficiency. Individual programmes differ in their design: On the one hand there are short-term training measures (TM, *Maßnahmen der Eignungsfeststellung und Trainingsmaßnahmen*), which last up to eight weeks. These training measures include, for example, job application training and computer or language courses. A welcome side effect is to test for the willingness to work. In some cases a short-term programme is followed by other active labour market measures, or different TM are combined. Short-term training measures have grown in importance during the observation period. This is due to the reforms of ALMP in Germany introduced in 1998 with a clear trend towards shorter programmes at lower costs.

Beside TM there are further vocational training (*berufliche Weiterbildung*) and retraining programmes (*Umschulung*). The latter provides training for a new occupation and lasts up to three years, whereas the former aims at upgrading the existing skills and usually lasts several months. While participating in a measure the participants receive a payment comparable to the unemployment benefit. Furthermore the local employment agency covers the total costs of teaching and provides travel grants as well as child care.

2.2.2 Wage Subsidies

Wage Subsidies (BBL, Beschaeftigungsbegleitende Leistungen) are payed out to private sector employers to encourage them to hire a jobless person. The direct objective is the integration of the unemployed by temporarily subsidizing their wage. Usually, the subsidies are payed for six to twelve months. When the subsidy expires the employer is obliged to keep the formerly subsidized employee for another six to twelve months. The expectation is that this temporary job will turn into a permanent employment relationship. However, the aim is not only to create additional jobs, but to help the unemployed in keeping in touch with the labour market. This is important especially for the long-term unemployed - though possibly at the expense of the short-term unemployed. Therefore, even if the wage subsidy is positive for an individual, the regional net employment gain (i.e. the outflow from unemployment into regular jobs) could be very small or zero due to large deadweight and substitution effects.

2.2.3 Job Creation Schemes

In 2004 job creation schemes (JCS, *Arbeitsbeschaffungsmaßnahmen, Strukturanpassungsmaßnahmen*) accounted for only six per cent of total spending on active measures in West Germany. These programmes, which are usually realized in the public and non-profit sectors, aim at maintaining the employability of the participants. Moreover, in regions with rather high unemployment rates they have an additional socio-political component. Most of the individual-based evaluation studies conclude that JCS have no or even a negative effect in helping unemployed persons into regular jobs. Furthermore, on the aggregate level there is the risk of crowding out regular private-sector jobs.

3 Modelling ALMP Effectiveness

3.1 The Augmented Matching Function

The possible existence of deadweight losses and substitution effects represent two major problems in the evaluation of ALMP on a micro level. Deadweight losses are caused by people who participated in the programme but would have been hired also without a participation. Substitution effects arise if an employer just replaces a worker or job-seeker who did not participate in a programme with a person who did participate, so that no new job creation takes place. In order to take these problems into account, one has to focus on aggregated outcomes in addition to the analysis on the individual level.
We measure the success of ALMP by using the variation in the participation in these programs across regions over time. We look whether this variation has an impact on the outflows from unemployment into employment. The traditional econometric methodology assumes that the observations for different cross-sections are independent from each other. But this assumption can hardly be justified in the case of our regional dataset. First, economic conditions affecting one region are very likely to affect neighbouring regions as well. Second, individuals that are searching for work typically do not restrict their search to one labour office district; they extend their search to other districts, too. The same reasoning applies to employers that have a vacancy. Both examples clearly show that labour market conditions are correlated between regions. Thus, we conclude that the assumption of independent observations across cross sections is invalid and specify and estimate econometric models with spatial dependencies., i.e., we estimate a matching function augmented by spatial effects and indicators of the labor market program intensities. We follow the specification of the matching function augmented by spatial effects derived in Burda and Profit (1996). In their model job seekers take job offers in neighbouring regions into account when forming their decisions. Expected benefits and search costs are assumed to depend on the distance between the residential region and the region where the job offer takes place. The model assumes that changes in unemployment exit probabilities in region i depend on the changes of the labour market conditions in all neighbouring regions. Burda and Profit (1996) and Burgess and Profit (2001) model these spatial dependencies by including a spatial lag of the unemployed and the vacancies in the neighbouring regions into the matching function. Furthermore, we follow the specification used in Boeri and Burda (1996) and include an indicator for the intensities of active labour market policies in the region into the equation.

The augmented matching function is given by the following log-linear equation[4]

$$\begin{aligned}\ln m_{it} &= \beta_1 + \alpha_1 \ln m_{i(t-1)} + \beta_2 \ln u_{i(t-1)} + \beta_3 \ln v_{i(t-1)} + \beta_4 \ln u^*_{i(t-1)} + \beta_5 \ln v^*_{i(t-1)} \\ &\quad + \sum_{s=1}^{S} \gamma^s(L) \ln a^s_{it} + \nu_{it}\end{aligned} \tag{3.1}$$

where m_{it} denotes the outflows from unemployment into employment in region i that take place between $t-1$ and t. $u_{i(t-1)}$ and $v_{i(t-1)}$ denote the number of job seekers (e.g. unemployed and participants of ALMP) and vacancies at the end of $t-1$, respectively. The terms $\ln u^*_{i(t-1)}$ and $\ln v^*_{i(t-1)}$ stand for the spatial lag of the unemployed and the vacancies respectively. The spatial lags are given by

[4] Since the elements for the boundary regions may change if new observations are added, the observations are assumed to form triangular arrays (see Anselin (2003)). Therefore it is common practice in theoretical papers to denote this dependence on the sample size by indexing the variables with N. We will suppress this dependence in order to simplify notation.

$u^*_{i(t-1)} = \sum_{j=1}^N w_{ij} u_{i(t-1)}$ and $v^*_{i(t-1)} = \sum_{j=1}^N w_{ij} v_{i(t-1)}$. We use two specifications for the weights w_{ij}. In the first version, the weights are chosen to be unity if the region i shares a common border with region j and zero if this is not the case. In a second version we set the weights according to a function based on the distance (D_{ij}) between the centres of the regions, $w_{ij} = \exp(-\eta D_{ij})$. We set $w_{ij} = 0$ if the distance between the regions exceeds 700 km, and, following the discussion in Molho (1995), we set $\eta = 0.02$. Furthermore, we do not consider any region to be a neighbour to itself, i.e. $w_{ij} = 0$ if $i = j$. The term $\gamma^s(L) = \gamma_1^s L + \gamma_2^s L^2 + \ldots + \gamma_q^s L^q$ is a polynomial in the lag operator. The term $\ln a^s_{it}$ contains the indicator for participation in the s-th active labour market programme. The terms β_i denote scalar unknown parameters and ν_{it} the error term.

We use two specifications to model participation in policy measures. In the first specification we augment the matching function by participants in the labour market programmes. In order to account for programme heterogeneity of the training measures we also estimate a specification where we split these measures into industrial training and the remaining training programmes. The second specification uses the outflows from the ALMP programmes as policy indicator. In this case, there should be no lock-in effects. Furthermore, we normalize all variables, in order to account for the varying size of the labor market districts. We divide the ALMP measures by the total number of job seekers and the remaining variables by the total labour force.

3.2 Econometric Specification

We assume for the error term

$$\nu_{it} = \lambda \sum_{i=1}^{N} w_{ij} \nu_{jt} + \upsilon_{it} \tag{3.2}$$

$$\upsilon_{it} = \mu_i + \varepsilon_{it} \tag{3.3}$$

where $\sum_{i=1}^N w_{ij}\nu_{jt}$ is the spatial lag in the error process, and υ_{it} is modeled as an error components model. The term μ_i denotes a regional specific effect and the term ε_{it} denotes the error component that varies over the regions and over time. We assume that both processes are i.i.d. with zero expectation and variance σ^2_μ and σ^2_ε, respectively. Furthermore, we assume that the processes are independent. However, we follow the view expressed e.g. in Arellano (2003) and Wooldridge (2002) and see the distinction between fixed and random effects estimation as a way of controlling for unobserved heterogeneity and not as an issue of sampling methods as in the traditional meaning of the terms. We will make no assumption about the correlation of the regressors and the individual specific effect, so that they are possibly correlated. Therefore we will first difference our model and estimate the parameters of the first differenced equations.

In order to analyze the model given above in more detail, we will rewrite the augmented matching function in more compact form. In contrast to the usual procedure in the panel data literature, we will stack the observations first over regions. We rewrite equation (3.1) as follows

$$\mathbf{y}_t = \alpha_1 \mathbf{y}_{t-1} + \mathbf{X}_{t-1}\boldsymbol{\delta} + \boldsymbol{\nu}_t \tag{3.4}$$

where we define

$$\mathbf{y}_t = \begin{pmatrix} \ln m_{1t} \\ \vdots \\ \ln m_{Nt} \end{pmatrix}; \boldsymbol{\nu}_t = \begin{pmatrix} \boldsymbol{\nu}_{1t} \\ \vdots \\ \boldsymbol{\nu}_{Nt} \end{pmatrix} \boldsymbol{\delta} = \begin{pmatrix} \beta_1 \\ \vdots \\ \beta_5 \\ \gamma_1^1 \\ \vdots \\ \gamma_q^s \end{pmatrix}$$

$$\mathbf{X}_{t-1} = \begin{pmatrix} 1 & \ln u_{1(t-1)} & \ln v_{1(t-1)} & \ln u^*_{1(t-1)} & \ln v^*_{1(t-1)} & \ln a^1_{1(t-1)} & \dots & \ln a^s_{1(t-q)} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & \ln u_{N(t-1)} & \ln v_{N(t-1)} & \ln u^*_{N(t-1)} & \ln v^*_{N(t-1)} & \ln a^1_{N(t-1)} & \dots & \ln a^s_{N(t-q)} \end{pmatrix} \tag{3.5}$$

in order to simplify notation.

