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Keywords

– Beveridge curve, crisis, labour market, mismatch, unemployment, structural unemployment, vacancies.

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JEL Classification: J62, J63, E24, E32

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1 Introduction

The Beveridge curve is one of the most established stylized facts in macroeconomics. It describes the relation between job vacancies and unemployment. During booms, vacancy rates are typically high and unemployment rates are low; conversely, during recessions, vacancy rates go down and unemployment rises. Movements along the curve are driven by cyclical factors. Shifts in the Beveridge curves, however, are often associated with structural changes in the labour market.

Even though shifts in the Beveridge curve have been heavily analysed in recent years, the literature on the reasons behind those shifts is limited. That said, especially for policymakers, it is of great importance to know the reasons for adopting adequate policies to tackle rising unemployment. This is the research gap we wish to close.

To date, it has often been argued[1] that, if the Beveridge curve shifts, aggregate stabilization policies are likely to fail to lower the unemployment rate all the way down to the levels that prevailed before the recession, since the labour market is presumed to be structurally less efficient than previously believed in creating successful matches. This interpretation, however, assumes that the outward shift itself is an indication of a sustained rise in structural unemployment. But, from an theoretical point of view, it is not clear whether this shift is truly related to efficiency problems or, for example, supply-side shocks, which can also lead to outward shifts in the Beveridge curve[2].

The Austrian labour market is of special interest because it was only slightly hit by the Great Recession of 2008/2009 compared to other European countries, although a substantial shift in the Beveridge curve was observed after 2014. The unemployment rate rose from 5% in 2014 to a record high of 6.2 in 2016, while the vacancy rate almost doubled from 0.6% to more than 1%. The increase in the unemployment rate (national definition) was even more severe. The reasons for this shift in the Beveridge curve have rarely been analysed. While some scholars argue that the shift was supply side-driven, others argue that matching efficiency decreased. That said, a clear empirical analysis is still missing.

This sheds light on the ongoing discussion about the Beveridge curve shift. With unique microdata on worker flows in the Austrian labour market, we depict changes in flows between unemployment, employment and inactivity. Our data set has a rotating panel structure with which we can follow workers for five consecutive quarters on the labour market between 2004 and 2016. This allows us to take a closer look at how changes in this flow influence the development of the unemployment rate. By using a newly established decomposition method introduced by Barnichon and Figura (2010), we can separate unemployment rate movements into demand-side, supply-side and matching factors.

Identifying the respective factors driving the unemployment rate is crucial for policy recommendations. Our paper is the first to inform policymakers on the desirability of different policies, such as job creation subsidies, firing taxes, employment tax credits to curb labour market entry or other policies to tackle mismatch problems.

[1]See, e.g., Dow and Dicks-Mireaux (1958).

[2]Diamond and Şahin (2015) argue that "outwards shift of the US Beveridge curve were not predictors of the unemployment rate levels that the economy attained at the end of the following expansions".

Our results suggests that the shift in the Austrian Beveridge curve after 2014 is mainly driven by an increase in matching efficiency, and not by supply-side or demand-side factors. These results suggest that there is a rising mismatch problem in the Austrian labour market, which should be tackled by policymakers.

This paper is structured as follows. The next section will give a short literature overview. Section 3 will introduce the data used in our analysis. The decomposition model will be described in detail in Section 4. The results will be presented in Section 5, while Section 6 concludes the paper.

2 Literature overview

The Beveridge curve relation is a well-established relation between the vacancy and the unemployment rate, which was formalized in the late 1980s by Abraham and Katz (1986) and Blanchard et al. (1989) as a tool to distinguish between structural and cyclical effects on the unemployment rate. The theoretical framework of the Beveridge curve was later popularized by the labour market model of Mortensen and Pissarides (1999). According to this 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 in labour demand (changes in unemployment due to changes in vacancies). On the other hand, shifts in the Beveridge curve are typically more complicated to interpret. Shifts in the Beveridge curve can occur for several reasons and could be either transitory or permanent. Often shifts in the Beveridge curve are interpreted as movements in structural unemployment; but, in fact, they can be caused by several other reasons. A demand-side shock, namely, changes in the intensity of the lay-offs, can lead to a Beveridge curve shift. Supply-side factors can also cause a shift in the Beveridge curve. Additionally, a change in the intensity of quits and changes in the labour force can explain such supply side-driven shifts.

Permanent shifts in the Beveridge curve are typically caused by a reduction in matching efficiency. There are several reasons which can lead to a reduction in matching efficiency. Changes in institutional settings (see, e.g., Blanchard et al. (1989), Boeri et al. (2011) and Klinger and Weber (2016)) can affect matching efficiency, while a skills mismatch, where workers' skills and demanded skills do not match (see, e.g., Böheim (2017)) or a regional mismatch, where the unemployed rate and vacancies do not match on a regional level (see, e.g., Wall and Zoega (2002)), can cause shifts in the Beveridge curve.

Since shifts in the Beveridge curve occurred after the Great Recession of 2008/2009 in many countries (see, e.g., Bonthuis et al. (2015)), more and more research has focused on the reasons for those shifts in the Beveridge curve. Barnichon and Figura (2010), Barnichon and Figura (2012), Daly et al. (2012), Bouvet (2012) and Klinger and Weber (2016) have developed decomposition methods for the Beveridge curve, which allow us to analyse unemployment dynamics and the underlying factors driving those dynamics.

Klinger and Weber (2016) employed an unobserved components model for Germany between 1979 and 2009 in order to decompose Beveridge curve movements and shifts.

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

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

In a later paper, Barnichon and Figura (2012) used a similar approach, allowing also for demographic changes in 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 share of young workers (male and female) especially contributing to the trend in unemployment. They also showed that the shift was not caused by improvements in matching efficiency or changes in firms' recruitment and lay-off policies.

In many European countries, vacancy rates fell sharply from the beginning of the Great Recession in 2008/2009. However, while vacancy rates recovered at the start of 2009, unemployment rates remained high or even continued to rise. These findings suggest a shift in the Beveridge curve and raise questions about structural changes in the labour market (see, e.g., Bonthuis et al. (2013)). Still, for most of these countries, except for Germany, detailed analyses of the reasons behind the shifts in the Beveridge curve are missing.

Austria is, to some extent, a special case in Europe because the Beveridge curve did not shift after the Great Recession of 2008/2009, contrary to economies hit harder by the crisis, such as Greece, Italy, Spain, France and the eurozone as a whole (see Bonthuis et al. (2015)). Still, in the years after 2013, we can observe rising unemployment rates, as well as an increase in the vacancy rate. Previous studies concerning the Austrian Beveridge curve are manifold. For example, Bonthuis et al. (2013) and Bonthuis et al. (2015) looked at the development of the Austrian Beveridge curve after the crisis until 2012 and 2014, respectively, finding no significant shift in this curve.

Christl et al. (2016) found a statistically significant shift in the long-term Beveridge curve in Austria after 2014, showing that the shift took place later than in other European countries. This shift mainly occurred in the four main sectors of construction, wholesale, transportation, and accommodation and food service activities in Austria. Furthermore, they found that these shifts are driven by an decrease in the matching efficiency. Böheim (2017) also attributes the shift in the Beveridge curve to a skills mismatch in 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."

