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Decomposing Variations in Labor Market Mismatch

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Contents

Abstract

This paper shows how changes in labor market mismatch can be attributed to the components unemployment, vacancies and matching efficiency. We find that unemployment is the most important factor and also drives the cyclical fluctuations, while the vacancy contributions are smaller and countercyclical. We differentiate by the source of unemployment and show that flows vis-à-vis employment increase mismatch, while this is not the case for non-employment and apprenticeship / training.

Zusammenfassung

Dieses Diskussionspapier zeigt, wie Veränderungen des Arbeitsmarkt-Mismatch auf die Komponenten Arbeitslosigkeit, offene Stellen und Matchingeffizienz zurückgeführt werden können. Wir stellen fest, dass die Arbeitslosigkeit der wichtigste Faktor ist und auch die zyklischen Schwankungen bestimmt, während die Beiträge der offenen Stellen geringer und antizyklisch sind. Wir unterscheiden nach der Ursache der Arbeitslosigkeit und zeigen, dass Ströme gegenüber der Beschäftigung den Mismatch verstärken, während dies für Nichtbeschäftigung und Ausbildung / Weiterbildung nicht der Fall ist.

JEL classification

J6, E24

Keywords

mismatch unemployment, worker flows, vacancy flows, decomposition

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1 Introduction

In recent years, there has been increased interest in mismatch unemployment in academic literature, as evidenced by the work of Şahin et al. (2014), Barnichon and Figura (2015), Hutter and Weber (2017), Turrini et al. (2022), Baley et al. (2022), and Bauer (2024). In particular, the fact that unemployed workers differ from the requirements of unfilled vacancies with regard to occupation, region or qualification represents a major source of structural unemployment. While previous studies have focused on measuring mismatch and its labor market impact, this paper sheds light on the sources of mismatch variation.

For that purpose, building on the mismatch concept of Şahin et al. (2014) we show how changes of their index over time can be analytically decomposed. Thereby, we distinguish between changes of mismatch connected to labor demand, labor supply, and matching efficiency. Thus, we separate the role of vacancy and unemployment flows.

Beyond providing a novel decomposition of the mismatch index, our framework also enables a systematic assessment of whether mismatch patterns are established by cyclical regularities or episode-specific adjustments. This sets our contribution apart from the existing literature, which typically focuses on stocks or on single-crisis episodes without distinguishing the underlying flow components.

The novel concept is applied to German administrative labor market data. As unemployment dynamics turns out to be the major driving factor, particularly during periods of economic weakness, we differentiate the results even more according to the type of labor market flows: vis-à-vis the education system, employment and inactivity.

While the following section explains the mismatch concept, section 3 derives the analytical decomposition. Subsequently, the data is introduced in section 4 and the results are discussed section 5. The last section concludes.

2 Measuring Mismatch

For measuring mismatch unemployment, we rely on the approach of Şahin et al. (2014). While frictions that prevent unemployed workers from matching with unfilled vacancies within submarkets create frictional unemployment, a suboptimal allocation of vacancies and unemployed individuals across submarkets (compared to a planner's solution) results in mismatch unemployment. This can be captured by an index of the following form:

$$M_t = 1 - \sum_{i=1}^{I} \frac{\phi_i}{\bar{\phi}_t} \frac{{v_{it}}^{\alpha}}{v_t} \frac{{u_{it}}^{1-\alpha}}{u_t} \tag{1}$$

where

$i =$	submarket
$\alpha =$	matching elasticity
$v_{it} =$	no. of vacancies in vacancies in submarket i
$u_{it} =$	no. of unemployed in submarket i
$v_t =$	total no. of vacancies
$u_t =$	total no. of unemployed
$\phi_i =$	matching efficiency in submarket i
$\bar{\phi}_t =$	$\left[\sum_{i=1}^{I} \phi_i^{\frac{1}{\alpha}} \left(\frac{v_{it}}{v_t}\right)\right]^{\alpha}$

The index ranges between 0 (no mismatch) and 1 (total mismatch). It relies on Cobb-Douglas type matching functions for the submarkets with constant returns to scale. Principally, the index compares the actual allocation of vacancies relative to unemployed to an optimal allocation. The optimal allocation in the model arises through a social planner solution, in which the planner can move unemployed persons costlessly across markets. This leads to an equalization of market specific labor market tightness (vacancy to unemployment ratio) across markets (weighted by matching efficiency), which implies "that the planner allocates more job seekers to those labor markets with more vacancies and higher matching efficiency" (Şahin et al., 2014: p. 3534).

