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Active labour-market policies in Germany

Do regional labour markets benefit?

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Contents

Abstract

Active labour-market policy (ALMP) not only affects the labour-market success of participants. Due to indirect effects, they might also affect the job perspectives of non-participants. Hence, even if ALMP programmes have a positive effect for the participants, this does not mean that ALMP improves the labour-market situation as a whole. Therefore, this paper deals with the question whether ALMP improves the matching-process between job-seekers and vacancies and thus increases the total number of outflows from unemployment into employment at the regional level. To answer this question, we use data for local employment offices of the German Federal Employment Agency for the time period 2006 to 2010 and focus on job-seekers subject to unemployment insurance. As microeconometric evaluation studies show, the search effectiveness of programme participants is low during participation due to the lock-in effect, but ideally increases at the end of the programme. In contrast to previous studies on aggregate effects of ALMP, we take this into account and explicitly differentiate current and former programme participants. The result from our augmented matching function shows that the lock-in effect is also present on the regional level. However, a higher search effectiveness after completion of the programme is not outweighed by potential indirect effects on non-participants. A higher share of former programme participants among the job-seekers in a region leads to an increase of the regional matches. This findings show that the application of ALMP improves the regional matching process. However, this effect varies largely between different types of programmes. Positive effects occur for long-term vocational training and wage subsidies as well as for in-firm training measures. Further, our results show that the effect of the different programme types depends to some extent on the regional labour-market situation.

Zusammenfassung

Aktive Arbeitsmarktpolitik (AAMP) beeinflusst nicht nur den Arbeitsmarkterfolg der Teilnehmer, sondern kann durch indirekte Effekte auch den Arbeitsmarkterfolg von Nichtteilnehmern beeinflussen. Auch wenn AAMP eine positive Wirkung auf die Teilnehmer hat, kann somit nicht geschlussfolgert werden, dass der Einsatz von AAMP mit einer allgemeinen Verbesserung der Arbeitsmarktsituation einhergeht. Diese Arbeit beschäftigt sich daher mit der Frage, ob es durch den Einsatz von AAMP gelingt, den Matching-Prozess zwischen Arbeitsuchenden und offenen Stellen zu verbessern und somit die Gesamtzahl der Übergänge aus Arbeitsuche in Beschäftigung zu erhöhen. Untersucht wird dies auf Ebene der Agenturen für Arbeit für den Zeitraum 2006 bis 2010 für Arbeitsuchende (Arbeitslose und Maßnahmeteilnehmer) im Rechtskreis Sozialgesetzbuch III (SGB III). Aus mikroökonomischen Evaluationsstudien ist bekannt, dass die Sucheffektivität der Teilnehmer während der Maßnahme aufgrund des Einbindungseffekts niedrig ist, gegen Ende der Maßnahme aber ansteigt. Im Gegensatz zu bisherigen Studien berücksichtigen wir dies in unseren Analysen und unterscheiden zwischen aktuellen und ehemaligen Maßnahmeteilnehmern. Wie unsere Ergebnisse auf Basis einer erweiterten Matching-Funktion zeigen, ist der Einbindungseffekt auch auf der regionalen Ebene zu beobachten. Eine höhere Sucheffektivität durch die Teilnahme an einer Maßnahme wird auf regionaler Ebene jedoch nicht (vollständig) durch mögliche indirekte Effekte auf die Nichtteilnehmer überlagert. Ein höherer Anteil von ehemaligen Maßnahmeteilnehmern unter den Arbeitsuchenden geht mit einem Anstieg der Übergänge aus Arbeitslosigkeit in Beschäftigung einher. Wie diese Ergebnisse verdeutlichen, verbessert der Einsatz von AAMP den regionalen Matching-Prozess. Dieser Effekt variiert deutlich zwischen verschiedenen Arten von Maßnahmen. Positive Effekte zeigen sich für den Anteil ehemaliger Teilnehmer im Fall des Eingliederungszuschusses und Maßnahmen zur Förderung der beruflichen Weiterbildung, die länger als sechs Monate dauern, sowie für Teilnehmer an betrieblichen Trainingsmaßnahmen. Weiterhin zeigen unsere Ergebnisse, dass der Effekt der verschiedenen Maßnahmen teils von der regionalen Arbeitsmarktsituation beeinflusst wird.

JEL classification: C23; H43; J64; J68

Keywords: Active labour-market programmes; evaluation; unemployment; search theory

1 Introduction

In 2010 the OECD countries spent on average 0.7 percent of their gross domestic product on active labour-market policy (ALMP) with the aim of combatting unemployment and promoting employment. The need to evaluate ALMP programmes to study whether these programmes achieved their goals was recognised at least 20 years ago by policy makers. Meanwhile there exists a large body of literature investigating the impact of such programmes on participants for many countries and a multiplicity of different programme types (see, for example, the studies summarised in Heckman/Lalonde/Smith, 1999; Greenberg/Michalopoulos/Robins, 2003; Kluve, 2010 and the appendix in Card/Kluve/Weber, 2010). These microeconometric evaluation studies try to answer the key counterfactual question: "What would have happened to a programme participant if he or she had not participated in the programme?". Kluve (2010) and Card/Kluve/Weber (2010) use a meta-analytical approach to reveal systematic patterns of the impact of ALMPs on the programme participants. Both studies find clear evidence that the effectiveness of labour-market programmes is mainly driven by the programme type rather than by labour-market institutions, the economic climate or country specific effects. Labour-market training shows modest positive effects on the programme participants. However, these positive effects only occur after a certain time lag. Job-search assistance is associated with positive impacts for the programme participants whereas public sector employment programmes are less effective. As regards subsidies for private sector employment, especially programmes including wage subsidies to employers seem to yield favourable impacts for participants.[1] Moreover, the results in Kluve (2010) show that youth programmes are less effective.

However, due to indirect effects such as substitution effects, ALMP not only has a direct influence on the participants but may also have (positive or negative) impacts on non-participants (see, for example, Calmfors, 1994; Calmfors/Forslund/Hemström, 2001, 2004; Layard/Nickell/Jackman, 2005). Microeconometric evaluation studies disregard the existence of such indirect effects. Compared to the large body of microeconometric evaluation studies the number of aggregate impact evaluation studies taking indirect effects of ALMPs into account is rather small (see below). Hence, Card/Kluve/Weber (2010) conclude that: *"A key unsettled question is whether ALMPs affect the outcomes of those who do not participate."* The aim of our paper is to shed light on this shortcoming. We do this by analysing the aggregate impact of ALMPs on participants and non-participants.

The main contribution of our paper is that we account for the findings of microeconometric evaluation studies in our aggregate analysis. A clear result from microeconometric evaluation studies is that the job-finding rate of participants completely differs between times in a programme and subsequently. Negative effects are found during programme participation and potentially positive effects generally only occur after programme completion. Transferring this result to the aggregate analysis, it becomes clear that it is crucial to differentiate between the effect of the number of job-seekers during and after programme participation. Previous aggregate studies used lagged values of the number of programme

[1] In contrast to Kluve (2010), Card/Kluve/Weber (2010) exclude wage subsidies for employers from their analysis. According to their findings, subsidies to private sector employment appear to be less effective compared to Kluve (2010).

participants to account for this difference in search effectiveness. However, following this approach solely leads to an average effect per programme that is the result of two separate processes. Hence, even if this average effect corresponds to zero, this does not mean that there are no direct or indirect effects of the programmes on the aggregate level. For example, a positive effect after programme completion outweighed by a negative effect during participation would result in a zero net effect. In contrast, our study explicitly differentiates between the number of current and former programme participants. We calculate separate aggregate impact effects for both groups. This enables us to be more specific about how direct and indirect effects influence the matching process.

In the case of aggregate impact analysis, the counterfactual question is: "What would have happened to a macroeconomic outcome variable if the intensity and mix of ALMP had been different?". In the absence of indirect effects, the intensity of ALMP should not affect the labour market outcomes of non-participants. Crépon et al. (2013) use an experimental setting to test for indirect effects of an assistance programme for young college-educated job-seekers in France. To control for a different programme intensity across regions, they randomly draw the proportion of job-seekers to be assigned to the programme for each regional labour market. Afterwards, they randomly assign the eligible job seekers to the programme according to these proportions. As the results of Crépon et al. (2013) show, the labour-market outcomes of the non-treated differ with regard to the programme intensity in a region. This provides evidence of indirect effects of the programme.

A randomisation of ALMP intensity as well as ALMP programme participation is often not feasible due to political, legal, or administrative reasons. This especially holds for the quantitatively important programmes with many participants. As a result, the application of an experimental framework to evaluate the effects of ALMP is usually limited to new programme types with a rather small number of participants or to a particular group among the job-seekers. Hence, it is common to follow a non-experimental approach to examine the aggregate effects of ALMP.

Usually, the variation in ALMP across cross sectional units and time is used to identify the aggregate effect of ALMP by means of a regression model. Several studies exist which focus on a cross section of different countries (see, for example, Bellmann/Jackman, 1996; Scarpetta, 1996; Elmeskov/Martin/Scarpetta, 1998; Nickell/Layard, 1999; Estevão, 2003 or Boone/van Ours, 2009). However, this approach has the disadvantage that programmes and labour-market institutions are very heterogeneous between countries. A more promising approach appears to be to use the regional variation in ALMP in a particular country to construct the counterfactual situation. This is the method we adopt here with each region corresponding to a local employment office district (*Arbeitsagenturbezirk*) of the German Federal Employment Agency (*Bundesagentur für Arbeit*). The local employment offices are directly responsible for assigning job-seekers to an ALMP programme.

Our paper is based on a matching function as described in Pissarides (2000) augmented by ALMP variables. There are several aggregate impact analyses that build on a matching function augmented by ALMP variables to examine whether ALMP affects the matching rate (see, for example, Boeri/Burda, 1996; Puhani, 2003; Hujer/Zeiss, 2003, 2005, 2006; Dmitrijeva/Hazans, 2007 and Hujer/Rodrigues/Wolf, 2009). This is because improving the matching efficiency is often regarded as the primary contribution of ALMP in reducing the number of unemployed and increasing the number of employees (see, for example, Calmfors/Forslund/Hemström, 2001). In this case, ALMP leads to an increasing number of outflows of job-seekers into employment given a constant number of job-seekers and vacancies. If ALMP only induces a redistribution of employment prospects between programme participants and the remaining job-seekers, the programme would go hand in hand with a favourable effect for programme participants. However, the total number of outflows of job-seekers into employment would be the same with or without the programme. In this case, ALMP would fail to improve the overall matching efficiency.

The results from previous empirical studies that follow a regional approach to examine the effects of ALMP on the matching efficiency are rather mixed. The aggregate impact of ALMP on the matching process differs both by programme type as well as between countries. Further, numerous of these studies fail to find a significant effect of ALMPs.

The results of studies analysing the effects of further vocational training are mixed. For example, Dmitrijeva/Hazans (2007) find positive effects for Latvia whereas Puhani (2003) finds insignificant effects for Poland and so do Dauth/Hujer/Wolf (2014) for Austria. The same holds for Germany where Hujer/Zeiss (2003) and Speckesser (2004) find positive effects and Hagen (2004), Hujer/Rodrigues/Wolf (2009) and Schmid/Speckesser/Hilbert (2001) find no significant effect. A positive effect is more likely to be found in western Germany than in eastern Germany. An exception are the results by Hagen/Steiner (2000) that indicate negative effects of further vocational training for western and eastern Germany. The negative effect might occur due to differences in the observation period. Hagen/Steiner (2000) is the only study that already starts in the beginning of the 1990s, shortly after German reunification.

Focusing on wage subsidies, Hujer/Rodrigues/Wolf (2009) and Schmid/Speckesser/Hilbert (2001) find no significant effects in western Germany. However, according to Dauth/Hujer/Wolf (2014), wage subsidies improve the matching efficiency in Austria.

