Christl *J Labour Market Res* (2020) 54:7
https://doi.org/10.1186/s12651-020-00271-z

Journal for Labour Market Research

ORIGINAL ARTICLE

Open Access

A Beveridge curve decomposition for Austria: did the liberalisation of the Austrian labour market shift the Beveridge curve?

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Abstract
The Austrian Beveridge curve shifted in 2014, leading to the ongoing academic discussions about the reasons behind this shift. While some economists have argued that the shift was caused by a supply shock related to the labour market liberalisation during the course of the eastern enlargement of the European Union (EU), others have stated that a decrease in matching efficiency led to the shift. Using a new decomposition method, we combine labour market flow data and disentangle labour supply, labour demand, separation and matching factors, which can be potential reasons behind the shift in the Austrian Beveridge curve. We find empirical evidence that the increase in the unemployment rate in Austria after 2011 can indeed be attributed to a supply shock related to the EU enlargement. On the contrary, the data reveals that the shift after 2014 and the related increase in unemployment was almost exclusively caused by a decrease in matching efficiency, indicating a rising mismatch problem in the Austrian labour market.

Keywords: Beveridge curve, Crisis, Mismatch, Unemployment, Structural unemployment, Vacancies

1 Introduction

The Beveridge curve is one of the most established and stylised facts in macroeconomics. It is a graphical representation of the relation between job vacancies and unemployment. During booms, vacancy rates typically go up and unemployment rates go down the curve, whereas during recessions, vacancy rates go down and unemployment rates go up. Movements along the curve are often driven by cyclical factors. Shifts in the Beveridge curve, however, are often associated with structural changes in the labour market.

In recent years, shifts in the Beveridge curve have been extensively studied; however, there is limited data on the reasons behind those shifts. In addition, policymakers should give more importance to know the reasons for adopting adequate policies to tackle rising unemployment. Dow and Dicks-Mireaux (1958) argue that if the Beveridge curve shifts due to changes in matching efficiency, then the aggregate stabilisation policies are likely to fail. The unemployment rate will probably not fall again to the levels that prevailed before the recession, since the labour market is presumed to be structurally less efficient in creating successful matches. Researchers, but especially policy makers relate such outward shifts itself as an indication of a sustained rise in structural unemployment. However, from a theoretical point of view, it is not clear whether this shift is truly related to efficiency problems, because also supply shocks can cause outward shifts in the Beveridge curve. E. g. Diamond and Şahin (2015) argue that the outward shifts of the US Beveridge curve were not predictors of the levels of unemployment rate which were attained at the end of the following expansions.

The Austrian labour market was only slightly hit by the Great Recession of 2008/2009 compared to other European countries. The unemployment rate rose from about 4% to 5.5% during the crises years, but a shift in the

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Beveridge curve was only visible after 2014. The unemployment rate rose from 5% in 2014 to a record high of 6.2% in 2016, whereas the vacancy rate almost doubled from 0.6% to more than 1%.[1] While some scholars argue that the shift in the Beveridge curve was driven by a labour supply shock related to the opening of the labour market for Eastern European countries, others argue that the shift was due to a decrease in matching efficiency. Furthermore, there is a lack of clear empirical evidence on the determinants that affected the shift of the Austrian Beveridge curve, which we intend to focus in this study. In addition, the strong economic and regional connection of Austria to many Eastern European countries makes it an interesting case to assess the impact of labour market liberalisation on a small, open economy.

With a unique micro-data on worker flows on the Austrian labour market, we trace the changes between unemployment, employment and inactivity. This data has a rotating panel structure which allows us to follow workers for five consecutive quarters on the labour market between 2004 and 2016. We analyse the changes in the labour market flows by using a newly established decomposition method proposed by Barnichon and Figura (2010). This methodology allows us to separate unemployment rate movements into labour supply, demand, separation and matching factors.

Identifying the factors which drive the unemployment rate is crucial for policy recommendations. Job creation subsidies, firing taxes, employment tax credits to curb labour market entry or other policies to tackle problems on the labour market might be more effective, depending on the reasons for the shifts in the Beveridge curve. While Schiman (2018) suggests in a macro framework that a supply shock caused a Beveridge curve shift in Austria, our analysis based on microdata highlights a rising mismatch problem, which can potentially stem from the enlargement of the European Union (EU), but has completely different policy implications.

This paper is structured as follows. Section 2 provides a short literature overview. Section 3 will introduce the data used in the analysis. Section 4 describes the decomposition model. Section 5 presents the results, and Section 6 concludes the paper.

2 Literature overview

The Beveridge curve is a well-established relation between the vacancy rates and unemployment rates, which was formalised in the late 1980s by Abraham and Katz (1986) and Blanchard et al. (1989) as a tool to distinguish between structural and cyclical nature of the curve dynamics. The theoretical framework of the Beveridge curve later became popular due to the labour market model proposed by Mortensen and Pissarides (1999). According to their model, the Beveridge curve is a downward-sloping steady-state relation between the vacancy rate and the unemployment rate.

Movements along the Beveridge curve are typically seen as cyclical movements (changes in unemployment due to changes in vacancies). However, shifts in the Beveridge curve can occur due to several reasons and could be either transitory or permanent. They are often interpreted as movements in structural unemployment, but in fact, they can be caused due to several other reasons, e.g., changes in the intensity of the lay-offs or quits can cause such a shift. Additionally, labour supply factors, e.g., changes in the labour force composition, can lead to supply driven shifts in the Beveridge curve. However, permanent shifts are often caused by a change in matching efficiency, which are often related to structural changes in the labour market.

In many European countries, the Great Recession of 2008/2009 caused a sharp decline in vacancy rate (see Bonthuis et al. (2013, 2015); however, while vacancy rates recovered at the start of 2009, unemployment rates remained high or even continued to rise. These findings raised questions about structural changes in the labour market. Since then, more and more research has been focused on the reasons behind these shifts. Several authors, e.g. Barnichon and Figura (2010); Barnichon and Figura (2012); Daly et al. (2012); Bouvet (2012) and Klinger and Weber (2016), have developed decomposition methods which allow to analyse the underlying factors that cause movements in the unemployment rate.

Barnichon and Figura (2010) introduced a modelling framework which allows to attribute unemployment fluctuations to labour demand, labour supply and matching factors. They found that, between 1976 and 2009, the cyclical movements in unemployment rate in the US are typically labour demand-driven, although changes in labour supply play a crucial role. They also discovered that matching efficiency plays a minor role in unemployment fluctuations, except during recession.

In a later paper, Barnichon and Figura (2012) used a similar approach, allowing also for demographic changes in the decomposition method for the US. They found that the gradual leftward shift in the US Beveridge curve was mainly driven by the ageing of the baby-boom generation with the decline in the proportion of young workers.

Klinger and Weber (2016) set up an unobserved components model for Germany between 1979 and 2009 in order to decompose Beveridge curve movements and shifts. They found that matching efficiency played a

[1] The increase in the unemployment rate measured by the national definition of being unemployed was even more severe. The national definition is based on registered unemployed at the Austrian Employment Service (AMS).

minor role in Beveridge curve dynamics between 1985 and 2005; however, after 2005, an increase in the matching efficiency, combined with a shrinking separation rate, allowed for an inward shift in the Beveridge curve.

