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# Mismatch and the Forecasting Performance of Matching Functions

Christian Hutter and Enzo Weber

## Abstract

This paper investigates the role of structural imbalance between job seekers and job openings for the forecasting performance of a labour market matching function. Starting from a Cobb-Douglas matching function with constant returns to scale (CRS) in each frictional micro market shows that on the aggregate level, a measure of mismatch is a crucial ingredient of the matching function and hence should not be ignored for forecasting hiring figures. Consequently, we allow the matching process to depend on the level of regional, qualificatory and occupational mismatch between unemployed and vacancies. In pseudo out-of-sample tests that account for the nested model environment, we find that forecasting models enhanced by a measure of mismatch significantly outperform their benchmark counterparts for all forecast horizons ranging between one month and a year. This is especially pronounced during and in the aftermath of the Great Recession where a low level of mismatch improved the possibility of unemployed to find a job again. The results show that imposing CRS helps improve forecast accuracy compared to unrestricted models.

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# 1 Introduction

Many approaches for relating unemployment and vacancies to job findings rely on matching theory (see, e.g., Mortensen and Pissarides (1994) and Petrongolo and Pissarides (2001)) and thus consider vacancies and unemployed as inputs into the production function of job findings. Most studies, however, assume the efficiency parameter to be constant over time. Only in recent years has this strong assumption been called into question. For instance, Sedlacek (2014), Klinger and Weber (2014) and Barnichon and Figura (2015) allow for time-varying matching efficiency. One source is given by mismatch (Sahin et al. (2014)), denoting the degree of structural imbalance between supply and demand.

We contribute to the literature by applying the concept of mismatch and, thus, a time-varying efficiency parameter from a forecasting perspective. Employing a mismatch index in forecasting regressions is an economically attractive way of modeling structural change in the relationship among unemployment, vacancies and job findings. Furthermore, asking whether a measure of imbalance helps improve hiring forecasts is a relevant question because it is usually far more difficult to prove a theory useful for forecasting exercises than it is to prove its in-sample significance. To date, the existing theoretical models have rarely been tested for their practical usefulness with respect to forecasting exercises. As a consequence, one hardly knows whether models that rely on matching theory truly can serve as a base for forecasting hirings.

In the literature, a variety of indices and interpretations coexist for the concept of mismatch.<sup>1</sup> Early approaches consider mismatch to be only a temporary phenomenon. For instance, the mismatch index developed by Lilien (1982) is based on the assumption that short-run shocks can lead to a change in the composition of sectoral demand in an economy. Because labour markets only adjust slowly, mismatch occurs when both unemployment (in the contracting sectors) and vacancies (in the expanding sectors) temporarily rise during the period of transition. Another concept (applied by Franz (1991), for instance) considers mismatch to be not solely a temporary phenomenon. It is built on a disequilibrium model in which the short side of any distinct labour market determines its level of employment. Under the assumption that the short side is not the same in all micro markets, unemployment and vacancies coexist at the aggregate level, which leads to employment being below the minimum of the aggregate supply and demand. As a consequence, a higher level of mismatch is attributable to a higher variance between the markets at the micro level. A main disadvantage of this approach to mismatch is that it rules out the coexistence of vacancies and unemployed within each micro market (usually called *frictional unemployment*). In contrast, the approach to mismatch that was embraced by Jackman and Roper (1987) accepts that frictional unemployment is inevitable within each distinct labour market. Therefore, incongruence at the micro level is measured relative to a more realistic (i.e., attainable) size of unemployment.

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<sup>1</sup>For an overview of various concepts for measuring mismatch, see, e.g., Schioppa (1991) or Canon et al. (2013).

Hence, the respective mismatch index measures how much structural unemployment contributes to total unemployment, i.e., "the proportion of unemployment attributable to structural imbalance" (Jackman and Roper (1987), p.14). However, this interpretation only holds under the assumption that the matching technology follows a Cobb-Douglas production function with constant returns to scale and equal elasticity of 0.5. Hence, in addition to the Jackman/Roper mismatch index, we investigate the performance of a more general mismatch indicator in which the assumption of equal elasticities is lifted.

We use data for Germany from the statistics department of the Federal Employment Agency (FEA), which allow for the disaggregation of unemployed and registered vacancies at the levels of 21 occupational segments, 50 labour market regions and three qualification groups. This enables us to gain detailed empirical evidence on the size and development of mismatch in Germany in the past 13 years, including the years after the Hartz labour market reforms.

After log-linearisation of the matching function, the mismatch indicator appears in an additive form in our forecasting equations. As a consequence, the usual out-of-sample test of Diebold and Mariano (1995) cannot be implemented. We thus employ the nested-model test described by Clark and West (2007) and apply a one-sided test for equal predictive accuracy, with the alternative hypothesis being worse forecast performance of the nesting model. We find that our enhanced matching function significantly outperforms its benchmark counterpart without a mismatch indicator for all forecast horizons ranging between one month and one year. It is especially pronounced in the aftermath of the Great Recession, where a low level of mismatch improved the job chances of the unemployed.

By gradually removing the occupational, regional and qualification-related dimensions from our index calculations, we generate alternative indices that allow the size and development of the different types of mismatch to be quantified separately. This identifies which of the aforementioned dimensions has the greatest impact on forecast accuracy. The results emphasise that calculating mismatch by using all of the available dimensions of imbalance between supply and demand ensures the most stable out-of-sample performance for all investigated forecast horizons.

The remainder of this paper is structured as follows. The theoretical background of our forecasting equations is introduced in the first part of Section 2. The second part describes the data used for both the forecast evaluation and the construction of the mismatch indices, and Subsection 2.3 shows their development over time. Section 3 compares the forecasting performance of a mismatch-enhanced labour market matching function to that of the corresponding benchmark models by using nested model out-of-sample tests. Furthermore, it discusses the question of which dimensions of mismatch provide the highest value added in forecasting German hiring figures. The last section concludes.

## 2 Theory and measurement

### 2.1 Theoretical background

The well-known search and matching theory <sup>2</sup> states that vacancies ( $V$ ) and unemployed ( $U$ ) form matches ( $H$  for hirings) through a Cobb-Douglas production function in the style of Equation (1).

$$H_t = \Phi \cdot V_t^\alpha \cdot U_t^\beta, \quad (1)$$

where  $\Phi$  denotes the efficiency parameter that carries the information about the location of the Beveridge curve and  $\alpha$  and  $\beta$  are the elasticities of new matches with respect to vacancies and unemployed, respectively. However, in many applications, the efficiency parameter is assumed to be constant over time although variations in the efficiency parameter can be substantial; for example, compare Klinger and Weber (2016) and Sedlacek (2014). Not accounting for these dynamics could not only lead to biased estimates of the structural parameters of the matching function but also (negatively) affect the accuracy in hiring forecasts.

To obtain an impression of what is missing in Equation (1), we follow Sahin et al. (2014) and start from a CRS Cobb-Douglas matching function in each frictional micro market  $i$  (similar also to Barnichon and Figura (2015)):

$$H_{it} = \Phi_t \phi_{it} \cdot V_{it}^\alpha \cdot U_{it}^{1-\alpha}, \quad (2)$$

where  $\Phi$  indicates the aggregate component and  $\phi_i$  the idiosyncratic micro market level component of matching efficiency. Note that  $\beta = 1 - \alpha$  due to the CRS assumption. Summing across markets yields the following:

$$H_t = \Phi_t \cdot V_t^\alpha \cdot U_t^{1-\alpha} \left[ \sum_{i=1}^I \phi_{it} \left( \frac{V_{it}}{V_t} \right)^\alpha \left( \frac{U_{it}}{U_t} \right)^{1-\alpha} \right]. \quad (3)$$

The term in brackets denotes the degree of structural balance between supply and demand. Any movement away from perfect balance makes it more difficult for given  $V$  and  $U$  to form matches. Sahin et al. (2014) show that Equation (3) can be rewritten as

$$H_t = (1 - MM_t) \bar{\phi}_t \Phi_t \cdot V_t^\alpha \cdot U_t^{1-\alpha}, \quad (4)$$

where  $\bar{\phi}$  is a weighted CES aggregator of the matching efficiencies at the micro level and

$$MM_t = 1 - \left[ \sum_{i=1}^I \left( \frac{\phi_{it}}{\bar{\phi}_t} \right) \left( \frac{V_{it}}{V_t} \right)^\alpha \left( \frac{U_{it}}{U_t} \right)^{1-\alpha} \right] \quad (5)$$