3 Analytical Decomposition

Since we are interested in the change of mismatch over time and the driving forces, we decompose the index analytically via total differentiation. First we rewrite the index in terms of shares:

$$M_t = 1 - \sum_{i=1}^{I} \hat{\phi}_{i,t} \hat{v}_{i,t}^{\alpha} \hat{u}_{i,t}^{1-\alpha} \tag{2}$$

The total differential then is:

$$dM_t = -\sum_{i=1}^{I} \frac{\delta M_t}{\delta \hat{\phi}_{i,t}} \cdot d\hat{\phi}_{i,t} - \sum_{i=1}^{I} \frac{\delta M_t}{\delta \hat{v}_{i,t}} \cdot d\hat{v}_{i,t} - \sum_{i=1}^{I} \frac{\delta M_t}{\delta \hat{u}_{i,t}} \cdot d\hat{u}_{i,t} \tag{3}$$

$$\begin{aligned} dM_t = & -\sum_{i=1}^{I} \hat{v}_{i,t}^{\alpha}\, \hat{u}_{i,t}^{1-\alpha} \cdot d\hat{\phi}_{i,t} \\ & + \sum_{i=1}^{I} \hat{\phi}_{i,t}\, \alpha \hat{v}_{i,t}^{\alpha-1} \hat{u}_{i,t}^{1-\alpha} \cdot \frac{1}{\alpha \hat{v}_{i,t}^{-\alpha-1}} \cdot d\hat{v}_{i,t} \\ & - \sum_{i=1}^{I} \frac{\hat{\phi}_{i,t} \hat{v}_{i,t}^{\alpha} (1-\alpha) \hat{u}_{i,t}^{1-\alpha}}{\hat{u}_{i,t}} \cdot d\hat{u}_{i,t} \end{aligned} \tag{4}$$

This expression decomposes changes of the mismatch index over time into changes of the matching efficiencies and changes of the allocation of vacancies and unemployed across submarkets ($dv_{i,t}$, $du_{i,t}$).

This analytic expression constitutes the key methodological advance of our approach. Earlier work typically inferred drivers of mismatch from changes in stocks or from simulated counterfactual reallocations, whereas our framework derives an exact, closed-form decomposition of mismatch variation into its components. This enables researchers to trace the separate contributions of vacancy flows, unemployment flows, and matching efficiency directly.

Equation 4 can be extended to bi-directional gross flows. Rewriting leads to:

$$d\hat{v}_{i,t} = \frac{v_{it}}{v_t} - \frac{v_{it-1}}{v_{t-1}} = \frac{\frac{v_{it}}{v_{it-1}} - \frac{v_t}{v_{t-1}}}{\frac{v_t}{v_{it-1}}} \tag{5}$$

$$d\hat{u}_{i,t} = \frac{u_{it}}{u_t} - \frac{u_{it-1}}{u_{t-1}} = \frac{\frac{u_{it}}{u_{it-1}} - \frac{u_t}{u_{t-1}}}{\frac{u_t}{u_{it-1}}} \tag{6}$$

The following law of motion connects stocks and flows, for the submarkets and in the total economy:

$$\mathrm{v}_{\mathrm{it}} = v_{it-1} + \text{inflows} - \text{outflows} = v_{it-1} + z_{it-1} - a_{it-1} \tag{7}$$

$$\Rightarrow \frac{v_{it}}{v_{it-1}} = 1 + \frac{z_{it-1}}{v_{it-1}} - \frac{a_{it-1}}{v_{it-1}} = 1 + \tilde{z}_{it-1} - \tilde{a}_{it-1} \tag{8}$$

$$v_t = v_{t-1} + \text{inflows} - \text{outflows} = v_{t-1} + z_{t-1} - a_{t-1} \quad (9)$$

$$\Rightarrow \frac{v_t}{v_{t-1}} = 1 + \frac{z_{t-1}}{v_{t-1}} - \frac{a_{t-1}}{v_{t-1}} = 1 + \tilde{z}_{t-1} - \tilde{a}_{t-1} \quad (10)$$

and

$$\mathrm{u}_{\mathrm{it}} = u_{it-1} + \text{inflows} - \text{outflows} = u_{it-1} + s_{it-1} - f_{it-1} \quad (11)$$

$$\Rightarrow \frac{u_{it}}{u_{it-1}} = 1 + \frac{s_{it-1}}{u_{it-1}} - \frac{f_{it-1}}{u_{it-1}} = 1 + \tilde{s}_{it-1} - \tilde{f}_{it-1} \quad (12)$$

$$\mathrm{u}_{\mathrm{t}} = u_{t-1} + \text{inflows} - \text{outflows} = u_{t-1} + s_{t-1} - f_{t-1} \quad (13)$$

$$\Rightarrow \frac{u_t}{u_{t-1}} = 1 + \frac{s_{t-1}}{u_{t-1}} - \frac{f_{t-1}}{u_{t-1}} = 1 + \tilde{s}_{t-1} - \tilde{f}_{t-1} \quad (14)$$