There is a lack of information regarding the reasons behind the shifts in the Beveridge curve after the Great Recession for most of the European countries. However, the Austrian labour market has witnessed a rising unemployment rate, as well as a rising vacancy rate after 2013. Several studies have discussed the Austrian Beveridge curve developments after the Great Recession, e.g, Bonthuis et al. (2013, 2015) but found no significant shift of the Beveridge curve in Austria. However, Christl et al. (2016) found a statistically significant shift in the long-term Beveridge curve in Austria after 2014, which according to them occurred in the four main sectors: construction, wholesale, transportation, and accommodation and food service activities. In line with Böheim (2017)[2], the authors attribute the shift to a decrease in the matching efficiency.

On the contrary, Schiman (2018) argues that the outward shift in the Austrian Beveridge curve is supply side driven, relating it to a deliberate policy decision in conjunction with European integration. He argues that the liberalisation of labour market access for several Central and Eastern European countries in May 2011 induced a significant labour supply shock which shifted the Beveridge curve later.

Fig. 1 General Labour market aggregates in Austria

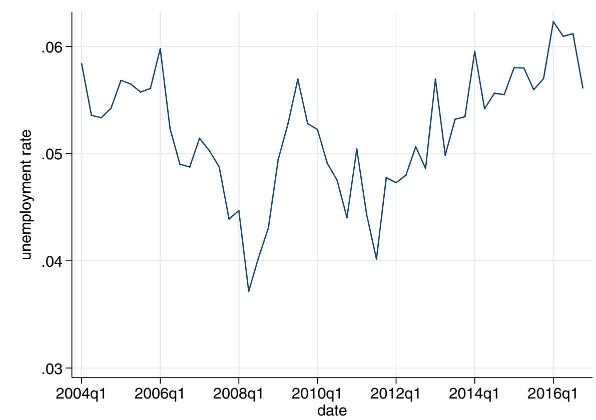


Fig. 2 The unemployment rate in Austria

3 Data

We use the Austrian Mikrozensus, a representative data set for the whole Austrian population. It contains the AKE/LFS (Arbeitskräfteerhebung), which is a specific part designed for labour market analysis. This data allows us, due to its rotational panel structure, to generate a longitudinal data set to analyse worker flows in the Austrian labour market[3] We match individuals between two consecutive quarters (between 2004 and 2016) to identify changes in the work status of individuals over time. Each quarter has approximately 45,000 individual observations which are used for a flow analysis of the Austrian labour market.

The survey is based on the official international labour statistics and follows the definitions of the labour market according to the ILO. Figure 1 highlights the Austrian labour market characterised by a gradual increase in the labour force, especially between 2004 and 2006, where both, employment and unemployment increased. This was driven by the pension reforms of 2003 and 2004 which aimed to keep people longer in employment by reducing the possibilities of early retirement[4].

The number of unemployed reached its lowest level (approximately 150,000 before the crisis hit in 2008), which again increased (up to 250,000). After a short recovery till 2012, the number of unemployed again increased after 2012, reaching its highest level in 2016 with more than 270,000 unemployed.

Figure 2 highlights that the Austrian labour market was characterised by a generally low unemployment rate of less than 4%, before the crisis in 2008 hit the Austrian economy. During the crisis, the unemployment rate went up to 5.5%. After a fast recovery between 2010 and 2012, the unemployment rate began to rise again and reached its highest level in 2016 of about 6.2%.

[2] The author attributes the shift in the Beveridge curve to a skills mismatch on the labour market, stating: "However, taken together, these facts are alarming, as they imply an increasing inefficiency in the labour market through, for example, a mismatch between demanded and supplied skills."

[3] See Schoiswohl and Wüger (2016).

[4] See Hofer and Koman (2006).

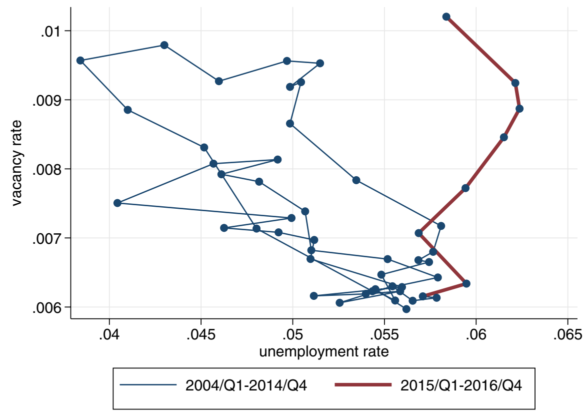


Fig. 3 The Beveridge curve for Austria

Due to the lack of long time-series data on overall vacancies in Austria, we use the vacancy data from the Austrian Employment Service (AMS), which only covers the registered vacancies, leaving out job openings which are not reported to the AMS. Job offers for people with a low and middle qualification are well covered, whereas those for highly qualified people are often not registered.

Statistik Austria, an alternate source for the overall vacancy data, estimates the vacancies in the Austrian economy, but unfortunately the data is available from 2009 onwards. However, we use this data to compare it with AMS data for the overlapping time period on vacancy data[5].

It is noteworthy that the number of unemployed people is well measured in existing surveys, but the estimates for the number of vacancies are typically less reliable. In fact, for the registered vacancies of the AMS, the measurement error should be a minor problem, but this measure does not cover vacancies which are not registered. However, since we are primarily focusing on changes in the vacancy rate, this should only be a minor issue.

Figure 3 shows (seasonally adjusted) quarterly data on both the unemployment rate and the vacancy rate, between 2004 and 2016. [6] We observe typical movements along the Beveridge curve between 2004 and 2014, but from the end of 2014, we see that in addition to the vacancy rate, the unemployment rate is also increasing. This phenomenon is known as a shift in the Beveridge curve.

[5] The results are discussed in the Appendix.

[6] Using monthly data from the AMS, Christl et al. (2016) show that the Beveridge curve in Austria was enormously stable between 1995 and 2014.

4 Methodology

In this section, we present a model which allows us to decompose unemployment rate movements. From a theoretical point of view, Beveridge curve movements are determined by labour market flows. While movements along the Beveridge curve are seen as demand side driven, other movements in the Beveridge curve can occur due to changes in labour demand, labour supply, separation behaviour as well as matching efficiency.

The model used in this paper was introduced first by Barnichon and Figura (2010). In this model, unemployment fluctuations can be decomposed into several factors:

- Movements along the Beveridge curve (labour demand)
- Shifts in the Beveridge curve due to changes in lay-offs and quits (separation)
- Shifts in the Beveridge curve due to changes in movements between inactivity and activity (labour supply)
- Shifts in the Beveridge curve due to changes in matching efficiency

It is noteworthy that the distinction between labour supply and labour demand is not straight forward. Barnichon and Figura (2010) suggested that labour supply responds to labour demand at cyclical frequencies, meaning that there is an interaction between supply and demand.

We follow a standard definition of labour market flows, where we distinguish between three states: unemployment U, employment E and inactivity I (outside the labour force). Therefore, we get nine possible flows. In each period the individual labour market status can change or remain same.