Furthermore, the matrix $\mathbf{W}$ collects the weights w_{ij} and the vector $\boldsymbol{\nu}_t$ collects all errors $fmnu_{it}$ for period t. Stacking the error term for period t gives

$$\boldsymbol{\nu}_t = \lambda \mathbf{W} \boldsymbol{\nu}_t + \boldsymbol{\upsilon}_t \tag{3.6}$$

$$\boldsymbol{\upsilon}_t = \boldsymbol{\mu} + \boldsymbol{\varepsilon}_t \tag{3.7}$$

Solving equations (3.6) for $\boldsymbol{\nu}_t$ yields

$$\boldsymbol{\nu}_t = (\mathbf{I}_N - \lambda \mathbf{W})^{-1} \boldsymbol{\upsilon}_t. \tag{3.8}$$

From these equations it is obvious that the parameter space of λ has to be chosen in such a way that the inverses exist. One widely used method is to normalize the weighting matrix in such a way, that the rows sum to unity and chose the interval (-1,1) as parameter space. Kelejian and Prucha (2006) criticize this procedure, since one uses a different scaling factor for each row, and therefor there is no rescaling factor available that yields the un-normalized model. Instead Kelejian and Prucha (2006) suggest to normalize the model by dividing the weighting matrix by its largest eigenvalue and to choose the the interval (-1,1) as parameter space.[5]

In order to remove the individual effects we transform equations (3.4) and (3.6) which yields

$$\Delta \mathbf{y}_t = \alpha_1 \Delta \mathbf{y}_{t-1} + \Delta \mathbf{X}_{t-1} \boldsymbol{\beta} + \Delta \boldsymbol{\nu}_t \tag{3.9}$$

$$\Delta \boldsymbol{\nu}_t = \lambda \mathbf{W} \Delta \boldsymbol{\nu}_t + \Delta \boldsymbol{\varepsilon}_t \tag{3.10}$$

As shown by Nickell (1981) the least squares dummy variable (LSDV) estimator for α_1 is inconsistent if the time dimension is finite, even if the cross sectional dimensions goes to infinity.[6] In addition one has to control for a possible endogeneity of the indicator for ALMP. The usual procedure is to find an instrumental variable for the ALMP indicator (see Calmfors and Skedinger (1995) or Boeri and Burda (1996)). The major problem with this procedure is the difficulty to find a reasonable set of instruments for the ALMP measures. Instead of trying to find such an instrument we use the advantages that a panel

[5] Note that in our case we have a moderate number of regions (141), so that it is no problem to compute these eigenvalues. If the sample size in the cross sectional dimension becomes large, these computations become infeasible. In fact, this was one of the reasons given in Kelejian and Prucha (1999) for the derivation of this estimator. In the case of a large number of regions, Kelejian and Prucha (2006) propose to normalize the weighting matrix by $\tau^* = \min\left(\max_{1\le i\le N} \sum_{j=1}^N |w_{ij}|, \max_{1\le j\le N} \sum_{i=1}^N |w_{ij}|\right)$. The parameter space for the transformed model would be again $(-1,1)$.

[6] First differencing the model and estimating the parameters by generalized least squares yields the LSDV estimator (see Arellano (2003)).

dataset offers. As stated in Blien (2002), ALMP funds are allocated to local employment agencies by a deterministic process depending on the job seeker rate, the rate of disadvantaged unemployed and the inflows from unemployment into employment. This allocation takes place based on the information in the previous year, so the variables enter the policy reaction function with several lags. Therefore, we model the moment conditions according to Blundell, Bond, and Windmeijer (2000).

We will impose the following moment conditions

$$
\begin{aligned}
E(y_{i(t-j)}\Delta\varepsilon_{it}) &= 0;\ \text{for } t=3,\dots,T \text{ and } 2\le j\le t-1 && (3.11)\\
E(\mathbf{x}_{i(t-j)}\Delta\varepsilon_{it}) &= \mathbf{0};\ \text{for } t=3,\dots,T \text{ and } 2\le j\le t-1 && (3.12)
\end{aligned}
$$

and will therefore instrument the right hand side variables in equation (3.9) by lagged values. These moment conditions were proposed by Arellano and Bond (1991). As stated in Blundell and Bond (1998) these moment conditions become uninformative in the case of a large autoregressive parameter and/or if the variance of the individual term is large relative to σ_ε^2. In addition we impose that

$$
\begin{aligned}
E(\Delta y_{i(t-1)}\upsilon_{it}) &= 0;\ \text{for } t=3,\dots,T && (3.13)\\
E(\Delta\mathbf{x}_{i(t-1)}\upsilon_{it}) &= \mathbf{0};\ \text{for } t=3,\dots,T && (3.14)
\end{aligned}
$$

and use the system estimator proposed in Blundell and Bond (1998).

4 Estimation of the Degree of Spatial Correlation

We use the instrumentation of the system GMM estimator proposed by Blundell and Bond (1998). It is well known that the efficient weighting matrix consists of the inverse of the covariance matrix of the moment conditions (see Hansen (1982)). This weighting matrix depends on the unknown parameters σ_μ^2, σ_ε^2 and λ. As shown in Mutl (2005) the moment conditions for the estimation of these parameters given in Kapoor, Kelejian, and Prucha (2004) stay valid in the case of a dynamic panel data model.

In order to present this generalized moments estimator we will stack equation (3.6) over time periods, which yields[7]

$$\boldsymbol{\nu} = \lambda(\mathbf{I}_T\otimes\mathbf{W})\boldsymbol{\nu} + \boldsymbol{\upsilon} \tag{4.1}$$

with $\boldsymbol{\upsilon} = (\mathbf{e}_T\otimes\boldsymbol{\mu}) + \boldsymbol{\varepsilon}$ where $\mathbf{e}_T$ denotes a T dimensional vector consisting of ones. For convenience we introduce the following notation:

$$
\begin{aligned}
\bar{\boldsymbol{\nu}} &= (\mathbf{I}_T\otimes\mathbf{W})\boldsymbol{\nu} && (4.2)\\
\bar{\bar{\boldsymbol{\nu}}} &= (\mathbf{I}_T\otimes\mathbf{W})\bar{\boldsymbol{\nu}}\\
\bar{\boldsymbol{\upsilon}} &= (\mathbf{I}_T\otimes\mathbf{W})\boldsymbol{\upsilon}
\end{aligned}
$$

Moreover, we introduce the following transformation matrices

$$
\begin{aligned}
\mathbf{Q}_0 &= \left(\mathbf{I}_T - \frac{\mathbf{J}_t}{T}\right)\otimes\mathbf{I}_N && (4.3)\\
\mathbf{Q}_1 &= \frac{\mathbf{J}_t}{T}\otimes\mathbf{I}_N && (4.4)
\end{aligned}
$$

where $\mathbf{J}_T$ is a $(T\times T)$ matrix of unit elements. Premultiplying a vector by $\mathbf{Q}_1$ results in a vector consisting of unit-specific sample means, whereas a transformation by $\mathbf{Q}_0$ subtracts the individual-specific sample

[7] We only present a summary of the procedures needed to implement this estimator. For the derivations of the moment conditions and a mathematical rigorous discussion of the estimator the reader is referred to Kapoor, Kelejian, and Prucha (2004) or Mutl (2005).

mean from each observation.[8] Using these transformations we get

$$\begin{aligned} E(\boldsymbol{\upsilon}\boldsymbol{\upsilon}') &= \sigma_\varepsilon^2 \mathbf{I}_{NT} + \sigma_\mu^2 (\mathbf{J}_T \otimes \mathbf{I}_N) && (4.5)\\ &= \sigma_\varepsilon^2 \mathbf{Q}_0 + \sigma_1^2 \mathbf{Q}_1 && (4.6)\end{aligned}$$

with $\sigma_1^2 = \sigma_\varepsilon^2 + T\sigma_\mu^2$. Our model assumptions given in section 3.2 imply the following moment conditions:

$$\begin{aligned} E(\boldsymbol{\upsilon}'\mathbf{Q}_0\boldsymbol{\upsilon}) &= N(T-1)\sigma_\varepsilon^2, & E(\boldsymbol{\upsilon}'\mathbf{Q}_1\boldsymbol{\upsilon}) &= N\sigma_1^2 && (4.7)\\ E(\bar{\boldsymbol{\upsilon}}'\mathbf{Q}_0\boldsymbol{\upsilon}) &= (T-1)\sigma_\varepsilon^2 \cdot tr(\mathbf{W}'\mathbf{W}), & E(\bar{\boldsymbol{\upsilon}}'\mathbf{Q}_1\boldsymbol{\upsilon}) &= N\sigma_1^2 \cdot tr(\mathbf{W}'\mathbf{W}) \\ E(\bar{\boldsymbol{\upsilon}}'\mathbf{Q}_0\bar{\boldsymbol{\upsilon}}) &= 0, & E(\bar{\boldsymbol{\upsilon}}'\mathbf{Q}_1\bar{\boldsymbol{\upsilon}}) &= 0 \end{aligned}$$

