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**Working Paper**

# Mismatch unemployment in Austria: The role of regional labour markets for skills

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JRC Technical Report

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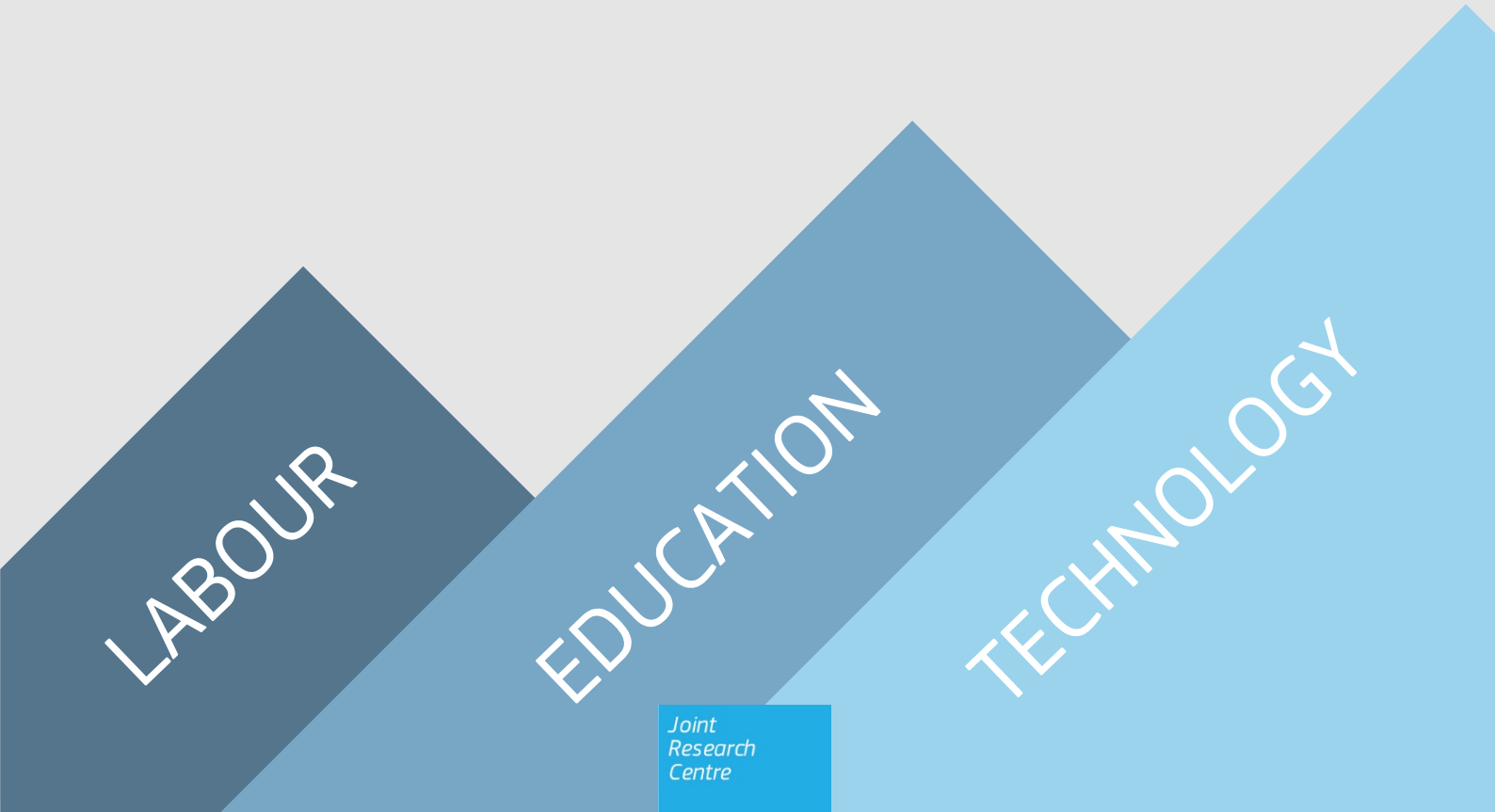
JRC Working Papers Series on
Labour, Education and Technology
2021/08

René Böheim and Michael Christl



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# Mismatch unemployment in Austria

## The role of regional labour markets for skills

René Böheim (Johannes Kepler University Linz) and Michael Christl (European Commission, Joint Research Centre)

## Abstract

During the last decade, the Austrian labour market experienced a substantial outward shift of the Beveridge curve - the relationship between the unemployment and the job vacancy rate. Using detailed administrative data on vacancies and registered unemployed by region and skill level, we test which factors caused this shift. We find that the Beveridge curve shifted primarily because mismatch increased substantially. Looking on the regional and skill dimension of mismatch unemployment, we find a substantial increase of mismatch unemployment for manual routine tasks as well as for the region of Vienna.