Let the levels of employment, unemployment and inactivity be N_t^i, and the gross worker flows N_t^{ij}, where $i, j \in E, U, I$ are defined as the flows between the working status i and j from period $t-1$ to period t. We can define the transition rate $\lambda_t^{i,j}$ (hazard rate) as the probability of transition from work status i to j:

$$\lambda_t^{ij} = \frac{N_t^{ij}}{N_{t-1}^{i}} \tag{1}$$

The hazard rates λ_t^{ij} are visualised in the Appendix. We can set up a system of differential equations which describe the changes in labour market variables:

$$\begin{cases} \dot{U}_t = \lambda_t^{EU} E_t + \lambda_t^{IU} I_t - (\lambda_t^{UE} + \lambda_t^{UI}) U_t \\ \dot{E}_t = \lambda_t^{UE} U_t + \lambda_t^{IE} I_t - (\lambda_t^{EU} + \lambda_t^{EI}) E_t \\ \dot{I}_t = \lambda_t^{EI} E_t + \lambda_t^{UI} U_t - (\lambda_t^{IE} + \lambda_t^{IU}) I_t \end{cases} \tag{2}$$

The steady-state unemployment rate can therefore be well approximated by:

$$u_t \simeq \frac{s_t}{s_t + f_t} \tag{3}$$

where $s_t = \lambda_t^{EU} + \frac{\lambda_t^{EI} * \lambda_t^{IU}}{1-\lambda_t^{II}}$ is the separation rate and $f_t = \lambda_t^{UE} + \frac{\lambda_t^{UI} * \lambda_t^{IE}}{1-\lambda_t^{II}}$ is the job-finding rate. Thus, the steady-state approximation for unemployment rate u_t can be written as:

$$u_t^{ss} \simeq \frac{s_t}{s_t + \lambda_t^{UIE} + \lambda_t^{UE}} \tag{4}$$

where $\lambda_t^{UIE} = \frac{\lambda_t^{UI} \lambda_t^{IE}}{1-\lambda_t^{II}}$. Usually, the number of new hires (m_t) is modelled with constant returns to scale in a Cobb-Douglas matching function[7]: $m_t = m_{ot} u_t^{\sigma} v_t^{1-\sigma}$, where m_{0t} is a parameter which is referred as an "aggregate matching efficiency", v_t the vacancies at time t and u_t the unemployed at time t. Petrongolo and Pissarides (2001) provide evidence that Cobb-Douglas matching functions with constant returns to scale perform generally well in modelling the number of new hires.

Modelling the job finding rate under the assumption of a stable matching function, we end up with:

$$u_t^{ss,bc} \simeq \frac{s_t}{s_t + \lambda_t^{UIE} + m_{0t}\left(\frac{v_t}{u_t}\right)^{1-\sigma}} \tag{5}$$

Allowing for changes in the matching function, we get:

$$u_t^{ss} \simeq \frac{s_t}{s_t + \lambda_t^{UIE} + \hat{\lambda}_t^{UE} e^{\epsilon_t}} \tag{6}$$

where $\epsilon_t = ln(\lambda_t^{UE}) - ln(\hat{\lambda}_t^{UE})$ captures deviations in the job finding rate compared to the one implied by a stable matching function.

Log-linearising eq. (6) around the mean of the hazard rates[8] leads to:

$$\begin{aligned} d(\ln u_t^{ss}) = {} & \alpha^{EI} d(\ln \lambda_t^{EI}) + \alpha^{IU} d(\ln \lambda_t^{IU}) \\ & + \alpha^{EU} d(\ln \lambda_t^{EU}) - \alpha^{IE} d(\ln \lambda_t^{IE}) - \alpha^{UI} d(\ln \lambda_t^{UI}) \\ & - \alpha^{UE} d(\ln \lambda_t^{UE}) + \eta_t \end{aligned} \tag{7}$$

where $\alpha^{UE} d(\ln \lambda_t^{UE}) = -\alpha^{UE} d(\ln \hat{\lambda}_t^{UE}) + \alpha^{UE} d(\epsilon_t)$.

In the next step, this approach allows us to decompose unemployment movements in a Beveridge curve framework into the several factors.

$$\begin{aligned} d(\ln u_t^{ss,bc}) = {} & d(\ln u_t^{shiftSEP}) + d(\ln u_t^{shiftLF}) \\ & + d(\ln u_t^{bc}) + d(\ln u_t^{eff}) + \eta_t \end{aligned} \tag{8}$$

where

$$d(\ln u_t^{shiftSEP}) = \alpha^{EU} d(\ln \lambda_t^{EU})$$

represents shifts due to changes in separation rates (either through lay-offs or quits).

$$\begin{aligned} d(\ln u_t^{shiftLF}) = {} & \alpha^{EI} d(\ln \lambda_t^{EI}) + \alpha^{IU} d(\ln \lambda_t^{IU}) \\ & - \alpha^{IE} d(\ln \lambda_t^{IE}) - \alpha^{UI} d(\ln \lambda_t^{UI}) \end{aligned}$$

represents shifts in the Beveridge curve due to changes in workers' attachment to the labour force (the movements of workers in and out of the labour force).

$$d(\ln u_t^{bc}) = -(1-\sigma) d(\ln \theta_t)$$

represents movements along the Beveridge curve and covers firm-induced movements in unemployment due to changes in vacancies. This is a typical labour demand factor.

$$d(\ln u_t^{eff}) = -\alpha^{UE} d(\epsilon_t))$$

represents shifts due to changes in matching efficiency.

These factors can then be further categorised as labour demand ($d(\ln u_t^{bc})$), labour supply ($d(\ln u_t^{shiftLF}$), separation ($d(\ln u_t^{shiftSEP})$) and matching factors ($d(\ln u_t^{eff})$), which drive the unemployment rate[9]

Following Fujita and Ramey (2009), we can separate several factors which contribute to the variance in unemployment rate:

$$\begin{aligned} Var(d(\ln u_t^{ss})) = {} & Cov(d(\ln u_t^{ss}), d(\ln u_t^{bc})) \\ & + Cov(d(\ln u_t^{ss}), d(\ln u_t^{shiftLF})) \\ & + Cov(d(\ln u_t^{ss}), d(\ln u_t^{shiftSEP})) \\ & + Cov(d(\ln u_t^{ss}), d + Cov(d(\ln u_t^{ss}), \eta_t) \end{aligned} \tag{9}$$

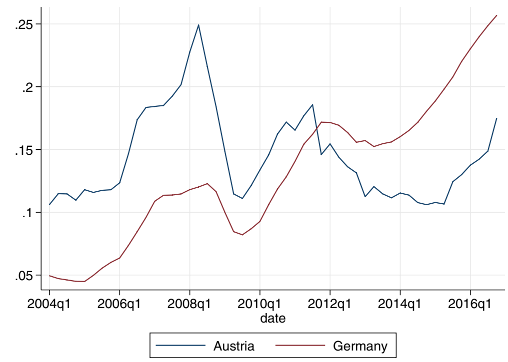
5 Results

In this section, we show step-by-step the model calibration. First, we take a closer look at labour market tightness in Austria, which is subsequently used to estimate the matching function needed for the decomposition of unemployment rate. In subsection 3, we decompose the

[7] See Barnichon and Figura (2015).

[8] For detailed information on the procedure, see also Barnichon and Figura (2010).

[9] Note that changes in job separation are hard to split into demand or supply. Barnichon and Figura (2010) argue that splitting separation into lay-offs and quit could potentially allow to distinguish demand and supply within separation.



Remarks: Please note, that the German data is obtained from the OECD database on Registered Unemployed and Job Vacancies.

Fig. 4 Labour market tightness in Austria

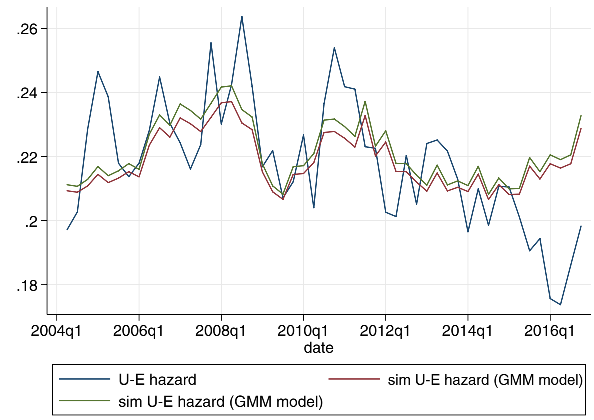


Fig. 5 Estimation of the UE hazard

unemployment rate into labour supply, labour demand, separation and matching factors. In subsection 4, we provide empirical evidence regarding the factors responsible for the fluctuations in unemployment rates in Austria between 2004 and 2016. Finally in subsection 5, we take a closer look on the drivers behind the increase in the Austrian unemployment rate.