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<sup>2</sup>See, e.g., Mortensen and Pissarides (1994), Petrongolo and Pissarides (2001), Shimer (2007), Yashiv (2007), Rogerson and Shimer (2011) and Mumtaz and Zanetti (2015).

is a mismatch indicator that measures the fraction of hires that are lost due to structural imbalances. Misallocation occurs when a large number of unemployed coincides with a small number of vacancies (and vice versa) in a given micro market. It can lead to long-run unemployment because workers and vacancies would not form a match, even in the absence of search frictions or imperfect information. As a consequence, a better congruence of both groups with respect to relevant attributes such as qualification, occupation and region is expected to improve the process of forming matches. Under the simplifying assumption that matching efficiency varies across time but not across micro markets, Equation (4) yields the following after log-linearisation:

$$h_t = \log(\Phi_t) + 1 \cdot \log(1 - MM_t) + \alpha \cdot v_t + (1 - \alpha) \cdot u_t, \quad (6)$$

where lower-case letters denote the natural logarithm. Equation (6) shows that a crucial ingredient of the matching function is the time-varying term containing a measure of mismatch. The main focus of Section 3 is to evaluate the benefit of adding  $\log(1 - MM)$  in terms of out-of-sample performance.

As of now, there are several restrictions on Equation (6), such as CRS or that the term containing the mismatch indicator enters the equation with a parameter of 1. Thus, Section 3 also shows how lifting these constraints influences forecast accuracy. Furthermore, one could consider extending Equation (6) to a more general stock-flow matching function.

## 2.2 Data

To construct the mismatch indices and evaluate their value added in out-of-sample forecasts, we use monthly data from the statistics department of the Federal Employment Agency (FEA). As a target variable, we take seasonally adjusted hiring figures on the aggregate level, i.e., the monthly outflow from unemployment into employment on the primary labour market. The reasons for focusing on the primary labour market are of both a theoretical and empirical nature. First, the matching theory described in section 2 suggests that hirings are *produced* through a Cobb-Douglas-style combination of vacancies and unemployed, which requires a certain market proximity of all variables. Therefore, to tackle the economic matching process, it is more appropriate to concentrate on the primary labour market and to exclude hirings into subsidised employment that very likely stem from policy-driven labour market measures. The second reason is predictability. Forecasting the outflow from unemployment into the secondary labour market is much more difficult because it depends highly on the range of instruments that are available to the respective authorities, unless these instruments themselves can be predicted quite precisely.

Figure 1 shows the development of the aggregate, seasonally adjusted outflow from unemployment into employment on the primary labour market, from January 2000 until March 2014. Among the variables on the right-hand side of our preferred forecast equation are the aggregate numbers of the stock and the inflow of unemployed and vacancies, respectively.