These moment conditions generalize the relationships given in Kelejian and Prucha (1999) for cross sections to the panel specification. Note that if $T = 1$ all moment conditions involving $\mathbf{Q}_0$ become uninformative, leaving only the conditions given in Kelejian and Prucha (1999). We can rewrite the moment conditions in terms of $\boldsymbol{\nu}$ using (4.1):

$$\boldsymbol{\upsilon} = \boldsymbol{\nu} - \rho\bar{\boldsymbol{\nu}} \tag{4.8}$$

After inserting (4.8) into (4.7) we can rewrite the moment conditions as

$$\boldsymbol{\gamma} = \boldsymbol{\Gamma}\boldsymbol{\alpha} \tag{4.9}$$

where $\boldsymbol{\alpha} = (\lambda, \lambda^2, \sigma_\varepsilon^2, \sigma_\mu^2)$, and

$$\boldsymbol{\Gamma} = E\begin{pmatrix} \gamma_{11}^0 & \gamma_{12}^0 & \gamma_{13}^0 & 0 \\ \gamma_{21}^0 & \gamma_{22}^0 & \gamma_{23}^0 & 0 \\ \gamma_{31}^0 & \gamma_{32}^0 & \gamma_{33}^0 & 0 \\ \gamma_{11}^1 & \gamma_{12}^1 & 0 & \gamma_{13}^1 \\ \gamma_{21}^1 & \gamma_{22}^1 & 0 & \gamma_{23}^1 \\ \gamma_{31}^1 & \gamma_{32}^1 & 0 & \gamma_{33}^1 \end{pmatrix}, \quad \boldsymbol{\gamma} = E\begin{pmatrix} \gamma_1^0 \\ \gamma_2^0 \\ \gamma_3^0 \\ \gamma_1^1 \\ \gamma_2^1 \\ \gamma_3^1 \end{pmatrix} \tag{4.10}$$

with $j = (0, 1)$ and

$$\begin{aligned} \gamma_{11}^j &= \frac{2}{N(T-1)^{1-j}}(\boldsymbol{\nu}'\mathbf{Q}_j\bar{\boldsymbol{\nu}}) & \gamma_{21}^j &= \frac{2}{N(T-1)^{1-j}}(\bar{\bar{\boldsymbol{\nu}}}'\mathbf{Q}_j\bar{\boldsymbol{\nu}}) \\ \gamma_{12}^j &= \frac{-1}{N(T-1)^{1-j}}(\bar{\boldsymbol{\nu}}'\mathbf{Q}_j\bar{\boldsymbol{\nu}}) & \gamma_{22}^j &= \frac{-1}{N(T-1)^{1-j}}(\bar{\bar{\boldsymbol{\nu}}}'\mathbf{Q}_j\bar{\bar{\boldsymbol{\nu}}}) \\ \gamma_{13}^j &= 1 & \gamma_{23}^j &= \frac{1}{N}tr(\mathbf{W}'\mathbf{W}) \\ \gamma_{31}^j &= \frac{-1}{N(T-1)^{1-j}}(\boldsymbol{\nu}'\mathbf{Q}_j\bar{\bar{\boldsymbol{\nu}}} + \bar{\boldsymbol{\nu}}'\mathbf{Q}_j\bar{\boldsymbol{\nu}}) & \gamma_1^j &= \frac{1}{N(T-1)^{1-j}}(\boldsymbol{\nu}'\mathbf{Q}_j\boldsymbol{\nu}) \\ \gamma_{32}^j &= \frac{-1}{N(T-1)^{1-j}}(\bar{\boldsymbol{\nu}}'\mathbf{Q}_j\bar{\bar{\boldsymbol{\nu}}}) & \gamma_2^j &= \frac{1}{N(T-1)^{1-j}}(\bar{\boldsymbol{\nu}}'\mathbf{Q}_j\bar{\boldsymbol{\nu}}) \\ \gamma_{33}^j &= 0 & \gamma_3^j &= \frac{1}{N(T-1)^{1-j}}(\boldsymbol{\nu}'\mathbf{Q}_j\bar{\boldsymbol{\nu}}) \end{aligned}$$

For estimation, the sample moments are used instead of the population moments. With a consistent parameter estimator at hand, we are able to estimate the residuals as follows

$$\hat{\boldsymbol{\nu}}_t = \mathbf{y}_t - \hat{\alpha}\mathbf{y}_{t-1} - \mathbf{X}_t\hat{\boldsymbol{\beta}} \tag{4.11}$$

and also the equation (4.9)

$$\hat{\boldsymbol{\gamma}} = \hat{\boldsymbol{\Gamma}}\boldsymbol{\alpha} + \boldsymbol{\vartheta} \tag{4.12}$$

[8] See Baltagi (2001) and Hsiao (2003) for the properties of this transformation matrices. Note that the matrices given in this text are modified in order to cope with the adopted ordering of the data.

where $\boldsymbol{\vartheta}$ can be viewed as a vector of residuals. Estimation is carried out by GMM, minimizing the following quadratic form:

$$M = (\hat{\boldsymbol{\gamma}} - \hat{\boldsymbol{\Gamma}}\boldsymbol{\alpha})'\hat{\boldsymbol{\Xi}}^{-1}(\hat{\boldsymbol{\gamma}} - \hat{\boldsymbol{\Gamma}}\boldsymbol{\alpha}) \tag{4.13}$$

where the weighting matrix is given by

$$\hat{\boldsymbol{\Xi}} = \begin{pmatrix} \frac{1}{T-1}\hat{\sigma}_\varepsilon^2 & 0 \\ 0 & \hat{\sigma}_1^2 \end{pmatrix} \otimes \mathbf{T} \tag{4.14}$$

and

$$\mathbf{T} = \begin{pmatrix} 2 & 2tr\left(\frac{\mathbf{W}'\mathbf{W}}{N}\right) & 0 \\ 2tr\left(\frac{\mathbf{W}'\mathbf{W}}{N}\right) & tr\left(\frac{\mathbf{W}'\mathbf{W}\mathbf{W}'\mathbf{W}}{N}\right) & tr\left(\frac{\mathbf{W}'\mathbf{W}(\mathbf{W}+\mathbf{W})}{N}\right) \\ 0 & tr\left(\frac{\mathbf{W}'\mathbf{W}(\mathbf{W}+\mathbf{W})}{N}\right) & tr\left(\frac{\mathbf{W}\mathbf{W}+\mathbf{W}'\mathbf{W})}{N}\right) \end{pmatrix}. \tag{4.15}$$

Note that Kapoor, Kelejian, and Prucha (2004) derive the covariance matrix of the sample moments given in (4.14) considering the assumption of normal distributed residuals. So, in the absence of normality (4.14) can be used as an approximation to the optimal weighting matrix. Because the matrix $\hat{\boldsymbol{\Xi}}$ depends on $\hat{\sigma}_\varepsilon^2$ and $\hat{\sigma}_1^2$ we need to estimate these parameters first. Since GMM stays consistent if we use any positive definite matrix as a weighting matrix, we can use $\hat{\boldsymbol{\Xi}} = \mathbf{I}_6$ in a first step and apply the estimators derived in a second step.

5 Data and Descriptives

The empirical analysis is mainly based on process data of the Federal Employment Agency. In particular, it is possible to use an integrated database which contains detailed information about registered unemployed, participants in programmes and recipients of unemployment benefits. Additional data about employees is taken from the employment statistics of the Federal Employment Agency which comprises all employees covered by social security system.
Our analysis is constrained to Western Germany. Because of quite large differences in the labour market situation between the eastern and western part of Germany it is not possible to pool the data. We use monthly data between January 2003 and December 2004 for the 141 local employment agencies. In the following we describe our data in more detail.

5.1 Outcome variable

One of the most important questions in every evaluation study concerns the appropriate outcome measure for quantifying the success of a treatment. According to §7,3 Social Security Code III the aim of almost all measures is the re-integration of participants into a regular job. This objective corresponds to the theoretical framework of the augmented matching function. In contrast to many other studies, we are able to distinguish between subsidised and non-subsidised jobs. In our analysis an integration into a subsidised job is not regarded as a success. Thus, the dependent variable is outflows of unemployed individuals into regular, non-subsidised employment in the period $t-1$ until t. Furthermore, the integration into regular employment should be sustainable. Therefore we distinguish two categories according to the time these persons remain in employment after the match: 7 days or 6 months. We obtain this information from a comparison of the unemployment statistics with the employment statistics.