**Keywords:** Beveridge curve, unemployment, matching efficiency

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# Contents

1 Introduction ..... 1
2 Theoretical Background ..... 2
3 Data and Calibration ..... 3
4 Results ..... 7
4.1 Results based on aggregated data for Austria ..... 7
4.2 Results by federal state ..... 9
4.3 Results by skill level ..... 10
4.4 Results by skill level and federal state ..... 11
5 Conclusion ..... 12
References ..... 14
List of figures ..... 16
List of tables ..... 17
Annex ..... 17

# 1 Introduction

The Austrian unemployment rate increased from about 4 percent at the beginning of 2000 to 5.6 percent in 2005 and, after the Great Recession, it increased to about 6 percent by 2015. The increasing unemployment rate and a substantial increase in the vacancy rate led to a marked outward shift of the Beveridge curve. Schiman (2018) argues in a macro-model framework that the Austrian Beveridge curve shifted due to a labour supply shock caused by the opening of the labour market to several Eastern European countries after 2008. However, Christl et al. (2016) and later Christl (2020) using detailed data labour-market transition argue that the shift was caused primarily by an increase in labour market mismatch.

Following Veracierto (2011) and Şahin et al. (2014), we test whether or not the outward shift of the Beveridge curve in Austria was caused by mismatch unemployment. Mismatch unemployment is defined as the unemployment that can be attributed to changes in the matching efficiency observed on the labour market. We first analyze aggregate data on the national level. We use unemployment data from the Austrian unemployment office (AMS) by skill level and labour market district level. We combine these data with information from the Austrian Mikrozensus, which includes detailed information on employment by skill levels and by regions. We subsequently provide analyses at different levels of disaggregation, by regions and skill levels, to provide more detailed evidence for the shift of the Beveridge curve.

As shown by Autor et al. (2006), Goos and Manning (2007), Goos et al. (2010), and Autor and Dorn (2013), the employment share of occupations in the middle of the skill distribution declined rapidly in the US and Europe while at the same time the upper and lower skill occupation share has increased substantially, however, this general phenomena can differ across countries due to different institutional settings, socio-demographic dynamics or migrations (see, e.g., Oesch and Rodríguez Menés (2011)). The literature on automation stresses that these jobs often consist of routine tasks that are relatively easy to automatize and which thus are disappearing due to reduced demand (Autor et al., 2003; Michaels et al., 2014). However, the literature on the impact of overall employment effects of automation suggests a rather small impact. Acemoglu et al. (2021), for example, show for the US that while artificial intelligence replaces human workers at different types of tasks, there is currently no aggregate effect on the labour market. When looking on the impact of robots on overall employment, the literature also suggests changes in the task content of jobs rather than a strong reduction of employment[1].

These changes in labour demand lead to substantial challenges in most developed countries. While the demand for certain skills may change quickly, supply side reactions are typically slow as the adjustment of workers requires more time for re-skilling or re-training. Such developments may lead to substantial mismatch and stress the importance of identifying reasons for labour market mismatch and appropriate policy responses.

Our results show that the outward shift of the Austrian Beveridge curve was primarily caused by a substantial increase of mismatch unemployment for manual routine tasks. We find that mismatch unemployment for manual routine tasks increased from about 2 percent to almost 8 percent between 2013 and 2016. This implies that under constant matching of workers and vacancies on the labour market, the mismatch unemployment rate for manual routine tasks, and therefore also the unemployment rate for manual-routine tasks would be 6pp lower. Mismatch unemployment for interactive non-routine tasks also increased, from about 1 to 3 percent. In contrast, we find that mismatch unemployment increased only moderately for other skill groups.

Our analysis also highlights regional differences in the increase of mismatch unemployment. We find that Vienna has the greatest overall increase in mismatch unemployment from about 1 percent in 2013 to more than 3 percent in 2016. Overall, however, the results do not suggest that insufficient regional mobility, due to e.g., house ownership (Farber, 2012), is the reason for increased mismatch.

[1] See, e.g., Klenert et al. (2020), Dauth et al. (2017) or Barbieri et al. (2019).

## 2 Theoretical Background

We use the model of Veracierto (2011) where each firm offers jobs. Jobs remain vacant or become filled by a worker's acceptance of the offer. Workers are either employed, unemployed or inactive. Employed workers separate from their jobs with a probability $\lambda_t^{EU}$. For simplicity, our notation does not distinguish between skills and regions, which are additional dimensions we consider below.