Figure 1: Aggregate number of hirings, seasonally adjusted

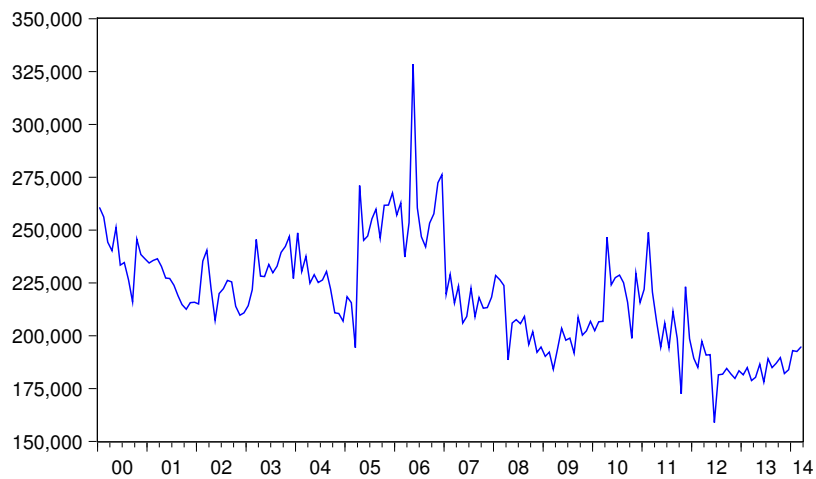


Figure 2: Unemployed and vacancies (stock variables), seasonally adjusted

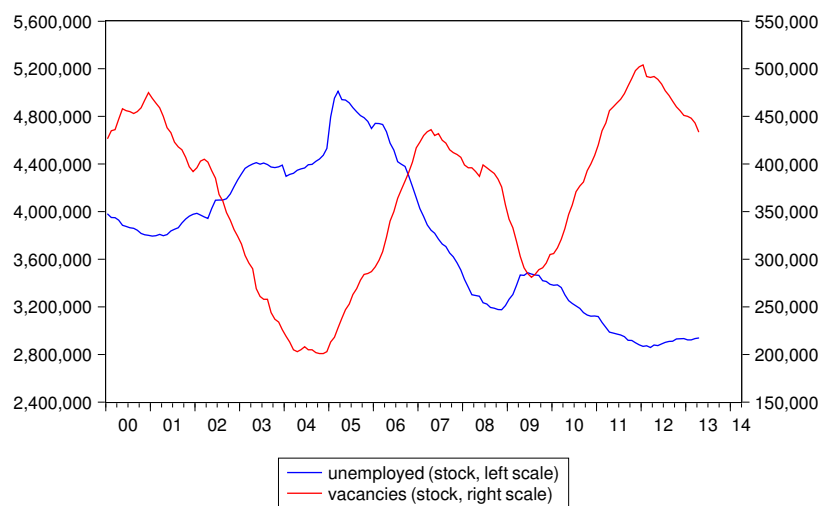


Figure 3: Unemployed and vacancies (monthly inflow), seasonally adjusted

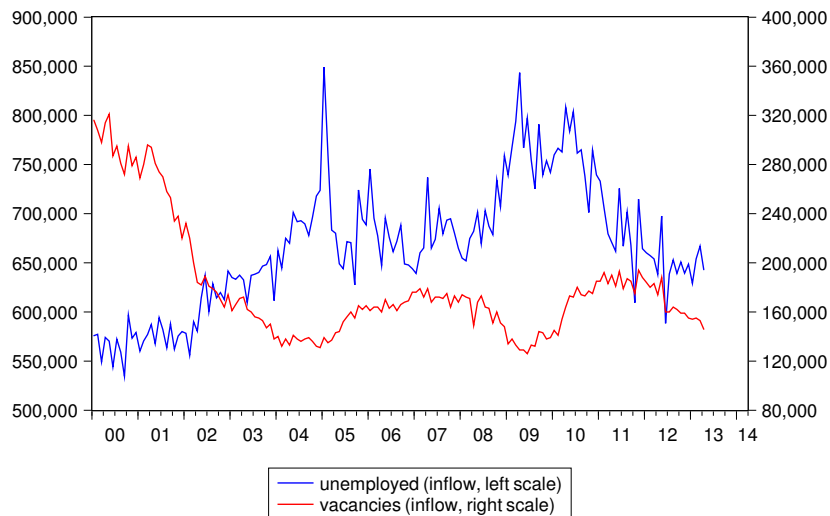


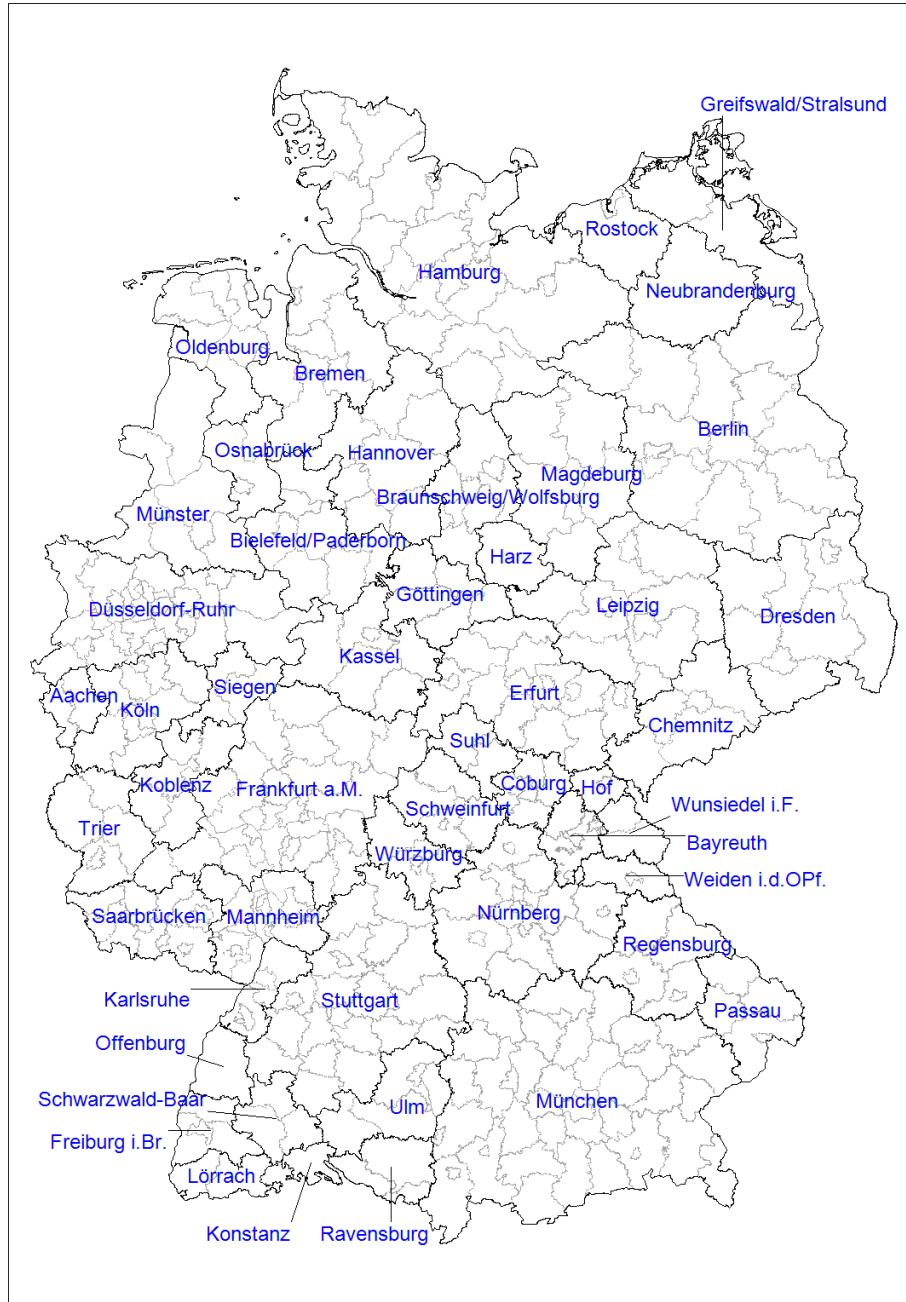
Figure 2 shows the stock of registered unemployed and vacancies (both seasonally adjusted), as reported by the FEA, from January 2000 until March 2013.<sup>3</sup> The vacancies comprise all job offers that employers report to the respective local agencies and are approved for placement. Consequently, they do not cover the entire job market. According to quarterly data from the German Job Vacancy Survey, the share of registered vacancies on all vacancies varies between 40 and 50 percent. However, there is no variable available at a monthly frequency that accounts for the potentially changing share, which is why we take monthly available registered vacancies. Figure 3 shows the aggregate number of the respective monthly inflows. Because the underlying stock and flow variables stem not from survey data but from administrative FEA data, they are highly reliable and not subject to revisions.

Constructing the mismatch indices as described in Subsection 2.3 requires detailed information about the regional, occupational and qualificatory distributions of both the respective job openings and unemployed on a monthly frequency. For this purpose, we exploit a large dataset from the FEA that allows us to account for the most relevant dimensions of mismatch. With regard to the qualification-related incongruence, we distinguish among the following three groups: experts (people with academic training), skilled workers and specialists (people with completed educational or vocational training), and helpers (people

<sup>3</sup>Our final estimation period ends in March 2013. Our evaluation period for 12-months-ahead forecasts ends in March 2014. As a consequence, the observation periods shown in Figure 2 and Figure 3 differ from that shown in Figure 1.



Figure 4: Germany's 50 labour market regions



**Notes:** The labour market regions (black borderlines) are taken from Kropp and Schwengler (2011) and slightly modified so they are in accordance with the most recent county borders (grey borderlines).

Table 1: The occupational segments

No.	occupational segment	exemplary occupations
1	Agricultural occupations	farmer, fisher, gardener, forester
2	Miner/chemical occupations	miner, mining engineer, chemical worker
3	Glass, ceramic, paper producer	ceramicist, glazier, paper producer, printer
4	Textile, leather producer	spinner, weaver, tailor, sewer, shoemaker
5	Metal producer	metal worker, plumber, mechanical engineer
6	Electricians	electrician, electrical engineer
7	Wood occupations	wood processor, woodworker, joiner
8	Construction occupations	bricklayer, carpenter, roofer, tiler
9	Hotel/restaurant occupations	baker, butcher, cook, barkeeper
10	Storage/transport occupations	conductor, motorist, driver, mail distributor
11	Merchandise occupations	merchant, cashier, accounting clerk, banker
12	White collar worker	accountant, clerk, member of parliament
13	Security occupations	gate keeper, firefighter, guard, chimney sweeper
14	Social/care occupations	child teacher, care taker, social worker
15	Medical occupations	nurse, helper in nursing, receptionist
16	Physicians	physician, dentist, veterinarian
17	Teaching professions	professor, teacher
18	Artists/Athlets	graphic designer, musician, professional sportsman
19	Natural scientists	chemist, physicist, mathematician
20	Humanists	publicist, translator, librarian, economist
21	Others	labourer without further specification of activity

Source: Matthes et al. (2008), p.22.

without completed vocational training). These categories are reported in the administrative data for both the supply and demand sides of the labour market.

Furthermore, we account for regional mismatch by using the 50 labour market regions proposed by Kropp and Schwengler (2014) and shown in Figure 4. The delineation of these functional labour market regions relies on commuter flows between all German municipalities since 1993. Its main advantages are its high stability over time and its excellent properties with respect to self-supply and the commuter ratio. On average, 87.4 percent (standard deviation: 4.4 percentage points) of the jobs are taken by workers who live within the respective labour market region. This high degree of self-supply emphasises that the chosen delineation is highly suitable for identifying distinct regional labour markets in the framework of the matching theory. In addition, there is no labour market region that could be considered a typical in- or out-commuter region. This is emphasised by very balanced commuter ratios.<sup>4</sup> The average commuter ratio is 98 percent, and there is little variation (standard deviation: 5.4 percentage points).

The third dimension of incongruence between demand and supply on the labour market is occupational mismatch. Similar to the regional delineation described in the previous paragraph, it is necessary to identify occupational segments that are characterised by both a high within-homogeneity and a high across-segregation. We follow Matthes et al. (2008) and use the 21 occupational segments shown in Table 1. A great advantage of using occupational segments instead of occupations is that the degree of homogeneity varies less across segments, which implies that the segments are more comparable with respect to the number of job alternatives within a segment. Furthermore, the occupational segments are characterised by a reasonably high degree of discriminatory power with respect to realized job mobility. To be more precise, in 95 percent of the segments, the number of occupational changes within the respective segment exceeds the number of occupational changes that involve other segments.

All necessary data are made available with a very small time lag. This enables us to immediately calculate the monthly value of the mismatch index and use it in the respective forecasting equations (as shown in Section 3).