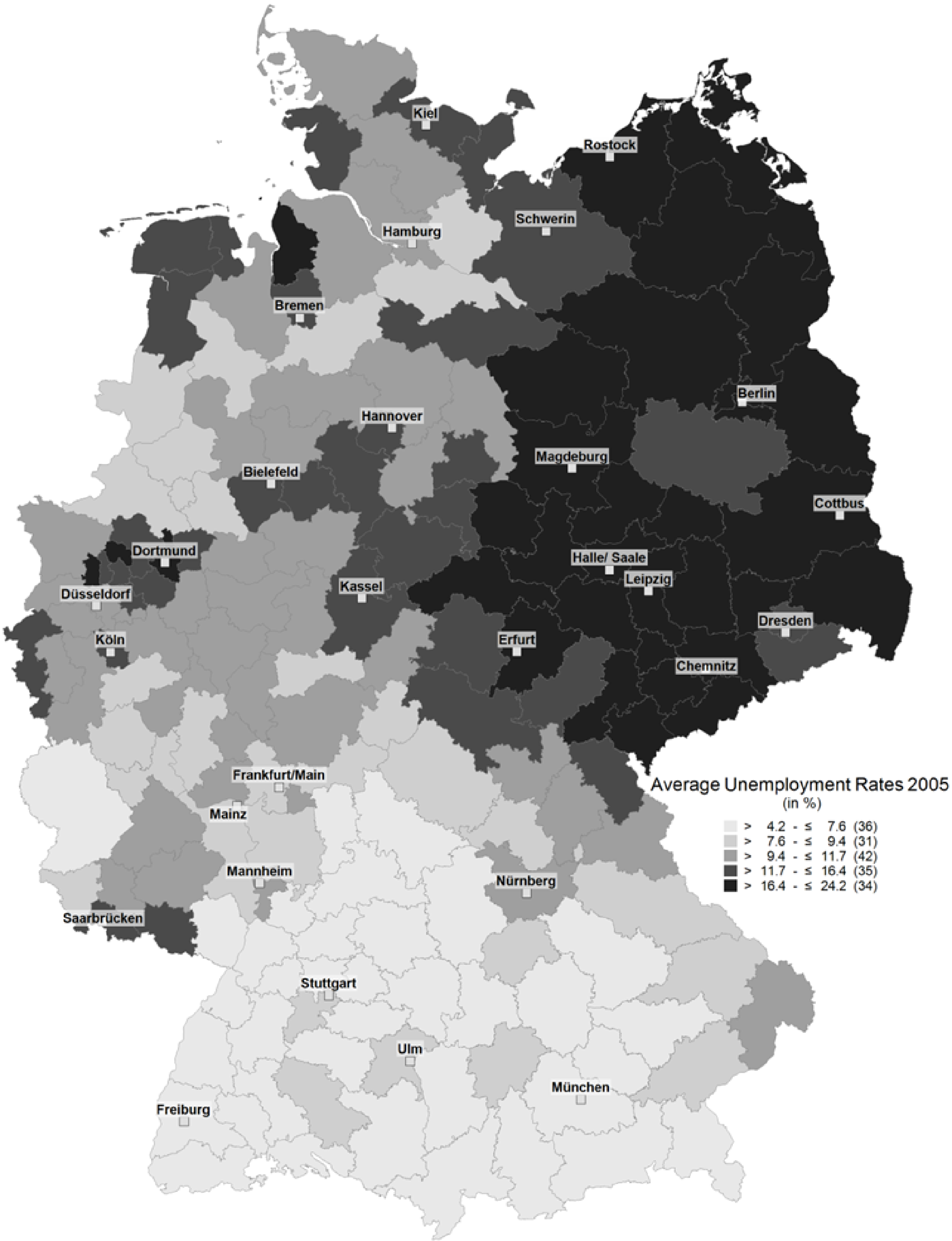
Hujer/Zeiss (2006) and Hujer/Rodrigues/Wolf (2009) provide results for the effect of training measures on the matching efficiency in western Germany. The results show no clear pattern. The direction and the significance of the effect seems to depend on the model specification and how the intensity of the programmes are measured.

The findings of the studies investigating the effects of ALMP in Germany indicate that the effectiveness of particular programmes on the matching process differs to some extent between eastern and western Germany. This might occur, for example, due to different labour-market conditions and economic structures. In general, regions in eastern Germany are characterised by an unfavourable labour-market situation whereas regions with favourable labour-market conditions are more likely to be located in western Germany. Indeed, Lechner/Wunsch (2009) show that the labour-market success of programme participants is affected by the regional labour-market conditions. Further, the results by Altavilla/Caroleo (2006, 2013) suggest that effects of ALMP programmes on regional labour markets differ between northern and southern Italy due to the different economic structure. In contrast, in his meta-study Kluve (2010: p. 915) comes to the conclusion “that there is little systematic relationship between program effectiveness and [...] the macroeconomic environment". However, in the literature on the effects of ALMP on the regional matching process, it is not systematically analysed whether the search effectiveness of participants in specific ALMP programmes varies with the regional labour-market situation. We do this by differentiating between those regions with "high" (i.e. above average) and those with "low" (i.e. below average) unemployment rates just prior to our observation period (see also, for example, Lechner/Wunsch, 2009). This is shown in Figure 1 where the above average regions are those with unemployment rates of 9.4 % or higher.

As described above, crucial for our approach is to be able to distinguish between current and former programme participants. Hence, we need to have precise information about an individual's labour-market biography. Such data is available in Germany in the Integrated Employment Biographies (IEB) of the German Institute for Employment Research (*Institut für Arbeitsmarkt- und Berufsforschung*). This dataset contains daily information on every individual at any time in which they are in employment covered by the social security system, in registered unemployment, or participating in ALMP. Aggregating the micro data on a regional level leads to a panel data set for 176 German local employment offices covering the time period from the beginning of the second quarter 2006 to the end of the fourth quarter 2010.

Our results show that if we simply include the number of programme participants as an exogenous variable, ALMP programmes have insignificant effects. This strategy is exactly the approach previously used in the literature. The fact that a coefficient is not significant could be either due to the fact that the programmes (as a whole) do not positively influence the matching efficiency. This could be the case if, for example, the lock-in effect of participants during participation reduces the local matching efficiency while at the same time the presence of former programme participants in the area increase matching efficiency because there is now less mismatch between them and labour-market demand. However, it could also be that counteracting indirect effects cancel out the direct effects. Hence, our preferred strategy to identify the effects of ALMP on the matching efficiency is to further differentiate the programme participants between those currently participating and former programme participants to account for differences in their search effectiveness. Using this approach, we find that the number of matches in a region does significantly decrease if there are relatively more (current) programme participants. Moreover, the number of matches significantly increases the higher the share of former programme participants amongst the job-seekers in a region is. This result means that the search effectiveness of former participants has increased due to participation (aggregated micro effect) and at the same time possible negative indirect effects on the remaining unemployed do not outweigh these positive effects. In our view, these results emphasise the importance of differentiating whether a participant is at the beginning of a measure or has (almost) finished a programme not only at a micro but also at a macro level.

Figure 1: Average Unemployment Rates in 2005



Source: Statistics of the Federal Employment Agency; own calculations.

If we further analyse the effects of different types of ALMP programmes separately, we find no macroeconomic effects for the share of current programme participants amongst the job-seekers except for short-term vocational training that negatively affects the matching efficiency. Positive macroeconomic effects result from higher shares of former participants in long-term vocational training and wage subsidies. Furthermore, in-firm training measures also show a positive effect.

The remainder of the paper is organised as follows. Below, we first provide institutional details about the German labour market and the programmes we consider. Subsequently, we describe the theoretical model and the empirical strategy resulting from this model. This is followed by a description of our data and descriptive findings. Then we present our results and draw conclusions.

2 Unemployment Insurance and Active Labour-Market Policy in Germany

From its introduction in 1998 until 2005, the Social Security Code III (*Sozialgesetzbuch (SGB) III*) was the only legal basis of labour-market policy in Germany. The Federal Employment Agency and its local branches at the regional level, so-called local employment offices, were responsible for all unemployed individuals. However, as part of the *Hartz*-reforms and the introduction of the Social Security Code II (*Sozialgesetzbuch II*) in 2005, the assistance of unemployed individuals not or no longer eligible for unemployment insurance moved from the Federal Employment Agency to the so-called job centres. Social Security Code III remained in force as the legal basis for unemployment insurance only. Unemployed subject to the unemployment insurance receive unemployment benefits funded by the social security contributions of employees and employers. The amount of the unemployment benefit depends on the former wage (and whether there are children in need of financial support) of the unemployed. Unemployed subject to the Social Code II receive the tax funded so-called unemployment benefit II that is means tested. Hence, despite its name, unemployment benefit II is more comparable to social assistance than to unemployment benefit. Therefore, our paper focuses on unemployed individuals subject to unemployment insurance.

A large number of measures of employment promotion exist in Germany for unemployed subject to unemployment insurance. If there are any significant effects of any measure on a macroeconomic level, then they are most likely to occur for programmes which have a "large" number of participants relative to the size of the labour market. For this reason, we concentrate our analysis on the following programmes: further (short- and long-term) vocational training, (in-firm and classroom) training measures, and employment subsidies. These are briefly described in the following.

Further vocational training measures (*Förderung der beruflichen Weiterbildung*) are designed to improve and/or adjust the qualifications of the unemployed to better fit labour demand. The measures differ considerably and can be broadly characterised as those lasting less than six months – which we call short-term vocational training – and long-term vocational training lasting up to three years. The latter retrain unemployed into new professions.

Closely related to short-term vocational training are training measures (*Trainingsmaßnahmen*). These can last up to eight weeks but are often much shorter. Here, individuals are coached how to write job applications or receive short language or computer courses. Training measures can be further divided into classroom training measures and training measures which take place in a firm. Sometimes, different training measures are combined or are followed by vocational training.

Although there are different employer subsidies in practice, we only include the employer wage subsidy (*Eingliederungszuschuss, EGZ*) as it is by far the most frequently used instrument. Is is payed to employers who hire people with placement difficulties, formerly unemployed elderly (over 50), or handicapped people. The subsidy is normally paid for a maximum of twelve months but is sometimes granted for up to eight years (e.g. for highly disabled elderly people). With the exception of the wage subsidy for elderly, there is a mandatory post subsidy employment requirement. This means that an employer must continue to hire the former participant for the same number of months that the subsidy was granted.[2]

Most important for this analysis, ALMP in Germany is determined locally. This means that the Federal Employment Agency allocates a lump sum for ALMP. The allocation of the overall budget from the federal to the regional level is part of the negotiations between the federal and local offices. The local employment offices then have a large degree of freedom as to how they divide the budget between different measures.

Nevertheless, the local employment offices cannot react instantaneously to changes in the number of unemployed. The budget-planning process for ALMP takes place in the last quarter of the previous year. This means there is a certain time lag between when measures are planned and when they can be allocated. Further, the local employment offices cannot spend the whole funds for ALMP they receive for new measures. Some of the funds are required to pay the current charges for ongoing programmes which is particularly important for long-term measures such as further vocational training and wage subsidies.

[2] If a participant is dismissed within this period for reasons that are attributable to the employer, then the employer can be asked to reimburse part of the subsidy. However, this option does not seem to be used very often.

Finally, the local employment offices do not conduct further vocational training and training measures on their own. They are carried out by so-called training providers. In the case of training measures this takes place by publishing an invitation to tender for a particular measure where the training provider with the most economical offer receives the contract. If the local employment offices require additional places for programme participants, they have to start a new award procedure. Until the award procedure is finished, they can not assign additional unemployed individuals to labour-market programmes.

3 Matching Procedure

Calmfors (1994) mentions three different mechanisms of how ALMP might facilitate the matching process. First, ALMP can help adapt the qualification of the job-seekers to the requirements of vacancies. Second, the search activity of job-seekers can be promoted. Third, and finally, ALMP can serve as a substitute for regular work experience and reduce the employer's uncertainty about the employability of job applicants. Ideally, all three mechanisms improve the matching efficiency, i.e. the rate at which job-seekers and vacancies find a fitting match on the labour market. For this reason, our analysis is based on the matching theory as described for example in Pissarides (2000).

The standard matching function describes the relationship between the number of new matches M, the number of job-seekers S and the number of vacancies V:

$$M = m(S, V) \tag{1}$$

The underlying assumption of the standard matching function (1) is that job-seekers are homogeneous and their search effectiveness is identical.[3] To analyse the effects of ALMP, it is necessary to take into account that the search effectiveness of programme participants and unemployed individuals differs. In order to do this, the standard matching function is augmented by differentiating the job-seekers S between programme participants $\bar{P}$ and the remaining (registered) unemployed U where $S = U + \bar{P}$ (see also, for example, Lehmann, 1995; Puhani, 1999 or Dmitrijeva/Hazans, 2007). Following Hynninen/Lahtonen (2007) and Ibourk et al. (2004), we define the number of "effective" job-seekers as $X = U + \bar{s}\bar{P}$. The search effectiveness is normalised to unity for the unemployed and is assumed to be $\bar{s}$ for programme participants. The augmented matching function can then be expressed as follows:

$$\begin{aligned} M &= m\left(X, V\right) \\ &= m\left(U + \bar{s}\bar{P}, V\right) \end{aligned} \tag{2}$$

At this point it is important to note that the effects of ALMP on the matches of all job-seekers are not only aggregated micro effects of participants but also include potential negative or positive indirect effects on non-participants. These indirect effects, for which the aggregate matching function implicitly accounts for, result from a redistribution of employment

[3] Following Nickell/Layard (1999: p. 3048), we define search effectiveness as "the ability and willingness of the unemployed to make themselves available for unfilled vacancies".

prospects between participants and non-participants. This occurs for instance when an employer decides to fill a vacancy with a programme participant instead of an unemployed. Therefore, from a macroeconomic perspective, $\bar{s}$ not only measures the direct effect on search effectiveness of programme participation for participants. It also measures the search effectiveness of the participants relative to that of non-participants where the latter can also change if, for example, more people start an ALMP programme.[4] This means $\bar{s}$ is determined by the aggregated individual search effectiveness $\bar{s}^*$ and indirect effects σ (see Lehmann, 1995). The number of "effective" programme participants is then given by $\bar{s}\bar{P} = (\bar{s}^* + \sigma) \cdot \bar{P}$. Estimating $\bar{s}$, as done in most existing empirical studies, gives information on the total net-effect of a change in ALMP (see, for example, Boeri/Burda, 1996; Dmitrijeva/Hazans, 2007; Hagen, 2004; Hagen/Steiner, 2000; Hujer/Rodrigues/Wolf, 2009; Hujer/Zeiss, 2003, 2005, 2006; Puhani, 2003; Schmid/Speckesser/Hilbert, 2001; Speckesser, 2004).

So far, the search effectiveness of programme participants $\bar{s}$ is identical irrespective of whether they have just started the programme or (almost) completed it. In our view, this is not adequate as it seems realistic to assume that the individual search effectiveness $\bar{s}^*$ is different during participation compared to afterwards. A programme participant reduces his/her search intensity during programme participation whereas search intensity increases after the programme finishes. In microeconometric evaluation studies this effect is known as "lock-in" effect and is often found to be substantial. Further, the aim of ALMP is that the productivity of a programme participant is higher at the end of the measure. Hence, during participation, the search effectiveness is low compared to the unemployed individuals because of a lower search intensity whereas the search effectiveness is high compared to the unemployed individuals at the end or after the programme because productivity is higher (see e.g. Lechner/Miquel/Wunsch, 2011). As we show in Appendix A.1 where we present the general equilibrium model, this leads to an ambiguous result with regard to the number of matches in a new equilibrium with more programme participants. On the one hand, a higher number of programme participants $\bar{P}$ reduces the search intensity leading to lower outflows. On the other hand, the productivity of the participants increases leading to higher outflows. However, $\bar{s}^*$ corresponds to the average relative search effectiveness and captures both effects. The sign of $\bar{s}^*$ depends on which of these two effects dominates which in turn is determined by the magnitude of the individual effects. Hence, for example, even if a programme worked "well", i.e. labour productivity is indeed much higher at the end than it was at the beginning but at the same time the number of participants in the programme (with relatively low search effectiveness) is much higher than the number of people who have completed the programme, then the average search effectiveness will be dominated by the current programme participants. In this case the average search effectiveness of programme participants is lower than the average search effectiveness of the remaining unemployed and therefore, ALMP does not improve the matching process.