On the contrary, Schiman (2018) argues that the outward shift in the Beveridge curve in Austria is supply side-driven. According to his analysis, a substantial part of the shift is related to a deliberate policy decision in conjunction with European integration. He argues that the liberalization 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.

This paper sheds light on the ongoing discussion about the reasons behind the shift in the Beveridge curve by decomposing the unemployment rate movements into movements related to supply-side, demand-side and matching factors.

Our paper uses a unique microdata set for flows in the Austrian labour market between employment, unemployment and inactivity. We apply the unemployment accounting framework, as suggested by Barnichon and Figura (2012), to another country, namely Austria, where vacancy data and labour force survey data are available.

This allows us, for the first time, to reveal the reasons behind the observed shift in the Beveridge curve for Austria in detail. Other studies on the Beveridge curve in Austria are based on macro-models[3] or do not have detailed data on labour market flows to disentangle the reasons behind the shift in the Austrian Beveridge curve[4].

3 Data

To establish a decomposition in a Beveridge curve framework in Austria, we need precise data on movements and vacancies in the Austrian labour market. This chapter will describe the data in more detail.

3.1 Labour market movements

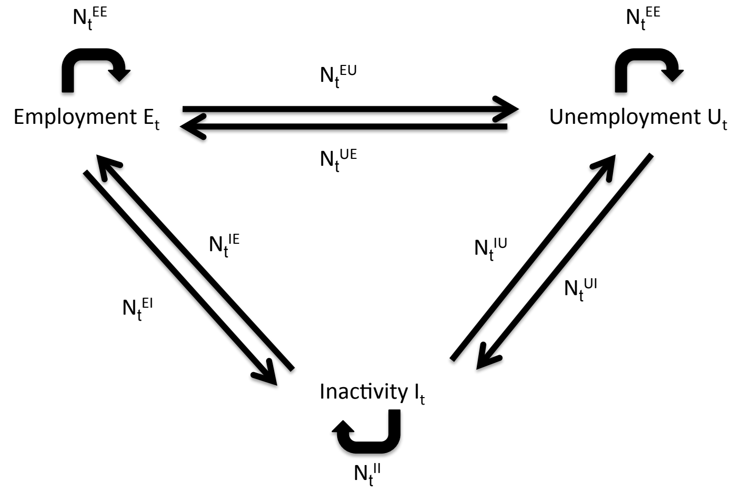
The microdata set, taken from the Mikrozensus, is a representative data set for the whole population of Austria and contains the AKE/LFS (Arbeitskräfteerhebung), which is a specific part of the Mikrozensus designed for labour market analysis. This data set allows us, due to its rotational panel structure, to generate a longitudinal data set to analyse worker flows in the Austrian labour market[5]. We match individuals between two consecutive quarters to identify changes in the work status of individuals over time. We follow workers for five consecutive quarters in the labour market between 2004 and 2016. Each quarter has approximately 45,000 individual observations which are used for a flow analysis of the Austrian labour market.

Analysing the Austrian labour market in more detail, we follow a standard definition of labour market flows, where we distinguish between three states: unemployment, employment and inactivity (outside the labour force). Therefore, we end up with nine possible flows which are visualized in figure 1.

At each point of time, people can either change their status in the labour market, e.g., they change from employment E to unemployment U or inactivity I. Additionally, individuals can stay with the same labour market status.

[3] see Schiman (2018).
[4] see Christl et al. (2016).
[5] See Schoiswohl and Wüger (2016).

Figure 1: Definition of worker flows



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. Subsequently, we can define the transition rate $\lambda_t^{i,j}$ as the probability of transition from work status i to j.

3.2 Vacancy data

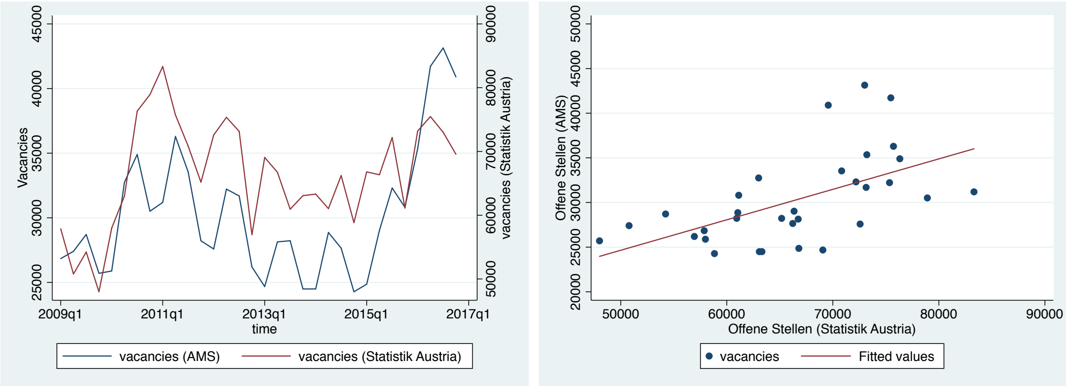
Due to lack of large time-series data on overall vacancies in Austria, we use vacancy data from the Austrian Employment Service (AMS). These data only cover the registered vacancies at the AMS, thus leaving out job openings which are not reported to the AMS. Typically, AMS data cover job offers for people with a low-level qualification very well, as job offers for highly qualified people are often not registered with AMS.

There are estimations available for overall vacancies in Austria from Statistik Austria. Unfortunately, those estimations only exist from 2009 onwards; therefore, this time series is not useful for our purposes. Still, to verify the use of AMS vacancy data, we compare both data sets for the overlapping time period.

Figure 2 shows that AMS vacancy data are highly correlated with overall vacancies, as typically measured by Statistik Austria, in the case of both time series. Still, we can see that the variations in the data are similar, even though there is a stronger increase at the end of our 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. The regression results can be found in the Appendix and are also visualized in Figure 2. 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).

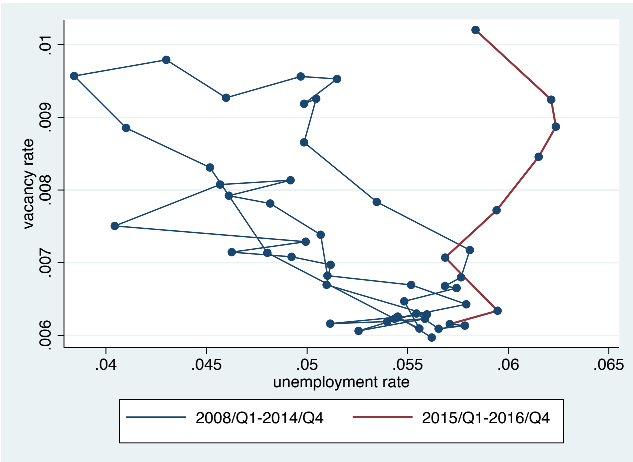
Figure 2: Vacancies according to different definitions



3.3 The Beveridge curve in Austria

Using (seasonally adjusted) quarterly data on both the unemployment rate and the vacancy rate, Figure 3 shows the Beveridge curve for Austria between 2004 and 2016. Using monthly data from AMS, Christl et al. (2016) show that the Beveridge curve in Austria was enormously stable between 1995 and 2014. In our data, we also observe typical movements along the Beveridge curve: when the vacancy rate increases, the unemployment rate typically decreases as well, indicating an economic upturn; when the vacancy rate decreases, the unemployment rate typically increases, indicating an economic downturn.