5.1 Measuring labour market tightness

There are several methods to measure labour market tightness, although the vacancy–unemployment ratio is typically used.[10] The labour market tightness concept usually adopts the employers' perspective. High vacancy rates paired with a low unemployment rate makes the labour market tight for firms, because it will be more complicated for them to recruit workers.

Figure 4 shows the development of labour market tightness (measured in terms of the vacancy–unemployment ratio) in Austria and Germany. We can see that from the perspective of a firm, labour market tightness increased substantially between 2006 and 2008 in Austria. Before the crisis, the unemployment rate was very low, and in combination with a high vacancy rate, the labour market was tight. With the outbreak of the crisis in 2008, tightness fell due to an increase in the unemployment rate and in the vacancy rate, but only for a short period. The labour market tightness increased again after 2009 until 2011, due to an increase in vacancy rate and a decrease in the unemployment rate, but fell again after 2012. Interestingly, the most recent increase at the beginning of 2015 was, in contrast to prior increases in labour market tightness, purely driven by a substantial increase in vacancy rates while unemployment rate also increased slightly[11].

The labour market tightness in Austria showed a similar development until 2013 as in Germany. Interestingly, the labour market tightness increased substantially in Germany after 2013, whereas in Austria this happened 2 years later. Since Germany and Austria are strongly connected economies, this is quite surprising.

5.2 Estimating a matching function

The concept of labour market tightness allows to estimate a matching function because, from a theoretical point of view, it is closely linked to the job finding rate. Intuitively, the tighter the labour market becomes, the greater the job finding rate[12].

The job finding rate $\lambda^{UE} = m_t/u_t$ is defined as the new hires m_t from the pool of unemployed u_t. Typically, the number of new hires is modelled with constant returns to scale in the Cobb-Douglas matching function $m_t = m_{ot} u_t^{\sigma} v_t^{1-\sigma}$[13].

Therefore, the job finding rate can be modelled as:

$$\ln \lambda_t^{UE} = (1-\sigma) ln\left(\frac{v_t}{u_t}\right) + ln(m_{0t}) + \epsilon_t \tag{10}$$

We estimate the matching equation by using the job market tightness measure discussed in the previous subsection and the job finding rate, which was obtained from the Austrian Mikrozensus. We use data from 2004/Q1 to 2016/Q4 and distinguish between two different models

[10] See Shimer (2005) or Mortensen and Pissarides (1999).

[11] See Fig. 22 in the Appendix.

[12] In Austria, we can see that there is a strong correlation between both variables, as highlighted in Fig. 21 in the Appendix

[13] See Pissarides (2000), who argues that "the usefulness of the matching function depends on its empirical viability".

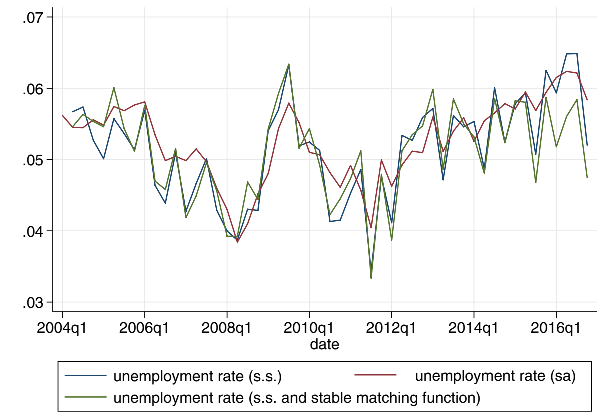


Fig. 6 Model prediction under several assumptions

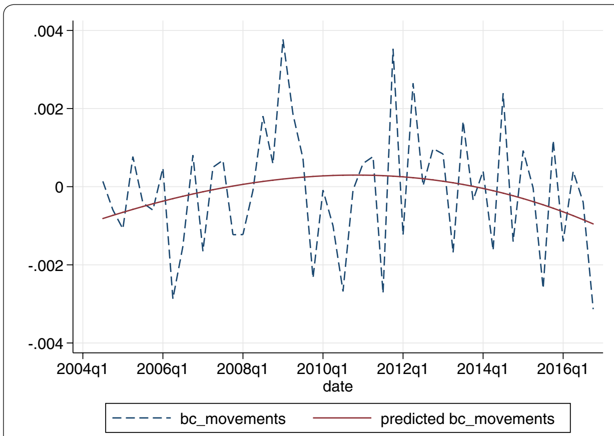


Fig. 7 Labour demand factors

which were also estimated by Barnichon and Figura 2011, 2015. In the first model, only the OLS estimate was used, whereas the second model uses a GMM estimate, where the first three lags of v and u are used as instruments to overcome potential problems[14]. Table 1 in the Appendix shows the results of regression analysis, which indicates a significant relation between the labour market tightness and the job finding rate.

Figure 5 points out the deviation in the job finding rate that is observed in the data and the one which is estimated by the two different models. We can see that both models capture the general trend of the hazard rate, even though some of the extreme values are not perfectly estimated. However, we can see a substantial difference after 2013 in the model estimates (stable matching function) and the real job finding rate (U-E hazard).

Using the estimated matching functions in our model, we distinguish between a model which assumes a stable matching function and the model which allows for changes in the matching efficiency. Figure 6 depicts similar behaviours of these two models at the beginning of the time period, indicating no big changes in the matching efficiency. However, there has been a substantial deviation in recent years between the unemployment predictions of the two models, indicating a change in matching efficiency.

To further promote this argument, if we assume a stable matching function, the unemployment rate that would have prevailed in Austria would have differed substantially from the realised unemployment rate (Fig. 6).

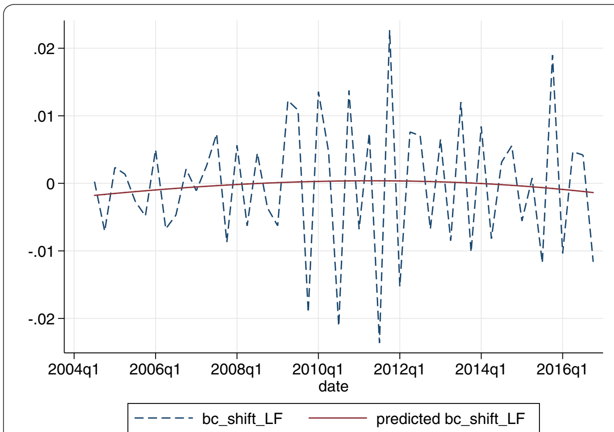


Fig. 8 Labour supply factors

The difference lies between 0.4 and 0.8 percentage points (pp) in 2016 [15].

5.3 Decomposition of unemployment rate

In this subsection, we decompose the unemployment movements into movements due to changes in labour demand, labour supply, separation behaviour and matching efficiency.

Labour demand In the analysis, movements along the Beveridge curve are the only demand-driven fluctuations in unemployment rate. Usually, they are seen as cyclical movements. Fig. 7 shows these fluctuations in unemployment rate, e.g., firm-induced movements in unemployment due to vacancies. We can see that, over the period in question, the labour demand trend has been negative

[14] See e.g. Barnichon and Figura (2015).

[15] As a robustness check, we also use the estimates of the GMM model, but the results are very similar to the one of the OLS model.