5.2 Policy measures

As already mentioned in section 2.2, in Germany ALMP includes various discretionary measures. For our analysis we group them into four categories: (1) Measures promoting qualification (FbW) (2) Training measures (TM) (3) Job Creation Schemes (JCS) (4) Wage Subsidies (BBL).[9] The results of various micro-econometric studies for these programmes look rather mixed at first glance. But as the meta analysis of Kluve (2006) for more than 100 European evaluation studies shows, there is a clear tendency. Direct employment programmes mostly have a negative effect, wage subsidies a mainly positive effect on the individual probability of leaving unemployment. Caliendo and Steiner (2005) come to a similar conclusion taking into account only evaluation studies for Germany. It is also commonly accepted that negative lock-in effects matter and that it takes time to outweigh these effects. For instance, Lechner, Miquel, and Wunsch (2005) and Fitzenberger, Osikominu, and Völter (2006) find positive long run effects for qualification programmes for West Germany several years after completing a programme.
In our study we use the stock of participants in the different programs at the end of $t-1$ and their lags as explanatory variables. In addition, we estimate a model with outflows from the various measures and their lags as explanatory variables to capture potential lock-in effects which occur during the programme participation. Nevertheless, we could only provide evidence on outcomes a few months after the programme has been completed. The programmes FbW, JCS and BBL are included with six lags, whereas only two lags are included for the training measures, since the latter programme has a significant shorter duration than the former ones. Since there are no lock-in effects with this specification, we only include two lags for each policy instrument when the outflows are used.

5.3 Other covariates

According to the theory of matching and the existing literature we include the number of job seekers (registered unemployed and ALMP participants) and the number of job vacancies at the end of $t-1$ as explanatory variables. Furthermore, we include some variables to control for the regional composition of the job seekers. We use the share of elderly and young unemployed, the share of short and long term unemployed and the share of German unemployed. Finally, we include the share of unemployed person without vocational training. To account for adjustment processes we use the dependent variable lagged by one period as additional explanatory variable.

6 Empirical Results

We estimate the augmented matching function for two different types of outflows into regular employment. We have information on the number of those still employed 7 days and 6 month respectively after taking up a job in period $t-1$ to t. Furthermore, we employ two different specifications for the spatial weighting matrix. In the first specification, we define the weights as equal to unity, if two regions share a border. In the second specification we define the weights as a function of the distance between the two regions' centers. Finally, we distinguish between training measures within firms and the remaining training measures and also estimate a matching function where we do not make this distinction. This leaves us with 16 specifications, whose results are collected in Tables 1 - 4. In the following, we will interpret in detail the results given in Table 1 and comment on the differences between the specifications. The interpretation of the results in tables 2 - 4 is analogous.

For the lagged dependent variable we find a positive and statistically significant coefficient in all specifications given in Table 1. The values range from 0.33 to 0.39, i.e., we find the dynamic component to be significant. There is indeed a regional adjustment process. The parameters of the matching function

[9] As we use outflows from unemployment into regular employment as a criterion for treatment success, measures promoting self-employment are excluded, because their objective is clearly not the integration into regular employment.

Tab. 1: Estimation Results (Spatial Weighting Scheme I)

	Participants				Outflows			
	(1) 7 Days		(2) 6 Month		(3) 7 Days		(4) 6 Month	
Dep. Variable: m_{it}	Coef.	t-Value	Coef.	t-Value	Coef.	t-Value	Coef.	t-Value
Matches Lag 1	0.325	15.939	0.390	18.937	0.333	19.314	0.388	22.365
Unempl.	0.911	17.743	0.994	16.072	0.992	21.694	1.139	19.703
Spatial Unempl.	0.009	0.303	0.038	1.118	0.016	0.620	0.048	1.398
Vacancies	0.040	3.662	0.023	1.757	0.036	3.620	0.020	1.666
Spatial Vacancies	-0.013	-0.686	-0.027	-1.166	-0.008	-0.467	-0.027	-1.193
Short-Run Vocational Training	-0.045	-1.192	-0.067	-1.474	0.001	0.237	-0.011	-1.615
Long-Run Vocational Training	-0.052	-1.471	-0.108	-2.283	-0.014	-1.388	-0.042	-3.112
Short-Run Training Meausres	-0.020	-1.265	-0.055	-2.866	-0.020	-2.273	-0.033	-3.113
Long-Run Training Measures	-0.037	-2.188	-0.046	-2.034	-0.036	-2.719	-0.042	-2.392
Short-Run Job Creation Schemes	0.002	0.166	-0.005	-0.328	-0.006	-1.560	-0.006	-1.350
Long-Run Job Creation Schemes	-0.019	-1.522	-0.043	-2.600	-0.007	-1.198	-0.011	-1.418
Short-Run Wage Subsidies	0.033	0.767	0.004	0.070	-0.021	-1.726	-0.038	-2.573
Long-Run Wage Subsidies	0.030	0.992	-0.038	-0.945	-0.037	-1.632	-0.062	-2.030
Elderly Unempl.	0.014	0.177	0.122	1.296	0.023	0.324	0.102	1.125
Young Unempl.	-0.056	-1.335	-0.072	-1.415	-0.094	-2.404	-0.105	-2.142
Unempl. Low Qualified	-0.091	-1.422	-0.154	-1.983	-0.136	-2.306	-0.223	-2.932
German Unempl.	0.827	9.297	0.836	7.691	1.025	12.900	1.117	10.958
Short Term Unempl.	0.023	0.726	0.096	2.423	-0.026	-0.863	0.034	0.903
Long Term Unempl.	-0.728	-13.326	-0.875	-12.974	-0.811	-18.125	-0.998	-17.516
ρ	0.479		0.545		0.505		0.579	
σ_μ	0.007		0.010		0.006		0.011	
σ_ε	0.012		0.017		0.012		0.017	
Sargan	1882.438		1763.003		2202.435		2114.3	
df	2279		2279		2501		2501	
p	1.000		1.000		1.000		1.000	

All regressions include time dummies.
df denotes the degrees of freedom.
The standard errors for the Long-Run multipliers were calculated using the Delta-Method.

are also positive and significant. Note however, that the estimated parameter for the vacancy rate is very small, compared to the parameter for the unemployment rate. This is due to the underreporting of vacancies to the local employment agencies, so that our estimated parameter should be interpreted rather as an approximation. With respect to the additional conditioning variables, we find by and large the theoretically expected effects. There are significant positive effects of the share of unemployed Germans with values varying between 0.83 and 1.12. The parameters for the share of long-term unemployed are negative and significant, ranging from -0.73 to -1. With respect to the share of unemployed without formal vocational training, we find negative significant effects for the specification in columns 2-4 of Table 1. The values range between -0.14 and -0.22. A bit surprising, we obtain insignificant parameters for the share of elderly and short-term unemployed. The parameters for the share of young unemployed are significant in columns 3 and 4, their values being -0.09 and -1.11 respectively. The negative sign could be due to the fact that young unemployed are often placed in various forms of training schemes instead in regular jobs. Another possibility is that they leave unemployment in order to attend schools providing vocational education. The coefficients of all additional exogenous variables increase in absolute values when we look at sustainable employment (at least 6 months), i.e. the structure of the regional unemployment is more important for explaining outflows into sustainable employment than it is for short-term employment.

With regard to the stock of participants in active labour market programmes (column 1 and 2), we find mostly insignificant parameter values for the short-run multipliers. This implies that the number of participants in one period has ceteris paribus no significant effect on the outflows from unemployment into regular jobs in the next period. There is one exception - the estimated coefficient for the training measures when using outflows in sustainable jobs (duration at least 6 months) as dependent variable. In this case, the coefficient for the short-run multiplier is negative significant. One reason for this could be that training measures are often used as a first step in a programme career, i.e. short-term training measures are followed by other programmes. A large number of participants in short-term training measures in one period would then lead to a large number of participants in other measures in the next period and so reduces ceteris paribus the outflows into regular jobs.[10]

Thus, in the short-run there are almost no negative indirect effects like substitution or displacement effects visible. On the other hand, it is important to note that not a single coefficient of the policy measures is positive. Such negative results for the effectiveness of labor market programs might be due to lock-in effects, since we use the stock of participants as an indicator. In order to circumvent these problems, we estimate the specifications where participation is proxied by the outflows from such programs. We therefore expect the estimated coefficients to be larger, relative the participants specification. In fact, for most of the policy measures this is the case. One important exception from this pattern is subsidized employment. Here, the short-run coefficient for outflows in sustainable employment is significantly negative. An explanation for this may be that after the subsidization ends, the firms replace the former subsidized employees before the 6 month period ends by new subsidized employment. This would imply a substitution effect at least in the short-run.

To account for the dynamic behaviour of inflows into regular employment, we also calculate the long-term multipliers of the marginal effects. These long-term effects differ between employment of at least 7 days and employment of a duration of at least 6 months. Very similar to the short-term coefficients the estimates are larger in absolute values when considering sustainable employment. For Vocational Training we find a significant value of -0.108 (second column), for TM we find values of -0.037 and -0.046 respectively (first and second column). Both are significant. The parameter for Job Creation Schemes is only significant in the second column, with a value of -0.043, whereas the long-term effects of Subsidized Employment are statistically insignificant. When considering outflows from ALMP the coefficients are once more smaller in absolute values in comparison with the number of participants specification. The parameter for JCS is no longer significant. Figures showing the corresponding lag and cumulated lag

[10] Another exception concerns the further vocational training. We find a significant negative effect for this policy measure when using a spatial weighting matrix, that contains the distance information instead of contiguity. If we use the binary weighting matrix the effect is insignificant.

coefficients can be found in Appendix A.