### 2.3 Measuring mismatch

Following the concept of Sahin et al. (2014), our preferred mismatch indicator  $MM$  in Equation (6) can be written as

$$MM_t = 1 - \left[ \sum_{i=1}^I \left( \frac{V_{it}}{V_t} \right)^\alpha \left( \frac{U_{it}}{U_t} \right)^{1-\alpha} \right]. \quad (7)$$

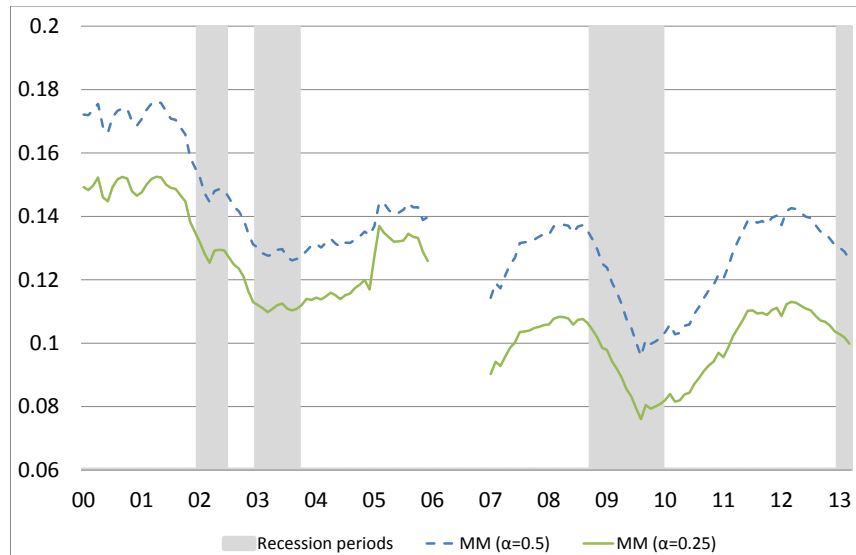
Under the additional assumption of  $\alpha = 0.5$ , Equation (7) becomes the

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<sup>4</sup>A commuter ratio denotes the ratio of commuters into (nominator) over those out of (denominator) the respective labour market region. Values greater than 100 percent signal that the respective region has an excess of in-commuters. Values less than 100 percent signal an excess of out-commuters.

mismatch index as proposed by Jackman and Roper (1987). If the ratio of unemployed equals that of vacancies in all micro markets,  $MM_t$  becomes zero, which indicates that there is no structural imbalance at all. If for each  $i$ ,  $V_{it} \cdot U_{it}$  equals zero, there is either no vacancy for the unemployed or no unemployed person for the vacancies in any micro market. As a consequence,  $MM_t$  becomes one, which means that 100 percent of unemployment is due to structural mismatch. Importantly, we focus on the role mismatch plays for forecasting, assuming the (sectoral) matching efficiencies to be constant beyond. More general approaches to model matching efficiency are provided by Klinger and Weber (2016) or Sedlacek (2014).

Figure 5: Development of mismatch, seasonally adjusted



Notes: The mismatch indicators are calculated according to Equation (7), with  $I = 3150$  and  $\alpha = 0.5$  or  $\alpha = 0.25$ , respectively. Grey areas denote periods of recessions.

Figure 5 shows the development of the seasonally adjusted mismatch indices covering all three dimensions of mismatch ( $I = 3150$ ) since January 2000. The mismatch indicators are calculated according to Equation (7), with  $I = 3150$  and  $\alpha = 0.5$  or  $\alpha = 0.25$ , respectively. Grey areas denote periods of recessions. Due to missing or unusable data, there is a gap in 2006. Along with this break comes a change in the way in which individuals are classified into the different qualificatory groups; thus, the level of mismatch before this break cannot be compared to that observed after the break. Throughout the forecast evaluation performed in Section 3, we control for this issue by using impulse dummies for all twelve months of 2006 and a level shift dummy starting in January 2007.

The dashed line in Figure 5 sets  $\alpha$  to 0.5 and thus provides an upper bound for the size of mismatch. Any deviation from  $\alpha = 0.5$  leads to lower levels of mismatch. The solid line in Figure 5 sets  $\alpha$  to 0.25, which is the value that

results from iterating Equation (6) until convergence is achieved.<sup>5</sup> Through this iteration process, we achieve a matching function that is fully consistent in terms of its elasticity parameter  $\alpha$ . Estimating  $\alpha$  recursively to check the stability of the parameter yields values between 0.19 and 0.29, which also holds for the period before the Great Recession. However, although the *level* of mismatch changes with  $\alpha$ , the *dynamics* are fairly similar, which is why the effect on out-of-sample performance is quite limited (see also Section 3). The development of mismatch is characterised by a relatively strong decline from approximately 0.15 in 2000 to approximately 0.11 in 2003, followed by a moderate increase in the following two years. The second half of our observation period is marked by fairly smooth up-and-down movements in the range between 0.08 and 0.11. Hence, approximately 8 to 11 percent of unemployment in Germany can be attributed to regional, occupational and qualification-related mismatch.

It is striking that the development of the mismatch indicator seems to depend – at least to some extent – on the business cycle. The grey areas in Figure 5 denote periods of recessions (identified by negative values of the year-on-year growth rate of the real GDP). We find that the mismatch tends to decline in late stages of expansions and during recessions and to increase again after recessions. This pattern is especially pronounced in the years immediately before, during, and immediately after the Great Recession of 2008/2009. Our finding that mismatch in Germany behaves counter-cyclically is in line with Bauer (2013) but differs from the results obtained for the US in Sahin et al. (2014) and Barnichon and Figura (2015). We comment further on the development in Germany at the end of section 3.2.

## 3 Forecast evaluation

### 3.1 Forecast evaluation setting

This Subsection tests the relevance of time-varying structural imbalance on the micro labour markets for forecasting aggregate hiring figures. For this purpose, it compares the forecasting performance of benchmark matching models, as introduced in Subsection 2.1, to that of the respective counterpart models that have been enhanced by a term containing  $MM$ , which is the mismatch indicator described in Subsection 2.3.

After log-linearisation, the measure of structural imbalance  $MM$  appears in additive form. As a consequence, the parsimonious benchmark model is nested in the larger model, which is of crucial importance in tests of equal predictive accuracy. Clark and West (2007) argue that the mean squared prediction error (MSPE) of the larger model is upward-biased due to additional noise stemming from the need to estimate a parameter that – under the null hypothesis of equal

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<sup>5</sup>Note that  $\alpha$  enters Equation (6) both inside and outside the mismatch index. Hence, we first estimate Equation (6) without the mismatch index and use the resulting estimated  $\alpha$  to calculate  $MM$ . Then, we estimate Equation (6) again, this time including the mismatch index, which yields a new estimated  $\alpha$ . The process is repeated until convergence.

predictive performance – is zero in population<sup>6</sup> and that is correctly set to zero in the parsimonious model. In a sense, the smaller benchmark model is more efficient and thus benefits from not carrying the burden of estimating the parameter of a redundant variable to zero. Consequently, the usual tests in the style of Diebold and Mariano (1995) are undersized and have poor power in a nested model environment. Therefore, we implement the nested-model test described by Clark and West (2007) and apply a one-sided test for equal predictive accuracy, with the alternative hypothesis being worse forecast performance of the nesting model. Because multiperiod-ahead forecast errors are usually autocorrelated, we use the heteroskedasticity and autocorrelation robust covariance estimator proposed by Newey and West (1987) in the case of multiple-step forecasts. Inference based on asymptotic critical values – as proposed by Clark and McCracken (2001) – might not be appropriate in cases of small sample sizes. Therefore, the fixed regressor bootstrap method proposed by Clark and McCracken (2012, 2013) is implemented. We argue that bootstrapping considerably strengthens the validity of our test results. Furthermore, horizon-specific sets of critical values are implemented.

To compute multi-step forecasts, we use direct, lead-time-dependent forecasts. At least in theory, direct forecasts are more immune to model misspecification than iterated forecasts because they use the chosen model only once.<sup>7</sup> By applying direct forecasts, we avoid forecasting the mismatch indicator itself and modeling feedback effects to our target variable. Furthermore, the asymptotic theory of the nested model test that we use in our application requires forecasts to be linear functions of parameters, which applies in direct forecasts but not in iterated approaches.

As described in Section 2.1, there are some restrictions on Equation (6), which – although they might be justified theoretically – could impair the out-of-sample performance. Thus, we also check more general matching models in our evaluation setting. For instance, allowing for a stock-flow matching model turned out to improve the forecast accuracy for all investigated forecast horizons. This model type differs from the basic model in that it is augmented by the respective flow counterparts of  $V$  and  $U$  (see, for instance, Coles and Smith (1998) or Ebrahimi and Shimer (2010)). The idea is that job searchers first screen the stock of job openings and firms first look at the stock of unemployed. Those agents on the demand or supply side who could not successfully fill the vacancy or find a job are assumed to search only among the newly incoming applicants or job openings. Further restrictions in Equation (6) are CRS and  $\gamma = 1$  (where  $\gamma$  denotes the parameter of the term containing the mismatch indicator). After lifting these constraints and hence allowing for more flexibility

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<sup>6</sup>For a discussion of the difference between a null hypothesis of equal accuracy in the *population* vs. *finite sample*, see, e.g., Clark and McCracken (2013, 2015).