The matching between unemployed workers and vacant jobs is modelled with a standard matching function, where the number of new matches $M_t$ is a function of the matching efficiency ($A_t$), the number of unemployed workers ($U_t$), and vacant jobs ($V_t$):

$$M_t = A_t U_t^{\alpha} V_t^{(1-\alpha)}, \tag{1}$$

where $\alpha$, $0 < \alpha < 1$ , imposes constant returns to scale (Petrongolo and Pissarides, 2001).

Workers move between three states, unemployment ($U$), employment ($E$), and inactivity ($I$). Hazard rates, $\lambda_t^{IJ}$, describe the transitions from labour market status $I$ to labour market status $J$ at time $t$. In other words, $\lambda_t$ is the share of workers who move from $I$ to $J$ at time $t$, $N_t^{IJ}$, over the number of workers who were in $I$ at time $t-1$, $N_{t-1}^{I}$. E.g., $\lambda^{IJ} = N_t^{IJ}/N_{t-1}^{I}$.

The movement of workers across labour market states is described by the following set of equations:

$$U_{t+1} = U_t + \lambda_t^{EU} * E_t + \lambda_t^{IU} * I_t - \lambda_t^{UI} * U_t^{\alpha} - A_t U_t^{\alpha} V_t^{(1-\alpha)}, \tag{2}$$

$$E_{t+1} = E_t + A_t U_t^{\alpha} V_t^{(1-\alpha)} + \lambda_t^{IE} * I_t - (\lambda_t^{EU} + \lambda_t^{EI}) * E_t, \tag{3}$$

$$I_{t+1} = I_t + \lambda_t^{EI} * E_t + \lambda_t^{UI} * U_t - \lambda_t^{UI} * U_t - (\lambda_t^{IE} + \lambda_t^{IU}) * I_t. \tag{4}$$

The steady state unemployment is given by:

$$u_t^{ss} = \frac{s_t}{s_t + f_t}, \tag{5}$$

where the separation rate is $s_t = \lambda_t^{EU} + (\lambda_t^{EI} * \lambda_t^{IU})/(1 - \lambda_t^{II})$ and the job finding rate is $f_t = \lambda_t^{UE} + (\lambda_t^{UI} * \lambda_t^{IE})/(1 - \lambda_t^{II})$.

We then define mismatch unemployment $u_t^{mm}$ as the difference between the steady state unemployment rate, $u_t^{ss}$, and the counterfactual unemployment rate, $u_t^{*}$, that would have been the outcome of stable matching function:

$$u_t^{mm} = u_t^{ss} - u_t^{*} = \frac{s_t}{s_t + \lambda_t^{UE} + \lambda_t^{UIE}} - \frac{s_t}{s_t + \lambda_t^{*UE} + \lambda_t^{UIE}}. \tag{6}$$

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

In order to calibrate the model, we calculate the parameter $\alpha$ of the matching function. We follow Barlevy (2011) and Veracierto (2011) and assume constant transition rates in the period before the Beveridge curve shift[2].

We assume a constant matching productivity $A$ over the observed period before the shift. Choosing the month with the strongest and the month with the weakest labour market tightness, separately by region and skill level, allows us to calculate the $\alpha$ parameter (Veracierto, 2011). We set $A$ to the average labour market tightness of the month with the strongest and the month with the weakest labour market tightness, separately for each combination of region and skill level. Following this approach, we calculate the $\alpha$ and use these estimates to calculate the matching efficiency parameter $A_t$[3].

We obtain hypothetical vacancy rates for the period after 2014, when we observe the shift in the Beveridge curve, by setting $A_t$ for this period to the average level of the period before 2014, conditional on the observed unemployment rate (Veracierto, 2011).

[2] As shown in Figure 3, this assumption seems to be reasonable also for the data we are using.

[3] For a general discussion on estimating matching efficiencies, see e.g., Crawley et al. (2021).

We calculate these parameters for all degrees of disaggregation (region, skill level, and their interaction). Following Barnichon and Figura (2010), we identify the source of Beveridge curve shifts. Shifts can be caused by several factors: supply-side factors, demand-side factors or a change in the efficiency of matches on the labour market. The shift of the Austrian Beveridge curve at the national level and the associated increase in unemployment after 2014 stems mainly from a change in matching efficiency, while other factors play only a minor role (Christl, 2020). We focus in particular on the changes at disaggregated levels to obtain more detailed information about the roots of the increasing labour market mismatch.