We use equations on the laws of motion (7) to (14) to rewrite equations (5) to (6):

$$\begin{aligned} d\hat{v}_{i,t} &= \frac{(1 + \tilde{z}_{it-1} - \tilde{a}_{it-1}) - (1 + \tilde{z}_{t-1} + \tilde{a}_{t-1})}{\frac{v_t}{v_{it-1}}} \\ &= \frac{(\tilde{z}_{it-1} - \tilde{z}_{t-1}) - (\tilde{a}_{it-1} - \tilde{a}_{t-1})}{\frac{v_t}{v_{it-1}}} \\ &= d_{in,t} - d_{out,t} \quad (15) \end{aligned}$$

$$\begin{aligned} d\hat{u}_{i,t} &= \frac{(1 + \tilde{s}_{it-1} - \tilde{f}_{it-1}) - (1 + \tilde{s}_{t-1} + \tilde{f}_{t-1})}{\frac{u_t}{u_{it-1}}} \\ &= \frac{(\tilde{s}_{it-1} - \tilde{s}_{t-1}) - (\tilde{f}_{it-1} - \tilde{f}_{t-1})}{\frac{u_t}{u_{it-1}}} \\ &= d_{s,t} - d_{f,t} \quad (16) \end{aligned}$$

So far, we have used the law of motion to express changes in the stocks of vacancies and unemployment by changes in the inflows and outflows, scaled by the ratio of labor market conditions in the submarket relative to the aggregate economy. These equations are substituted into the total differential:

$$\begin{aligned} dM_t = & -\sum_{i=1}^{I} \hat{v}_{i,t}^{\alpha} \hat{u}_{i,t}^{1-\alpha} \cdot d\hat{\phi}_{i,t} - \sum_{i=1}^{I} \frac{\delta M_t}{\delta \hat{v}_{i,t}} \cdot (d_{in,t} - d_{out,t}) \quad (17) \\ & -\sum_{i=1}^{I} \frac{\delta M_t}{\delta \hat{u}_{i,t}} \cdot (d_{s,t} - d_{f,t}) \end{aligned}$$

$$dM_t = -\sum_{i=1}^{I} \hat{v}_{i,t}^{\alpha} \hat{u}_{i,t}^{1-\alpha} \cdot d\hat{\phi}_{i,t} \quad (18)$$

$$+\sum_{i=1}^{I}\hat{\phi}_{i,t}\,\alpha\hat{v}_{i,t}^{\alpha-1}\hat{u}_{i,t}^{1-\alpha}\cdot\frac{1}{\alpha\hat{v}_{i,t}^{-\alpha-1}}\cdot d_{in,t}$$

$$-\sum_{i=1}^{I}\hat{\phi}_{i,t}\,\alpha\hat{v}_{i,t}^{\alpha-1}\hat{u}_{i,t}^{1-\alpha}\cdot\frac{1}{\alpha\hat{v}_{i,t}^{-\alpha-1}}\cdot d_{out,t}$$

$$-\sum_{i=1}^{I}\frac{\hat{\phi}_{i,t}\hat{v}_{i,t}^{\alpha}\alpha\hat{u}_{i,t}^{1-\alpha}}{\hat{v}_{i,t}}\cdot d_{s,t}$$

$$+\sum_{i=1}^{I}\frac{\hat{\phi}_{i,t}\hat{v}_{i,t}^{\alpha}\alpha\hat{u}_{i,t}^{1-\alpha}}{\hat{v}_{i,t}}\cdot d_{f,t}$$

Based on this expression, it is straightforward to decompose the mismatch contributions further by the type of flow. For instance, in the results, we will decompose $d_{s,t}$-$d_{f,t}$ into unemployment flows vis-à-vis employment, nonemployment and apprenticeship.