Figure 3: The Beveridge curve for Austria



But we can see different behaviour starting from the end of 2014 onwards. While vacancies increased, the unemployment rate also increased: a phenomenon which is typically called a shift in the Beveridge curve.

4 The model

The Beveridge curve describes the relation between job vacancies and unemployment. During booms, vacancy rates are typically high and unemployment rates are low; meanwhile, during recessions, vacancy rates go down and unemployment rises. Movements along the curve are typically driven by cyclical factors. Shifts, however, are often associated with structural changes in the labour market.

In this section, we present a model which takes a closer look at labour market flows and attributes changes in the unemployment rate to the changes in those flows.

From a theoretical point of view, Beveridge curve movements are determined by labour market flows. While movements along the Beveridge curve are typically seen as demand side-driven, other movements in the Beveridge curve can occur due to factors relating to the demand side, supply side or 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 (demand side)
- Shifts in the Beveridge curve due to lay-offs and quits (mostly supply side)
- Shifts in the Beveridge curve due to movements between inactivity and activity (supply side)
- Shifts in the Beveridge curve due to changes in matching efficiency

Given those factors, we are unable to see to what extent the unemployment rise in Austria after 2014 was driven by movements along the Beveridge curve (demand side), by changes in supply-side factors (supply shock) and by changes in matching efficiency. To tackle high unemployment, it is essential for policymakers to know the exact reason behind an increase in unemployment, since some policies are more efficient in addressing, e.g., supply-side and demand-side shock unemployment, or conversely in addressing matching efficiency.

Methodology

Let U_t, E_t and I_t be the number of unemployed, employed and inactive and λ_t^{AB} be the hazard rate of moving from state A to B. We can then set up a system of differential equations:

$$\begin{cases} \dot{U}_t = \lambda_t^{EU} E_t + \lambda_t^{IU} I_t - (\lambda_t^{UE} + \lambda_t^{UI}) U_t \\ \dot{E}_t = \lambda_t^{UE} U_t + \lambda_t^{IE} I_t - (\lambda_t^{EU} + \lambda_t^{EI}) E_t \\ \dot{I}_t = \lambda_t^{EI} E_t + \lambda_t^{UI} U_t - (\lambda_t^{IE} + \lambda_t^{IU}) I_t \end{cases} \tag{1}$$

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

$$u_t \simeq \frac{s_t}{s_t + f_t} \tag{2}$$

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.

From that, the steady state approximation for the unemployment rate u_t with a job-finding rate, as modelled by a Cobb-Douglas matching function, can be written as:

$$u_t^{ss} \simeq \frac{s_t}{s_t + \lambda_t^{UIE} + \lambda_t^{UE}} \tag{3}$$

where $\lambda_t^{UIE} = \frac{\lambda_t^{UI} \lambda_t^{IE}}{1-\lambda_t^{II}}$.

Under the assumption of a stable matching function, we end up with:

$$u_t^{ss,bc} \simeq \frac{s_t}{s_t + \lambda_t^{UIE} + m_0 \left(\frac{v_t}{u_t}\right)^{1-\sigma}} \tag{4}$$

Allowing for changes in the matching function, we end up with:

$$u_t^{ss} \simeq \frac{s_t}{s_t + \lambda_t^{UIE} + \hat{\lambda}_t^{UE} e^{\epsilon_t}} \tag{5}$$

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-linearizing (5) around the mean of the hazard rates[6] leads to:

$$d(\ln u_t^{ss}) = \alpha^{EI} d(\ln \lambda_t^{EI}) + \alpha^{IU} d(\ln \lambda_t^{IU}) + \alpha^{EU} d(\ln \lambda_t^{EU}) - \alpha^{IE} d(\ln \lambda_t^{IE}) - \alpha^{UI} d(\ln \lambda_t^{UI}) - \alpha^{UE} d(\ln \lambda_t^{UE}) + \eta_t \tag{6}$$

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 factors already mentioned.

$$d(\ln u_t^{ss,bc}) = d(\ln u_t^{shiftsSEP}) + d(\ln u_t^{shiftLF}) + d(\ln u_t^{bc}) + d(\ln u_t^{eff}) + \eta_t \tag{7}$$

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). Note that, in Austria, compared to quits, lay-offs are rare events due to strict labour law[7]. Lay-offs are not especially common, meaning that changes in this parameter could be mostly attributed to the supply side, and not the demand side.

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

[7] According to the OECD, the strictness of employment protection (individual dismissals) in Austria had a value of 2.37 compared to the OECD average of 2.04.

Figure 12, in the Appendix, shows that the lay-off rate, which is the number of lay-offs (and workers with an expired short-term contract) divided by the number of employed. The lay-off rate lies between 1 and 2% with a low variation over time. Even after the Great Recession of 2008/2009, the lay-off rate did not increase. This is most probably driven by the strengthening of short-time working arrangements in Austria in order to buffer the occupational impact of the crisis[8]

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

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

$$d(\ln u_t^{bc}) = -(1-\sigma) d(\ln \theta_{0t})$$

represents movements along the Beveridge curve and covers firm-induced movements in unemployment due to vacancies. This is a typical demand-side 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 categorized as demand-side factors ($d(\ln u_t^{bc})$) and supply-side ($d(\ln u_t^{shiftLF}) + d(\ln u_t^{shiftSEP})$) factors and matching factors($d(\ln u_t^{eff})$), which drive the unemployment rate[9].

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

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

[8]See, e.g., Sacchi et al. (2011).

[9]Note that counting all changes in job separation as supply side-driven might cause a bias in our estimates.

5 Results

In this chapter, we show, step by step, the model calibration by firstly interpreting the development of hazard rates. Then 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 the unemployment rate. In a next step, we decompose the unemployment rate into supply-side, demand-side and matching factors. In the last part of this section, we provide empirical evidence concerning the factors responsible for unemployment fluctuations in Austria between 2004 and 2016.