<sup>7</sup>Conversely, parameter estimates are more efficient in the iterated approach because they usually allow residual autocorrelation to be eliminated. The literature on this topic is ambiguous and ranges from emphasising the advantages of direct forecasts (e.g., Klein (1968)) over mixed results (e.g., Kang (2003)) to the finding of an empirical study on 170 U.S. macroeconomic variables that iterated forecasts typically outperform direct forecasts (Marcellino et al. (2006)).

and after adding autoregressive terms to Equation (6), the general lead-time-dependent estimation specification for the natural logarithm of aggregate hires<sup>8</sup>  $h$  follows:

$$(1 - \rho_1 \cdot L^f - \rho_2 \cdot L^{f+1})h_{t+f} = c_t + \alpha_{st} \cdot v_t + \beta_{st} \cdot u_t + \alpha_{fl} \cdot \dot{v}_t + \beta_{fl} \cdot \dot{u}_t + \gamma \cdot \log(1 - MM_t) + \text{impulsedummies} + \epsilon_{t+f}, \quad (8)$$

where the aggregate (log of) unemployment and vacancies enter the regression as both stock ( $u, v$ ) and flow ( $\dot{u}, \dot{v}$ ) variables. The corresponding parameters are indexed by  $st$  and  $fl$ , respectively.  $f$  denotes the forecast horizon,  $L$  the lag-operator, and  $\epsilon$  the error term. We do not index the coefficients by  $f$  for simplicity.  $c_t$  is the logged  $\Phi_t$ , which Sahin et al. (2014) try to capture by including time trend variables. However, neither in-sample nor out-of-sample do time trend variables improve the performance of Equation (8). Instead, we include several shift dummies to capture changes in institutional settings or structural breaks in our target variable  $h$ . In January 2005, for instance, the final stage of the Hartz labour market reforms came into effect. Along with this step, there was a change in the way in which the unemployed are counted, which led to a sudden jump in the official unemployment figures (see Figure 2) and, shortly thereafter, in the number of hirings (see Figure 1). The main reason for this jump is that former welfare recipients who had been classified as incapable of working are counted in the group of unemployed since the Hartz reforms because they receive unemployment benefits (Arbeitslosengeld II). We find that a level-shift dummy that is zero before and 1 as from April 2005 is well suited to control for this issue. Furthermore, we include another dummy that takes on the value 1 from January 2007 to allow for a potential level shift in the mismatch indicator after the period of missing values. This dummy would also allow the decline in hiring figures in January 2007 to be accounted for, if preferred by the estimation. Because autoregressive lags are included in Equation (8), the corresponding lags of the two dummy variables are also employed.

As described in Section 2, there is a short period of missing or unusable data with respect to the mismatch indicator (see Figure 5). If  $MM$  is included, we thus employ impulse dummies for all twelve months of 2006. The level-shift dummy of 2007 described above captures the break not only in our target variable but also in the mismatch indicator. The last dummy employed in Equation (8) is an impulse dummy for December 2001, a month in which it was necessary to impute the value of  $MM$  due to unusable data.

Note that all of the variables on the right-hand side are observed in  $t$ , the time when the forecast is conducted. This is also in accordance with the release dates of the data. A great advantage of our data is that all of the variables on the right-hand side are available in  $t$  and can thus be used for h-step-ahead forecasts without lagging them.

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<sup>8</sup>Throughout the evaluation process, we target forecasts of aggregate hiring figures (and hence not forecasts of the job finding rate).

Because we are interested in forecasting the number of hires and not the natural logarithm of  $h$  and for ease of interpretation, we use the exponential to undo the log.<sup>9</sup> To avoid a systematic underestimation of the expected value of  $h$  due to the nonlinear transformation, we use the adjustment proposed by Wooldridge (2009):

$$\hat{h} = e^{\frac{\hat{\sigma}^2}{2}} \cdot e^{\widehat{\log(h)}}, \quad (9)$$

where  $\hat{\sigma}$  is the standard error of our regression stemming from Equation (8). Because we cannot reject the null of  $h$  having a log-normal distribution, we can be confident that the adjustment of Equation (9) produces consistent predictions of the number of hirings.

We now discuss the choice of the underlying parsimonious benchmark model. One could think of models relying solely on the own past such as AR(p)-models or the random walk (RW). In their GDP growth application, Clark and West (2007) use an AR(1) with a constant as benchmark model, whereas Clark and McCracken (2015) use models with only a constant to predict stock returns. Occasionally, AR models of higher order, as determined by in-sample information criteria, are employed. The Bayesian Information Criterion (BIC) with monthly hiring data from 2000 to 2007 (excluding the data from our evaluation period) gives evidence for using AR models with an order no higher than 2.<sup>10</sup> As expected from the very low persistence in the hirings variable (see Figure 1), neither the information criteria nor the out-of-sample performance improve by forcing  $\rho(L)$  to have a unit root (i.e., by modeling the first difference of hirings).

Our benchmark model does not include the mismatch indicator ( $\gamma = 0$ ) and the dummy variables that are necessary to account for the data limitations inherent to *MM* (see Subsection 2.3).<sup>11</sup> Because we use the direct approach, the model type changes with forecast horizon. For instance, the first model becomes an *AR*(1) for 1-step-ahead forecasts and an *AR*(6) without the first five lags for 6-step-ahead forecasts. Because any direct  $f$ -step-ahead forecasting equation implies a *MA*( $f-1$ ) error structure, we also considered the respective *ARMA* models. However, the out-of-sample performance of these models turned out to be worse than that of their *AR* counterparts in most cases, so we do not report any *ARMA* results.

It is not clear a priori how long it takes until changes in the incongruence between the profiles of supply and demand are fully effective in the matching process. This is why we investigate all forecast horizons ranging from one to twelve months. We divide the sample into an estimation period, which is updated for each iteration, and an evaluation period. The initial estimation period for 1-step-ahead forecasts ranges from March 2000 to February 2008 (96 observations), using data from January and February 2000 as initial observations.

<sup>9</sup>The approximation in Equation (9) affects the forecasts of both the benchmark and the unrestricted model and does not substantially influence the results of the evaluation exercises.

<sup>10</sup>This result remains valid if data after 2007 are included.

<sup>11</sup>We also checked the out-of-sample performance of a benchmark model that did not include *MM* itself but did include the corresponding dummy variables. However, the forecast accuracy turned out to be worse in most cases.



Our evaluation period ranges from March 2008 to April 2013 in the case of 1-step-ahead forecasts and from February 2009 to March 2014 in the case of 12-step-ahead forecasts. As a consequence, the evaluation period consists of 62 forecasts for all forecast horizons. The estimation period is regularly updated by adding the month that has become recently available (recursive scheme). Hence, the last estimation period ends in March 2013 for all forecast horizons. Each time the forecasts are calculated, the respective forecasting model is re-estimated first. Because we use lead-time-dependent forecasts, the necessary number of initial observations differs across forecast horizons.

### 3.2 Performance of the standard mismatch indicator

This Subsection treats the performance of the standard mismatch indicator ( $I = 3150$ ) in forecasting hirings. Table 2 shows the test results for the 1-, 2-, 6- and 12-steps-ahead forecasts, respectively. The first column displays the forecast horizon. The second column shows the mean squared prediction errors (MSPEs) of the benchmark stock-flow matching model following Equation (8), and the third column displays the MSPEs of the alternative larger model enhanced by the mismatch indicator.<sup>12</sup> Adjusted for the upward bias (fourth column), all of the reported test statistics are significantly positive at least at the 10 percent level. Hence, the test results show that the null hypothesis of equal predictive accuracy can be rejected and that models enhanced by the mismatch indicator outperform their benchmark counterparts. This supports our hypothesis that – from an out-of-sample perspective – models based on stock-flow matching can be improved even further by enhancing them with an appropriate measure of structural imbalance on the micro labour markets. This potential for an improvement in forecast accuracy is verified for all investigated forecast horizons between 1 and 12 months.