# 3 Data and Calibration

We use data from the Austrian public employment services (PES) from 2004 to 2016, which provide detailed information on the skill levels of the unemployed and the required tasks of posted vacancies (AMS Österreich, 2020). Following Spitz-Oener (2006), we group 119 specific occupations (ISCO-08) into five categories, manual routine tasks, manual non-routine tasks, analytical non-routine tasks, interactive non-routine tasks, and cognitive routine tasks. The detailed list of how occupations are classified is given in Table 6.

The data are quarterly data from 2004:Q1 until 2016:Q4 for five skill categories, aggregated to the nine federal states. We use the Austrian Labour Force Survey (LFS, 'Arbeitskräfteerhebung') to estimate the job finding rate and employment levels by federal state and skill level[4]. The LFS uses the same occupational classification (ISCO-08, at three-digit level) as the Austrian PES. Before 2011, the ISCO-88 classification was used and we convert both classifications to five skill categories[5], following Bock-Schappelwein et al. (2017). The Austrian LFS has a rotating panel structure which allows us to follow workers for five consecutive quarters. This allows us to estimate job finding rates by skill category and by region.

Table 1 shows the distribution of unemployment and employment across federal states in Austria. About 19.2 percent of employed persons and 31.9 (36.0) percent of unemployed persons were in Vienna. In the table, we report the region's share of unemployed persons based on both the number of registered unemployed observed by the PES and the number of the unemployed observed in the LFS which uses the ILO's definition of unemployment. In general, the unemployment shares are fairly similar in both sources, although the unemployment rates typically differ substantially due to the different definition of unemployment.

[4] See, e.g., Statistik Austria (2020) and Moser (2010).

[5] Table 6 in the Appendix shows the exact categories used for each skill group.

*Table 1: Employment and unemployment shares, by federal state.*

| | Employment (%) | Unemployment (%, PES) | unemployment (%, ILO) |
|---|---|---|---|
| Burgenland | 3.3 | 3.2 | 3.0 |
| Carinthia | 6.3 | 7.7 | 6.0 |
| Lower Austria | 19.2 | 17.1 | 16.9 |
| Salzburg | 6.6 | 4.6 | 4.2 |
| Styria | 14.3 | 13.6 | 12.1 |
| Tyrol | 8.9 | 7.2 | 5.3 |
| Upper Austria | 17.6 | 11.4 | 12.8 |
| Vienna | 19.2 | 31.9 | 36.0 |
| Vorarlberg | 4.6 | 3.5 | 3.7 |
| total | 100 | 100 | 100 |

*Source: Data on registered unemployed (PES) obtained from AMS Österreich (2020); data on employment and ILO unemployment from Statistik Austria (2020).*

*Notes: Percentages are calculated on pooled data 2004:Q1 to 2016:Q4.*

Table 2 lists the employment and unemployment shares by skill category, pooled over the sample period. Before 2011, the LFS did not survey skill categories and we cannot compare the unemployment rates of the LFS and the PES data. Of all jobs, about 30 percent were manual non-routine tasks, about 22 percent were interactive non-routine jobs, and about 19 percent were cognitive routine tasks. About 15 percent of jobs were analytical non-routine tasks and about 13 percent of jobs were manual routine tasks.

*Table 2: Employment and unemployment, by skill category.*

| | Employment (%) | Unemployment (%) |
|---|---|---|
| Analytical non-routine tasks | 15.4 | 7.3 |
| Interactive non-routine tasks | 21.6 | 13.4 |
| Cognitive routine tasks | 19.2 | 14.6 |
| Manual routine tasks | 13.3 | 31.7 |
| Manual non-routine tasks | 30.5 | 30.7 |

*Source: Data on registered unemployed (PES) obtained from AMS Österreich (2020); data on employment obtained from Statistik Austria (2020).*

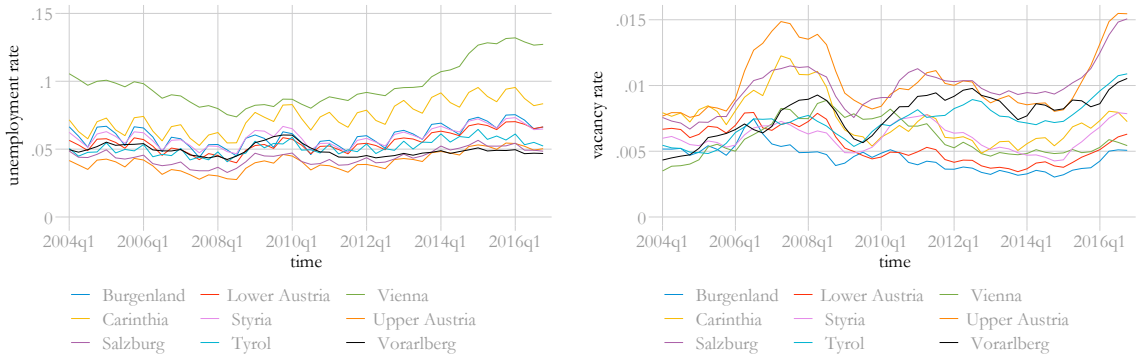
*Notes: Shares are calculated as a fraction of total values for Austria. Percentages are calculated on pooled data 2004:Q1 to 2016:Q4. ISCO-08 occupations are grouped as manual routine tasks, manual non-routine tasks, analytical non-routine tasks, interactive non-routine task, and cognitive routine tasks. See Table 6 for details.*