5.1 Hazard rates

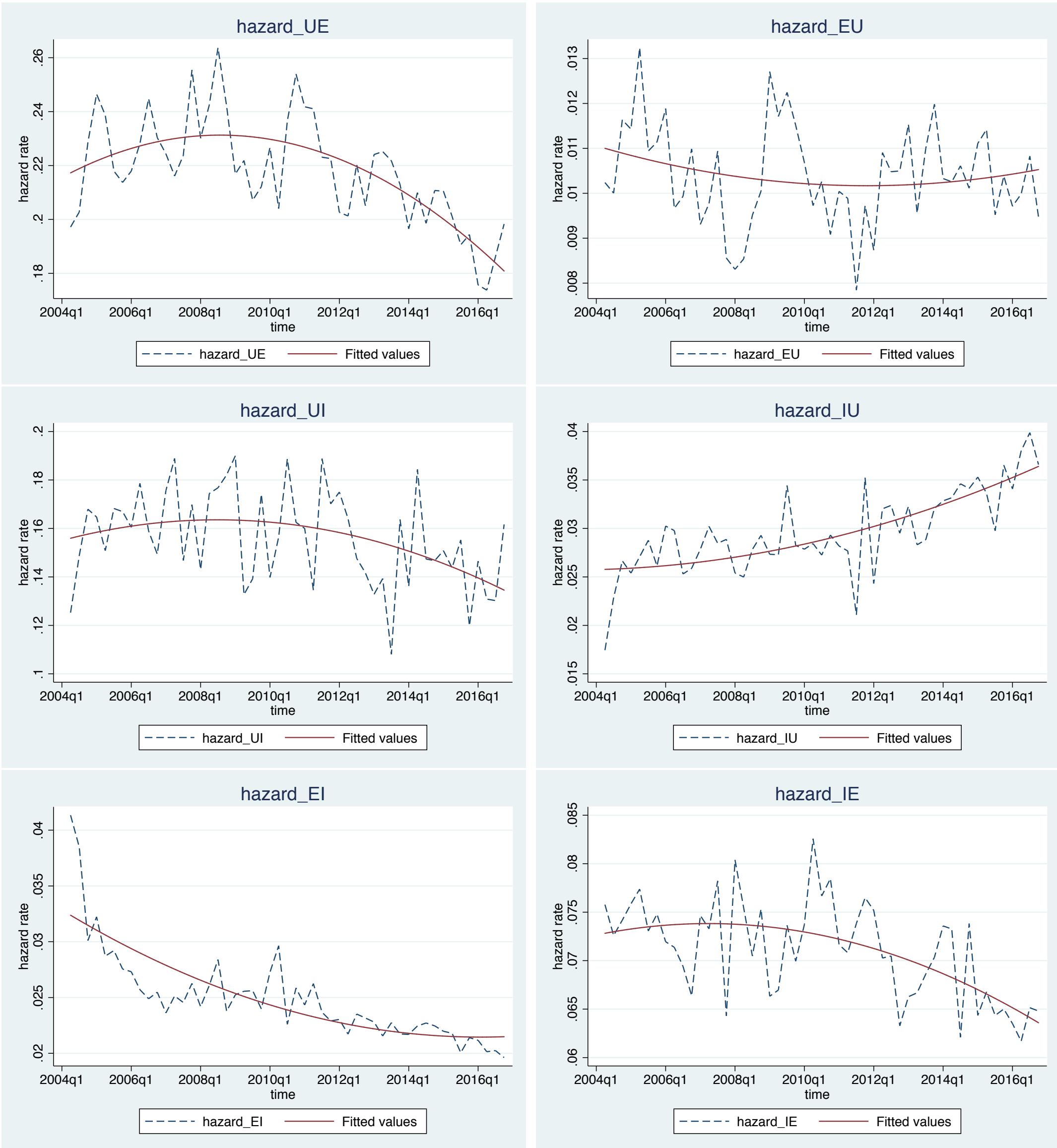
First, we try to visualize the movements in and out of the Austrian labour market between 2004 and 2016. We compare worker flows (transition rates) between the three states of unemployment (U), employment (E) and inactivity (I) in the Austrian labour market.

Figure 4 shows the derived hazard rates between 2004 and 2016. Taking a closer look at the transition from unemployment to employment (upper-left panel), we see that, in general, between 20% and 25% of the unemployed population are moving into employment each quarter. We can also see a strong fluctuation in the UE (movements from unemployment to employment) hazard due to the typical seasonal patterns of the Austrian labour market, which are mostly driven by the tourism and construction sector. Looking at the long-term trend, we can see a rather stable relation (with a slight upward trend) in the hazard rate until 2012. From 2012 onwards, we can see that the trend in the UE hazard is declining, indicating that proportionally fewer people have moved from unemployment to employment compared to the period before 2012.

The hazard rate from employment to unemployment (line 1, right) varies, in general, between 0.8% and 1.4%. Again, a strong seasonal pattern is visible. Taking a look at the trend for the EU hazard, we do not find a clear picture. Even though there would appear to have been some slight changes over the years, the trend in the hazard rate, from employment to unemployment, has been rather stable over the years.

Line 2 in Figure 4 shows the transitions between unemployment and inactivity. We can see that the hazard rate from unemployment to inactivity (UI hazard) has a high fluctuation with values between 11% and 19%, while hazards from inactivity to unemployment (IE hazard) vary between 2% and 4%. Taking a closer look at the trend, there seems to have been a decline in the hazard rate from unemployment to inactivity; in recent years, the hazard rate from inactivity to unemployment has especially increased. In theory, this could be an empirical sign of the added worker effect. The added worker effect basically states that more people enter the labour market in times of recession (times of high unemployment) to compensate for wage losses in the household. On the contrary, the discouraged worker effect would suggest that people in a recession tend to leave the labour force because they stop looking for a job or lose unemployment benefits. But this would imply that movements out of the labour market should increase, which is clearly not the case. Still, we have to take a closer look at movements from inactivity to employment (and

Figure 4: Movements between employment, unemployment and inactivity



vice versa) to reach any conclusion in this regard.

Line 3 in Figure 4 shows the hazard rates for moving from inactivity to employment (and vice versa). While the EI hazard (movements from employment to inactivity) varies between 2% and 4%, the IE hazard (movements from inactivity to employment) varies between 8.5% and 6%.

Our calculations show that the hazard rate for moving from employment to inactivity decreased constantly, especially in the years between 2004 and 2006. Additionally, the hazard rate for moving from inactivity to employment decreased especially in recent times.

While the the IE hazard up to 2010 was quite stable, we can observe a noticeable decrease in recent years.

This is contrary to the added worker hypothesis. It seems that, in recent years, people who entered the labour force typically found a job immediately on a less often basis, but became unemployed more often. On the other hand, fewer people were employed and fewer people who were unemployed left the labour force compared to former times.

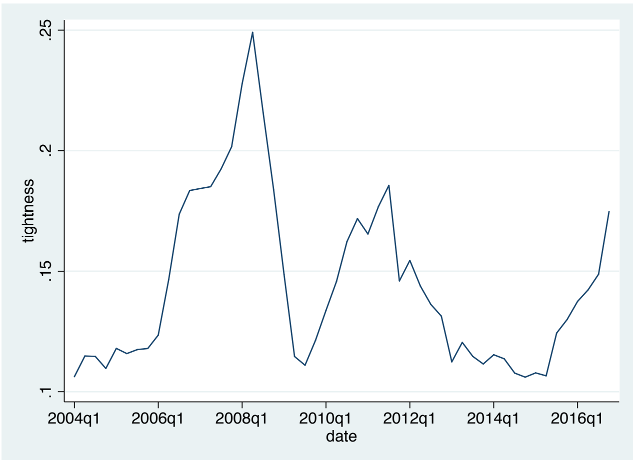
5.2 Measuring labour market tightness

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 employers' perspective. High vacancies paired with a low unemployment rate makes the labour market tight for firms, since it will be more complicated for them to recruit workers.