In contrast to Table 2, Table 3 shows the test results in the case that CRS is imposed on Equation (8).<sup>13</sup> In general, the MSPEs are substantially lower than those in the unrestricted case. This emphasises the potential of efficiency gains through model restrictions in out-of-sample settings. Furthermore, three of the four reported test statistics are significantly positive at the 1 percent level (one at 5 percent). Hence, a proper measure of the (im)balance between supply and demand turns out to be a crucial ingredient for forecasting hirings at the aggregate level and should not be ignored. Though the flow variables contribute substantially to the forecasting performance, we also performed the evaluation by using pure stock models. The results (available on request) showed that the advantage of models enhanced by the mismatch indicator is still present, although not as pronounced as found above.

<sup>12</sup>Note that our preferred version of  $MM$  ( $\alpha = 0.25$ ) has been used throughout this section because it is consistent with the theory proposed in Section 2. Although the out-of-sample performance does not differ substantially, the MSPEs in case of  $\alpha = 0.25$  were smaller in most cases than were those based on the alternative index in the style of Jackman/Roper ( $\alpha = \beta = 0.5$ ).

<sup>13</sup>In our empirical model, the CRS restriction reads  $\alpha_{st} = 1 - \rho_1 - \rho_2 - \beta_{st} - \alpha_{fl} - \beta_{fl}$ .

Table 2: Evaluation of monthly forecasts of hirings

forecast horizon	$MSPE_1$	$MSPE_2$	adj. term	$\Delta MSPE_{adj}$ (test statistic)
1 month	205.4	168.9	15.7	52.2 (3.61)***
2 months	221.5	190.6	18.5	49.4 (1.85)**
6 months	252.1	157.0	65.0	160.1 (2.52)***
12 months	545.9	552.2	81.8	75.6 (1.23)*

**Notes:**  $MSPE_1$  is the out-of-sample MSPE of the parsimonious benchmark model.  $MSPE_2$  is the out-of-sample MSPE of the alternative larger model that includes the lagged mismatch indicator. adj. term is the adjustment term according to Clark and West (2007).  $\Delta MSPE_{adj}$  presents a point estimate of the adjusted difference in MSPEs with the respective test statistic in parentheses. All figures (except test statistics) are to be multiplied by  $10^6$ . \*, \*\*, \*\*\* denote significance at the 10, 5, 1 percent levels, respectively. Critical values are calculated following the fixed regressor bootstrap procedure proposed by Clark and McCracken (2012) using 9,999 replications. The heteroskedasticity and autocorrelation robust covariance estimator proposed by Newey and West (1987) was used in the case of multiple-step forecasts.

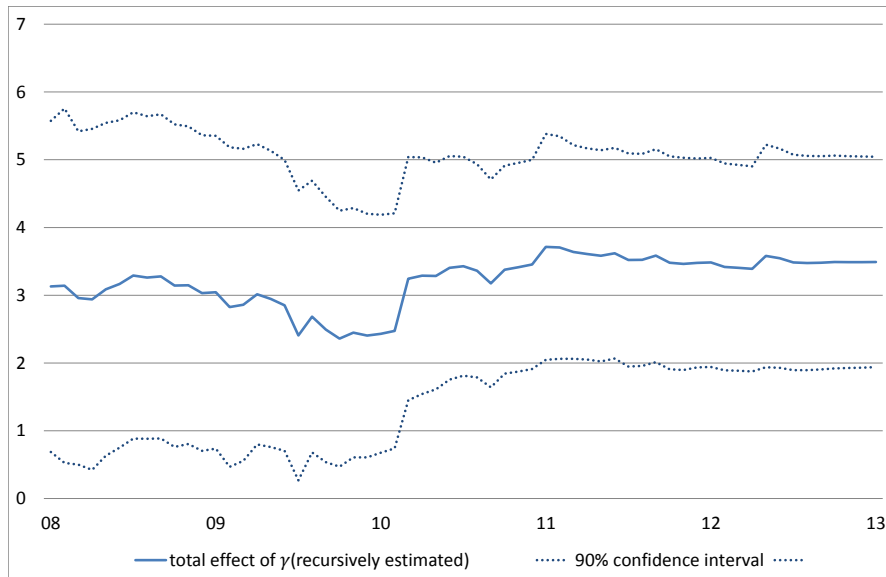
Table 3: Evaluation of monthly forecasts of hirings under the assumption of CRS

forecast horizon	$MSPE_1$	$MSPE_2$	adj. term	$\Delta MSPE_{adj}$ (test statistic)
1 month	182.3	155.2	17.8	44.9 (3.67)***
2 months	182.8	152.7	13.2	43.3 (2.66)***
6 months	245.5	155.3	63.8	154.0 (2.80)***
12 months	550.1	454.5	65.3	160.9 (1.70)**

**Notes:** See Table 2.

To corroborate the evidence found so far, we examine the respective in-sample results. First, for all forecasting horizons, we find  $\gamma$  to be significant. The total effect of  $\log(1 - MM)$  on hirings estimated from Equation (8) (considering the autoregressive terms) amounts to 3.49 in the case of  $f = 1$ . Hence, moving from the 25th percentile (0.104) to the 75th percentile (0.127) of the empirical distribution of the mismatch index (which is equivalent to a decrease in structural balance between supply and demand) hampers job findings – *ceteris paribus* on average – by 9.3 percent, which is approximately 85 percent of the standard deviation of hirings (11 percent).

Figure 6: The development of the total effect of  $\gamma$



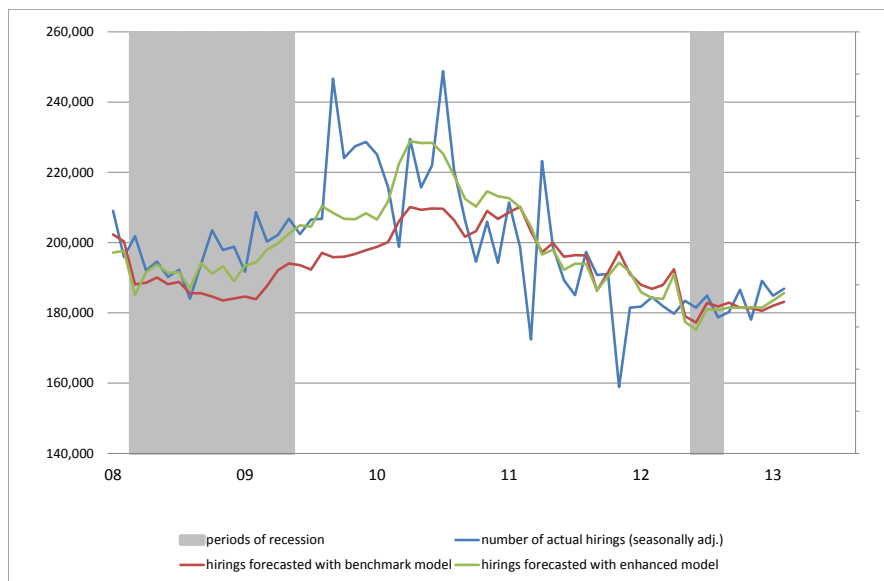
**Notes:** The graph shows the development of the total effect of  $\gamma$  in Equation (8) under the assumption of CRS when estimated recursively.

Second, Figure 6 shows the development of the total effect of  $\gamma$  during the evaluation period (which includes the Great Recession) when it is estimated recursively. The fairly stable evolution emphasises that the specification of our preferred model is quite robust. Another result of Figure 6 is that the constraint  $\gamma = 1$  emerging from Equation (6) can be rejected during half of the evaluation period at the 10 percent level.<sup>14</sup>

A further interesting aspect of the out-of-sample performance of our model based on an enhanced labour market matching function can be uncovered by comparing the forecasts of the benchmark model to those of the enhanced model *over time*. This is especially important because parts of the evaluation period

<sup>14</sup>This finding is also in line when investigated in an out-of-sample setting. In general, imposing  $\gamma = 1$  leads to worse forecast accuracy, which is why we do not report the respective results here.