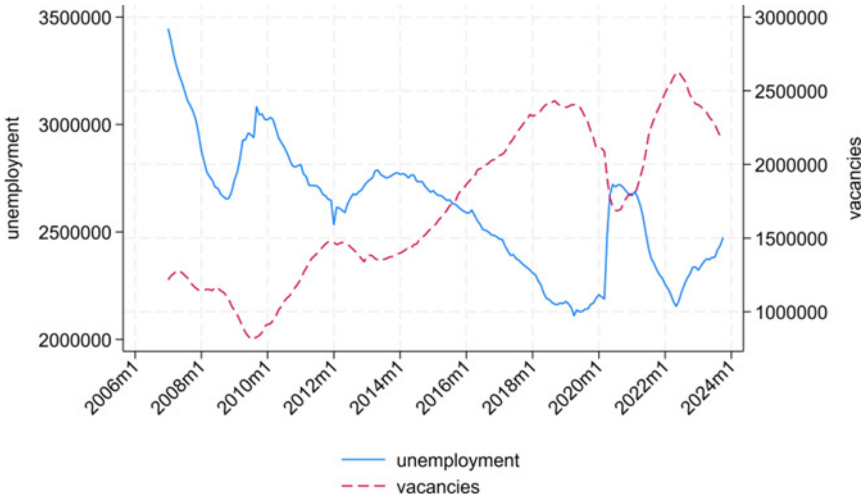
4 Data and empirical strategy

We apply our analytical framework to German administrative data on unemployment and vacancies spanning the years 2007–2023, which are aggregated data from the Data Warehouse of the Federal Employment Agency. As an entity for a sub-market, we choose a medium scale occupation classification ("occupational segments", see Matthes et al. (2008)), which comprises 14 different occupations after refinement. We group unemployed workers into these occupational segments according to their occupation before unemployment.

Our vacancy data comprise vacancies registered at the Federal Employment Agency. For the flows, we use transitions from unemployment (searching for work while unemployed, in subsidized training, or marginal employment) to employment (subject to social security contributions), nonemployment / inactivity and apprenticeship (including active labor market policy measures), and vice versa.

Figure 1 shows the labor market development throughout the sample. Unemployment followed a downward and vacancies an upward trend. This was interrupted by four downturns: the Great Recession, the euro crisis, the Covid-19 pandemic and the energy crisis. Table 1 gives an overview of the occupations. It shows the distribution of unemployment and vacancy shares across occupational segments. While occupations in traffic and logistics have the highest unemployment share, occupations in production technology have the highest vacancy share.

Figure 1: Evolution of unemployment and vacancies across time



Note: Left scale unemployment, right scale vacancies.

Source: Data Warehouse of the Federal Employment Agency; own calculations. © IAB

5 Results

Figure 2 shows the mismatch index computed given the stocks as in equation 1 and multiplied by 100. This index serves as a base for the computation of the differential. For assessing the matching elasticity α, we run panel regressions of the job-finding rate on labor market tightness (v-u-ratio) both in logs, which gives a value of 0.48. This value is a little higher than the literature suggests (Klinger and Rothe (2012); Bauer (2013); Kohlbrecher et al. (2016)) due to the longer period covered by our data.

Figure 2: Mismatch Index

Note: Mismatch index in percent, recession dates based on Euro Area Business Cycle Dating Committee (EABCDC).
Source: Data Warehouse of the Federal Employment Agency; own calculations. © IAB

Table 1: Distribution of unemployment and vacancy shares across occupation segments