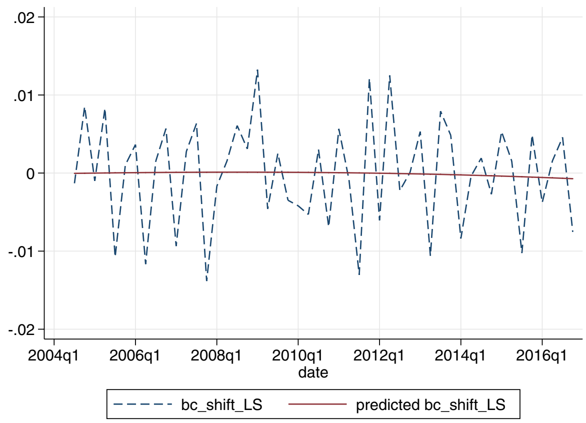


Fig. 9 Separation factors

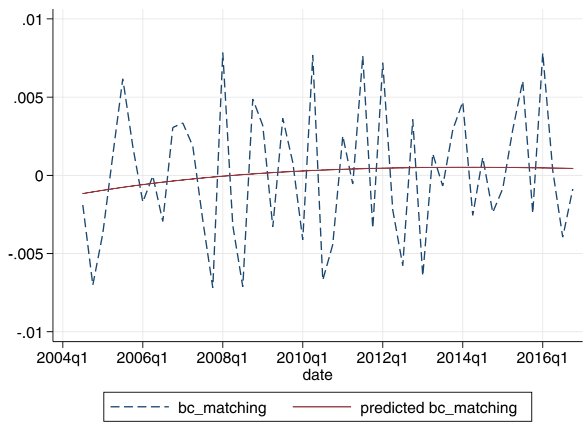


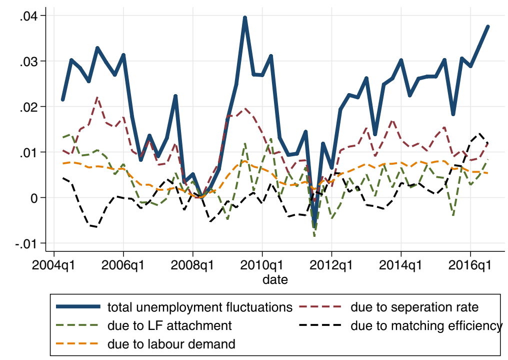
Fig. 10 Matching factors

in recent years, meaning that labour demand reduced the unemployment rate.

During the crisis of 2008, e.g., we can see that labour demand factors had an important impact on the increase in unemployment rate. However, in general, the impact on unemployment rate seems to be limited and in a range of − 0.4 and 0.4 pp.

Labour supply For labour supply, we consider movements in and out of the labour force, which have a strong influence on the evolution of unemployment rate (Fig. 8). These fluctuations changed the unemployment rate by almost 2 pp. Looking at the long-term trend, we can see an upward trend, which is reversed between 2012 and 2014, reaching a level below 0 in 2014.

After the crisis of 2008, the movements in and out of the labour force had a big effect on the unemployment rate movements. The impact became less pronounced again after 2012, but there was also a big hike at the end of 2015. Between 2009 and 2012, we can see a particularly big impact of supply factors on unemployment rate.



Remark: 2008/Q2 has been chosen as the base level, since it is one of the years with the lowest unemployment rate in the analysed period.

Fig. 11 Drivers of the unemployment rate

Separation behaviour For the separation behaviour, we consider changes in the structure of lay-offs and quits. This part of the decomposition can be seen as an interaction between labour demand and supply, since we can not clearly distinguish between lay-offs and quits. Furthermore, it is not clear whether quits and lay-offs are driven by supply or demand.

Figure 9 highlights that separation behaviour influences unemployment rate substantially, ranging from − 1 to 1 pp. While the long-term trend seems to be quite stable and close to 0, we can also see an increase between 2011 and 2013.

Matching efficiency Another factor which can shift the Beveridge curve is a change in matching efficiency.

As shown in Fig. 10, matching efficiency influenced unemployment movements by up to 0.7 pp. The trend in the matching factor shows that, at the beginning of the observed time period, matching efficiency contributed substantially to lower the unemployment rate. But this changes when we look at the period after 2012. We can see a clear upward trend indicating that, at the end of the observed time period, the matching efficiency decreased and even led to an increase in the unemployment rate. This finding is consistent with the findings of Christl et al. (2016), who reported that the average matching efficiency was stable until 2013 in Austria but has been steadily decreasing ever since.

5.4 Drivers of fluctuations in the unemployment rate

To visualise the decomposition of fluctuations in the unemployment rate, we show several components which influence the unemployment rate, namely labour supply, labour demand, separation and matching factors. Figure 11 shows the fluctuation of the unemployment rate in total, as well as the development of the components over time. We can see that overall, matching efficiency (dashed black line) alone would not have led to major fluctuations over time. But we also note that after 2014, the effect of matching efficiency on the unemployment rate increased substantially. In recent years, the unemployment rate increased by almost 1.5 pp, due to the decrease in matching efficiency.

Fluctuations due to labour demand are quite stable over time (dashed yellow line). However, we can see that especially during the crisis after 2008, the demand-side led to a substantial increase in the unemployment rate.

The changes in labour supply (LF attachment, dashed green line) had a big impact on the unemployment rate, especially before the crisis. After 2011, we can see that labour supply increased the unemployment rate substantially, which can be attributed to the impact of liberalisation of the Austrian labour market for Eastern European countries in 2011.

Furthermore, the separation factor (changes in the structure of lay-offs and quits, dashed red line) had a substantial effect on the unemployment rate. We see a strong increase in the unemployment rate due to separation after 2008, which was quickly reversed till 2011. But later, the unemployment rate increased due to changes in the separation behaviour, which can be attributed to the liberalisation of the Austrian labour market from Eastern European countries in 2011.

From a historical perspective, the reduction in the unemployment rate before the Great Recession of 2008/2009 was clearly driven by the separation behaviour in combination with labour supply. Furthermore, the increase during and after the crisis seems to be driven especially by labour supply and separation.

In line with findings of Schiman (2018), we find empirical evidence to confirm that the increase in the unemployment rate after 2011 was mostly driven by the labour supply and changes in separation behaviour. Our model suggests that these two factors increased the (seasonally adjusted) unemployment rate by more than 1 pp. This indicates that the liberalisation of labour market access for several Eastern European countries in 2011 induced a significant increase in the unemployment rate at that time.

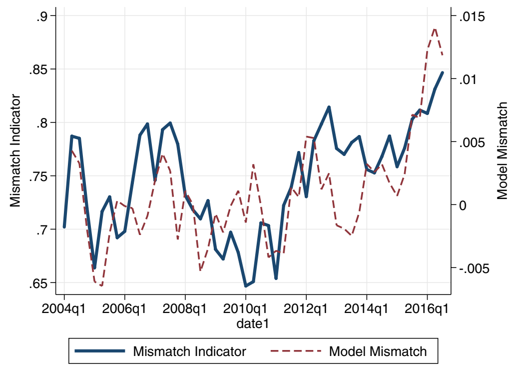
We also show that the increase in the unemployment rate after 2014 is clearly (and almost entirely) driven by a decrease in matching efficiency, while other factors play only a minor role. The decrease in matching efficiency increased the unemployment rate by more than 0.5 pp. This is in stark contrast with the findings of Schiman (2018), who argues that the shift in the Austrian Beveridge curve 'is related to labour supply shocks due to job-related immigration.' Our results also contrast the conclusion, that the unemployment rate and the vacancy rate will move back to their pre-shock levels.