The results presented in Table 2 correspond to the specification underlying the discussion of Table 1, with the difference that we now use the distance between regions as weights. The overall findings, with respect to the effects of labor market programs, remain valid. Although the short-run multipliers differ from one specification to the other, we find very similar values when comparing the long-run multipliers. For example, the effects for the long-term multipliers in column two changes for the case of Vocational Training from -0.108 in the first Table to -0.110 in the second Table. We conclude that the results for the long term effects of labor market programs are robust to a change of the weighting matrix.

The parameter for the lagged endogenous variable is also robust to the change of the weighting matrix, with values varying between 0.32 and 0.40 for the specifications with distance based weights. The values for the vacancy rates are again similar in both cases. Differences between the estimation results can be found in the parameter values for the unemployment rate: they are lower if we use distances as weights. For example, the value drops from 0.994 to 0.908 in the second column of both tables. The main difference between both specifications occurs for the spatial lags. Whereas we find no significant spatial spillover in the unemployment and the vacancy rate, under a binary weighting scheme, we find significant spillover effects if we use distances as weights.

Disentangling the effects for training measures, in order to account for the possibility of program heterogeneity, the overall picture does not change either. Comparing the results of Tables 2 and 1 the main conclusions remain valid. We still have either negative or insignificant long run multipliers for labor market policies. As regards training measures, we may conclude that within-firm training has no significant impact in column 1 and 3 of Table 2 and a negative impact in column 2 and 4. The effects of the remaining training measures are negative in all columns.

The differences in the estimation results, when changing the spatial weights from a binary specification to a distance function, are analogous to the discussion above. Again, the most striking change are for the spatial lags, which are significant, if the weights are chosen according to the distances between regions. Regarding the long term effects of labor market policies, they remain unaffected by changes in spatial weights.

Summarizing the results, we find either insignificant or negative long term effects on the matching process for the labor market programs under consideration. It is important to mention, that the findings concerning the effects of ALMP remain constant if the weighting matrix is changed. This is not a trivial finding since, as mentioned in Bell and Bocksael (2000), other results seem to be sensitive to the specific form of the weighting matrix. This can also be observed in our analysis, where the parameters measuring spatial spillover effects become statistically significant when using distances between regions as weights.

Our results are in accordance with evaluation results at the individual level for Germany. Almost all of these studies find a significant negative treatment effect of various active labour market programmes when the observation period lasts for only a few months after the programme has been completed. Only for an extended observation period do some of the effects become positive. Lechner, Miquel, and Wunsch (2005) demonstrate this for Further Vocational Training and Fitzenberger, Osikominu, and Völter (2006) for TM. Our study at the aggregate level reveals further evidence to support this pattern. Treatment effects increase when outflows rather than program participants are chosen, but they remain negative in a statistically significant way. A very important finding - which micro economic evaluation studies should take into account - is, that the impact of ALMP is much more negative when considering sustainable employment.

Tab. 2: Estimation Results (Spatial Weighting Scheme II)

	Participants				Outflows			
	(1) 7 Days		(2) 6 Month		(3) 7 Days		(4) 6 Month	
Dep. Variable: m_{it}	Coef.	t-Value	Coef.	t-Value	Coef.	t-Value	Coef.	t-Value
Matches Lag 1	0.320	15.974	0.385	19.160	0.333	19.913	0.399	24.082
Unempl.	0.860	17.742	0.908	15.701	0.946	22.294	1.059	19.837
Spatial Unempl.	0.061	1.811	0.102	2.486	0.079	2.451	0.149	3.584
Vacancies	0.035	3.214	0.020	1.553	0.031	3.064	0.017	1.368
Spatial Vacancies	-0.078	-2.347	-0.111	-2.734	-0.066	-2.146	-0.108	-2.763
Short-Run Vocational Training	-0.066	-1.715	-0.112	-2.363	0.002	0.382	-0.009	-1.238
Long-Run Vocational Training	-0.062	-1.752	-0.110	-2.297	-0.017	-1.577	-0.043	-2.955
Short-Run Training Measures	-0.025	-1.536	-0.068	-3.339	-0.024	-2.586	-0.038	-3.318
Long-Run Training Measures	-0.046	-2.668	-0.066	-2.810	-0.044	-3.273	-0.059	-3.120
Short-Run Job Creation Schemes	0.000	-0.015	-0.007	-0.407	-0.006	-1.644	-0.009	-1.928
Long-Run Job Creation Schemes	-0.019	-1.504	-0.041	-2.494	-0.009	-1.375	-0.015	-1.751
Short-Run Wage Subsidies	0.042	0.944	-0.004	-0.074	-0.018	-1.401	-0.035	-2.232
Long-Run Wage Subsidies	0.033	1.139	-0.060	-1.543	-0.019	-0.812	-0.044	-1.354
Elderly Unempl.	0.029	0.396	0.119	1.355	0.051	0.749	0.118	1.351
Young Unempl.	-0.015	-0.377	-0.048	-0.972	-0.038	-0.994	-0.060	-1.220
Unempl. Low Qualified	-0.045	-0.715	-0.093	-1.222	-0.109	-1.838	-0.168	-2.187
German Unempl.	0.843	9.935	0.885	8.614	1.057	13.822	1.187	12.094
Short Term Unempl.	-0.025	-0.807	0.044	1.114	-0.094	-3.159	-0.032	-0.843
Long Term Unempl.	-0.796	-14.813	-0.952	-14.259	-0.894	-20.155	-1.137	-20.028
ρ	0.514		0.572		0.522		0.506	
σ_μ	0.007		0.010		0.007		0.012	
σ_ε	0.013		0.019		0.013		0.020	
Sargan	1966.611		1863.157		2325.965		2250.005	
df	2279		2279		2501		2501	
p	1.000		1.000		0.994		1.000	

All regressions include time dummies.
df denotes the degrees of freedom.
The standard errors for the Long-Run multipliers were calculated using the Delta-Method.

Tab. 3: Estimation Results (Spatial Weighting Scheme I)

	Participants				Outflows			
	(1) 7 Days		(2) 6 Month		(3) 7 Days		(4) 6 Month	
Dep. Variable: m_{it}	Coef.	t-Value	Coef.	t-Value	Coef.	t-Value	Coef.	t-Value
Matches Lag 1	0.325	15.885	0.391	18.904	0.334	19.339	0.391	22.466
Unempl.	0.899	17.358	0.965	15.439	0.980	21.123	1.101	18.872
Spatial Unempl.	0.005	0.165	0.045	1.312	0.016	0.598	0.055	1.600
Vacancies	0.041	3.723	0.023	1.711	0.035	3.518	0.021	1.683
Spatial Vacancies	-0.014	-0.731	-0.029	-1.261	-0.007	-0.401	-0.024	-1.067
Short-Run Vocational Training	-0.048	-1.253	-0.072	-1.568	0.002	0.395	-0.009	-1.423
Long-Run Vocational Training	-0.061	-1.699	-0.122	-2.548	-0.012	-1.148	-0.039	-2.798
Short-Run TM-firm	0.016	0.677	-0.017	-0.597	-0.005	-0.387	-0.020	-1.273
Long-Run TM-firm	-0.012	-0.486	-0.067	-2.059	-0.020	-0.953	-0.067	-2.351
Short-Run TM-rem.	-0.013	-1.384	-0.028	-2.443	-0.014	-2.808	-0.020	-3.176
Long-Run TM-rem.	-0.033	-2.775	-0.033	-2.121	-0.026	-3.192	-0.026	-2.406
Short-Run Job Creation Schemes	0.003	0.219	-0.006	-0.351	-0.006	-1.658	-0.006	-1.423
Long-Run Job Creation Schemes	-0.018	-1.481	-0.043	-2.604	-0.008	-1.298	-0.012	-1.506
Short-Run Wage Subsidies	0.039	0.911	0.013	0.250	-0.023	-1.830	-0.040	-2.648
Long-Run Wage Subsidies	0.038	1.240	-0.025	-0.620	-0.040	-1.756	-0.068	-2.218
Elderly Unempl.	0.004	0.057	0.093	0.986	0.023	0.325	0.089	0.990
Young Unempl.	-0.054	-1.295	-0.079	-1.560	-0.087	-2.236	-0.115	-2.349
Unempl. Low Qualified	-0.086	-1.356	-0.163	-2.094	-0.151	-2.568	-0.238	-3.154
German Unempl.	0.833	9.292	0.881	7.992	1.022	12.717	1.143	11.145
Short Term Unempl.	0.021	0.649	0.099	2.495	-0.027	-0.889	0.036	0.951
Long Term Unempl.	-0.730	-13.301	-0.872	-12.837	-0.799	-17.761	-0.979	-17.117
ρ	0.472		0.533		0.503		0.570	
σ_μ	0.007		0.010		0.006		0.010	
σ_ε	0.012		0.017		0.012		0.017	
Sargan	1846.367		1716.332		2172.646		2084.536	
df	2191		2191		2427		2427	
p	1.000		1.000		1.000		1.000	

All regressions include time dummies.
df denotes the degrees of freedom.
The standard errors for the Long-Run multipliers were calculated using the Delta-Method.