The variation of unemployment shares over skill category during our observation period was greater than for employment shares. For example, about 15 percent of jobs were analytical non-routine tasks and about 7 percent of the unemployed had such a job prior to becoming unemployed. Of all jobs, about 13 percent were manual routine tasks, however, about 32 percent of the unemployed had such a job prior to becoming unemployed. The second most common type of employment, interactive non-routine tasks (22 percent of jobs), had about 13 percent of the unemployed.

We plot the quarterly unemployment rates and vacancy rates by region in Figure 1. While the unemployment rate in Vienna was greater than in other regions throughout the sample period, we observe an increase from the lowest value, about 8 percent, in 2008 to almost 13 percent in 2016. The unemployment rate also increased in other regions, such as Upper Austria, Salzburg, and Tyrol,

but to a lesser extend. The vacancy rate, in contrast, increased in most regions and we see particular strong increases in Upper Austria and Salzburg.

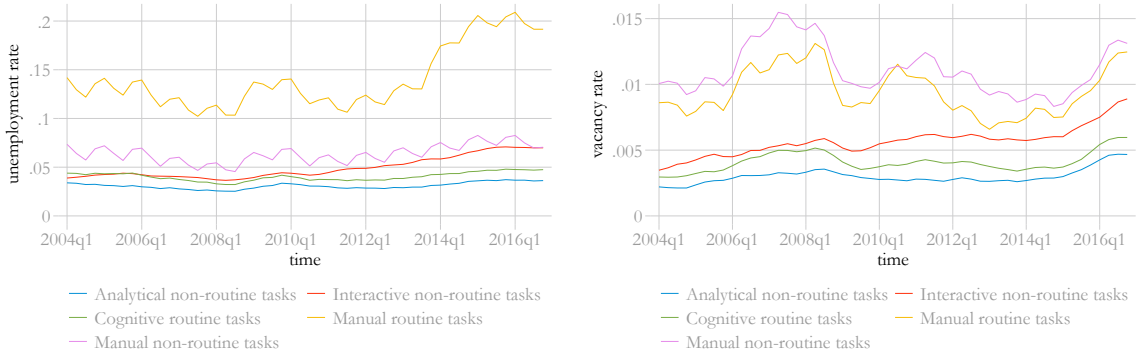
*Figure 1: Unemployment rates and vacancy rates, by region.*




*Source: Vacancies and unemployment obtained from AMS Österreich (2020); data on employment obtained from Statistik Austria (2020).*

In Figure 2, we plot the unemployment rates and the vacancy rates by skill category. We observe a substantial increase in the unemployment rate for manual routine tasks, starting in about 2013. We also observe a moderate increase in the unemployment rates of interactive non-routine tasks. The unemployment rates for the other skill categories remained fairly stable during this period. We see, however, an increase of the vacancy rates for all skill categories, in particular for manual routine and manual non-routine tasks.

*Figure 2: Unemployment rates and vacancy rates, by skill category.*



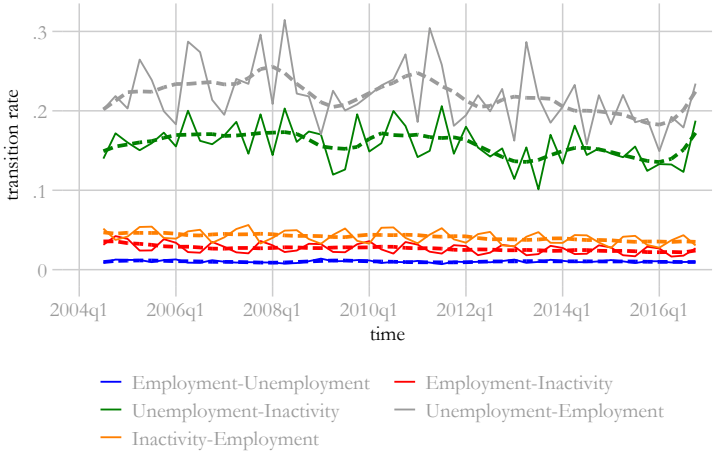

*Source: Vacancies and unemployment obtained from AMS Österreich (2020); data on employment obtained from Statistik Austria (2020).*
*Notes: ISCO-08 occupations are grouped as manual routine tasks, manual non-routine tasks, analytical non-routine tasks, interactive non-routine task, and cognitive routine tasks. See Table 6 for details.*

The unemployment rate also differed substantially over regions and skill categories. For example, the unemployment rate in Vienna was about 9.8 percent of the labour force and in Upper Austria it was about 4.1 percent. We also observe differences by skill category, for example, the unemployment rate for analytical non-routine workers was 3.1 percent and it was about 14.1 percent for manual routine workers.