4 See equation (A.2) in the appendix from which it can be seen that the job-finding rate of the unemployed depends on the share of programme participants.

Such counteracting effects have so far not been analysed in the literature.[5] We overcome this shortcoming in our paper by explicitly taking both effects into account. We augment the matching function by differentiating the programme participants $\bar{P}$ between those for whom we assume a high search effectiveness because the programme is about to finish soon or has recently been completed (which in the following we will label as Q) and other programme participants for which this is not the case (which in the following we will label as P), i.e. $\bar{P} = P + Q$.

Beside heterogenous programme effects for individual programme participants during or at the end of a programme, the indirect effects σ on the remaining job-seekers U also differ between those caused by P and Q, respectively. On the one hand, a high number of "locked-in" participants in a region relative to all job-seekers could increase the employment prospects of those unemployed that are not currently participating in an ALMP programme. This means that the unemployed in a region benefit from the lower search effectiveness of the programme participants P as the prospects of getting a job increase because competition for new jobs is less intense. This is the indirect effect σ_P caused by the programme participants P. On the other hand, a high number of former participants Q in a region relative to all job-seekers could decrease the employment prospects of those unemployed and not participating in a programme. In this case, the unemployed in a region are at a disadvantage because of the higher search effectiveness of former participants Q. This is the indirect effect σ_Q caused by the former programme participants. To account for this potential redistribution of employment prospects we include σ_P and σ_Q as potential indirect effects of the current and former programme participants, respectively. The number of "effective" programme participants is then given by

$$\bar{s}\bar{P} = s_P P + s_Q Q = (s_P^* + \sigma_P)P + (s_Q^* + \sigma_Q)Q$$

where s_P and s_Q is the search effectiveness of the current and former programme participants, respectively. These parameters include the direct effects on search effectiveness (s_P^* and s_Q^*) as well as the indirect effects on the remaining job-seekers (σ_P and σ_Q), and therefore give information on the total net-effect of a change in the number of current programme participants and of a change in the number of participants who completed their participation, respectively.

From the above, our matching function (2) now becomes:

$$\begin{aligned} M &= m\,(X, V) \\ &= m\left(U + (s_P^* + \sigma_P)P + (s_Q^* + \sigma_Q)Q, V\right) \end{aligned} \tag{3}$$

Assuming a Cobb-Douglas specification and the matching technology A, the augmented matching function (3) can be rewritten as:

$$\begin{aligned} M_t &= A X_{t-1}^{\alpha} V_{t-1}^{\beta} \\ &= A\left(U + (s_P^* + \sigma_P)P + (s_Q^* + \sigma_Q)Q\right)_{t-1}^{\alpha} V_{t-1}^{\beta} \end{aligned} \tag{4}$$

[5] Dauth/Hujer/Wolf (2014) have applied our idea to the Austrian labour market.

The number of "effective" job-seekers X can be expanded as follows:

$$\begin{aligned} X &= U + P + Q + (s_P^* + \sigma_P)P + (s_Q^* + \sigma_Q)Q - P - Q \\ &= S + (s_P^* + \sigma_P - 1)P + (s_Q^* + \sigma_Q - 1)Q, \qquad S = U + P + Q \end{aligned}$$

Inserting this expression for X into equation (4) leads to:

$$\begin{aligned} M_t &= A\left(S + (s_P^* + \sigma_P - 1)P + (s_Q^* + \sigma_Q - 1)Q\right)_{t-1}^{\alpha} V_{r,t-1}^{\beta} \\ &= AS_{t-1}^{\alpha}\left(\frac{S}{S} + (s_P^* + \sigma_P - 1)\frac{P}{S} + (s_Q^* + \sigma_Q - 1)\frac{Q}{S}\right)_{t-1}^{\alpha} V_{t-1}^{\beta} \end{aligned}$$

After taking logarithms, the augmented matching function can be expressed as:

$$\begin{aligned} \ln M_t &= k + \alpha \ln S_{t-1} + \underbrace{\alpha \ln\left(1 + (s_P^* + \sigma_P - 1)\frac{P}{S} + (s_Q^* + \sigma_Q - 1)\frac{Q}{S}\right)_{t-1}}_{\approx (s_P^* + \sigma_P - 1)\frac{P}{S} + (s_Q^* + \sigma_Q - 1)\frac{Q}{S}} + \beta \ln V_{t-1} \\ &= k + \alpha \ln S_{r,t-1} + \alpha_p \tilde{P}_{r,t-1} + \alpha_q \tilde{Q}_{r,t-1} + \beta \ln V_{r,t-1} \qquad (5) \end{aligned}$$

where $\alpha_p = \alpha(s_P^* + \sigma_P - 1), \alpha_q = \alpha(s_Q^* + \sigma_Q - 1), \tilde{P} = P/S$ and $\tilde{Q} = Q/S$.[6] In order to be able to interpret α_P and α_Q, it needs to be clear which effects they capture. They measure the net-effects of the share of current participants and former participants on the number of matches in a region during a quarter, respectively. As mentioned above the net-effect includes direct and indirect effects of ALMP. A negative α_P means that a high share of current programme participants has a negative effect on the number of matches. Due to the relative lower search effectiveness of programme participants, we assume $s_P^* < 1$. In addition, although positve, the indirect effects on U, must also be small. A positive α_Q means that a high share of former programme participants has positive effects on the number of matches. Due to the relative higher search effectiveness of former programme participants, we assume $s_Q^* > 1$. In addition, although negative, the indirect effect on U, must also be smaller (in absolute terms).

4 Data

The empirical analysis in our study is based on the comprehensive data on individual labour market activities in the Integrated Employment Biographies (IEB) of the Institute for Employment Research, Germany (*Institut für Arbeitsmarkt- und Berufsforschung*). The IEB is based on process data from administrative sources such as the German Federal Employment Agency. This data set contains daily information on every individual in employment covered by the social security system, in registered unemployment, or participating in ALMP.[7]

6 The approximation $\ln(1+(s_P^*+\sigma_P-1)P/S+(s_Q^*+\sigma_Q-1)Q/S) \approx (s_P^*+\sigma_P-1)P/S+(s_Q^*+\sigma_Q-1)Q/S$ is only valid for values of P/S and Q/S close to zero. In our case, we have a mean value for P/S of 0.07 and for Q/S of 0.04. Hence, the above transformation is a close approximation.

7 For more details see vom Berge/König/Seth (2013).

Using this data set, we aggregate the daily information on the individual level to quarterly data by local employment offices. This leads to a panel data set for 176 German local employment offices covering the time period from second quarter 2006 to fourth quarter 2010.[8] We start our analysis in 2006 because substantial labour market reforms took place in Germany in 2005 (see Section 2) leading to large variation in the data in 2005, which is partly due to statistical artifacts.

The stock of job-seekers S contains all unemployed people and all programme participants on the last day of a quarter. In contrast to previous aggregate impact studies we explicitly account for the fact that the search effectiveness of programme participants varies over time. Therefore, the job-seekers S are divided into three groups. Firstly, programme participants P who remain in a programme during the whole quarter or who complete their programme in the second half of a quarter. The reason why we also assign them to group P if they complete the programme in the second half of a quarter is that we believe that the average search effectiveness in that quarter is dominated by the programme participation effect. Secondly, programme participants Q completing their programme within the first half of a quarter. Third and finally, the remaining registered unemployed U.

A special case are wage subsidies (*EGZ*) and training measures. Employers who hire employees and receive a wage subsidy have to employ these workers for the same amount of time as they received the subsidy once the subsidy runs out. This has to be taken into account when computing the group of programme participants. We include this mandatory post subsidy employment requirement associated with the employer wage subsidy to the programme length. Hence, we not only count a person as a programme participant P while the employer receives the subsidy, but also during the subsequent mandatory employment period. The reason for this is that we assume that in this period, in which a person is fully employed, he or she will have a similar relatively low search effectiveness as during the actual programme participation. In the case of wage subsidies, we count programme participants as Q if they complete the subsequent mandatory employment period in the first half of a quarter. Otherwise, we count them as P. There is one exception to this: if the mandatory post subsidy employment requirement expires in a quarter and the person remains in the firm, we conclude that the programme was "successful" in that it raised worker productivity to a level where the employer is willing to hire him or her without a subsidy. Hence, we count these programme participants as Q irrespectively of whether they complete the mandatory employment period in the first or second half of a quarter.

Training measures are only of short duration, usually a few days or weeks. Hence, all participants in training measures at the end of a quarter generally complete this programme in the first half of the current quarter and would be assigned to group Q. It appears to be inappropriate to distinguish between two groups of programme participants according to their search effectiveness in a certain quarter. Therefore, in order to treat participants in training measures consistently, we consider them as one group.

[8] During the time period of our analysis there were 178 such offices. We aggregate the three offices in Berlin to one unit.

We count a successful match M in a certain quarter as the inflow into unsubsidised employment lasting at least seven days from the stock of job-seekers at the end of the previous quarter. In the case of wage subsidies, a "true" match in our sense of the meaning only takes place if the employment relationship continues after the mandatory period. Only if a worker whose employer formerly received such a subsidy switches firms is this immediately counted as a match. Finally, vacancies V are the stock of vacancies registered at the Federal Employment Agency for unsubsidised jobs (which are subject to social insurance contributions) at the end of a quarter.

As additional control variables we include information on job-seekers' characteristics, regional economic structure, and seasonal effects into our regression. Data on job-seekers' characteristics are gathered from the IEB whereas data on the regional economic structure and seasonal effects stem from the statistics of the Federal Employment Agency.

5 Descriptive Statistics

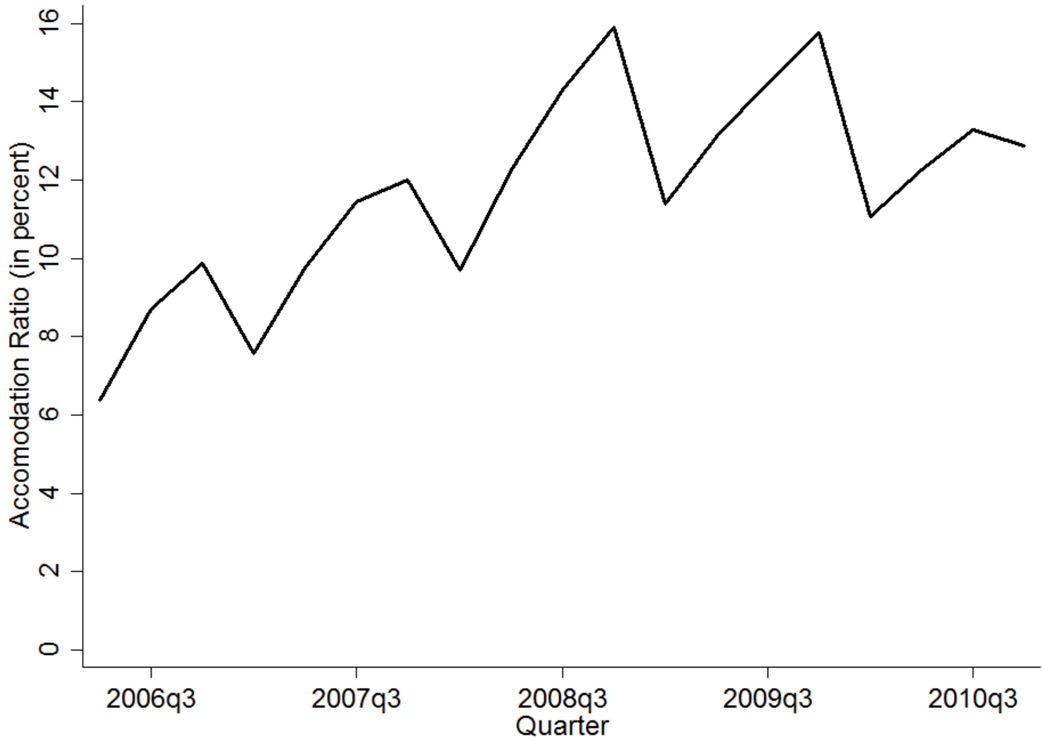
Figure 2 shows the development of the number of matches, job-seekers, and vacancies from the second quarter 2006 to the fourth quarter 2010. The development of all three variables shows a clear seasonal pattern.

Figure 2: Number Job-Seekers, Vacancies, and Matches in Germany, 2006QII – 2010QIV

Source: IER Integrated Employment Biographies (IEB) Version 09.01, Nuremberg 2012; own calculations.

The development of the number of job-seekers is characterised by a downward trend. Further, a slight increase in the number of vacancies is observable. The economic crisis that reached the German labour market in 2009, only had temporary effects. Already starting at the end of 2010, the number of job-seekers and the number of vacancies almost reached their pre-crisis values. The development of the number of matches appears to be mainly driven by seasonal patterns and exhibits no clear trend. Even in 2009 the number of outflows into regular employment remained relatively stable. The increasing number of job-seekers in 2009 was the result of increasing inflows into unemployment rather than decreasing outflows.