On the contrary, by analysing labour market tightness from employees' perspective, the unemployment-vacancy ratio gives more insights. It is high when there are significant numbers of unemployed workers looking for only a few vacancies.

Figure 5 shows the development of labour market tightness (measured in terms of the vacancy-unemployment ratio) in Austria. We can see that, from a firm perspective, labour market tightness increased substantially between 2006 and 2008. Before the crisis, the unemployment rate was very low and, in combination with a high number of vacancies, the labour market was tight from the firm perspective. With the outbreak of the crisis in 2008, tightness fell due to an increase in unemployment and in vacancies, but only for a short period. Tightness increased again after 2009 until 2011, due to an increase in vacancies and a decrease in the unemployment rate, but fell again after 2012.

Figure 5: Labour market tightness in Austria



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

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 vacancies, while unemployment also increased slightly[11].

It is noteworthy that the concept of labour market tightness has some shortcomings. The number of unemployed people is typically well measured in existing surveys, but the estimates for the number of vacancies are typically less reliable. In fact, the vacancy variable we are using is the number of vacancies advertised by the AMS, implying that the measurement error is a minor problem. But we face the problem that our vacancy measure does not cover vacancies which are not registered at the AMS. Still, since we are primarily concerned with changes in the vacancy rate, this should be a minor issue.

5.3 Estimating a matching function

The concept of labour market tightness is necessary to estimate a matching function because, from a theoretical point of view, labour market tightness is closely linked to the job-finding rate. Intuitively, the tighter the labour market becomes, from a firm perspective (high vacancies paired with low unemployment), the more the job-finding rate increases.

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 $m_t = m_o u_t^{\sigma} v_t^{1-\sigma}$ (see, e.g., Pissarides (2000)).

Therefore, the job-finding rate can be modelled as:

$$\ln \lambda_t^{UE} = (1-\sigma) ln(\frac{v_t}{u_t}) + ln(m_0) + \epsilon_t \tag{9}$$

Taking a closer look at the data which we use for our model, from a theoretical point of view, the job-finding rate should be closely linked to the tightness of the labour market. Even though this might be a theoretical suggestion, in Austria, we can see that there is a strong correlation between both variables[12].

Table 1: Matching function estimation

	(1) $\ln \lambda_t^{UE}$	(2) $\ln \lambda_t^{UE}$
ln(tightness)	0.1546***	0.0649
	(3.74)	(1.63)
$\ln \lambda_{t-1}^{UE}$		0.6538***
		(6.59)
Constant	-1.2231***	-0.4005***
	(-14.81)	(-2.72)
Observations	51	50

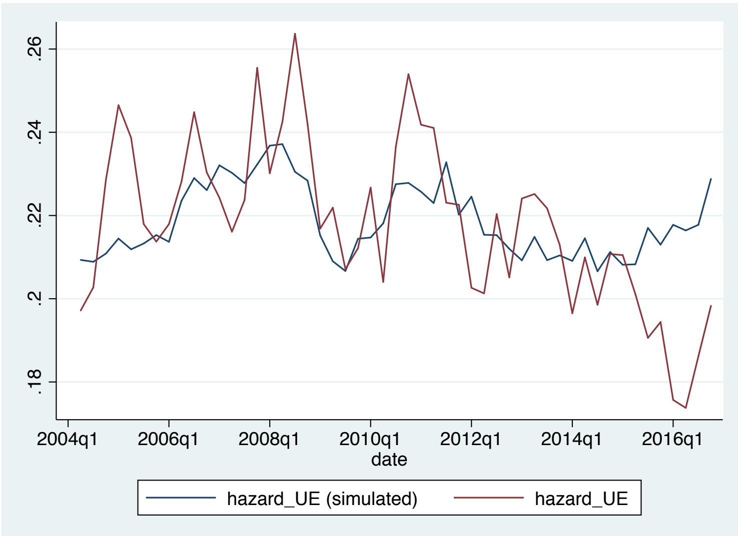
[11]See Figure 13 in the Appendix.
[12]See Figure 11 in the Appendix.

We estimate this regression by using the job market tightness measure discussed in the previous section and the job-finding rate, which we obtained from the Austrian Mikrozensus. We use data from 2004Q1 to 2016Q4.

When we regress the labour market tightness on the job-finding rate (Model 1), we find a significant correlation between both variables, but the estimated elasticity σ is fairly high with a value of 0.85. In addition to the standard regression, we allow for a first-order serial correlation by adding a lagged term to the estimation (Model 2).

Compared to the US, the elasticity in Austria is lower, indicating that the reaction of the job-finding rate to changes in the tightness of the labour market is lower in Austria.

Figure 6: Estimation of the UE hazard



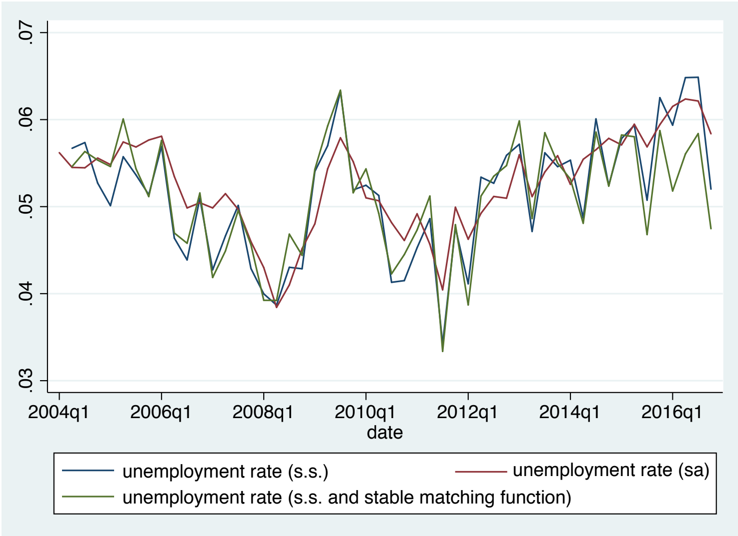
Taking a closer look at the fit of the model, we can see that the matching function models the hazard rate quite well. Both of the discussed models assume a stable matching function. Figure 6 shows the deviation in the job-finding rate and the simulation with the matching function. While the results of the steady-state model and the model assuming a stable matching function are quite similar at the beginning of the time period, we can see that there has been a substantial deviation in recent years, indicating a change in matching efficiency.

To further this argument, if we assume a stable matching function, the unemployment rate that would have prevailed in Austria would have differed substantially from the realized unemployment rate, as Figure 7 indicates. The difference lies between 0.4 and 0.8 percentage points in 2016.

5.4 The decomposition of the unemployment rate

As already mentioned before, we are able to decompose the unemployment movements into changes due to changes in labour demand, labour supply and matching efficiency.