The transition rates between different labour market statuses on aggregate level, which are plotted in Figure 3, changed only slightly over this period. During the 2008/2009 financial crisis, the transition rate from unemployment to employment dropped significantly. Factors related to labour supply shocks that determine the location of the Beveridge curve, such as movements in and out of the labour force,

were also relatively stable. Only the transition rate from unemployment to inactivity dropped slightly after 2012.

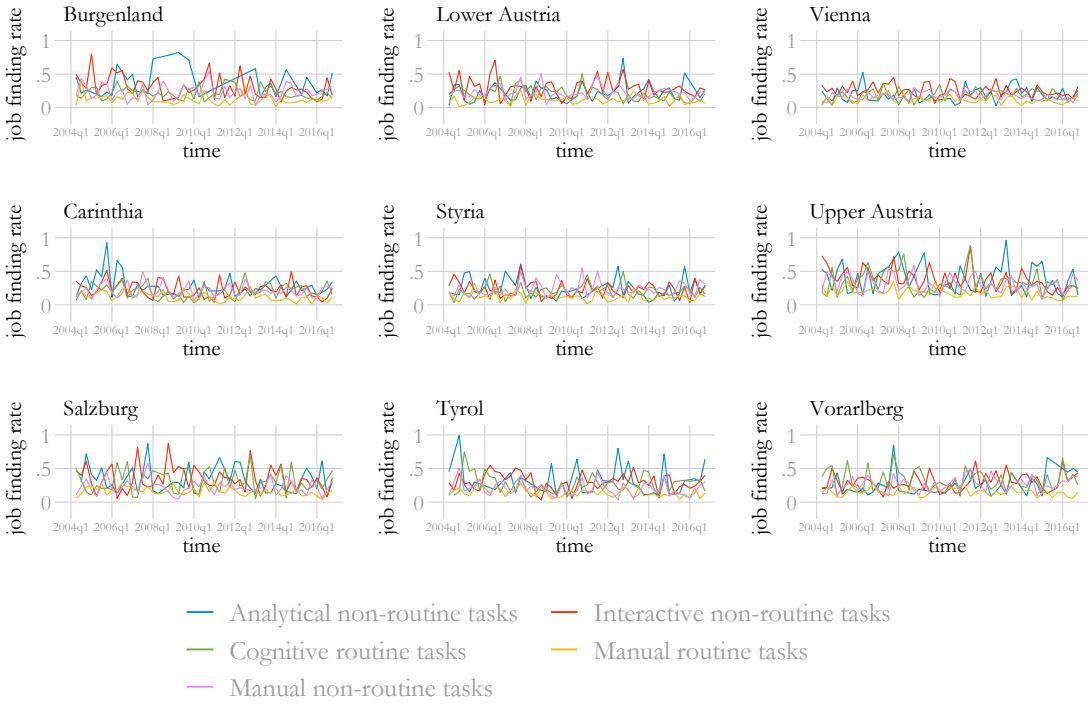
*Figure 3: Transition rates, aggregated data for Austria, 2004--2016.*




*Source: Own calculations, based on quarterly data from 2004 to 2016 from (Statistik Austria, 2020).*

Matching efficiency, the productivity of the process for matching job-seekers to available jobs, determines the job-finding rate. We provide a detailed view on the job finding rate and plot these by skill category and region in Figure 4.

*Figure 4: Job finding rates, by region and skill category.*




*Source: Own calculations, based on quarterly data from 2004 to 2016 from (Statistik Austria, 2020).*

*Notes: ISCO-08 occupations are grouped as manual routine tasks, manual non-routine tasks, analytical non-routine tasks, interactive non-routine task, and cognitive routine tasks. See Table 6 for details.*

These plots highlight regional, but also skill-specific differences. The average job finding rate was lowest for manual routine work (13.1 percent) and it was greatest for interactive non-routine workers (27.9 percent). Regional differences were also substantial, for example, the job-finding rate was on average 28.0 percent in Upper Austria and only 18.3 percent in Vienna. Detailed summary statistics by region and skill categories are presented in the Appendix, Tables 4 and 5.