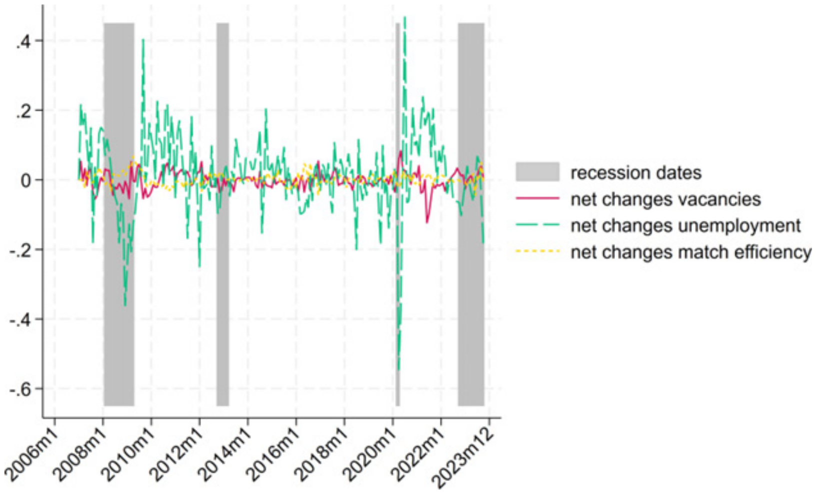
occupational segments	U-shares	V-shares
11: Occupations in agriculture, forestry and horticulture	0.0388	0.0155
12: Manufacturing occupations	0.0729	0.1152
13: Occupations concerned with production technology	0.0555	0.1495
14: Occupations in building and interior construction	0.0885	0.0937
21: Occupations in the food industry, in gastronomy and in tourism	0.0959	0.0832
22: Medical and non-medical health care occupations	0.0465	0.1071
23: Service occupations in social sector and cultural work	0.0643	0.0473
31: Occupations in commerce and trade	0.1235	0.0864
32: Occupations in business management and organisation	0.0947	0.0458
33: Business related service occupations	0.0311	0.0629
41: Service occupations in the IT-sector and the natural sciences	0.0187	0.0313
51: Safety and security occupations	0.0365	0.0188
52: Occupations in traffic and logistics	0.1454	0.1206
53: Occupations in cleaning services	0.0876	0.0228
Total	1.0000	1.0000

Note: Unemployment and vacancy shares across occupation segments.
Source: Data Warehouse of the Federal Employment Agency; own calculations. © IAB

Figure 2 reveals that labor market mismatch has a downward trend over time but also distinct procyclical movements. The changes in mismatch are negative at the onset of recessions and then recover. In contrast, Şahin et al. (2014) find clearly countercyclical behavior of mismatch in the US. In the following, we shed light on our result for Germany based on the novel decomposition. The final chapter will further relate the findings to insights from the relevant literature.

Figure 2 plots the monthly mismatch contributions of changes in the unemployment and vacancy shares, as well as the changes in matching efficiency, across time. This allows us to inspect what drives the changes in mismatch. Evidently, the movements were dominated by changes in the unemployment shares. While this part also generates the procyclicality, the vacancy contributions are smaller and countercyclical. As a quantitative measure, we calculate the mean absolute values of the three factors through the whole sample. These importance measures of the monthly contributions result as 0.082 for unemployment, 0.019 for vacancies and 0.013 for matching efficiency.

Figure 3: Contribution of changes of vacancies, unemployment and match efficiency to changes in mismatch



Note: Monthly mismatch contributions of changes in the unemployment (green dashed line) and vacancy shares (red solid line), as well as the changes in matching efficiency (yellow dotted line) across time.
Source: Data Warehouse of the Federal Employment Agency; own calculations. © IAB

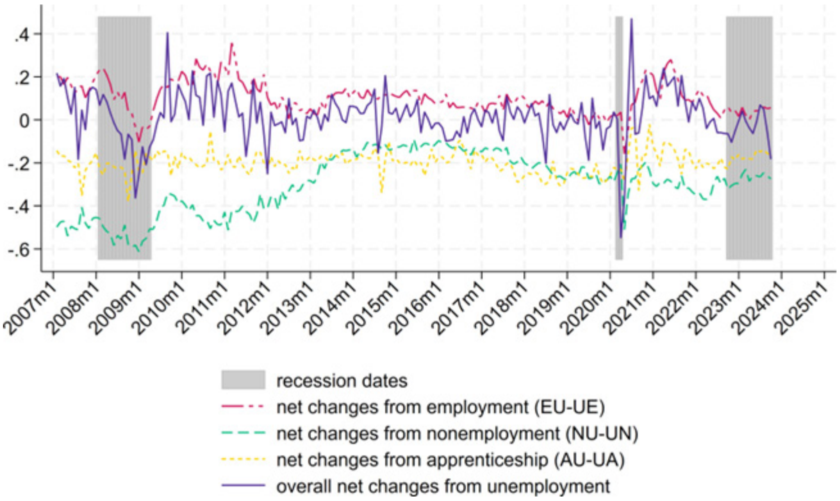
Since we find that mismatch is driven especially by changes in unemployment, we further decompose this part. In particular, we can distinguish unemployment flows vis-à-vis employment (EU-UE, i.e., job findings, separations), vis-à-vis apprenticeship or labor market measures (AU-UA), or vis-à-vis any other type like nonemployment (NU-UN).