The reasons for the contradictory results using a micro-or a macro-approach can be manifold. Schiman (2018) uses of a structural VAR model which relies on sign restrictions, meaning that the sign of the impulse response function is set in advance and used to identify the relevant shocks. Additionally, the model is calibrated based on the monthly data from 1988 to 2017 and thus represents the effects implied by the average parameters over that time horizon. Even though we use a shorter time horizon, the micro-model can capture the observed time frame in a more detailed way, whereas the macro-model would assume that there were no parametric changes over this time horizon. This is also true for the matching efficiency, where we show that it deviated from the long-run average in recent times. This difference in model assumption could potentially explain the differences in the results, which highlights the importance of studying labour market phenomena at different degrees of time granularity.

5.5 Digging further: the reasons behind the decrease in matching efficiency

To identify adequate policy responses to a decrease in matching efficiency, it is important to analyse the reasons behind this decrease. The literature reports several kinds of mismatches:

- A so-called skills mismatch occurs when the demanded and supplied skills in the labour market differ. Information on specific skills among the unemployed population, as well as needed skills in certain occupations, is rare; therefore, such a skills mismatch is often hard to measure (see, e.g., Sahin et al. (2011) or Herz and Van Rens (2011)).
- A geographical or regional mismatch occurs when vacancies and unemployed people are not located in the same region of a country (see, e.g., Nenov (2012) or Wall and Zoega (2002)).
- A reduction in search intensity by workers could lower the matching efficiency. Extended unemployment benefit can cause such a decrease (see e.g. Valletta and Kuang (2010)).
- A reduction in firms' recruiting intensity can lead to a decline in matching efficiency (see, e.g., Davis et al. (2010)).
- In general, changes in the composition of the unemployment pool might cause a mismatch problem (see, e.g., Barnichon and Figura (2011)).



Remark: The mismatch indicator only covers two potential mismatch dimensions, skill mismatch and regional mismatch.

Fig. 12 A mismatch indicator for Austria

- Changes in institutional settings can affect the matching efficiency (see, e.g., Blanchard et al. (1989), Boeri (2011) and Klinger and Weber (2016)).

We use a multi-dimensional mismatch indicator [16], which is calculated as follows:

$$MI = \sum_{i=1}^{I} \sum_{j=1}^{J} |vs_{i,j} - us_{i,j}| \tag{11}$$

where i is the skill mismatch dimension, j is the regional mismatch dimension, vs is the vacancy share and us is the unemployment share.

If vacancies are bundled either in regions or in skill groups with high unemployment rate, the mismatch indicator would have a low value, whereas if vacancies can be mainly found in skill groups or regions where there is a low unemployment rate, the mismatch indicator will be high.

We use monthly data provided by the AMS between 2004 and 2016, with detailed information on the skill levels of the unemployed (the exact occupation the unemployed worked before) and the required tasks for the vacancies (measures by the detailed occupation).[17] Following Spitz-Oener (2006), the 119 specific occupations (ISCO-08) are grouped into five categories of skills/tasks: manual routine tasks, manual non-routine tasks, analytical non-routine tasks, interactive non-routine tasks and cognitive routine tasks. Additionally, the regional component covers all 85 labour market districts ('Arbeitsmarktbezirke') in Austria.

Figure 12 depicts the evolution of the regional skill mismatch indicator between 2004 and 2016. The mismatch between 2011 and 2012 increase slightly but fall again till 2014. The small increase of the mismatch indicator might be linked to the inflow of workers due to the opening of the Austrian labour market to many Eastern and Central European countries, which mostly entered the labour market in the east, where the unemployment rate is higher than in the west of Austria.

Nevertheless, if we look at the development after 2014, we see a strong increase in the mismatch indicator. In other words, the regional skill mismatch increased substantially, reaching the highest level measured between 2004 and 2016 in the end of 2016 [18]. If we compare the development of the matching efficiency estimated by the model over time and the estimated mismatch indicator, we can see that even though we follow a different approach, both approaches point out a similar development over time. Both models suggest a substantial increase in the mismatch on the Austrian labour market.

6 Conclusions and discussion

The shift in the Austrian Beveridge curve after 2014 has attracted much attention not only among researchers but also among policy makers and the media. To date, there is no clear empirical evidence to explain this phenomenon. Therefore, we aim to shed some light behind the reasons for this shift. We use a newly developed decomposition method Barnichon and Figura (2010), which allows us to dig deeper to find the reasons behind the shift in the Austrian Beveridge curve. Using data on worker flows in the Austrian labour market, we were able to disentangle movements in the unemployment rate into labour demand, labour supply, separation and matching factors.

Our study shows that the increase in the unemployment rate after 2011 was indeed driven by the labour supply shock due to the liberalisation of the Austrian labour market. However, after 2014, the acute decrease in matching efficiency was almost solely responsible for the increase in the unemployment rate. Taking a closer look at the regional skill structure of the vacancies and the unemployed, we find a substantial increase in the regional skill mismatch in Austria after 2014.

These finding are in stark contrast to the findings of Schiman (2018), who related the Beveridge curve shift to a labour supply shock induced by the liberalisation of the labour market access for several Central and Eastern

[16] This indicator is similar to the one-dimensional mismatch indicator used by Christl et al. (2016), but does not take employment share into account.

[17] The data were obtained with kind permission of the Austrian Unemployment Office (arbeitsmarktdatenbank.at). Special thanks to Veronika Murauer for the help with the data.

[18] These results are in line with the calculation of other mismatch indicators that can be found in the Appendix. Those calculation use several dimensions (region, education and sector) to construct several one-dimensional mismatch indicators for the Austrian labour market.

European countries in May 2011, but in line with previous studies who reported mismatch problems on the Austrian labour market[19].

The mismatch problem has important policy implications in Austria. Cyclical problems in the labour market are usually caused by a lack of labour demand and therefore is transitory. The same holds true for shifts due to labour supply shocks, which are usually not persistent. However, a decrease in matching efficiency is typically persistent. As such, a decrease in matching efficiency requires different policy responses. Given that many unemployed people in Austria have low-level skills, an increase in training intensity might be an important policy tool to tackle the skill-mismatch problem.

Additionally, by taking a closer look at the regional skill structure of the vacancies and the unemployed, we find a substantial increase in the regional skill mismatch. For policy makers, there are means to overcome a regional skill mismatch arising from low mobility. Other countries have introduced financial incentives to tackle such problems. Germany, e.g., introduced an active labour market policy which offers a 'reallocation assistance'. This was part of the 'Hartz reforms', which covers relocation costs to incentivise unemployed people to seek jobs outside their region. This strategy offers financial support to the unemployed people who move to a distant region, which is defined as a daily commuting time of more than 2.5 hours.

This programme has been evaluated in the past, showing that not only is it financially beneficial for the unemployed people who agree to move for a job but also can decrease the regional mismatch in the labour market[20].

Such a program ('Übersiedelungsbeihilfe') existed in Austria between 2008 and 2016. AMS covered costs up to 5000 Euros for those unemployed people who were willing to relocate within Austria. AMS registered the highest participation (156 participants) in 2012, leading to the abolition of the programme [21].

We conclude by saying that policies which increase incentives for the unemployed to take up jobs (due to, e.g., financial incentives to move or front-loading of unemployment benefits), as well as better trans-regional job placements, are key to overcome the regional mismatch problems in Austria. Additionally, training and upskilling of the unemployed people are important tools to overcome the potential skills mismatch.