Tab. 4: Estimation Results (Spatial Weighting Scheme II)

	Participants				Outflows			
	(1) 7 Days		(2) 6 Month		(3) 7 Days		(4) 6 Month	
Dep. Variable: m_{it}	Coef.	t-Value	Coef.	t-Value	Coef.	t-Value	Coef.	t-Value
Matches Lag 1	0.322	16.088	0.387	19.233	0.334	19.970	0.402	24.228
Unempl.	0.850	17.443	0.881	15.122	0.934	21.837	1.012	19.078
Spatial Unempl.	0.060	1.800	0.102	2.507	0.075	2.362	0.143	3.520
Vacancies	0.037	3.407	0.023	1.720	0.031	3.135	0.017	1.400
Spatial Vacancies	-0.081	-2.451	-0.110	-2.700	-0.063	-2.057	-0.102	-2.648
Short-Run Vocational Training	-0.071	-1.830	-0.119	-2.516	0.002	0.449	-0.008	-1.217
Long-Run Vocational Training	-0.070	-1.956	-0.128	-2.658	-0.014	-1.359	-0.041	-2.828
Short-Run TM-firm	-0.006	-0.251	-0.040	-1.341	-0.015	-1.131	-0.036	-2.119
Long-Run TM-firm	-0.033	-1.366	-0.099	-3.109	-0.033	-1.526	-0.098	-3.304
Short-Run TM-rem.	-0.010	-1.054	-0.032	-2.599	-0.016	-2.932	-0.022	-3.256
Long-Run TM-rem.	-0.033	-2.729	-0.039	-2.394	-0.029	-3.480	-0.031	-2.647
Short-Run Job Creation Schemes	0.001	0.104	-0.008	-0.483	-0.007	-1.817	-0.009	-1.888
Long-Run Job Creation Schemes	-0.018	-1.446	-0.042	-2.543	-0.010	-1.607	-0.014	-1.644
Short-Run Wage Subsidies	0.036	0.827	-0.004	-0.076	-0.017	-1.369	-0.036	-2.269
Long-Run Wage Subsidies	0.029	0.992	-0.055	-1.399	-0.017	-0.732	-0.043	-1.338
Elderly Unempl.	0.028	0.385	0.069	0.774	0.037	0.537	0.073	0.840
Young Unempl.	-0.019	-0.478	-0.060	-1.220	-0.040	-1.047	-0.066	-1.357
Unempl. low qualified	-0.051	-0.805	-0.110	-1.447	-0.118	-1.982	-0.179	-2.372
German Unempl.	0.846	9.816	0.950	9.013	1.071	13.752	1.231	12.458
Short Term Unempl.	-0.025	-0.793	0.047	1.208	-0.092	-3.100	-0.032	-0.866
Long Term Unempl.	-0.787	-14.622	-0.933	-13.942	-0.883	-19.802	-1.104	-19.471
ρ	0.515		0.574		0.519		0.507	
σ_μ	0.007		0.009		0.007		0.011	
σ_ε	0.013		0.019		0.013		0.020	
Sargan	1928.823		1837.842		2289.229		2235.636	
df	2191		2191		2427		2427	
p	1.000		1.000		0.978		0.998	

All regressions include time dummies.
df denotes the degrees of freedom.
The standard errors for the Long-Run multipliers were calculated using the Delta-Method.

7 Conclusion

The purpose of this paper was to estimate the macroeconomic effects of active labour market policies in West-Germany. We excluded the eastern part of Germany from our analysis, since the labor market in this part of the country still has different characteristics, when compared to the western part. We estimated an augmented matching function, in order to quantify the effects of the programmes. The matching function was augmented by spatial effects and indicators for the intensity of the labour market programmes. We used a dynamic panel estimator based on Blundell and Bond (1998), where the spatial effects in the disturbance term was modelled according to Mutl (2005). In order to analyze how robust our findings are with respect to several modelling strategies, we estimated in total 16 different specifications. To avoid possible lock-in effects, we used the outflows from the programs as indicators in addition to the participants of the programs, as is standard in many macroeconomic evaluation studies (see e.g. Hagen (2003)). A further specification variant was given by using different weighting matrices, in order to model spatial spillovers. Since, e.g., Bell and Bocksael (2000) found that parameter estimates are more sensitive to changes of the weighting matrices than to the selection of the estimation method, it is common in spatial analysis to use different weighting matrices.

We analyzed the effects of four major categories of labour market programmes in Germany, FbW, TM, JCS and BBL. In order to disentangle possible program heterogeneities in the case of training measures, we also estimated a specification where these programs were separated into industrial training and remaining training measures. The broad conclusion that we draw from our analysis is that we find no evidence of positive effects of these programmes on the matching process in West-Germany. Although, the effects increase when using outflows instead of programme participants, they remain negative in a statistical significant way. These findings are robust to the programme indicator, the outcome measure and the choice of the weighting matrix.

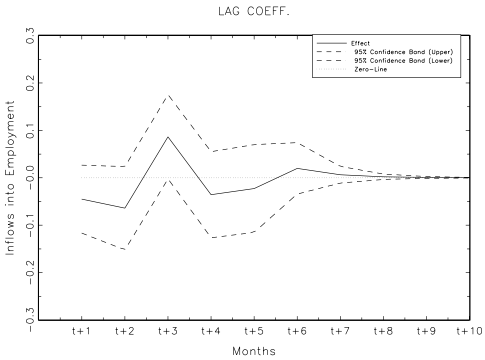
A Graphs belonging to Table 1

In this section, we include the graphics showing the lag- and cumulated lag-coefficients belonging to the estimation results presented in Table 1.

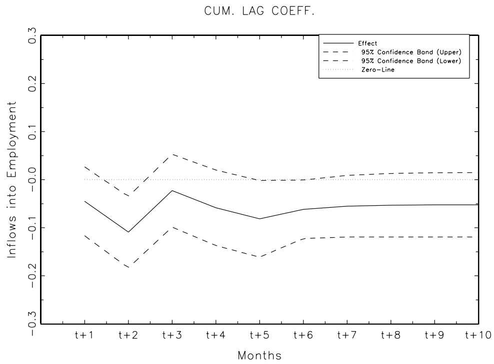
Fig. 1: Lag Coefficients 7Days;Participants;TM-Alle;FD;Binary [A]

FBW

Lag Coeff.

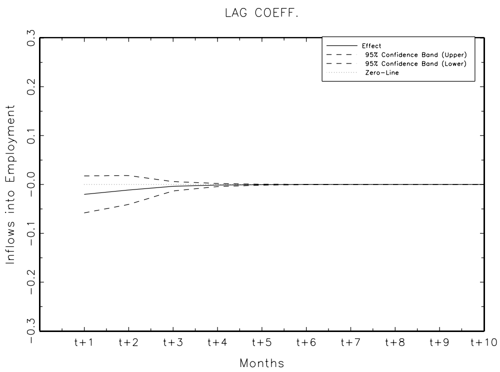


Cum. Lag Coeff.

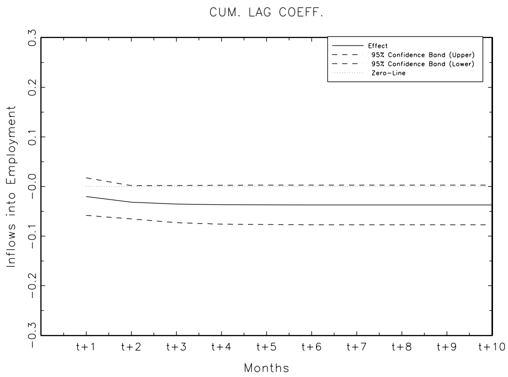


TM-ALLE

Lag Coeff.

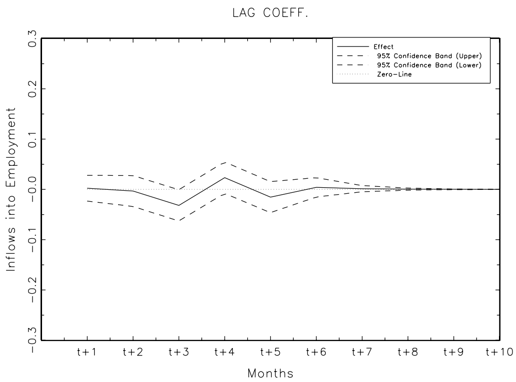


Cum. Lag Coeff.

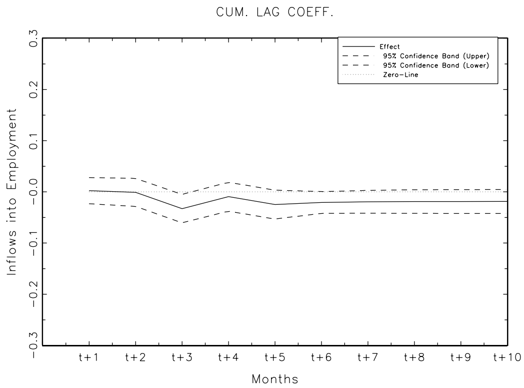


JCS

Lag Coeff.