Figure 3 shows that the flows between employment and unemployment contribute positively to changes in mismatch over the whole sample except the two deep recessions. This results if predominantly good (i.e., mismatch-reducing) risks leave unemployment and predominantly bad risks enter unemployment. Logically, since mismatch overall has fallen, there must also be decreasing factors.

Indeed, from Figure 4 it becomes clear that the net flows between unemployment and both apprenticeship and nonemployment reduce mismatch. Thus, the training system appears to be no critical mismatch driver. Net flows vis-à-vis nonemployment saw the strongest change of their impact: In the weak labor market in the 2000s, the share of good risks in unemployment increased via the nonemployment channel. However, the strengthening of the labor market over the following ten years attenuated this effect. Based on the gross flow decomposition in 0.18, we find that this was connected to inflows from nonemployment to unemployment: NU flows moved significantly across the period while UN flows were relatively stable.

Figure 4: Contribution of unemployment flows to changes in mismatch

Line chart for Germany from 2007 to 2025 showing four series of monthly **net changes from unemployment**: from employment (red dashed), from nonemployment (green dashed), from apprenticeship (yellow dashed), and the overall net change from unemployment (purple solid), all moving around zero with noticeable spikes during recession periods. Grey shaded vertical bars mark recession dates along the time axis.



Note: U=Unemployment, E=Employment, N=Nonemployment, A=Apprenticeship/labor market policy measure.
Source: Data Warehouse of the Federal Employment Agency; own calculations. © IAB

6 Conclusion

Mismatch unemployment is often considered a given condition. We open the black box and analyze the dynamic emergence of mismatch via an analytic decomposition. Taking this new concept to the data, mismatch in Germany turns out to be procyclical. Unemployment flows vis-à-vis employment increase mismatch except for the deep recessions, while the contributions of non-employment and the apprenticeship/training market are negative.

The procyclicality stands in contrast to results for the US (Şahin et al. (2014), Barnichon and Figura (2015)). Based on our novel decomposition, we can shed light on how this stylized fact for a major Continental economy arises. First, it turns out that mismatch is driven primarily by unemployment changes. Second, we find that the procyclicality is dominated by unemployment flows vis-à-vis employment. These facts establish a connection to the concepts of cleansing (Shleifer (1986), Caballero and Hammour (1994)) and sullying (Barlevy, 2002): For the US, Baley et al. (2022) state that recessions reduce mismatch among ongoing work relations because underqualified workers are laid off, and increase mismatch among new hires since overqualified workers are recruited. As the first effect overweighs, the mismatch on-the-job turns out to be procyclical. In unemployment, this is usually mirrored by countercyclical mismatch. In the same vein, Chodorow-Reich and Wieland (2020) demonstrate that industry reallocation contributes to higher local unemployment during recessions.

In this regard, our framework provides a new perspective by decomposing mismatch unemployment and analyzing its cyclicality. Thereby, we can observe that in the German labor market, recessions see an increasing weight of good mismatch risks in unemployment. This also sheds light on the German job miracle in the Great Recession and the quick recovery after the pandemic: Not only did firms make use of labor hoarding (Burda and Hunt, 2011), was separation propensity shrinking (Klinger and Weber (2016), Hutter et al. (2022), Hartung et al. (2025)) and matching efficiency following a positive trend (Weber, 2015), but lower mismatch also favored hiring in the aftermath of the recessions (Hutter and Weber, 2017). With employment picking up during the following upswing, mismatch increases again.

Furthermore, the decomposition allows us to place other observations within a broader cyclical perspective. Recent literature on the COVID-19 crisis has highlighted unusual short-run patterns in both job-search behavior (Carrillo-Tudela et al. (2022), Hartl et al. (2021)) and matching efficiency (Turrini et al., 2022). By separately tracing inflows and outflows over the entire sample period, we can distinguish mechanisms that recur in earlier recessions from those that were specific to the pandemic. The finding that unemployment flows are the main driver of mismatch emerges as a robust, recession-wide regularity, whereas some crisis-induced search shifts among particular groups appear more specific. In this sense, our approach not only sheds light on the COVID period but also provides a framework for separating cyclical from crisis-specific components of labor-market mismatch.

The insights can help find policy answers to general but also specific mismatch problems. For instance, this includes decisions which efforts to allocate to placement vs. training, to activation measures, job retention schemes, transitions from education or job creation support, and how to focus such activities through the business cycle. Future research might apply the new concept to further countries in order to establish new stylized facts. Moreover, age groups could be considered in more detail in order to shed light on retirement and education flows.

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Figures

Tables

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