Acknowledgements

The author is grateful to Jesus Crespo Cuaresma, Harald Oberhofer, Rene Böheim, Monika Köppl-Turyna, Wolfgang Nagl, the participants of the Annual Conference 2019 of the German Economic Association in Leipzig, the participants of the Spring Meeting of Young Economists 2019 in Brussels and the participants of the Annual Meeting of the Austrian Economic Association in Graz and two anonymous referees for their helpful comments. The content of this article does not reflect the official opinion of the European Commission. Responsibility for the information and views expressed in the article lies entirely with the author.

Authors' contributions

All contributions to the manuscript were done by the sole author of the manuscript (OC). The author read and approved the final manuscript.

Competing interests

The authors declare that they have no competing interests.

Appendix

Labour market states definition

According to the International Labour Organization (ILO), the labour market states are defined as follows:

The unemployed comprise all persons of working age who were:

- Without work during the reference period, i.e. were not in paid employment or self-employment;
- Currently available for work, i.e. were available for paid employment or self-employment during the reference period; and
- Seeking work, i.e. had taken specific steps in a specified recent period to seek paid employment or self-employment.

Persons who did not look for work but have a future labour market stake are also counted as unemployed, as well as participants in skills training or retraining schemes within employment promotion programmes, who on that basis, were "not in employment", not "currently available" and did not "seek employment" because they had a job offer to start within a short subsequent period generally not greater than three months and persons "not in employment" who carried out activities to migrate abroad in order to work for pay or profit but who were still waiting for the opportunity to leave.

Employment comprises all persons of working age who during a specified brief period, such as one week or one day, were in the following categories: paid employment (whether at work or with a job but not at work); or self-employment (whether at work or with an enterprise but not at work).

[19] See, e.g., Christl et al. (2016) or Böheim (2017). Furthermore, a new qualitative study by Kerler and Steiner (2018) points out that there is a substantial mismatch problem in the Austrian labour market.

[20] Caliendo et al. (2017) show that participants of this programme receive higher wages and more stable jobs compared to non-participants. Additionally, this policy has led to a better job match due to the increased search radius of the participants.

[21] The low participation could be potentially driven by high social benefits that causes the workforce to be less mobile. E.g. Fernandez (2019) shows that a cut in unemployment benefits in Spain increased the mobility of the work force, especially the one of non-married males.

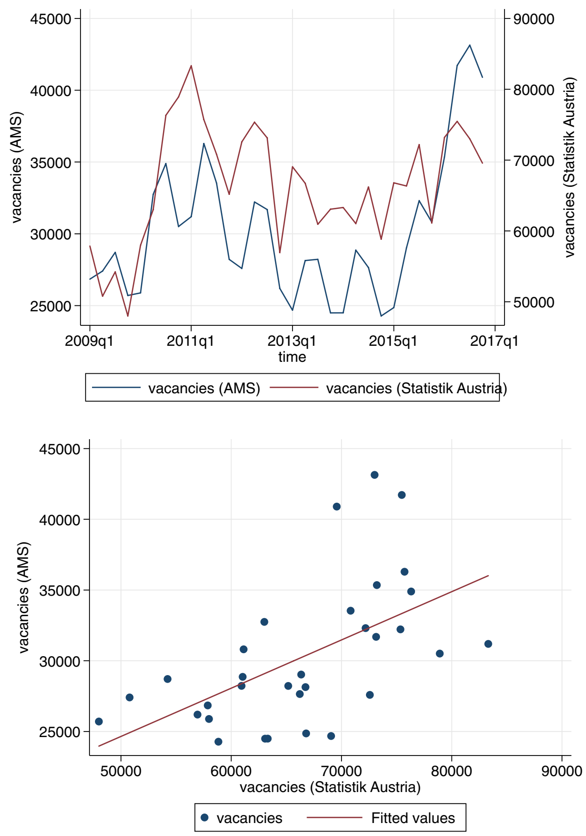


Fig. 13 Vacancies according to different definitions

The working-age population is the population above the legal working age, but for statistical purposes it comprises all persons above a specified minimum age threshold for which an inquiry on economic activity is made. To favour international comparability, the working-age population is often defined as all persons aged 15 and older, but this may vary from country to country based on national laws and practices (some countries also apply an upper age limit)."

Vacancy data

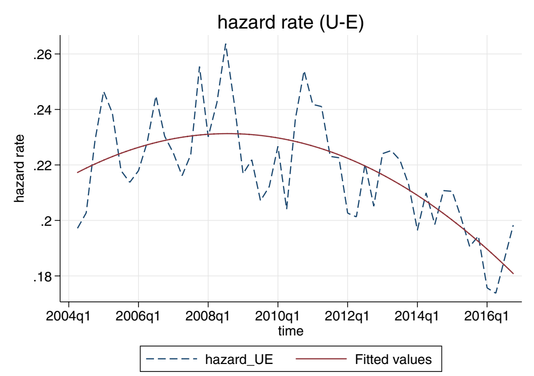
In Austria, there are two main sources of vacancy data: Austrian Employment Service (AMS) and Statistic Austria. AMS reports administrative data source covering all vacancies at firms registered at the AMS. Obviously, this data does not cover all vacancies in the economy, since not all firms hire via the AMS. The second data is the estimated vacancies by Statistic Austria, which is a quarterly time-series data based on estimations on the overall vacancies in the Austrian economy.

Unfortunately, this data is only available from 2009 onwards. Figure 13 shows AMS vacancy data, which shows high correlation with overall vacancies, as typically measured by Statistik Austria. Still, we can see that the variations in the data are similar, even though there is a stronger increase at the end of the sample in the AMS data.

The regression shows a highly significant coefficient of 0.94 when we regress both time series on each other, indicating that the AMS vacancy data can be used as a proxy for overall vacancies. This indicates that registered vacancies (typically, lower-qualification vacancies) have developed in a similar way to those vacancies which have not been registered with the AMS (most likely, higher-qualification vacancies).

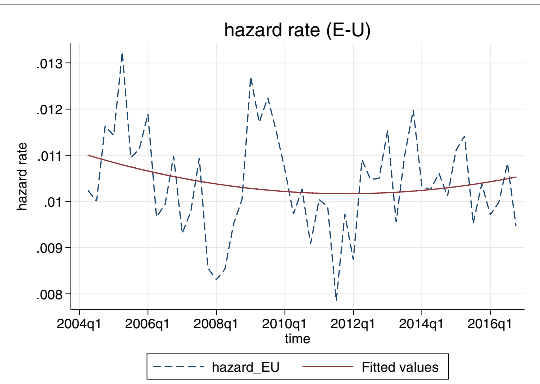
Hazard rates

Figures 14, 15, 16, 17, 18, 19 help us to visualise the movements on the Austrian labour market between 2004 and 2016. We compare worker flows (transition rates) between the three states of unemployment (U), employment (E) and inactivity (I).



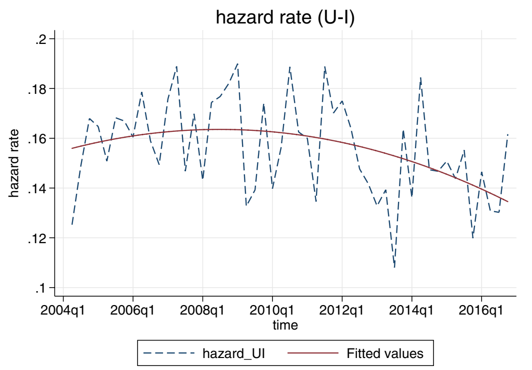
Remark: Hazard rate $i - j$ is the probability of transition from work status i to j. Changes are calculated quarter on quarter (QOQ).