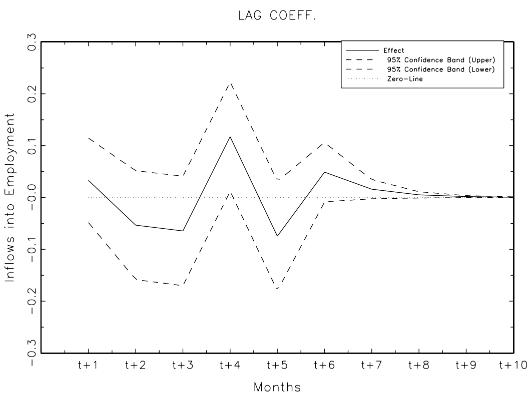


Cum. Lag Coeff.

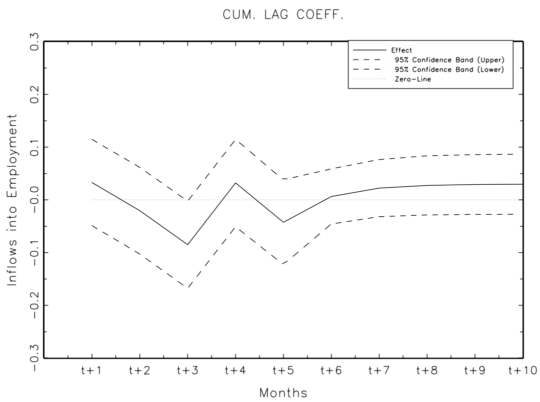


BBL

Lag Coeff.



Cum. Lag Coeff.

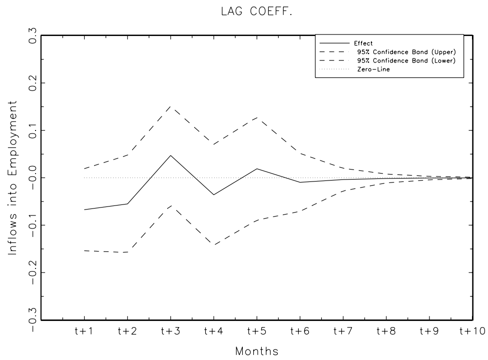


[A] Confidence bands are calculated by the Delta-Method

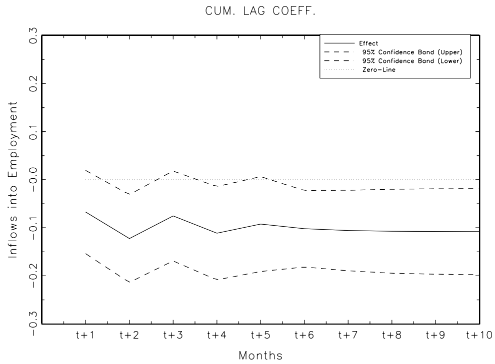
Fig. 2: Lag Coefficients 6month;Participants;TM-Alle;FD;Binary [A]

FBW

Lag Coeff.

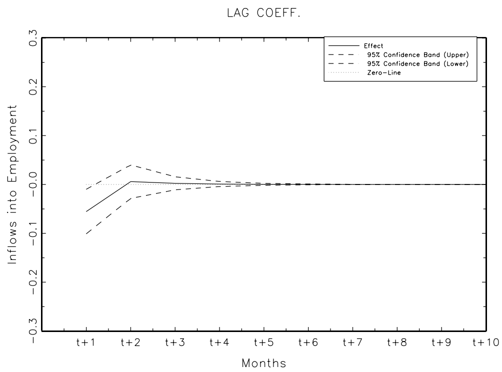


Cum. Lag Coeff.

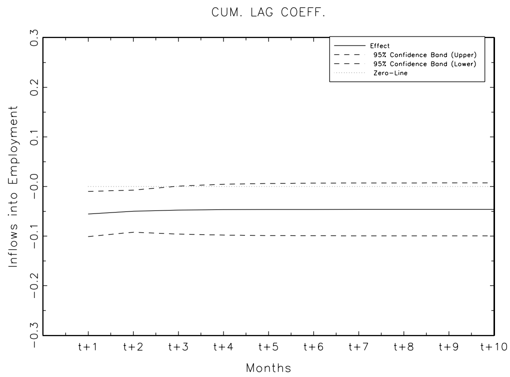


TM-ALLE

Lag Coeff.

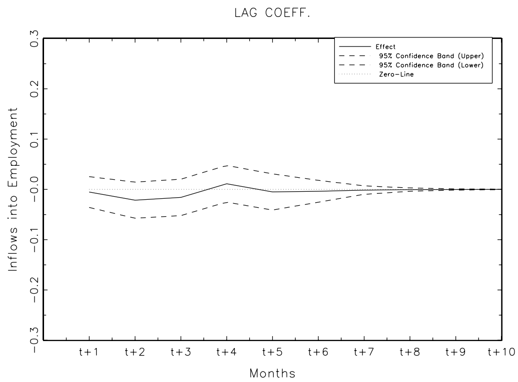


Cum. Lag Coeff.

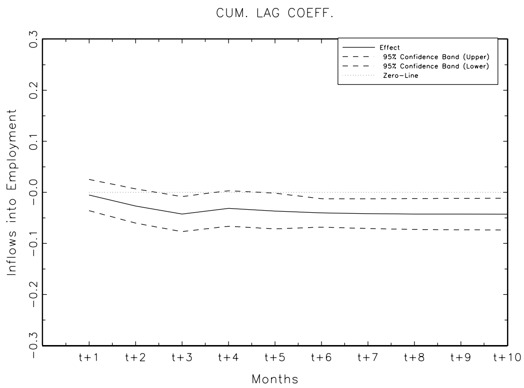


JCS

Lag Coeff.

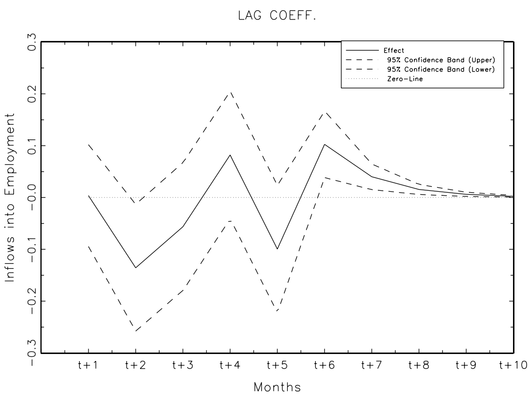


Cum. Lag Coeff.

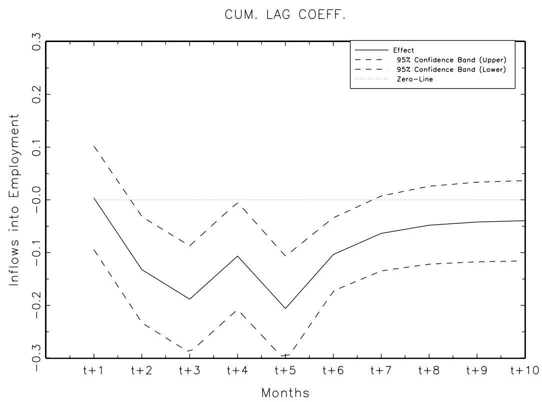


BBL

Lag Coeff.



Cum. Lag Coeff.

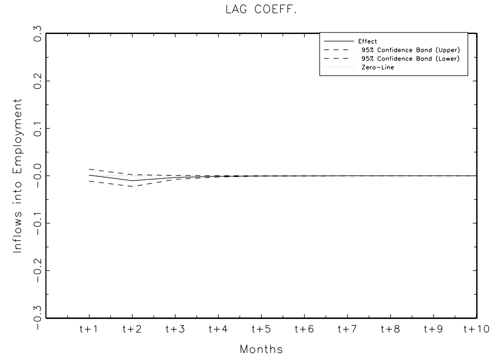


[A] Confidence bands are calculated by the Delta-Method

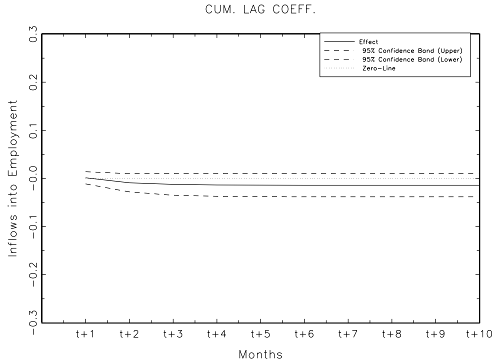
Fig. 3: Lag Coefficients 7Days;Outflows;TM-Alle;FD;Binary [A]

FBW

Lag Coeff.

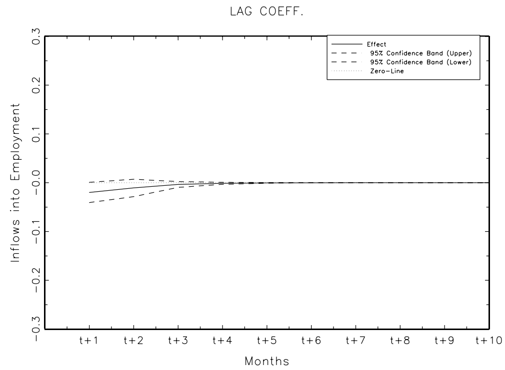


Cum. Lag Coeff.