Figure 7: Comparison of 6-months-ahead forecasts over time



**Notes:** The graph shows the number of actual hirings together with forecasts of hirings based on a CRS stock-flow matching model and forecasts of hirings based on the same model enhanced by the mismatch indicator calculated according to Equation (7) with  $I = 3150$  and  $\alpha = 0.25$ . Forecast horizon: 6 months. Grey areas denote periods of recessions.

coincide with the Great Recession of 2008/2009, when forecasts on the German labour market became very difficult due to its astounding resilience and robustness.

Figure 7 compares the 6-months-ahead forecasts stemming from the parsimonious benchmark model to those based on our enhanced labour market matching function over time. The evaluation period starts in August 2008 and ends in September 2013. The larger model performs better than the smaller model both during the Great Recession and in its aftermath. Given that all forecasts are based on data that had been available six months earlier, we conclude that the relatively low levels of mismatch in 2009 and 2010 helped predict the subsequent upswing in the hiring figures especially well.

One reason for the relatively low levels of mismatch in the late stages of the Great Recession was an inflow into the pool of job searchers due to cyclical rather than structural reasons. The additional unemployment was not due to mismatch problems and thus laid the foundation for a rather quick and strong upswing. Figure 9 clarifies that the occupational and regional dimensions were responsible for the decline in structural imbalance at that time. This is backed by the finding that the enormous financial and economic crisis hit some sectors (and hence occupations) more than others, e.g., the export-dependent sectors in the southern and western parts of Germany.

To gain further intuition for the mismatch indicator, we shed light on the roles of the supply and the demand side. Although mismatch could be driven by migrations on the supply side, the composition of vacancies could have changed and thereby contributed to the rather low level of mismatch at the end of the Great Recession. One approach to investigate which side of the labour market drives the dynamics of the mismatch indicator is to alternately hold one side constant and allow the other side to change in time.

Therefore, we define fictitious mismatch indices as follows:

$$MM_t^{\bar{U}} = 1 - \sum_{i=1}^I \left( \frac{V_{it}}{\bar{V}_t} \right)^\alpha \cdot \left( \frac{\bar{U}_i}{\bar{U}_t} \right)^{1-\alpha} \quad (10)$$

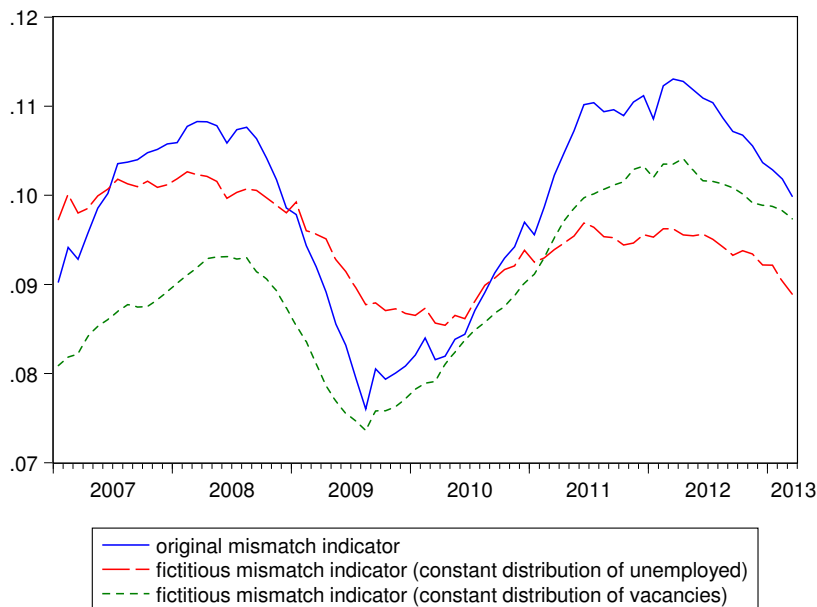
$$MM_t^{\bar{V}} = 1 - \sum_{i=1}^I \left( \frac{\bar{V}_i}{\bar{V}_t} \right)^\alpha \cdot \left( \frac{U_{it}}{\bar{U}_t} \right)^{1-\alpha}, \quad (11)$$

where  $\bar{U}_i$  and  $\bar{V}_i$  are the average numbers of unemployed and vacancies in micro market  $i$ , respectively. Consequently,  $MM_t^{\bar{U}}$  is the index that holds constant the supply side while  $MM_t^{\bar{V}}$  holds constant the demand side.

Figure 8 shows the development of the original mismatch indicator  $MM$  (solid line) since 2007<sup>15</sup> together with the two fictitious mismatch indicators. Although both sides of the labour market contribute to the dynamics of structural imbalance, the changing distribution of the unemployed dominated the development of mismatch in the last several years. This finding is supported by a remarkably high correlation between  $MM^{\bar{V}}$  and  $MM$  of 0.901, whereas

<sup>15</sup>This period covers all values after the phase of missing data in 2006.

Figure 8: The mismatch indicators with constant supply or demand side



**Notes:** The graph shows the original mismatch indicator (solid line) and the notional mismatch indicators freezing the distribution of unemployed (dashed line) or vacancies (dotted line) at its average level.  $\alpha$  is set to 0.25

the correlation between  $MM^{\bar{U}}$  and  $MM$  is only 0.687.<sup>16</sup> Thus, the mismatch indicator was indeed primarily driven by changes in the distribution of the unemployed, especially with respect to occupational imbalance, and mismatch fell due to cyclical unemployment.

Furthermore, the results shed some light on the German job miracle. Not only did firms make use of labour hoarding, but the fit of the stock of unemployed to the demand side of the labour market was improved. In the following, the German labour market could regain its positive pre-crisis dynamics in the years 2010 and 2011, a period in which a lowering speed due to the phasing-out of the Hartz-reform effects was already expected.

<sup>16</sup>These results are very similar to those of the 2000-2005 period. At that time, a large part of the decrease in mismatch occurred during and shortly after the recession periods of 2002 and 2003. Hence, there is evidence suggesting that the sort of cyclical shift that we observed during the Great Recession has happened before.

### 3.3 The importance of the different dimensions of mismatch

The mismatch indicator accounting for all three dimensions of mismatch ( $I = 3150$ ) obviously provides the most complete picture of structural imbalance given the available dataset. This does not necessarily mean that it performs best in out-of-sample forecasts. In theory, including an additional dimension can add valuable information or improve the lead-time properties of the respective measures of mismatch. However, it can also add nonessential information and thus lead to worse predictions of hirings. Therefore, this subsection investigates whether ignoring certain dimensions harms or improves predictability of hirings and, if so, at which forecast horizons is this the case. For this purpose, we calculate the mismatch indicator of Equation (7) using two or only one instead of three dimensions of mismatch.

Table 4: The dimensions of mismatch

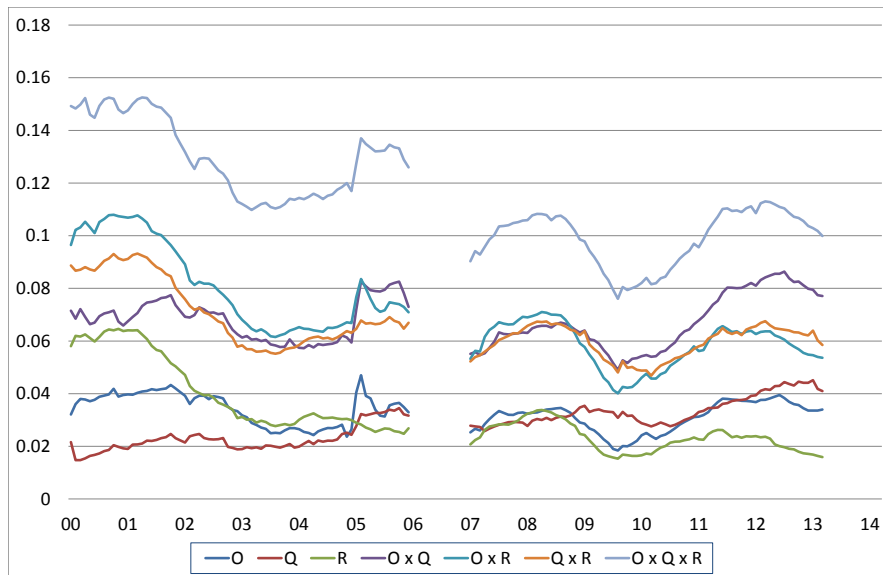
combination of dimensions	no. of micro markets
region x occupation x qualification	3150
region x occupation	1050
region x qualification	150
occupation x qualification	63
region	50
occupation	21
qualification	3