Fig. 14 Movements from unemployment (U) to employment (E)



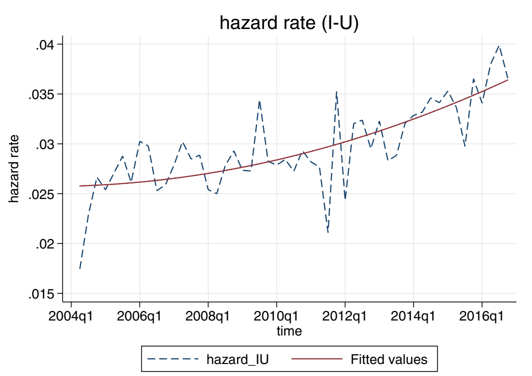
Remark: Hazard rate $i - j$ is the probability of transition from work status i to j. Changes are calculated quarter on quarter (QOQ).

Fig. 15 Movements from employment (E) to unemployment(U)



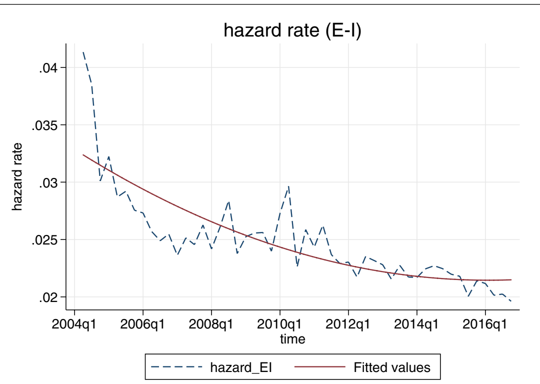
Remark: Hazard rate $i - j$ is the probability of transition from work status i to j. Changes are calculated quarter on quarter (QOQ).

Fig. 16 Movements from unemployment (U) to inactivity (I)



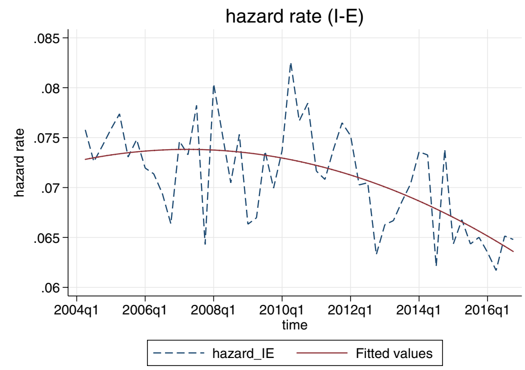
Remark: Hazard rate $i - j$ is the probability of transition from work status i to j. Changes are calculated quarter on quarter (QOQ).

Fig. 17 Movements from inactivity (I) to unemployment (U)



Remark: Hazard rate $i - j$ is the probability of transition from work status i to j. Changes are calculated quarter on quarter (QOQ).

Fig. 18 Movements from employment (E) to inactivity (I)



Remark: Hazard rate $i - j$ is the probability of transition from work status i to j. Changes are calculated quarter on quarter (QOQ).

Fig. 19 Movements from inactivity (I) to employment (E)

Additional mismatch indicators

In addition to the previous analysis, we calculated mismatch indicator similar to Christl et al. (2016):

$$MI = \sum_{i=1}^{I} e_i |vs_i - us_i| \tag{12}$$

where i is the mismatch dimension, es is the employment share, vs is the vacancy share and us is the unemployment share. The advantage of this approach is, that, we can weight the indicator by employment shares., Tthe disadvantage is, that, we can not combine the two or three dimensions, as we have done before. We use data provided by the AMS between 2008 and 2016 with information on vacancies, employment and unemployment across several sectors (sectorial mismatch), as well as several districts (regional mismatch). To analyse sectorial mismatch, we use the NACE classification, which covers 89 sectors of the Austrian labour market. For the regional mismatch, we use AMS data at the labour district ('Arbeitsmarktbezirke') level in Austria, which covers all 85 labour market districts of Austria. Vienna is counted as one district. For the skills mismatch, we use information on the minimum requied education for certain vacancies. Here, we can only distinguish between seven educational levels.

If vacancies are bundled into regions, sectors or educational groups with high unemployment, the mismatch indicator would have a low value; however, if vacancies can be mainly found in sectors or regions, where there is a low number of unemployed, the mismatch indicator will be high.

Figure 20 depicts the evolution of the sectorial and regional mismatch indicator between 2008 and 2016. In comparison to Christl et al. (2016), who use monthly data on bigger sectors in the Austrian labour market, we find

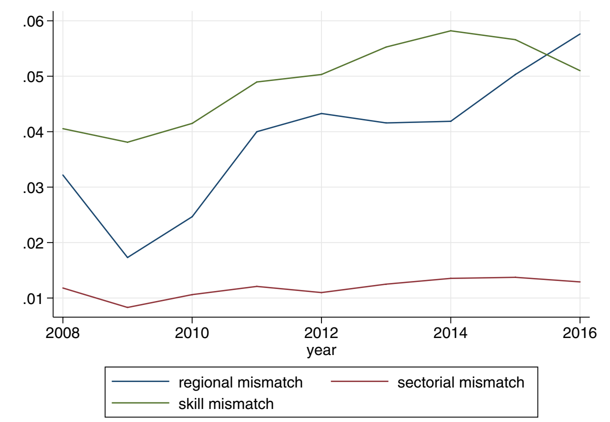


Fig. 20 Mismatch indicators for Austria

Fig. 22 The unemployment and vacancy rates in Austria

Table 1 Matching function estimation

	Model 1 (OLS)	Model 2 (GMM)
	ln λ_t^{UE}	ln λ_t^{UE}
ln (tightness)	0.1546^{***} (3.74)	0.1691 (4.46)
Constant	-1.1823^{***} (-14.81)	-0.4005^{***} (-16.13)
Observations	51	49

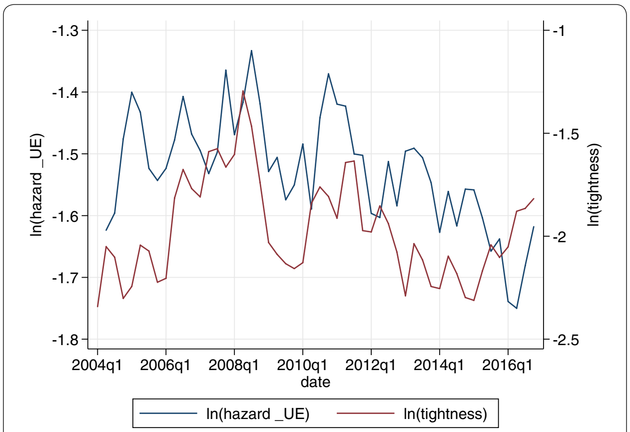


Fig. 21 Labour market tightness and job-finding rate

a slight increase in the sectorial mismatch between 2012 and 2015. Compared to the changes in the other mismatch indicators, this increase does not seem to be an issue.

For the skills mismatch, we see a slight increase between 2012 and 1014, but it is offset between 2014 and 2016.

On the contrary, the regional mismatch highlights a significant increase, especially after 2014. This effect is much stronger in size than the increase in sectorial mismatch. as well as the reduction in skills mismatch. We see this as an indicator of a growing regional mismatch problem in the Austrian labour market, which drives the general mismatch problem in this context.

Caution must be exercised, since we are not able to identify a possible skills mismatch in more detail due to data limitations. Still, the analysis reveals an acute increase in regional mismatch in the Austrian labour market, whereas sectorial mismatch seems to play no significant role.

Received: 29 April 2019 Accepted: 15 June 2020
Published online: 03 July 2020

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