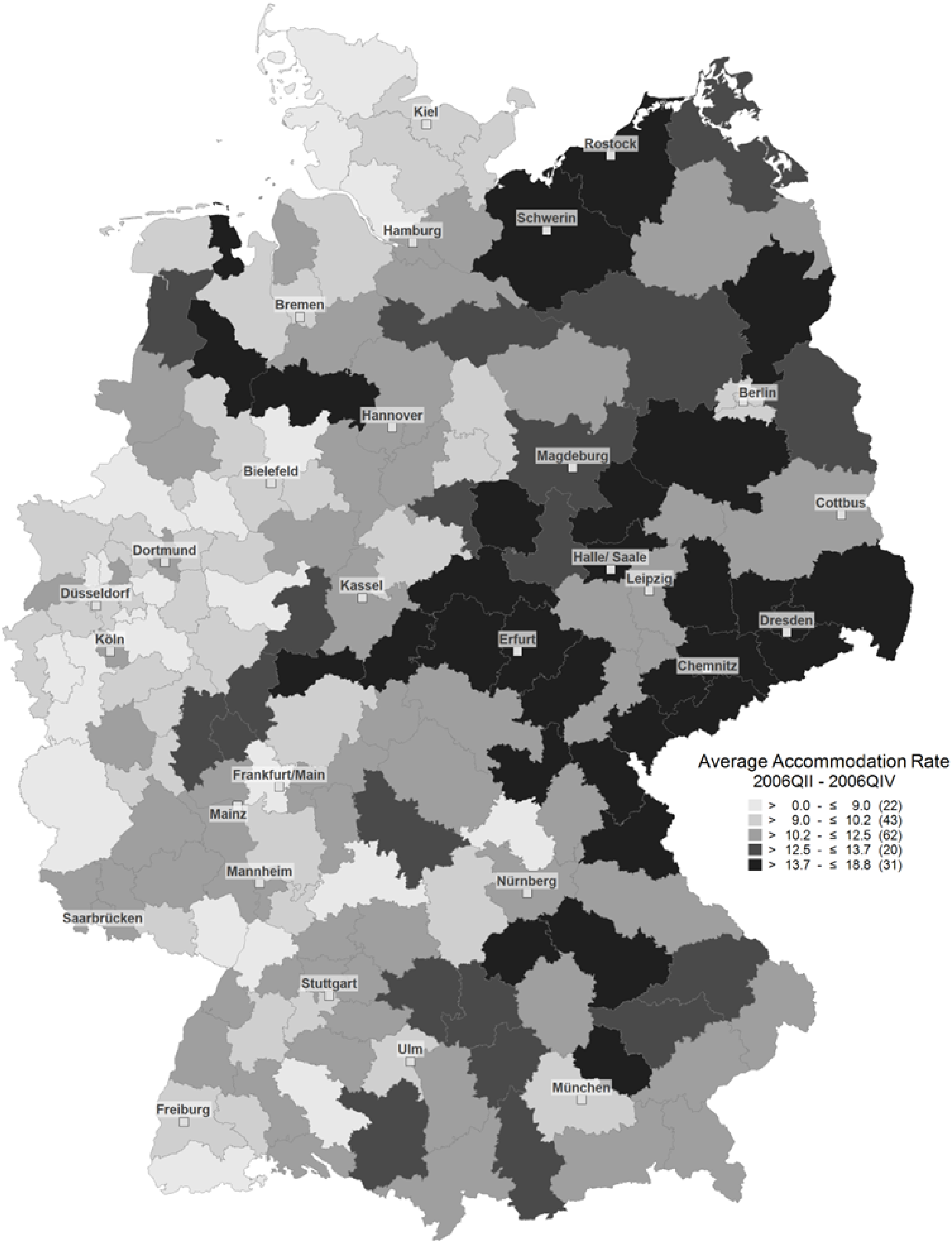
Figure 3: Accommodation Rate for Selected Programmes in Germany, 2006QII – 2010QIV



Source: IER Integrated Employment Biographies (IEB) Version 09.01, Nuremberg 2012; own calculations.

Figure 3 shows the intensity of ALMP in Germany measured by the accommodation rate (defined as the share of programme participants among the job-seekers). The accommodation rate is calculated for the total number of participants in programmes we consider in our analysis: further vocational training, training measures, and wage subsidies. The development of the accommodation rate shows a clear seasonal pattern. Further, Figure 3 reflects that the number of job-seekers and the number of programme participants do not move strictly in unison. For the time period 2006 to 2008, an increase in the number of programme participants is observable whilst the number of job-seekers is decreasing. This leads to an increase of the German accommodation rate from 6.4 percent in the second quarter 2006 to 15.9 percent in the fourth quarter 2008.

Figure 4: Average Accommodation Rates in Local Employment Offices, 2006QII – 2010QIV



Source: IER Integrated Employment Biographies (IEB) Version 09.01, Nuremberg 2012; own calculations.

Figure 4 shows the regional intensity of ALMP measured by the average accommodation rate of the local employment offices during the the observation period. On average, 11.4 percent of the job-seekers were participants in one of our considered programmes. However, the accommodation rate clearly varies between the local employment offices. Among the local employment offices, Duisburg reported the lowest accommodation rate with 6.8 percent whereas Riesa reported the highest accommodation rate with 18.8 percent.

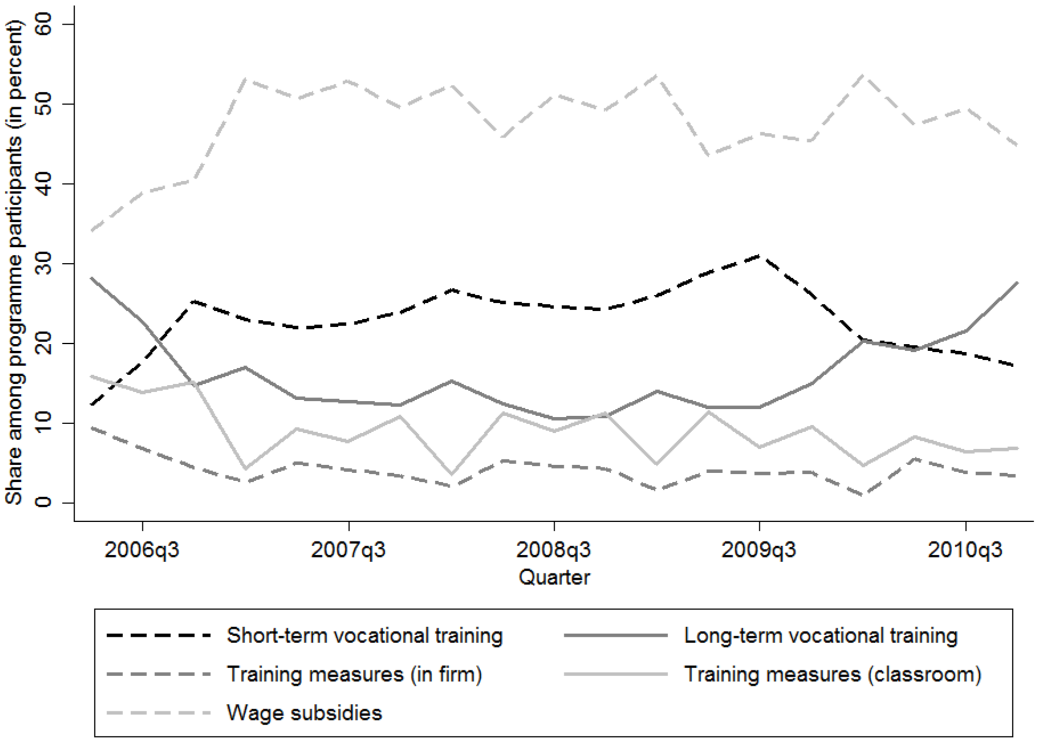
The spatial distribution of unemployment in Germany is characterised by high unemployment in eastern Germany compared to western Germany. Within western Germany, unemployment is high in the North and low in the South (see, Figure 1). As Figure 4 shows, high (low) unemployment does not necessarily imply a high (low) intensity of ALMP. Indeed, most of the local employment offices with high accommodation rates are located in eastern Germany. However, the local employment offices located in the South, where unemployment is low, report low as well as high accommodation ratios. Local employment offices with below average accommodation rates are generally located in the West where unemployment is often rather high.

As Figure 5 shows, the employer wage subsidy is the quantitatively most important programme. Between one third and one half of the programme participants among the programmes we consider in our analysis worked in a subsidised job. In contrast, the training measures are the quantitatively least important programmes. The share of participants in in-firm training measures was about 4.2 percent and the share of participants in classroom training measures was about 9.0 percent. The rather small share of participants in training measures stems from the fact that training measures are only of short duration. The high frequency of inflows and outflows in the case of the training measures leads to a small stock of programme participants compared to programmes with a long duration. Figure 5 also shows that the observation period was characterised by a change in the structure of further vocational training. At the very beginning, there were more participants in long-term vocational training than in short-term vocational training. Then long-term vocational training became less important compared to short-term vocational training. However, in 2010 long-term vocational training was the only measure with an increasing number of programme participants. At the end of the observation period, the share of programme participants in long-term vocational training again exceeded the share of programme participants in short-term vocational training.

6 Empirical Methodology

As shown in Appendix A.1.5, from the theoretical model it is by no means clear whether an increase in the number of programme participants leads to a higher number of matches in a region or not. Hence, in the following, we empirically test the theoretical model. Therefore, we need to derive an empirical estimation of equation (5) to estimate our main parameters of interest a_p and a_q. This enables us to assess the aggregate effect of ALMP on the number of matches in a region. Furthermore, the coefficients we obtain for these two parameters will enable us to test our hypothesis that the search effectiveness significantly differs for the two groups P and Q.

Figure 5: Share of Programme Participants in Germany, 2006QII – 2010QIV



Source: IER Integrated Employment Biographies (IEB) Version 09.01, Nuremberg 2012; own calculations.

We develop our empirical model in four steps. First, we start with the classical matching function as shown in equation (1). Assuming a Cobb-Douglas matching function and taking logarithms of this equation leads to the following matching function which serves as the starting point for our empirical analysis:

$$\ln M_{rt} = k + \rho \ln M_{r,t-1} + \alpha \ln S_{r,t-1} + \beta \ln V_{r,t-1} + \sum_{j=1}^{J} \gamma_j X_{jr,t-1} + d_t + d_r + \epsilon_{rt} \quad (6)$$

Our observational unit is the local employment office r ($r = 1, \ldots, 176$) at quarter t, where t ranges from the second quarter of 2006 to the fourth quarter of 2010 ($T = 19$).[9] M_{rt} represents the number of matches during a quarter t in a local employment office r realised from the stock of job-seekers $S_{r,t-1} = U_{r,t-1} + P_{r,t-1} + Q_{r,t-1}$ in that region at the end of the previous quarter at time $t-1$. As is standard in the empirical matching function literature based on regional data (see, for example, Burda/Profit, 1996; Burgess/Profit, 2001; Fahr/Sunde, 2006), we formulate a fixed effects regression model using the panel character of our data. The log of the matching technology A is decomposed into a constant k, fixed effects for regions (d_r) and fixed effects for quarters (d_t) to take into account regional and time heterogeneities. ϵ_{rt} is the usual random error term. To control for partial adjustment processes, we use a dynamic specification by including the lagged dependent

[9] As a dynamic panel data model is specified, the number of times-series observations is actually 18.

variable $\ln M_{r,t-1}$ as an additional explanatory variable. The autoregressive parameter ρ shows how quickly the number of matches adjusts to changes in the explanatory variables or to random shocks. X_j ($j = 1, \ldots, J$) are additional control variables, which are described in detail below.

To assess the effects of ALMP on the number of matches, we augment the classical matching function (1) in Section 3 by the shares of current programme participants $\tilde{P}$ and former programme participants $\tilde{Q}$. Here, we first augment equation (6) to include the sum of the shares of current $\tilde{P}$ and former programme participants $\tilde{Q}$, i.e. $\tilde{\bar{P}} = \tilde{P} + \tilde{Q}$. These effects are identified while the total number of job-seekers $S_{r,t-1}$ and vacancies $V_{r,t-1}$ are held constant.

$$\ln M_{rt} = k + \rho \ln M_{r,t-1} + \alpha \ln S_{r,t-1} + \alpha_{\bar{p}} \tilde{\bar{P}}_{r,t-1} + \beta \ln V_{r,t-1} + \sum_{j=1}^{J} \gamma_j X_{jr,t-1} + d_r + d_t + \epsilon_{rt} \quad (7)$$

In a third step, we explicitly differentiate between current and former programme participants as it is derived in equation 5 theoretically.

$$\ln M_{rt} = k + \rho \ln M_{r,t-1} + \alpha \ln S_{r,t-1} + \alpha_p \tilde{P}_{r,t-1} + \alpha_q \tilde{Q}_{r,t-1} + \beta \ln V_{r,t-1} + \sum_{j=1}^{J} \gamma_j X_{jr,t-1} + d_r + d_t + \epsilon_{rt} \quad (8)$$

We are not only interested in the aggregate effect of programme participation. ALMP are heterogeneous and hence we expect that their influence on the matching process differs. Therefore, in a fourth step we differentiate between the programmes i with $i = 1 \ldots I$ as described in Section 2 and obtain the following matching function:

$$\ln M_{rt} = k + \rho \ln M_{r,t-1} + \alpha \ln S_{r,t-1} + \sum_{i=1}^{I} \alpha_{pi} \tilde{P}_{ir,t-1} + \sum_{i=1}^{I} \alpha_{qi} \tilde{Q}_{ir,t-1} + \beta \ln V_{r,t-1} + \sum_{j=1}^{J} \gamma_j X_{jr,t-1} + d_r + d_t + \epsilon_{rt} \quad (9)$$

Lechner/Wunsch (2009) as well as Altavilla/Caroleo (2006, 2013) show in their evaluation of ALMP that the impact of a specific measure can differ depending on the regional labour-market situation. As in Germany the regional unemployment rates differ to a large extent (see Figure 1) it is of great importance to analyse whether these different impacts are present in Germany too. We do this by differentiating between local employment offices with “high” (i.e. above average) and those with “low” (i.e. below average) unemployment rates at the beginning of our observation period. Hence, we augment equation (9) and include interaction effects indicating if a local employment office belongs to the group of “high” unemployment regions or not.

$$\ln M_{rt} = k + \rho \ln M_{r,t-1} + \alpha_1 \ln S_{r,t-1} + \alpha_2 I_r^l \ln S_{r,t-1} + \sum_{i=1}^{I} \alpha_{1pi} \tilde{P}_{ir,t-1} + \sum_{i=1}^{I} \alpha_{2pi} I_r^l \tilde{P}_{ir,t-1} + \sum_{i=1}^{I} \alpha_{1qi} \tilde{Q}_{ir,t-1} + \sum_{i=1}^{I} I_r^l \alpha_{2qi} \tilde{Q}_{ir,t-1} + \beta_1 \ln V_{r,t-1} + \beta_2 I_r^l \ln V_{r,t-1} + \sum_{j=1}^{J} \gamma_{1j} X_{jr,t-1} + \sum_{j=1}^{J} \gamma_{2j} I_r^l X_{jr,t-1} + d_r + d_t + \epsilon_{rt} \quad (10)$$

with I_r^l equal to 1 if r belongs to the group of high unemployment regions and 0 otherwise.