# 4 Results

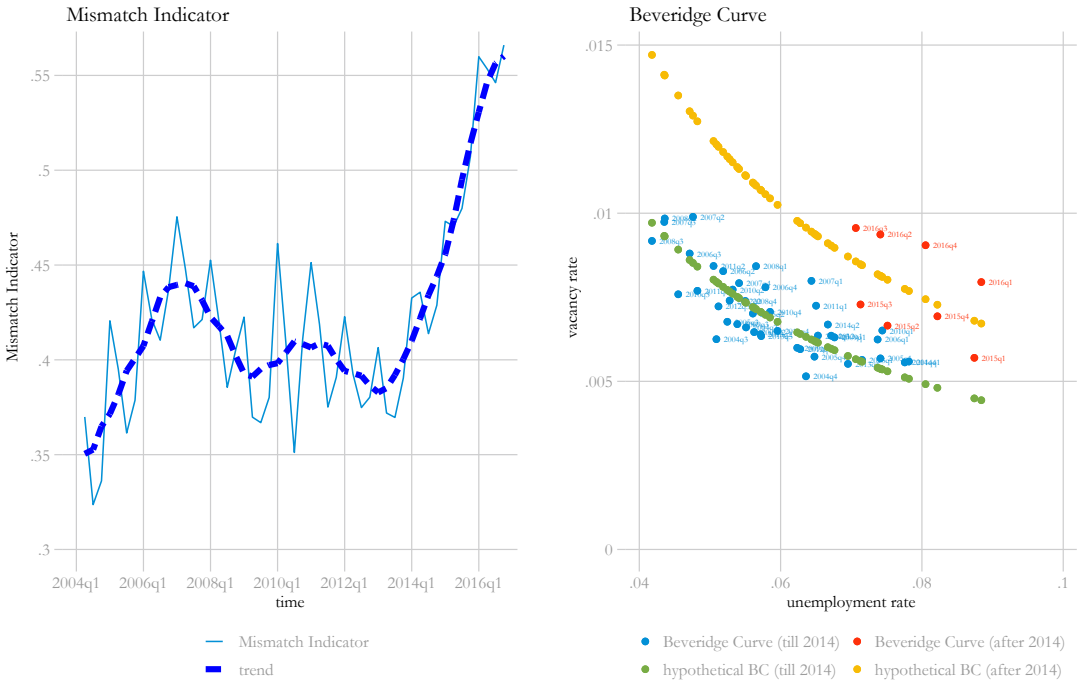
We present first the results for aggregate data. In a second step, we analyse the Beveridge curves on a disaggregated levels: on skill level, as well as on federal state level. In the third part, we use the full disaggregation to distinguish at the same time the regional and skill dimension to use our detailed data set in all dimensions.

## 4.1 Results based on aggregated data for Austria

In Figure 5, we plot the estimated mismatch indicator[6] (left) and the resulting Beveridge curves (right) based on aggregated quarterly data from 2004 until 2016.

[6]The mismatch indicator is defined as 1/A, therefore, an increase in the matching efficiency $A$ would lead to a decrease in the mismatch indicator.

*Figure 5: Mismatch Indicator and Beveridge Curves, aggregated data for Austria, 2004--2016.*




*Source: Own calculation based on data from Statistik Austria (2020) and AMS Österreich (2020).*

*Notes: Trend obtained by local linear smoothing. The hypothetical Beveridge curves are estimated with the average matching efficiency before 2014 and after 2014.*

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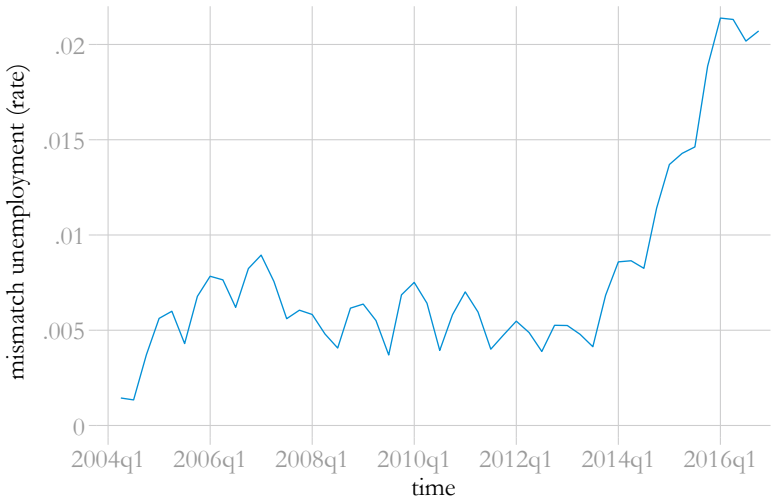
The mismatch indicator suggests a substantial increase in mismatch after 2014. To illustrate the effect of the increased mismatch, we split the sample into two periods, before 2014 and after 2014. We plot the Beveridge curves for the pre-2014 period (blue dots) and the quarters after 2014 (red dots). The predicted Beveridge curve, calibrated with the data from 2004–2014 is plotted in green. The predicted Beveridge curve, calibrated with data from 2014–2016, is plotted in yellow. The distance between the post-2014 labour market outcomes (red dots) and the predicted Beveridge curve (yellow) suggests a deterioration of the matching function.