Figure 7: LModel prediction under several assumptions



Additionally, we can see how the unemployment rate is driven by those factors.

Demand-side factors In our analysis, movements along the Beveridge curve are the only demand-driven fluctuations in the unemployment rate; typically, they are also seen as cyclical movements in the unemployment rate. Figure 8 shows the fluctuations in the unemployment rate due to demand-side factors, namely, firm-induced movements in unemployment due to vacancies. We can see that, over the period in question, the demand-side trend has been negative in recent years, meaning that labour demand has tended to reduce the unemployment rate.

In the crisis of 2008, for example, we can see that demand-side factors had an important impact on the increase in the unemployment rate. But, in general, the impact on the unemployment rate seems to be limited and in a range of -0.4 and 0.4 percentage points.

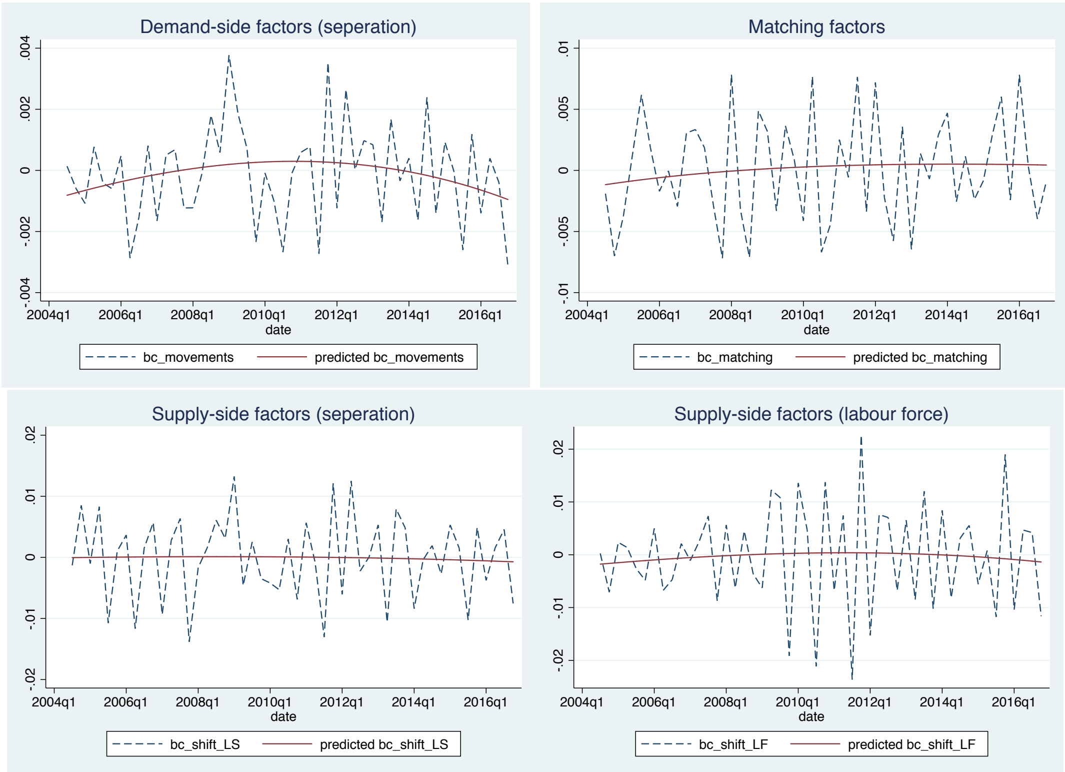
Compared to the results for the US[13], these numbers are small but not surprising, since business cycle movements in the unemployment rate are, in general, rather small in Austria compared to the US.

Supply-side factors On the supply side, we consider two factors: changes in the structure of lay-offs or quits[14] and movements in and out of the labour force, which have a strong influence on the evolution of the unemployment rate, as Figure 8 demonstrates. Those fluctuations changed the unemployment rate by almost two percentage points. Looking at the long-term trend, we can see an upward trend, which is reversed between 2012 and 2014,

[13]See Barnichon and Figura (2010).

[14]Again, we assume this factor as mainly supply side-driven, because lay-offs play almost no role in our data.

Figure 8: Demand-side, matching and supply-side factors



reaching a level below zero in 2014.

Especially in the years after the crisis of 2008, the movements in and out of the labour force had a big influence on unemployment rate movements. The impact became less pronounced again after 2012, but there was also a big hike at the end of 2015. In the years between 2009 and 2011, we can see a particularly big influence of supply-side factors on the unemployment rate.

We can also see that separation behaviour influences the unemployment rate substantially, ranging from -1 to 1 percentage points. While the long-term trend seems to be quite stable and close to zero, we can also see here an increase between 2011 and 2013.

Comparing again those results with results for the US[15], we can see that the magnitude of the supply side-driven contribution to the unemployment fluctuation is similar to the that in the US.

Matching efficiency Another factor which can shift the Beveridge curve is a change in matching efficiency. There are many factors which can influence matching efficiency and cause a shift in the Beveridge curve. Often skills mismatches, regional mismatches or sectoral mismatches can cause such a decrease in the matching efficiency of the labour

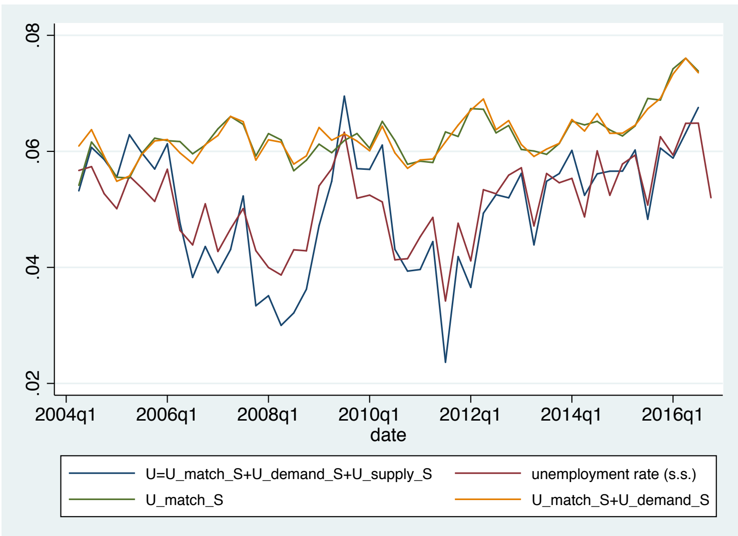
[15]See Barnichon and Figura (2010).

market.

Matching efficiency (see Figure 8), in the case of Austria, has tended to influence unemployment movements by up to 0.7 percentage points. This magnitude is in line with the findings of Barnichon and Figura (2010) for the US. The trend in the matching factor shows that, at the beginning of the observed time period, matching efficiency contributed substantially to lowering the unemployment rate. But this picture 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.