Table 4 shows all seven possible versions of the mismatch indicator together with the size of the underlying matrices. One can see that the level of disaggregation, i.e., the number of micro markets considered in Equation (7), varies from  $I = 3$  to  $I = 3150$ . The development of the resulting mismatch indices is shown in Figure 9. It depicts the seasonally adjusted development of mismatch accounting for occupational (O), qualificatory (Q), and regional (R) imbalance between unemployed and vacancies or for any combination of the three dimensions. It demonstrates that considering an additional factor increases the value of the respective mismatch index at any point in time.<sup>17</sup>

The pronounced decline in mismatch in the early part of our observation period is solely attributable to a decreasing regional mismatch. This development coincides with a longstanding adjustment process through domestic migration out of structurally disadvantaged regions into prospering regions. Indeed, since German reunification, the net figures of internal migration have been negative for the eastern part of Germany, with the lion's share of internal migrants moving to the southern federal states. Although this internal migration can help

<sup>17</sup>However, the dynamics do not necessarily add up exactly due to covariance among the three dimensions. A formal proof of the fact that the mismatch index is increasing in the level of disaggregation can be seen in the Online Appendix of Sahin et al. (2014).

Figure 9: The various dimensions of mismatch



**Notes:** The graph shows the seasonally adjusted development of mismatch accounting for the occupational (O), qualificatory (Q), and regional (R) imbalance between unemployed and vacancies or for any combination of the three dimensions ( $\alpha = 0.25$ ).

approximate the shares of vacancies and unemployed across German labour market regions, it does not automatically mitigate the problems of occupational or qualification-related incongruence.

Similar to Table 3, Table 5 shows the results of the forecast evaluation test following Clark and West (2007). Instead of using the mismatch indicator that accounts for all three dimensions of structural imbalance, two or even only one dimension is accounted for. We find that the MSPEs are higher than those presented in Table 3 in most cases. In general, the mismatch indicator solely considering regional incongruence ( $I = 50$ ) performs worst. Only for the more distant future, i.e., in case of forecasts 6 or even 12 months ahead, incorporating occupational mismatch or occupational together with qualification-related mismatch as the only factors of  $MM$  seems to pay off because the test statistics are highest here. Although regional incongruence seems to be of minor use when it is incorporated as the sole factor, the results show that it indeed plays a role in improving forecasts of hirings when it is implemented together with the other two dimensions. To conclude, we recommend calculating  $MM$  by using all available dimensions of imbalance between supply and demand because doing so ensures the most stable out-of-sample performance for all investigated forecast horizons.



Table 5: Forecast evaluation using different dimensions of mismatch

dimensions		forecast horizon			
		f=1	f=2	f=6	f=12
O x Q	$MSPE_2$	175.8	164.7	202.8	456.7
	adj. term	26.5	24.8	29.9	31.2
	$\Delta MSPE_{adj}$	33.0	42.9	72.6	124.6
	test statistic	2.09 ***	2.50 ***	3.87 ***	2.91 ***
O x R	$MSPE_2$	161.5	168.8	193.5	515.1
	adj. term	9.8	5.8	65.6	139.7
	$\Delta MSPE_{adj}$	30.6	19.8	117.6	174.7
	test statistic	2.48 ***	1.58 **	2.29 ***	1.24 *
Q x R	$MSPE_2$	156.6	154.0	200.0	538.8
	adj. term	12.7	16.8	100.4	95.2
	$\Delta MSPE_{adj}$	38.4	45.7	155.2	106.4
	test statistic	2.79 ***	2.13 **	2.22 **	1.10
O	$MSPE_2$	167.1	166.0	191.3	353.4
	adj. term	14.5	8.1	22.4	51.3
	$\Delta MSPE_{adj}$	29.7	24.9	76.6	248.0
	test statistic	3.20 ***	2.72 ***	2.88 ***	2.37 ***
Q	$MSPE_2$	173.8	167.4	241.9	623.2
	adj. term	33.4	53.2	19.4	12.6
	$\Delta MSPE_{adj}$	41.9	68.6	22.9	-60.6
	test statistic	2.02 ***	2.34 ***	1.52 *	-1.78
R	$MSPE_2$	174.5	181.9	221.8	543.3
	adj. term	4.8	5.0	70.0	101.0
	$\Delta MSPE_{adj}$	12.6	6.0	93.6	107.7
	test statistic	1.27 **	0.60	1.87 **	1.03

**Notes:** The table shows the results of the forecast evaluation test following Clark and West (2007). The implemented mismatch indicators account for occupational (O), qualificatory (Q) or regional (R) imbalance between unemployed and vacancies or for any combination of the three dimensions.  $MSPE_2$  is the out-of-sample MSPE of the enhanced model including the mismatch indicator. adj. term is the adjustment term according to Clark and West (2007).  $\Delta MSPE_{adj}$  presents a point estimate of the adjusted difference in MSPEs. All figures (except test statistics) are to be multiplied by  $10^6$ . \*, \*\*, \*\*\* denote significance at the 10, 5, 1 percent levels, respectively. Critical values are calculated following the fixed regressor bootstrap procedure proposed in Clark and McCracken (2012) using 9,999 replications. The heteroskedasticity and autocorrelation robust covariance estimator proposed in Newey and West (1987) was used in case of multiple-step forecasts.

## 4 Conclusion

This paper aimed to enhance a basic stock-flow matching function by an appropriate measure of structural imbalance between the demand and supply sides of micro labour markets. We investigated whether and to what extent the enhanced model performs better in out-of-sample forecasts of hirings. This is a relevant question because to date, the existing theoretical models have rarely been tested for their practical usefulness with respect to forecasting exercises. It also connects to the forecasting of unemployment rates, which could be improved

by using labour market flows (compare Barnichon and Nekarda (2012)).

Starting from a CRS Cobb-Douglas matching function at the disaggregate level, we argue that not accounting for a proper measure of structural imbalance in aggregate matching functions might lead not only to biased in-sample results, but also negatively affect forecasts of aggregate hiring figures. Consequently, we allow the matching process to depend on the level of regional, qualificatory and occupational mismatch between unemployed and vacancies. In a sense, we go beyond the purely quantitative view of considering the plain number of vacancies and unemployed in our forecasting equations and add a qualitative perspective of how well the two groups match with respect to relevant categories.

Our data set reveals detailed empirical evidence on the size and development of mismatch in Germany in the past 13 years, including the years after the Hartz labour market reforms. We find a pronounced decline in regional mismatch, especially in the early part of our observation period. In contrast, both occupational and qualificatory mismatch show an increasing tendency.

In pseudo out-of-sample tests that account for the nested model environment, we find that forecasting models that are enhanced by a term that contains the mismatch indicator outperform their benchmark counterparts. This supports our hypothesis that – from an out-of-sample perspective – models based on stock-flow matching can be improved by allowing for a time varying efficiency parameter and based on a measure of structural imbalance on the micro labour markets. This potential for an improvement in forecast accuracy is verified for all investigated forecast horizons between 1 and 12 months. It is especially pronounced in the aftermath of the Great Recession, where a low level of mismatch raised the possibility that the unemployed would find a job again. The results show that imposing CRS helps improve forecast accuracy even further.

Furthermore, we find that – although both sides of the labour market contribute to the dynamics of structural imbalance – the changing distribution of the unemployed dominated the development of mismatch in the last couple of years. Consequently, mismatch fell due to cyclical unemployment, i.e., the persons becoming unemployed during the Great Recession were mostly those needed to match the demand side for the subsequent upswing. In the following, unemployment could regain its strong pre-crisis dynamics in the years 2010 and 2011, a period where a lowering speed due to the phasing-out of the Hartz-reform effects was already expected.

Prospective research could benefit from extending the concept of measuring mismatch to the newly incoming vacancies and unemployed. Such an approach would consider two measures of structural incongruence: one for the stock and the other for the flow variables, which would probably complement the stock-flow matching model even better. Furthermore, one could investigate whether and to what extent further potential driving factors of the efficiency parameter (such as intensity of job search) can improve forecasts of hirings.

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