Concerning potential omitted variables bias in all our specifications, it should be noted that the fixed regional and quarter effects account for all unobserved factors that are region- or time-specific, respectively. However, there are of course other time-region varying determinants of the number of regional matches during a specific quarter. Therefore, we include additional control variables X_j ($j = 1, \ldots, J$). These variables can be grouped into three main categories: job-seekers' characteristics, regional economic structure and seasonal effects. With regard to job-seekers' characteristics, we include the share of female job-seekers, the share of job-seekers younger than 25 and the share of job-seekers who are 50 years or older as well as the share of non-native job-seekers.[10]

To control for the regional economic structure, we first concentrate on the regional employers' and employees' characteristics. We include the share of employees working in large establishments (250 or more employees) and the share of employees working in medium-sized establishments (10 to 249 employees). Further, we add the share of female employees, the share of (high-)qualified employees and the share of employees working in service professions. As the number of new matches in a region is also likely to be affected by the structure of the unemployed, we include the share of unemployed subject to the means tested unemployment benefit II. It is likely that in regions with poor labour-market conditions it takes longer to find a job. Hence, we expect these regions to have a higher share of long-term unemployed which mainly receive unemployment benefit II.

The recession in 2008/2009 occurred during our observation period and although Germany's unemployment rate increased by far less than in other countries, there was still undoubtedly a large macroeconomic impact. The German government reacted to this recession by making short-time work compensation (*Kurzarbeitergeld*) much more attractive to employers. Hence, we use the share of employees covered by this specific measure relative to all employees in a region as an additional explanatory variable.

The third category of control variables concerns seasonal effects. This is particularly important as we have quarterly data were seasonal fluctuations play a large role. As not all local employment offices undergo the same seasonal pattern for which the time fixed effects would control, we further include an interaction effect of seasonal dummies and region type. Following a classification of local employment offices developed by Blien/Hirschenauer/Phan thi Hong (2010), we differentiate between 13 different types of local employment offices based on their labour-market conditions in 2007. In addition, we include two variables to account for differences in the regional development of employment

[10] This group is comprised of people with a non-German nationality as well as Ethnic Germans who have a German nationality.

and unemployment. To make sure that these are unaffected by seasonal patterns, we use the growth rate with regard to the same quarter of the previous year. Finally, to control for the seasonal span, we also include the deviation of actual employment from its seasonally adjusted level.

If local employment offices immediately react to changing economic conditions, i.e. there is a political reaction function, then there is a potential endogeneity problem with our ALMP-variables in equations (7) – (10). In this case, the number of matches and the intensity of ALMP are determined simultaneously and the number of matches in a region during a quarter are one determining factor when deciding on the ALMP intensity. Ignoring such a reverse causality – if it exists – leads to a simultaneity bias (see Calmfors/Skedinger, 1995). One strategy to deal with this problem is to apply an instrumental variable approach. Calmfors/Skedinger (1995), for example, suggest using the share of a region's seats in parliament associated to left parties. However, in our case, it is reasonable to assume that the simultaneity problem is not present or at least it is not severe. There are several reasons for this: First, our ALMP variables are not measured as the stock of (former) participants but as the share of (former) participants of all job-seekers in a region. As Calmfors/Skedinger (1995) state, such a specification lessens the extent of simultaneity. Second, as explained in Section 2, given the Federal Employment Agency budgeting rules for an individual local employment office, it is practically impossible to instantaneously increase or decrease the number (or type of) measures to changing labour-market conditions. The number and types of measures have to be planned and budgeted several months prior to their start. Third, the timing of our approach reduces the problem. There is no reason to assume that the number of matches during a quarter affects the stock of job-seekers or the local ALMP intensity at the end of the previous quarter. Therefore, we are able to consider our ALMP variables as weakly exogenous. Fourth and finally, as we show in Section 7.2, the Sargan test does not reject the null hypotheses that all the instruments we use are valid instruments. This implies that the exogeneity hypothesis for our explanatory variables could not be rejected.

7 Results

7.1 Estimation methodology

As outlined in Section 6, we specify a dynamic panel fixed effects model as our main estimation model. As fixed effects estimates are biased because of the correlation between the residuals and the lagged endogenous variable, we use the GMM framework initially proposed by Arellano/Bond (1991). Following the literature, we use the first-step heteroscedasticity-robust estimation versions of the difference GMM estimator as well as of the System GMM estimator (see Arellano/Bover, 1995 and Blundell/Bond, 1998). To test the assumptions necessary for the consistency of these estimators, we show the p-values of the Arellano and Bond test for serial autocorrelation (see Arellano/Bond, 1991) as well as the results of the Sargan/Hansen test of overidentifying restrictions for each estimated model.

Due to the dynamic specification of the model, the estimated coefficients show only the contemporary effects of the explanatory variables. To calculate the long-run effects, one must take the autoregressive parameter ρ into account. The calculation formula is analogous to the autoregressive distributed lag models (see Greene, 2008: p. 684), i.e.:

$$\widehat{\beta}_{lr} = \frac{\widehat{\beta}}{1-\widehat{\rho}}$$

The respective standard errors are calculated by the delta method.

7.2 Baseline results

Table 1 shows our baseline results, which will provide the benchmark for the other empirical estimates discussed in subsections 7.3 and 7.4. We estimate several different specifications as explained in Section 6. Initially we test the standard matching function with only the job-seekers S and vacancies V as arguments (Model 1) for Germany as a whole.[11] The next specifications (Models 2 – 4) focus on the effects of ALMP on the matching process. In Model (2) the standard matching function is augmented by the share of job-seekers which are in one of our considered ALMP programmes at the end of the previous quarter. Hence, this model corresponds most closely to the approach used in other macroeconomic studies which do not take the fact explicitly into account that the search effectiveness of programme participants changes whilst being in the programme. Model 3 shows the results when differentiating the programme participants further into P and Q according to the point in time when they complete their programme. Finally, Model 4 shows the results when accounting for potential heterogeneity in the influence of different programmes on the regional matching process.

Before we turn to the interpretation of our estimated coefficients, the appropriateness of our estimation procedure needs to be discussed. The Arellano-Bond tests leads to the conclusion that the assumption of serially uncorrelated errors could not be rejected. The Sargan test statistics imply that all our instruments are valid.[12]

Turning now to the interpretation, it can be seen from the results of Model (1) (see Table 1) that the estimated long-run elasticity with respect to job-seekers is 0.832 and with respect to vacancies 0.064. The coefficient of the vacancies is rather small. However, it is in line with the findings of other studies that use the matches of unemployed individuals instead of all hirings as dependent variable (see, for example, Broersma/van Ours, 1999). The sum of both estimated elasticities is not significantly different from one. Thus, the German matching function is characterised by constant returns to scale in the observation period of 2006 to 2010. This is also true for the specifications where ALMP is included (Models 2 – 4).

[11] In each specification, further exogenous variables are taken into account to control for the regional and time varying composition of the job-seekers and employees as well as for regional effects that exhibit seasonal variation. See Table A.1 for the full results.

[12] The above defined models are estimated by the system GMM estimator using all available lags of the dependent variable as instruments. When reducing the number of instruments the results are qualitatively and also quantitatively almost the same. The same is true when using the Arellano-Bond GMM estimation procedure instead of the system GMM. Results are available upon request from the authors.

Table 1: Estimation Results – Long Run Coefficients

Dep. Variable: Log Matches	Model 1	Model 2	Model 3	Model 4
Lagged no. of matches	0.106***	0.105***	0.104***	0.077***
	(0.024)	(0.024)	(0.023)	(0.024)
Log no. of job-seekers	0.832***	0.827***	0.838***	0.877***
	(0.055)	(0.054)	(0.054)	(0.052)
Log no. of vacancies	0.064***	0.065***	0.070***	0.066***
	(0.015)	(0.015)	(0.014)	(0.014)
Share of P and Q		-0.089		
		(0.122)		
Share of P			-0.580***	
			(0.144)	
Share of Q			0.837***	
			(0.227)	
Share of short-term voc. train. P				-0.841***
				(0.288)
Share of short-term voc. train. Q				-0.178
				(0.372)
Share of long-term voc.train. P				-0.215
				(0.375)
Share of long-term voc. train. Q				1.873**
				(0.929)
Share of wage subsidies P				-0.263
				(0.226)
Share of wage subsidies Q				4.225***
				(0.493)
Share of classroom training measures				0.063
				(0.284)
Share of in-firm training measures				2.611**
				(1.275)
Sargan test statistic	148.140	147.074	143.745	141.132
Sargan (p-value)	0.875	0.887	0.921	0.942
AR1 (p-value)	0.000	0.000	0.000	0.000
AR2 (p-value)	0.686	0.719	0.829	0.951

Note: Results are robust, one-step system GMM estimates. The standard errors (in parentheses) are calculated by the delta method. *** Significant at the 1%-level; ** Significant at the 5%-level; * Significant at the 10%-level. All models include time and regional fixed-effects as well as further exogenous variables. Table A.1 in the appendix shows the results for all exogenous variables. For all regressions $N = 3168$.

Model 2 includes the share of ALMP programme participants. Here, the regional intensity of ALMP at the end of a quarter has a negative but non-significant effect on the number of matches in regular employment that could be realised in this region during the subsequent quarter. The fact that the coefficient is not significant could be either due to the fact that the programmes (as a whole) do not have a positive influence on the matching efficiency. However, it could also be due to the fact that there are counteracting effects as described above which cancel each other out. Hence, our preferred strategy to identify the effects of ALMP on the matching efficiency is to differentiate the programme participants further into current and former programme participants, e.g. using two explanatory variables (see Model 3).

Concerning the current programme participants, the number of matches in a region significantly decreases if there are relatively more programme participants in the district of a local employment office. This means that the individual direct effect during participation – the lock-in effect – is also present at the aggregate level. Even if a redistribution of employment prospects between locked-in participants and other unemployed took place, it is not large enough to outweigh the direct negative effects. Thus, there seems to be evidence of a macroeconomic lock-in-effect. Moreover, the number of matches significantly increases the higher the share of former programme participants Q amongst the job-seekers in a region is. This result has two implications. First, the aggregated effect of a higher intensity of former ALMP participants on the matching efficiency is positively significant. This can only be the case if the search effectiveness of the former participants is increased due to participation (aggregated micro effect) and at the same time possible negative indirect effects on the remaining unemployed do not outweigh these positive effects for the individual participants. Such an increased search effectiveness after participation on the individual level is found in many micro-empirical evaluation studies for Germany (see, for example, Lechner/Miquel/Wunsch, 2011) and is now confirmed to be also present on the aggregate level. The second implication is that we find clear evidence of the counteracting effects which lead to the ambiguous result of ALMP in our theoretical model. Our result shows that it is important to differentiate between the two groups of participants according to the point in time when they complete their programme as the different search effectiveness on the micro level is also existent at the macro level.

Based on the fact that the effects for the individual participants differ between different types of ALMP programmes we expect the influence on the matching process to vary, too. Therefore, in Model 4 we differentiate between five types of programmes. As can be seen from Table 1, the coefficient of the share of current programme participants is either insignificant or significantly negative, the coefficient of the share of former programme participants is either insignificant or significantly positive. The only significant coefficient for the share of the current participants is the one for short-term vocational training. The lock-in effect at the individual level, which is found e.g. by Biewen et al. (2014), is also present at the macro level even when indirect effects are also accounted for. However, for long-term vocational training and wage subsidies, this is not the case. An increasing share of current programme participants in these two programmes has no significant effect on the number of matches in the subsequent quarter in a region. This means that although the individual participants are locked-in and therefore are less likely to realise a match, the total number of matches in that region still stays the same. This can only be the case if a redistribution of employment prospects between the several subgroups of job-seekers takes place. Hence, there is a positive substitution effect whereby the remaining job-seekers benefit from the reduced competition and therefore are more likely to realise a match.

Regarding the share of the former programme participants, two of the three considered programmes show significantly positive coefficients. Both a higher share of former participants in long-term vocational training as well as in wage subsidies increase the matches in a region. However, the latter effect is much stronger. The necessary condition for such a positive aggregate effect is that the individual participants benefit from their participation. For Germany, such positive effects on the employment prospects for participants in long-term vocational training were recently found by Kruppe/Lang (2014). The fact that the coefficients are significant at the regional level means that even if there are negative indirect effects on the other job-seekers, they are not large enough to outweigh the aggregated positive effects of these programmes. Regarding the share of former participants in short-term vocational training, the coefficient could be insignificant for two reasons: First, there are no positive direct effects for the participants of this measure, or second, negative indirect effects outweigh existing positive effects. Considering the existing results of the micro empirical evaluation studies for this programme type (see Lechner/Miquel/Wunsch, 2011; Kluve et al., 2012) which all find a positive effect for the individual participant in short-term vocational training, the second explanation is more convincing.