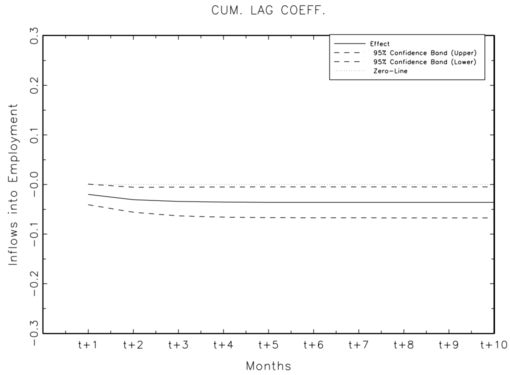


TM-ALLE

Lag Coeff.

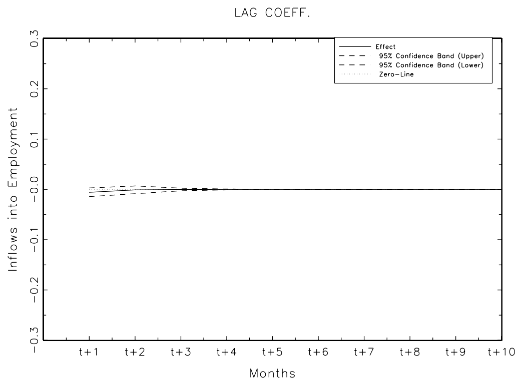


Cum. Lag Coeff.

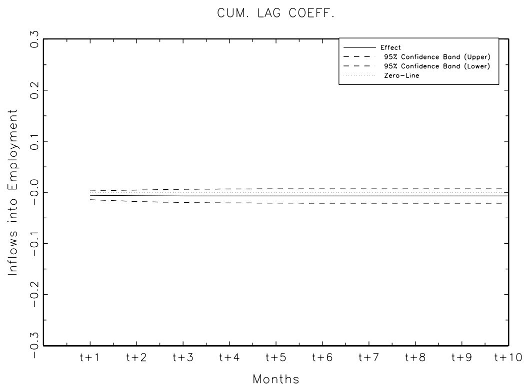


JCS

Lag Coeff.

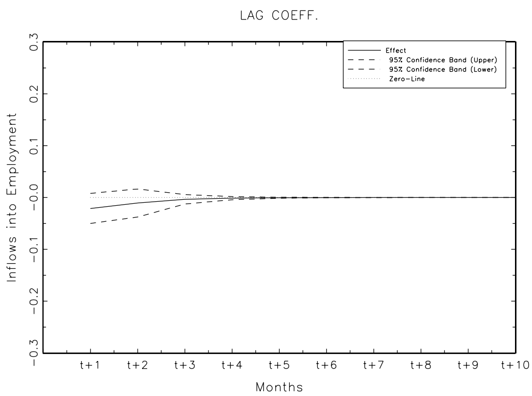


Cum. Lag Coeff.

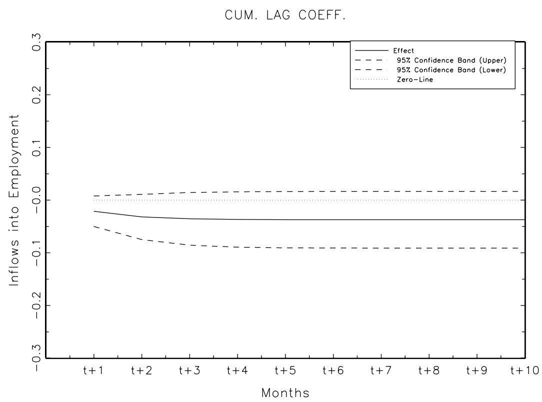


BBL

Lag Coeff.



Cum. Lag Coeff.

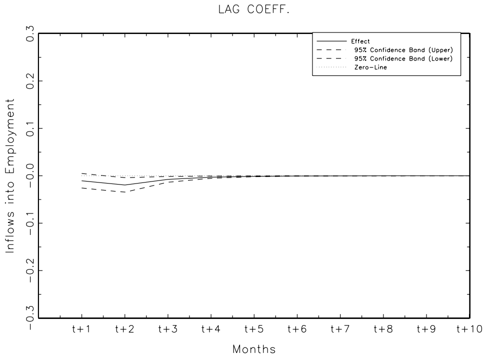


[A] Confidence bands are calculated by the Delta-Method

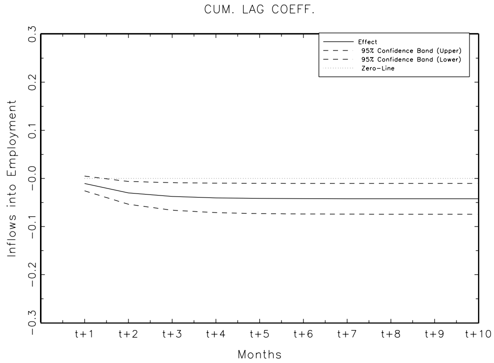
Fig. 4: Lag Coefficients 6month;Outflows;TM-Alle;FD;Binary [A]

FBW

Lag Coeff.

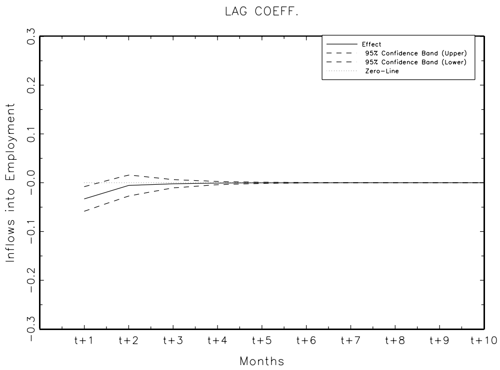


Cum. Lag Coeff.

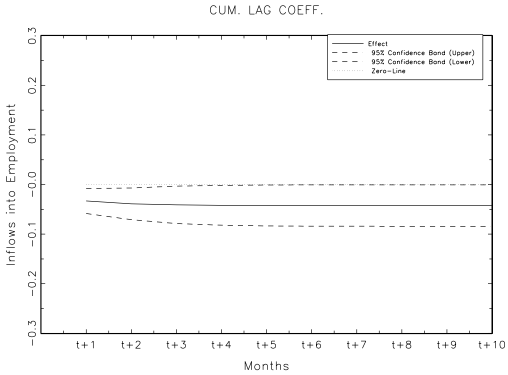


TM-ALLE

Lag Coeff.

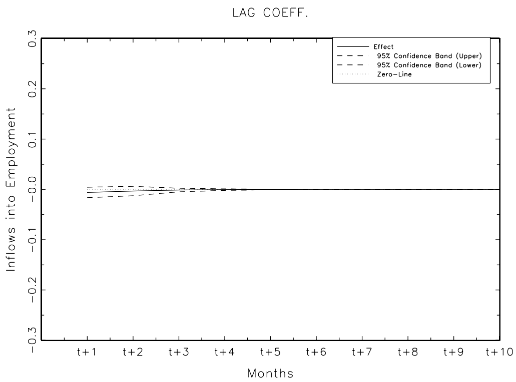


Cum. Lag Coeff.

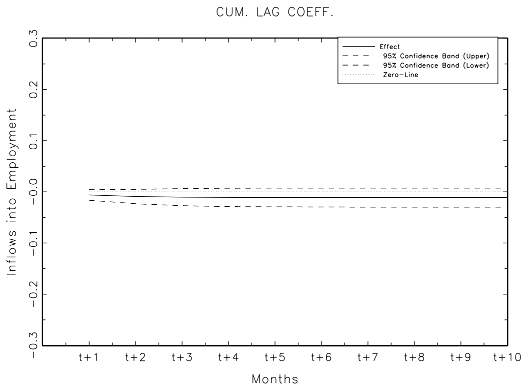


JCS

Lag Coeff.

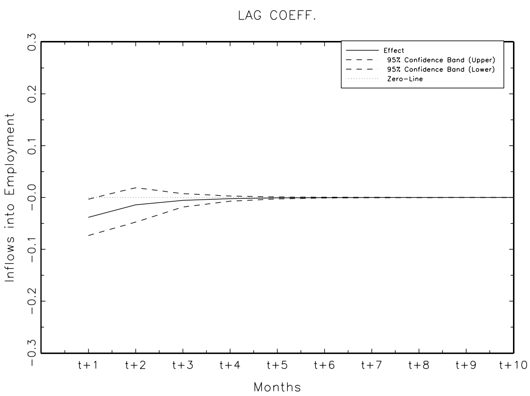


Cum. Lag Coeff.

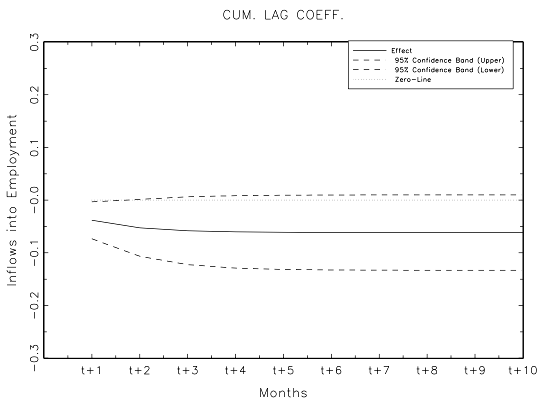


BBL

Lag Coeff.



Cum. Lag Coeff.



[A] Confidence bands are calculated by the Delta-Method

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