Implications for the unemployment rate To visualize, in more detail, the decomposition of the fluctuation in the unemployment rate, we show the influence of supply-side, demand-side and matching factors on the unemployment rate. Figure 9 shows the unemployment rate which would have prevailed only when considering some of the factors driving the unemployment rate. We can see that matching efficiency (green line) alone would not have lead to major fluctuations over the time period in general. When we add the demand-side factors, the fluctuations on the demand side did not in fact change this picture. The big movements in the unemployment rate (red line), before and after the crisis of 2008, were mainly driven by supply-side factors (which are covered together with demand-side factors and matching efficiency by the blue line).

Figure 9: Drivers of the unemployment rate



Note: For a better visualization, the changes in the single factors have been smoothed. Figure 14 with the non-smoothed values can be found in the Appendix.

We can see that most of the fluctuations in the unemployment rate in Austria were driven by supply-side shocks. The reduction in the unemployment rate before the Great Recession of 2008/2009 was clearly supply side-driven. Further, the increase during the crisis was mainly supply side-driven[16], even though we can see that the demand-side contribution also increased at this time.

In line with the findings of Schiman (2018), we find empirical evidence to confirm that the increase in the unemployment rate after 2011 was mostly supply side-driven. Our model suggests that this shock increased the (seasonally adjusted) unemployment rate by more than one percentage point. This indicates that the the liberalization of labour market access for several Eastern European countries in 2011 induced a significant increase in the unemployment rate at that time.

But, in contrast with Schiman (2018), we observe an increase in the unemployment rate after 2013, which was clearly driven by a decrease in matching efficiency, while supply-side factors played only a minor role. The decrease in matching efficiency increased the unemployment rate by approximately 0.5 percentage points. 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. However, the counterclockwise movement induced by labour supply shocks in the Beveridge Space is not yet complete. While the outward shift might last for several years, it will ultimately reverse as unemployment and vacancy rates will move back (close) to their pre-shock levels." This would only hold true if the increase in the unemployment rate were to be supply-driven.

Our analysis points to a clear sign of an increasing mismatch problem in the Austrian labour market. Using a new decomposition method, combined with data on labour market flows, we show that the outward shift of the Beveridge curve after 2104 was not supply side-driven, but driven by a decrease in matching efficiency. This is also in line with findings reported in the literature[17]. Further, a new qualitative study on the AMS[18] points out that there is a substantial mismatch problem in the Austrian labour market, which implies that the unemployment rate in Austria will probably not move back to its pre-shock level, in turn highlighting the importance of policies aimed at overcoming these mismatch problems in the Austrian context.

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. In the literature, there are several kinds of mismatches in the labour market:

- A so-called skills mismatch occurs when the demanded and supplied skills in the labour market differ. Information on specific skills among the unemployed popula-

[16] Please note that, especially during the crisis, some demand-side factors may have been covered by the supply-side variable, since we cannot distinguish between lay-offs and quits.

[17] See Christl et al. (2016) or Böheim (2017).

[18] See Kerler (2018).

tion, as well as needed skills in certain occupations, is rare; therefore, such a skills mismatch is hard to measure (see, e.g., Sahin et al. (2011) and 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)).
- A reduction in search intensity by workers could lower the matching efficiency. Extended unemployment benefit can cause such a decrease (see, e.g., Valletta et al. (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)).

We use a similar mismatch indicator as Christl et al. (2016), which is calculated as follows:

$$MI = \sum_{i=1}^{I} e_i \left| vs_i - us_i \right| \tag{10}$$

where i is the mismatch dimension, es is the employment share, vs is the vacancy share and us is the unemployment share.

We use data provided by the AMS between 2008 and 2016 with information on vacancies, employment and unemployment across several sectors (sectoral mismatch), as well as several districts (regional mismatch). To analyse sectoral 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 required education required for certain vacancies. Here we can only distinguish between seven educational levels.

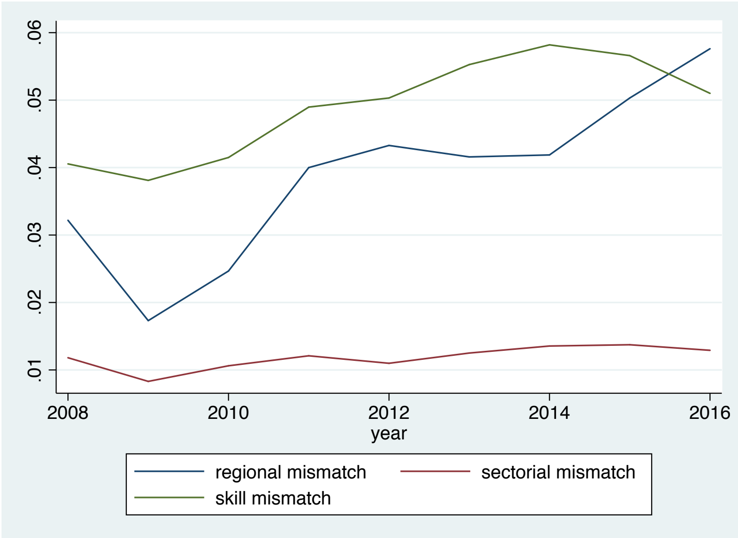
If vacancies are bundled into regions, sectors or educational groups with high unemployment, our mismatch indicator would have a low value; meanwhile, if vacancies can be mainly found in sectors or regions, where there is a low number of unemployed, the mismatch indicator will be high.

Figure 10 depicts the evolution of the sectoral and regional mismatch indicator between 2008 and 2016. In line with Christl et al. (2016), who use monthly data on bigger sectors in the Austrian labour market, we find a slight increase in the sectoral mismatch between 2012 and 2015. Compared to the changes in the other mismatch indicators, this increase does not seems to be an issue.

For the skills mismatch, we can see a slight increase between 2012 and 1014, but this increase is again 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 sectoral mismatch. as well as

Figure 10: Mismatch indicators for Austria



the reduction in skills mismatch. We see this as an indicator of a growing regional mismatch problem in the Austrian labour marker, 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, our analysis reveals an acute increase in regional mismatch in the Austrian labour market, while the sectoral mismatch seems to play no significant role.

6 Conclusions

The Beveridge curve shift in Austria after 2014 has attracted much attention, not only among researchers, but also among policymakers and the media. Indeed, an increasing vacancy rate and a rising unemployment rate after 2014 prompted further research on this topic.

Our paper aims to answer the question as to why the Austrian Beveridge curve has shifted. To date, many opinions have been expressed, but no clear analytical results to explain the shift in the Beveridge curve in Austria have been presented. Some have argued that the shift has been driven by a decrease in matching efficiency, indicating a structural problem in the Austrian labour market. Others have argued that a supply shock, due to the liberalization of the labour market, has shifted the Beveridge curve, implying that the shift is only temporary. Our paper makes a first attempt to answer this question in more detail.

We use a newly developed decomposition method from Barnichon and Figura (2010), which allows us to dig deeper in order to find the reasons behind the shift in the Austrian

Beveridge curve. Using detailed data on worker flows in the Austrian labour market, we are able to disentangle movements in the unemployment rate into supply-side factors, demand-side factors and matching factors.