Finally, we consider the effects of two kinds of training measures – in-firm and classroom – on the matching process. Due to the short duration of these programmes we do not distinguish between current and former programme participants. The results show that a higher share of participants in classroom training in a region does not significantly increase the matches in that region in the subsequent quarter. Again this could be caused by a missing effect on the level of the individual participants or due to negative indirect effects from the participants on the other job-seekers. However, with regard to in-firm training measures, a higher share has a significantly positive effect on the number of matches. This difference in the effects of the two types of training measures is also confirmed in an micro-level study by Stephan/Rässler/Schewe (2006).

Apart from the variables shown in Table 1, we also control for job-seekers' characteristics, the regional economic structure and seasonal effects. The results for all variables are as expected and extremely stable for all our models – see Table A.1. As the negative effect of the share of women among the job-seekers shows, women have more difficulties than men in finding new jobs. This could be due to the fact that with the exception of the recession in 2009, our time span is characterised by a strong economic upturn in which men traditionally are more likely to find jobs (just as their chances of loosing their jobs during a downturn are also higher). Older job-seekers and non-natives both have significantly lower chances of finding new jobs.

With regard to the regional economic structure, we find large (and significant) positive effects for the tertiary sector, (high-)skilled workers as well as for large establishments, (i.e. 250 or more employees). In the first two cases, this is plausible as both the tertiary sector as well as (high-)skilled employment has been growing steadily in the last years. The number of employees in the tertiary sector only slightly went down during the recession. With regard to large establishments, by definition they are likely to hire more people in a given time interval simply because of their large size. In contrast, we find a strong negative effect for the share of females employed in a region. This somewhat surprising result may be driven by the large differences in the female labour-force participation between eastern and western Germany. It seems plausible that within these two regions there is relatively small regional variation and that hence, this variable is highly correlated with our regional structure. In Section 7.3 we explicitly take this regional variation in labour-market conditions into account and find that – unlike the other control variables – the coefficients for the share of females in the labour force are different from those presented here and also between the two types of regions.

The German labour-market benefit system is divided into two main parts. We expect regions with a higher share of unemployed people subject to unemployment benefit II to also exhibit fewer matches as this is a sign of bad regional labour-market conditions. This is confirmed by our regression results.

Germany's labour market proved to be very robust during the recession in 2009. One of the reasons for this was that many firms used "short-time" work measures which were heavily subsidised by the government and made it attractive for employers to reduce the number of hours a person worked without having to dismiss them. Although this measure helped keep many people in work, at the same time during the recession it was particularly difficult for an unemployed individual to find a new job. Again, this microeconomic finding is also confirmed at the regional level.

Not surprisingly, regions with high growth rates of unemployment in the past twelve months exhibit lower job-finding rates and the opposite is true if a region exhibited net employment growth in that time. Finally, the deviation of actual employment from the seasonally adjusted level shows a strong and significant negative coefficient. Hence, if employment growth was relatively strong in the recent past, then fewer jobs are started in the current quarter.

7.3 Low- and high unemployment regions

As shown in Section 1 and 4, there are large regional labour-market disparities in Germany. This means that the extent of programme participation, the composition of the programme participants and also potentially the effects of the individual programmes might be different. To see if ALMP effects vary depending on the labour-market situation, we augment our estimation equation and include interaction effects indicating if a local employment office belongs to the group of "high" unemployment regions (see equation 10).

As above, we differentiate between five types of active labour-market programmes (see Table 2). Regarding the two main variables of the matching function – job-seekers and vacancies – we observe that the number of vacancies only has a significant effect on the number of matches in the subsequent period in the group of high-unemployment regions. The coefficient is positive and significant as well as significantly greater than the effect for the low-unemployment regions. As Andrews et al. (2013) show, the stock of new vacancies has an additional positive effect on the job-finding rate of the job-seekers. The vacancies are on average "older" in low-unemployment regions compared to high-unemployment regions, which might explain the differences between low- and high-unemployment regions.

Relating to the ALMP variables the pattern is by and large very similar to the results for Germany as a whole. Again, the coefficients of the share of current programme participants for the different programme types is either insignificant or significantly negative. The corresponding coefficients of the share of former programme participants is either insignificant

Table 2: Estimation Results for “Low” and “High” Unemployment Areas – Long Run Coefficients

Dep. Variable: Log Matches	Model 4 Low	Model 4 High	Difference High-Low
Lagged no. of matches	0.080***		
	(0.023)		
Log no. of job-seekers	1.110***	1.005***	0.105
	(0.087)	(0.101)***	
Log no. of vacancies	0.016	0.087***	-0.071**
	(0.018)	(0.023)	
Share of short-term voc. train. P	-0.636*	-0.905**	0.269
	(0.337)	(0.443)	
Share of short-term voc. train. Q	-0.224	0.552	-0.776
	(0.399)	(0.523)	
Share of long-term voc. train. P	-0.001	-0.865	0.864
	(0.437)	(0.736)	
Share of long-term voc. train. Q	1.171	3.974**	-2.803
	(1.033)	(1.652)	
Share of wage subsidies P	-0.684**	-0.307	-0.376
	(0.280)	(0.333)	
Share of wage subsidies Q	3.567***	5.341***	-1.774**
	(0.574)	(0.668)	
Share of classroom training measures	0.274	-0.323	0.597
	(0.303)	(0.466)	
Share of in-firm training measures	3.567**	1.565	2.002
	(1.446)	(1.640)	
Sargan test statistic	120.691		
Sargan (p-value)	0.998		
AR1 (p-value)	0.000		
AR2 (p-value)	0.846		

Note: Results are robust, one-step system GMM estimates. Standard errors (in parentheses) are calculated by the delta method. *** Significant at the 1%-level; ** Significant at the 5%-level; * Significant at the 10%-level. Model includes time and regional fixed-effects as well as further exogenous variables. Table A.2 in the appendix shows the results for all exogenous variables. $N = 3168$.

or significantly positive. The coefficient of the share of current participants in short-term vocational training remains significantly negative for high- and low-unemployment regions. However, we find significant positive effects for the share of former participants in long-term vocational in high-unemployment regions and for the share of former participants in in-firm training measures in low-unemployment regions. The estimated coefficients do not significantly differ between high- and low-unemployment regions in both cases.

Further, it seems that in particular the effects of wage subsidies are more favourable in high-unemployment regions. The coefficient of the share of current programme participants is only significantly negative in low-unemployment regions. Such a negative effect for current participants in wage subsidies could be due to two reasons. First, it could be that the lock-in effect for participants is so strong that it is also observable at the regional level. Second, there might be negative indirect effects on the remaining job-seekers. These might occur because in the case of wage subsidies the programme participants are already employed. Once a vacancy is filled with a subsidised employee, the employer no longer needs to hire other job-seekers. This leads to a reduction of the number of matches if the number of subsidised jobs negatively affects the number of unsubsidised jobs, i.e. there is a substitution effect between the two. The results by Boockmann et al. (2012) are in line with this point of view. A more generous organisation of the availability of wage subsidies induces a decrease of unsubsidised hirings by almost the same amount as the subsidised hirings increase. Especially the second effect is very likely to be larger in regions with a relatively good local labour market. Wage subsidies are a measure for people with placement difficulties. For this group among the unemployed it is very hard to find a new job even if the regional labor-market situation is good. As a result, it is first and foremost the group with placement difficulties that remains unemployed in low-unemployment regions. If there is a substitution effect between subsidised and unsubsidised jobs, the rather low number of vacancies for unemployed with displacement difficulties decreases. This would reduce the number of possible unsubsidised matches. Hence, wage subsidies might be associated with stronger negative effects on non-participants in low-unemployment regions compared to high-unemployment regions. However, the difference between the coefficients for low- and high-unemployment regions is not significant.

Nevertheless, neither in low- nor in high-unemployment regions do the potential negative effects of wages subsidies outweigh the increase of the search effectiveness after programme completion. For both types of regions a high share of job-seekers that received wage subsidies in the past increases the number of matches in the subsequent period, but the effect in high-unemployment regions is significantly larger. This tendency was also found on the level of individual participants by Stephan (2010). Hence, with the exception of wage subsidies, ALMP programmes have the same effect in high- and low-unemployment regions.

7.4 The Role of Timing: When Do Effects of Programmes Begin and End?

So far, only job-seekers that were assigned to a programme at the end of the previous quarter could be in the group of current programme participants P and former programme participants Q. This implies that changes in the search effectiveness due to programme participation only occurs for this particular group among the job-seekers. This might be a rather restrictive assumption. Firstly, this implies that completing the programme before the end of the previous quarter does not affect search effectiveness in the following quarter and, hence, the probability to realise a match. Secondly, it rules out that the unemployed might anticipate future programme participation. As first pointed out by Ashenfelter (1978), it could be that potential future programme participants reduce their search intensity prior to a programme start because they know that they will participate in an ALMP programme. In this case, their search effectiveness might not be comparable to that of the unemployed. However, it is also possible that the opposite effect occurs and that an unemployed person increases his or her search effectiveness to avoid programme participation. For example, van den Berg/Bergemann/Caliendo (2009); Bergemann et al. (2011) or van den Berg/Bozio/Costa Dias (2013) find empirical evidence in favour of this assumption. Therefore, we perform additional robustness checks to examine whether our results are sensitive with regard to the assignment of job-seekers to the groups of current programme participants P and the group of former programme participants Q.

The first robustness check we perform, is a redefinition of our group of former programme participants Q. We now additionally count a job-seeker as a Q if he or she completed an ALMP programme in the past and programme completion does not date back longer than the average duration of the programme type.[13] Compared to our baseline model, this corresponds to an expansion of the time span we allow ALMP programmes to affect the search effectiveness of the participants. Hence, the Qs are given more time to search for a new job after they have completed their programme.

The second robustness check we perform is to reclassify our group of Ps according to the time span before a programme starts. We additionally count a job-seeker as a P starting from one month before actual programme begin in the case of short-term vocational training and wage subsidies and two months prior to the start of a long-term vocational training. The reason for the longer time interval with respect to long-term vocational training is that these programmes often only start a few times each year which means that participants have more knowledge about the start of their forthcoming measure than is the case with the other ALMP considered here. For the short training measures, the time span was set to one week.

In both cases, the number of job-seekers remains constant but we now count more people as Q and P respectively, and less as U. Table 3 presents the results when reclassifying group Q and Table 4 present the results when reclassifying group P as described above. For better comparison we also include the results of our standard model from the previous section. As the results in Table 3 and Table 4 show, neither reclassifying group Q nor reclassifying group P alters our results qualitatively or quantitatively. In general, the hypotheses of no difference to the baseline result is not rejected. The only exception are the findings for the former programme participants in wage subsidies. But even in this case, the differences to the coefficients from the baseline model are very small. Our findings are robust with regard of the underlying assumption of assigning the job-seekers to the group of former and current programme participants.[14]

8 Conclusion

ALMP programmes might be associated with (favourable or unfavourable) indirect effects on non-participants. Therefore, even if ALMP programmes have positive effects on the participants, it is not possible to conclude that they also improve the labour-market situation on the whole. This might be the case if the labour-market success of programme participants occurs at the expense of non-participants. The main goal of our analysis is to examine the effects of ALMP programmes on the matching process between unemployed and vacancies in local labour markets. This provides insights into whether the application

[13] The average time interval is 54 days for short-term vocational training, 222 days for long-term vocational training, 12 days for in-firm training measures, 32 days for classroom training measures and 172 days in the case of wage subsidies.

[14] When reclassifying group Q, we face the potential risk of focusing on a non-representative group of Qs, namely those who seem to have the most difficulties (i.e. need the longest time) to find a new job if we let the time length between programme completion and job start become “too large”. Hence we ran an additional regression where the time span after programme completion was reduced to 90% of the average programme duration. These results are almost identical to the results shown in Table 3.

Table 3: Estimation Results for “Low” and “High” Unemployment Areas by Time after Programme Completion – Long Run Coefficients

	Low-Unemployment Areas			High-Unemployment Areas		
	Baseline	Reclassified Q	Diff. signif.?	Baseline	Reclassified Q	Diff. signif.?
Share of short-term voc. train. P	-0.636	-0.562	no	-0.905	-0.880	no
Share of long-term voc. train. P	-0.001	0.112	no	-0.865	-0.462	no
Wage subsidies P	-0.684	-0.714	no	-0.307	-0.524	no
Share of short-term voc. train. Q	-0.224	0.001	no	0.552	0.564	no
Share of long-term voc. train. Q	1.171	1.784	no	3.974	3.028	no
Wage subsidies Q	3.567	3.416	yes	5.340	5.295	yes
Share of classroom training measures	3.567	2.719	no	1.565	1.844	no
Share of in-firm training measures	0.274	-0.050	no	-0.323	0.608	no

Table 4: Estimation Results for “Low” and “High” Unemployment Areas by Time before Programme Starts – Long Run Coefficients

	Low-Unemp. Areas			High-Unemp. Areas		
	Baseline	Reclassified P	Diff. signif.?	Baseline	Reclassified P	Diff. signif.?
Share of short-term voc. train. P	-0.631	-0.636	no	-0.978	-0.905	no
Share of long-term voc. train. P	-0.135	-0.001	no	-0.802	-0.865	no
Wage subsidies P	-0.956	-0.684	no	-0.517	-0.307	no
Share of short-term voc. train. Q	-0.155	-0.224	no	0.520	0.552	no
Share of long-term voc. train. Q	1.017	1.171	no	3.743	3.974	no
Wage subsidies Q	3.369	3.567	yes	5.158	5.341	yes
Share of classroom training measures	3.141	3.567	no	1.676	1.565	no
Share of in-firm training measures	0.141	0.274	no	-0.281	-0.323	no

of ALMP increases the total number of inflows of job-seekers into employment and, hence, improves the overall matching efficiency. To this end, we first extend the standard matching model to be able to explicitly differentiate job-seekers between programme participants and unemployed. This is the standard approach used in the literature so far.

In contrast to previous studies, we explicitly take into account the findings of the microeconomic evaluation literature which compare participants with their statistical twins when analysing the aggregate effects of ALMP. As shown in this branch of the literature, there is often a lock-in effect associated with programme participation reducing the search effectiveness of the programme participants. This leads to a reduced job-finding rate whilst in the programme but to a higher rate after programme completion which indicates that they are now better matched to labour demand. For this reason, we test a macroeconomic matching model in which we divide the job-seekers in those currently in ALMP programmes (for whom we expect a low search effectiveness due to a lock-in effect), those who have recently completed an ALMP programme (for whom we expect a higher job-finding rate than for the unemployed without ALMP), and the remaining unemployed. In order to do this, we need detailed regional and individual information. The "Integrated Employment Biographies" (IEB) – a dataset comprising daily information for all unemployed, programme participants and employees in Germany – is ideally suited to these needs.

As our results show, the matching function for Germany is characterised by constant returns to scale. Further, it becomes clear, that differentiating between the programme participants with regard to their search effectiveness provides in-depth insights into the aggregate effects of ALMP programmes on the regional matching process. As often found in the literature, there is a non-significant effect from being in an ALMP programme. However, differentiating between current and former programme participants shows that such counteracting effects observable for individuals during programme participation are also present on a regional scale leading to insignificant coefficients for ALMP. We find a negative significant macroeconomic effect if there are more current ALMP-participants in a region and a positive significant effect if there are more former programme participants in a region (here defined as a labour-market district of the Federal Employment Agency). The negative effect for current programme participants shows that the lock-in effect occurring on the individual level during programme participation is also observable on the regional level. A possible redistribution of employment prospects between programme participants and the remaining unemployed is not large enough to outweigh the lock-in effect on the aggregate level. The positive effect for the former programme participants implies that programme participation increased their search effectiveness. Further, the improvement of search effectiveness for the individual programme participant is not outweighed by possible negative indirect effects on non-participants on the aggregate level.

The effect of ALMP programmes on the matching process is clearly associated with the programme type. Further differentiating between several types of ALMP programmes shows that the share of current programme participants among the job-seekers has insignificant or in the case of short-term vocational training measures negative effects (on the job-finding rate). In contrast, we find (significant) positive effects with increasing shares of people formerly in long-term vocational training and wage subsidies. Also in-firm training measures improve the matching process. Several robustness checks confirm these results.

As the labour-market performance varies greatly within Germany, we analyse the effects of the different ALMP for high- and low-unemployment regions separately. Our findings show that the regional labour-market situation influences the effect of ALMP on the matching process to some extent. The coefficient for the share of participants in in-firm training measures remains significantly positive for low-unemployment regions only, whereas the coefficient for the share of former participants in long-term vocational training remains positive for high-unemployment regions only. However, we find the largest differences with regard to wage subsidies that seem to have a more favourable effect in low-unemployment regions than in high-unemployment regions. The coefficient of the share of current programme participants in wage subsidies is only significantly negative in low-unemployment regions. Further, the positive effect from a higher share of former participants of wage subsides is significantly larger in high-unemployment regions. We argue that the differences might occur because negative indirect effects associated with wage subsidies are more pronounced in low- unemployment regions than in high-unemployment regions.

As our findings show, ALMP programmes are able to improve the regional matching process. A successful completion of ALMP programmes appears to increase the search effectiveness of the participants. On the aggregate level, the higher search effectiveness is not outweighed by negative indirect effects on non-participants. Just as in microeconomic studies, we also find that the effects differ to a large extent between different programme types on the aggregate level. Further, the magnitude of the effect seems to depend to some extent on the regional labour-market situation.

Appendix

A.1 Full Theoretical Model

As microeconometric evaluation studies have unanimously shown, (see e.g. Kluve 2006) there is a pronounced "lock-in-effect" whereby programme participants' search effectiveness decreases greatly (relative to that of the unemployed) during programme participation as they have much less time to actively look for a job. However, this may change towards the end of the programme and shortly after completion of the programme, when they should be more successful than "similar" non-programme participants in finding a job – at least if the programme is "successful". For these reasons, we augment the standard matching function and define it as:[15]

$$M = m(U + sP, V_u + V_p), \qquad P = \sum_{z=1}^{Z} P_z \tag{A.1}$$

with V_u and V_p as the vacancies posted for the unemployed and programme participants respectively. On the one hand, if a programme participant becomes unemployed directly after programme completion, he or she presumably has at least the same amount of time and effort which she can devote to search for a job as an unemployed individual who has not completed such a measure. On the other hand, she obviously differs from an unemployed individual who has not participated in a programme due to the training she has received. Therefore, we interpret the search effectiveness s as an average search effectiveness which is valid for the time span from the beginning of programme participation until "shortly" after programme completion.

Although the unemployed have a higher search intensity, we assume that they also have a lower on-the-job productivity and, as they are presumably less flexible in a job, a higher probability of losing their job. Therefore, firms must decide whether to open up a vacancy V_u for the currently unemployed (and not about to enter an ALMP), or for those who are either currently in a programme or have just completed a programme V_p.[16] Hence, there are actually two type of of job-seekers: First, those who are not about to or have not recently completed a programme (U). Second, those who are either currently in a programme and those who are unemployed but have recently completed a programme (P).[17] It is assumed that the unemployed U have a higher search effectiveness but lower productivity whereas the programme participants P have a lower average search effectiveness but are more productive and can be employed more flexibly within a firm in case the firm receives a negative shock.

[15] In order to simplify the notation and where no information is lost, we suppress the time index t.

[16] Obviously, firms will not write this in the job advertisement. However, it seems realistic to assume that firms will screen applications and only pick those that seem suitable for the job that they are offering.

[17] In the empirical analysis in Section 7 we differentiate between three groups and additionally distinguish between current and former programme participants.

The matching function (A.1) is strictly increasing in its arguments. Labour-market tightness is defined as $\theta = (v_u + v_p)/(u + sp)$, where variables in small letters are simply the stock variables relative to the size of the labour force L, e.g. $u = U/L$. The mass of job-seekers relative to the size of the labour force is the weighted sum of unemployed and programme participants, i.e. $u + sp$. The proportion of unemployed amongst this mass is denoted by $\phi = u/(u + sp)$ from which follows that the share of programme participants is given by $1 - \phi$. Given this and the above matching technology, firms will fill their vacancies with previously unemployed at the rate:

$$\frac{m\phi}{v_u + v_p} = m\left(\frac{1}{\theta}, 1\right) = \phi q(\theta) \tag{A.2}$$

and at the rate

$$\frac{m(1-\phi)}{v_u + v_p} = m\left(\frac{1}{\theta}, 1\right) = (1-\phi) q(\theta) \tag{A.3}$$

with people who are or were participating in a programme.

Denoting the share of vacancies for the unemployed by $\eta = v_u/(v_u + v_p)$ means that they find jobs at the rate:

$$\frac{m\eta}{u + sp} = \eta\theta q(\theta) \tag{A.4}$$

and similarly, the rate for the programme participants is:

$$\frac{m(1-\eta)}{u + sp} = (1-\eta)\theta q(\theta) \tag{A.5}$$

The properties of the matching function imply that the matching rate of workers (firms) is increasing (decreasing) in labour-market tightness θ and further that $\lim_{\theta \to 0} q(\theta) = \lim_{\theta \to \infty} \theta q(\theta) = \infty$ and $\lim_{\theta \to \infty} q(\theta) = \lim_{\theta \to 0} \theta q(\theta) = 0$.

A.1.1 Job Creation

Firms create new jobs as long as the expected returns are at least as high as the expected costs. It is assumed that output from a position that is occupied by a person coming directly out of unemployment is $y_u > 0$. When former programme participants are hired output is y_p with $y_p > y_u$. To fill a new position, firms must first post a vacancy and engage in (costly) search equal to $c > 0$ per unit time. From above, the rate at which jobs find new workers is given by $q(\theta)$ with each firm taking labour-market conditions, i.e. θ, as given.

Profit-maximisation requires that the profit from an additional vacancy is zero. If $V_k, k \in \{p, u\}$ denotes the present-discounted value of the expected profit from a vacancy and J_k the same value from an occupied job, then the intertemporal optimisation solution for the vacancy-supply decisions is given by:

$$\rho V_u = -c + \phi q(\theta)(J_u - V_u) \tag{A.6}$$

$$\rho V_p = -c + (1-\phi)q(\theta)(J_p - V_p) \tag{A.7}$$

with ρ as the interest rate. As can be seen, this equation implies that the capital cost (l.h.s.) is equal to the expected return (r.h.s). Since in equilibrium all profit opportunities are exploited, the value of a vacancy must be zero, which implies:

$$J_u = \frac{c}{\phi q(\theta)} \tag{A.8}$$

$$J_p = \frac{c}{(1-\phi)q(\theta)} \tag{A.9}$$

i.e. that the expected profit from a new job equals the expected costs of hiring a new worker.

It is assumed that per unit time there is a constant probability that a job needs to be terminated due to negative idiosyncratic shocks. However, it is further assumed that people who were in a training programme are more skilled and therefore also more flexible as to which tasks they can perform within a firm. Therefore, if a job needs to be terminated, it is easier to transfer these people within the company than it is for those who were never in such a programme. Therefore, $\lambda_u > \lambda_p$ with $\lambda_k, k \in \{p, u\}$ as the respective job-destruction rate. Using this, the optimal asset value of an occupied job (again under the condition that the value of a vacancy is zero in equilibrium) is

$$\rho J_u = y_u - w_u - \lambda_u J_u \tag{A.10}$$

$$\rho J_p = y_p - w_p - \lambda_p J_p \tag{A.11}$$

where $w_k, k \in \{p, u\}$ is the wage paid to a worker of type k. Equations (A.10) and (A.11) imply that the capital costs of maintaining the job (l.h.s) are equal to the returns which is the difference between the output the worker produces, his or her wage $w_k, k \in \{p, u\}$ and the probability that the job needs to be terminated.

From (A.8), (A.9), (A.10) and (A.11) it follows

$$y_u - w_u - \frac{(\rho + \lambda_u)c}{\phi q(\theta)} = 0 \tag{A.12}$$

$$y_p - w_p - \frac{(\rho + \lambda_p)c}{(1-\phi)q(\theta)} = 0 \tag{A.13}$$

A.1.2 Workers

Workers bargain with the firms they meet up with over the wage level. The wage level they are willing to accept will depend on the income they receive during search and the expected income at other firms. It is assumed that a worker earns a fixed amount of (unemployment) benefits b whilst unemployed or in a programme. U_u and U_p denote the respective present-discounted value of being unemployed or being in a programme. $W_k, k \in \{p, u\}$ is the value of being employed. From this, an equilibrium is characterised by

$$\rho U_u = b + \eta\theta q(\theta)(W_u - U_u) \tag{A.14}$$

and similarly for programme participants

$$\rho U_p = b + (1-\eta)\theta q(\theta)(W_p - U_p) \tag{A.15}$$

Employed workers earn a wage $w_k, k \in \{p, u\}$ but at each moment in time face the probability $\lambda_k, k \in \{p, u\}$ of losing their job. Of those laid off, a proportion ψ join the pool of unemployed and $(1-\psi)$ start an active labour market programme. However, the individual cannot influence this decision as the labour-market institution which finances the programme determines who becomes a participant and who does not. Hence, the equilibrium conditions are:

$$\rho W_u = w_u + \lambda_u[\psi(U_u - W_u) + (1-\psi)(U_p - W_p)] \tag{A.16}$$

and

$$\rho W_p = w_p + \lambda_p[\psi(U_u - W_u) + (1-\psi)(U_p - W_p)] \tag{A.17}$$

Equations (A.14) and (A.16) can be combined to yield

$$\rho U_u = \frac{b(\rho + \psi\lambda_u) + \eta\theta q(\theta)[w_u + \lambda_u(1-\psi)(U_p - W_p)]}{\rho + \psi\lambda_u + \eta\theta q(\theta)} \tag{A.18}$$

By analogy, the net difference in being employed as a former programme participant is

$$\rho U_p = \frac{b(\rho + (1-\psi)\lambda_p) + (1-\eta)\theta q(\theta)[w_p + \lambda_p\psi(U_u - W_u)]}{\rho + (1-\psi)\lambda_p + (1-\eta)\theta q(\theta)} \tag{A.19}$$

A.1.3 Wage Determination

Once a firm and suitable worker meet, they must agree on a wage. Each job-match yields an economic rent equal to the sum of the expected search costs of the firm and worker, respectively. This rent is shared according to the Nash-bargaining solution.

The wage rate will differ depending on the previous status of the worker as the time it takes to search for a new worker, the productivity of the worker and the expected job-termination date all depend on whether the worker was previously unemployed or in a programme.

The wage given by the Nash-bargaining solution maximises the weighted product of the firms's and worker's net return from the match where the weights are determined by the respective bargaining power of the negotiating parties, i.e.

$$w_k = \arg\max_{w_k} (W_k - U_k)^{\beta} (J_k - V_k)^{1-\beta}, \qquad k \in \{p, u\}$$

with β as the workers bargaining power. From this it follows that

$$W_k - U_k = \beta(J_k - V_k + W_k - U_k), \qquad k \in \{p, u\} \tag{A.20}$$

Inserting equations (A.10), (A.11) as well as (A.16) and (A.17) into the above equation yields:

$$w_u = \beta y_u + (1-\beta)\rho U_u + \frac{(1-\psi)\lambda_u[(1-\beta)\rho U_p + \beta y_p - w_p]}{\psi \lambda_p} \tag{A.21}$$

for the unemployed and

$$w_p = \beta y_p + (1-\beta)\rho U_p + \frac{\psi \lambda_p[(1-\beta)\rho U_u + \beta y_u - w_u]}{(1-\psi)\lambda_u} \tag{A.22}$$

for programme participants.