Our paper shows that the increase in the unemployment rate after 2011 was indeed mainly supply side-driven. But, after 2014, we can observer an acute decrease in matching efficiency, while supply-side factors play only a minor role in the increase in the unemployment rate after 2014. We see this as a worrying sign of a mismatch problem in the Austrian labour market.

The identified structural changes have important policy implications. Cyclical problems in the labour market are usually caused by a lack of labour demand and therefore transitory. The same holds true for shifts due to supply-side shocks, which are typically not persistent.

But a decrease in matching efficiency is typically caused by a mismatch in the labour market and therefore often persistent. As such, a decrease in matching efficiency requires different policy responses. It is especially important to target labour policies at this mismatch problem. Given that many in the unemployed workforce in Austria have low-level skills, an increase in training intensity for this workforce could be an important policy tool to tackle associated problems.

Additionally, by taking a closer look at the regional structure of the vacancies and the unemployed, we find that most unemployed people are in regions where vacancies are limited, while other Austrian regions which offer many vacancies are close to full employment. Our analysis suggests that this is the main driver of the mismatch.

For policymakers, there are means to overcome the regional mismatch problem arising out of low mobility. Other countries have introduced financial incentives to tackle regional mismatch problems. Germany, for example, has introduced an active labour market policy which offers a "reallocation assistance". This was part of the 'Hartz reforms', which cover relocation costs in order to incentivize unemployed people to seek jobs outside their region. In detail, this offers financial support to unemployed people to meet the costs associated with a move to a distant region. Every unemployed person is eligible if he or she is not able to find a job locally. A distant region 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 unemployed people who agree to moving for a job, but such a policy can decrease the mismatch in the regional labour market[19].

Such a programme existed in Austria between 2008 and 2016, but the highest participation was registered in 2012 with 156 participants, leading to the abolition of the programme. This could be a sign that high social benefits, which can be obtained for a long time, might additionally make the workforce immobile.

We conclude that policies which increase incentives for unemployed people to take up jobs (due to, e.g., financial incentives to move or reweighting of unemployment benefits),

[19] Caliendo et al. (2017) show that those who participate in 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 participants.

as well as better transregional job placements, are key to overcoming regional mismatch problems in the Austrian labour market. Additionally, training and upskilling of the unemployed population are important tools to overcome the potential skills mismatch.

In general, since unemployment benefits can be claimed for a long period in Austria, workers may not be willing to agree to relocate for a new job. This implies that structural unemployment may not be persistent when new jobs are created in regions with high unemployment. However, there is a high risk that the long-term unemployed population will face problems with reintegration into the labour market, even if there are new jobs in the region. This will lead to further structural problems.

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Appendix

Table 2: Regression results of vacancy time series

	(1) vacancies (AMS)
vacancies (Statistik Austria)	0.94***
	(3.80)
Constant	38979.93***
	(5.31)
Observations	32

Figure 11: Labour market tightness and job-finding rate

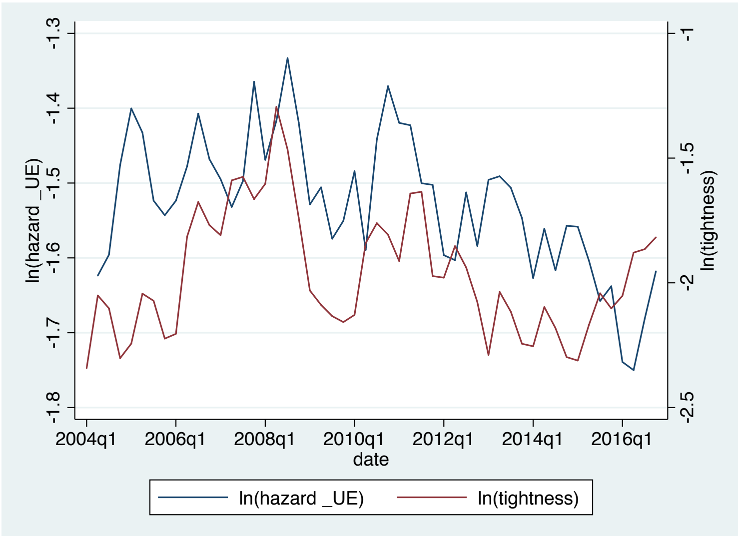

Figure 12: Lay-off rate in Austria

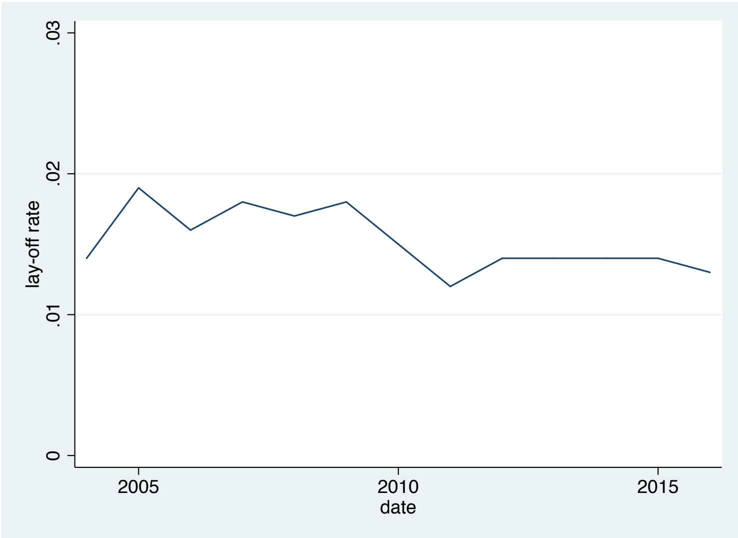

Figure 13: The unemployment and vacancy rates in Austria

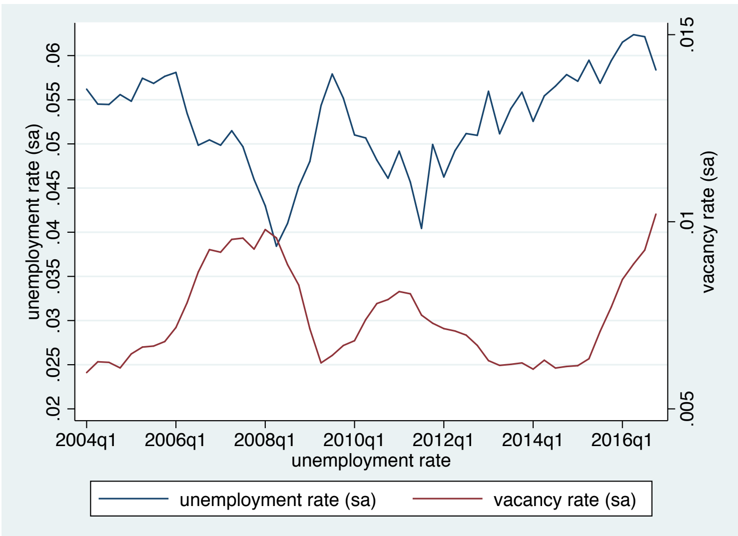

Figure 14: Drivers of the unemployment rate