Inserting equations (A.8) and (A.14) into equation (A.20) and noting that $V_k = 0$ in equilibrium yields

$$\rho U_u = b + \frac{\beta c \eta \theta}{\phi(1-\beta)} \tag{A.23}$$

Similarly, from (A.9), (A.15) and (A.20) it follows that

$$\rho U_p = b + \frac{\beta c (1-\eta)\theta}{(1-\phi)(1-\beta)} \tag{A.24}$$

Combining (A.21) with (A.23) and (A.24) means that the wage for the previously unemployed can be rewritten as:

$$\begin{aligned} w_u = & \frac{1}{(1-\phi)\phi(\lambda_p(\beta\rho\psi - (1-\beta)\lambda_u - \rho) - \rho(\rho + \lambda_u(1-\beta(1-\psi))))} \times \\ & \Big\{ (\rho + \lambda_u)(\beta\phi\lambda_u(1-\psi)(c\beta\theta(1-\eta) - (y_p - b)(1-\phi)(1-\beta)) - \\ & \quad (1-\phi)(c\beta\eta\theta + b\phi(1-\beta))((1-\beta\psi)\lambda_p + \rho)) - \\ & \quad \beta(1-\phi)\phi y_u(\rho(\rho + \psi\lambda_u) + \lambda_p(\rho(1-\beta\psi) + (1-\beta)\psi\lambda_u)) \Big\} \end{aligned} \tag{A.25}$$

Similarly, the wage of former programme participants is

$$w_p = \frac{1}{\lambda_p(\rho + \lambda_u(1-\beta) - \beta\rho\psi) + \rho(\rho + \lambda_u(1-\beta(1-\psi)))} \times \Bigg\{ \beta y_p\big((1-\psi)\lambda_p(\rho + \lambda_u - \beta\lambda_u) + \rho(\rho + \lambda_u(1-\beta(1-\psi)))\big) + \frac{(\rho+\lambda_p)\big(c\beta\theta(1-\eta) + b(1-\beta)(1-\phi)\big)(\rho + \lambda_u(1-\beta(1-\psi)))}{1-\phi} - \frac{(\rho+\lambda_p)\beta\psi\lambda_p\big(c\beta\eta\theta - \phi(1-\beta)(y_u - b)\big)}{\phi} \Bigg\} \tag{A.26}$$

A.1.4 Labour-Market Equilibrium

The number of unemployed who find jobs in any arbitrary small time interval δt is given by $\eta\theta q(\theta)uL\delta t$. Due to adverse shocks, during the same time interval, a worker faces the exogenous probability of $\lambda_k\delta t, k \in \{p, u\}$ of losing his or her job. Therefore, per unit time the average number of workers who found a job directly out of unemployment but are now dismissed is

$$\phi(1-u-p)\lambda_u L\delta t \tag{A.27}$$

In a steady-state equilibrium, these two flows must be equal, hence

$$\eta\theta q(\theta)uL = \phi(1-u-p)\lambda_u L$$

from which follows

$$u = \frac{\phi(1-p)\lambda_u}{\phi\lambda_u + \eta\theta q(\theta)} \tag{A.28}$$

The analogous steady-state condition for programme participants is

$$p = \frac{(1-\phi)(1-u)\lambda_p}{(1-\phi)\lambda_p + (1-\eta)\theta q(\theta)} \tag{A.29}$$

A.1.5 Steady-State Equilibrium

The general equilibrium must simultaneously satisfy the job-creation conditions (A.12) and (A.13), the wage equations (A.25) and (A.26) and the labour-market equilibrium conditions (A.28) and (A.29).

Of central interest here is what happens to the equilibrium unemployment rate if the (relative) number of programme participants is increased, i.e. ϕ decreases. This rate can be derived by first inserting (A.29) into (A.28) and solving for u which yields:

$$u = \frac{(1-\eta)\phi\lambda_u}{\phi\lambda_u + \eta\lambda_p - \phi\eta(\lambda_p + \lambda_u) + (1-\eta)\eta\theta q(\theta)} \tag{A.30}$$

from which the aggregate unemployment rate $\tilde{u} = \phi u + (1-\phi)p$ is determined as:

$$\tilde{u} = \frac{\eta\lambda_p(1-2\phi) + \phi^2(\eta(\lambda_p - \lambda_u) + \lambda_u)}{\phi\lambda_u + \eta\lambda_p - \phi\eta(\lambda_p + \lambda_u) + (1-\eta)\eta\theta q[\theta]} \tag{A.31}$$

This equation symbolises the Beveridge curve.

In the equilibrium, the share of unemployed amongst all job-seekers must be equal to the share of workers who are dismissed and subsequently do not participate in a programme, i.e. $\phi = \psi$. Noting this, the job-creation curve is derived by eliminating w_u and w_p from equations (A.12), (A.13), (A.25) and (A.26) which results in:

$$\begin{aligned}
&\frac{1}{q[\theta]\big(\lambda_p(\rho + (1-\beta)\lambda_u - \beta\rho\phi) + \rho(\rho + (1-\beta(1-\phi))\lambda_u)\big)} \times \\
&\qquad\Bigg\{\Bigg(\rho + \lambda_u\Bigg)\Bigg((c\rho + q[\theta](c\beta\eta\theta - \phi(1-\beta)(y_u - b)))(\rho + (1-\beta\phi)\lambda_p) + \\
&(c\rho(1-\beta(1-\phi)) + \beta\phi q[\theta]((1-\phi)(1-\beta)(y_p - b) - c\beta\theta(1-\eta)) + c(1-\beta)\lambda_p)\lambda_u\Bigg) - \\
&\qquad\Bigg(\rho + \lambda_p\Bigg)\Bigg(c\big(\lambda_p(\rho - \beta\rho\phi + (1-\beta)\lambda_u) + \rho(\rho + (1-\beta(1-\phi))\lambda_u)\big) + \\
&\qquad\qquad q[\theta]\big(\beta(1-\phi)(\phi(1-\beta)(y_u - b) - c\beta\eta\theta)\lambda_p + \\
&\qquad\qquad (c\beta\theta(1-\eta) + (1-\beta)(1-\phi)b)(\rho + (1-\beta(1-\phi))\lambda_u) - \\
&\qquad\qquad\qquad (1-\beta)(1-\phi)y_p(\rho + (1-\beta(1-\phi))\lambda_u)\big)\Bigg)\Bigg\} = 0
\end{aligned} \tag{A.32}$$

The general equilibrium is found in the intersection of the Beveridge curve (A.31) and the steady-state job-creation condition (A.32). Unfortunately, there is no unique solution for labour-market tightness θ. Hence, at least theoretically it is not possible to say whether putting more (unemployed) people into active labour-market programmes will actually reduce the (local) unemployment rate or not.

A.2 Full Results

Table A.1: Full Estimation Results – Long Run Coefficients

Dep. Variable: Log Matches	Model 1	Model 2	Model 3	Model 4
Lagged no. of matches	0.106***	0.105***	0.104***	0.077***
	(0.024)	(0.024)	(0.023)	(0.024)
Log no. of job-seekers	0.832***	0.827***	0.838***	0.877***
	(0.055)	(0.054)	(0.054)	(0.052)
Log no. of vacancies	0.064***	0.065***	0.070***	0.066***
	(0.015)	(0.015)	(0.014)	(0.014)
Share of P and Q		-0.089		
		(0.122)		
Share of P			-0.580***	
			(0.144)	
Share of Q			0.837***	
			(0.227)	
Share of short-term voc. train. P				-0.841***
				(0.288)
Share of short-term voc. train. Q				-0.178
				(0.372)
Share of long-term voc. train. P				-0.215
				(0.375)
Share of long-term voc. train. Q				1.873**
				(0.299)
Share of wage subsidies P				-0.263
				(0.226)
Share of wage subsidies Q				4.225***
				(0.493)
Share of classroom training measures				0.063
				(0.284)
Share of in-firm training measures				2.611**
				(1.275)
Share of females amongst job-seekers	-1.026***	-1.018***	-0.983	-0.998***
	(0.194)	(0.191)	(0.188)	(0.182)
Share of under 25 amongst job-seekers	0.092	0.083	0.150	0.056
	(0.212)	(0.213)	(0.216)	(0.209)
Share of 50+ amongst job-seekers	-1.413***	-1.425***	-1.440***	-1.371***
	(0.261)	(0.262)	(0.261)	(0.248)

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Dep. Variable: Log Matches	Model 1	Model 2	Model 3	Model 4
Share of non-natives amongst job-seekers	-2.857***	-2.855***	-2.874***	-2.685***
	(0.399)	(0.396)	(0.399)	(0.416)
Share of workforce in plants with 10–249 empl.	1.591	1.581	1.580	1.139
	(1.437)	(1.436)	(1.411)	(1.318)
Share of workforce in plants with 250+ empl.	2.190*	2.196*	2.182*	1.767
	(1.281)	(1.278)	(1.261)	(1.201)
Share of females in workforce	-3.574***	-3.521***	-3.071**	-3.184**
	(1.353)	(1.342)	(1.309)	(1.244)
Share of empl. in tertiary sector	2.006**	1.949**	1.707**	1.610**
	(0.871)	(0.861)	(0.852)	(0.814)
Share of (high-)skilled in work-force	2.966***	3.005***	2.764***	2.086***
	(0.685)	(0.691)	(0.669)	(0.680)
Share of unemployed receiving unemp. benefit II	-0.822***	-0.794***	-0.781***	-0.800***
	(0.149)	(0.156)	(0.151)	(0.143)
Share of empl. in short-time work	-0.858***	-0.847***	-0.848***	-0.826***
	(0.256)	(0.254)	(0.248)	(0.233)
Unemployment growth rate in past 12 months	-0.190***	-0.194***	-0.207***	-0.195***
	(0.045)	(0.046)	(0.046)	(0.044)
Employment growth rate in past 12 months	0.016**	0.016**	0.016**	0.015**
	(0.007)	(0.007)	(0.007)	(0.006)
Current empl. level relative to annual moving average	-8.518***	-8.478***	-8.385***	-8.035***
	(0.759)	(0.759)	(0.751)	(0.721)
Sargan test statistic	148.140	147.074	143.745	141.132
Sargan (p-value)	0.875	0.887	0.921	0.942
AR1 (p-value)	0.000	0.000	0.000	0.000
AR2 (p-value)	0.686	0.719	0.829	0.951

Note: Results are robust, one-step system GMM estimates. The standard errors (in parentheses) are calculated by the delta method. *** Significant at the 1%-level; ** Significant at the 5%-level; * Significant at the 10%-level. All models also include time and regional fixed-effects. For all regressions $N = 3168$.

Table A.2: Full Estimation Results for “Low” and “High” Unemployment Areas – Long Run Coefficients

Dep. Variable: Log Matches	Low	High
Lagged no. of matches	0.080***	
	(0.023)	
Log no. of job-seekers	1.110***	1.005***
	(0.087)	(0.101)***
Log no. of vacancies	0.016	0.087***
	(0.018)	(0.023)
Share of short-term voc. train. P	-0.636*	-0.905**
	(0.337)	(0.443)
Share of short-term voc. train. Q	-0.224	0.552
	(0.399)	(0.523)
Share of long-term voc. train. P	-0.001	-0.865
	(0.437)	(0.736)
Share of long-term voc. train. Q	1.171	3.974**
	(1.033)	(1.652)
Share of wage subsidies P	-0.684**	-0.307
	(0.280)	(0.333)
Share of wage subsidies Q	3.567***	5.341***
	(0.574)	(0.668)
Share of classroom training measures	0.274	-0.323
	(0.303)	(0.466)
Share of in-firm training measures	3.567**	1.565
	(1.446)	(1.640)
Share of females amongst job-seekers	-0.744***	-1.109***
	(0.200)	(0.253)
Share of under 25 amongst job-seekers	-0.114	0.076
	(0.232)	(0.318)
Share of 50+ amongst job-seekers	-1.623***	-0.584
	(0.267)	(0.397)
Share of non-natives amongst job-seekers	-3.243***	-3.684***
	(0.479)	(0.925)
Share of workforce in plants with 10–249 empl.	0.619	2.491
	(1.765)	(2.252)
Share of workforce in plants with 250+ empl.	-1.162	4.035**
	(1.876)	(2.041)
Share of females in workforce	1.337	-0.321
	(2.491)	(2.744)

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Dep. Variable: Log Matches	Low	High
Share of empl. in tertiary sector	2.042	0.221
	(1.281)	(2.216)
Share of (high-)skilled in workforce	3.006***	2.306**
	(0.899)	(1.130)
Share of unemployed receiving unemp. benefit II	-0.215	-0.981**
	(0.235)	(0.431)
Share of empl. in short-time work	-0.915***	-0.306
	(0.204)	(0.485)
Unemployment growth rate in past 12 months	-0.078*	0.052
	(0.045)	(0.066)
Employment growth rate in past 12 months	0.039***	0.011*
	(0.004)	(0.006)
Current empl. level relative to annual moving average	-7.566***	-7.582***
	(0.789)	(0.771)
Sargan test statistic	120.691	
Sargan (p-value)	0.998	
AR1 (p-value)	0.000	
AR2 (p-value)	0.846	

Note: Results are robust, one-step system GMM estimates. The standard errors (in parentheses) are calculated by the delta method. *** Significant at the 1%-level; ** Significant at the 5%-level; * Significant at the 10%-level. Model also includes time and regional fixed-effects. $N = 3168$.

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