In a first step, we predict the unemployment rate under the assumption that the matching efficiency was constant at the average level of the period before 2014[7]. We also predict the unemployment rate based on a model where we allow the matching efficiency to change over time, using the observed matching efficiency. We calculate mismatch unemployment as the difference of the two predicted unemployment rates. In Figure 6, we plot the predicted mismatch unemployment rate and we observe a strong increase after 2014. In 2016, the observed unemployment rate was above 7 percent, while the unemployment rate under stable matching would have been close to 5 percent, suggesting a mismatch unemployment of more than 2%-points. The mismatch unemployment in 2016 exceeds all other values in this period.

[7] The predictions are plotted in Figures 11, 14, and 17 in the Appendix.

*Figure 6: Mismatch unemployment, aggregated data for Austria, 2004--2016.*




*Source: Own calculation based on data from Statistik Austria (2020) and AMS Österreich (2020).*

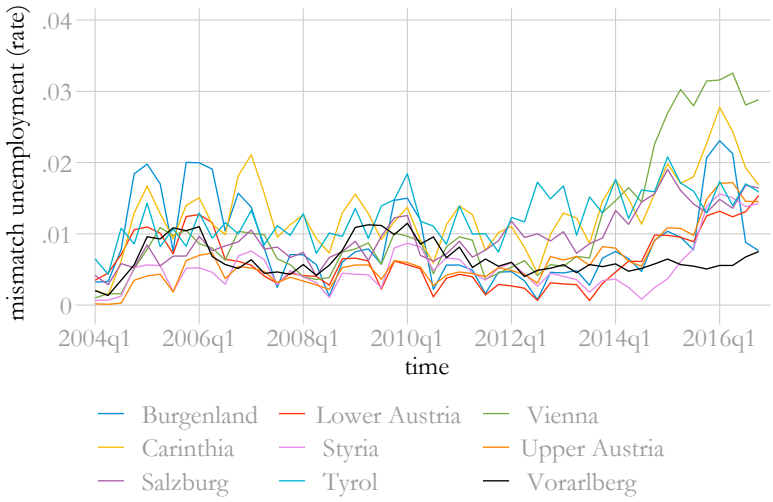
*Notes: Mismatch unemployment is the difference between the unemployment rate under a stable matching productivity and the steady-state unemployment rate.*

## 4.2 Results by federal state

Increased mismatch could result from diverging development of the Austrian regions, from supply shocks or changes in the matching productivity. We repeat our analyses and estimate Beveridge curves for all nine federal states. In Figure 12 in the Annex, we plot the resulting mismatch indicators. For most states, we observe an increased mismatch after 2014. In the Burgenland, Carinthia, and in Vorarlberg the mismatch was stable over time while in Tyrol and Salzburg, the mismatch increased over the whole period. Only in Lower Austria, Styria, Upper Austria, and in Vienna do we find a marked increase after 2014. These changes in the mismatch efficiency over time are reflected in the predicted Beveridge curves in Figure 13 in the Annex. We note substantial shifts in the Beveridge curves after 2014, especially in Salzburg, Tyrol, Upper Austria, and Vienna.

This shifts could be potentially driven by labour market mismatch. Therefore, we estimate the regional mismatch unemployment rates and plot them in Figure 7. The comparison of the regional mismatch unemployment rates indicate the particular strong increase in Vienna, where mismatch unemployment rises from about 1 percent to about 3 percent after 2014. We observe increased mismatch unemployment in most other regions, although at lower levels. Only in Vorarlberg and Tyrol, the mismatch unemployment rate remained stable during this period.

*Figure 7: Mismatch unemployment, by region.*




*Source: Own calculation based on data from Statistik Austria (2020) and AMS Österreich (2020).*

*Notes: Mismatch unemployment is defined as the difference between the unemployment rate under a stable matching productivity and the steady-state unemployment rate.*

## 4.3 Results by skill level

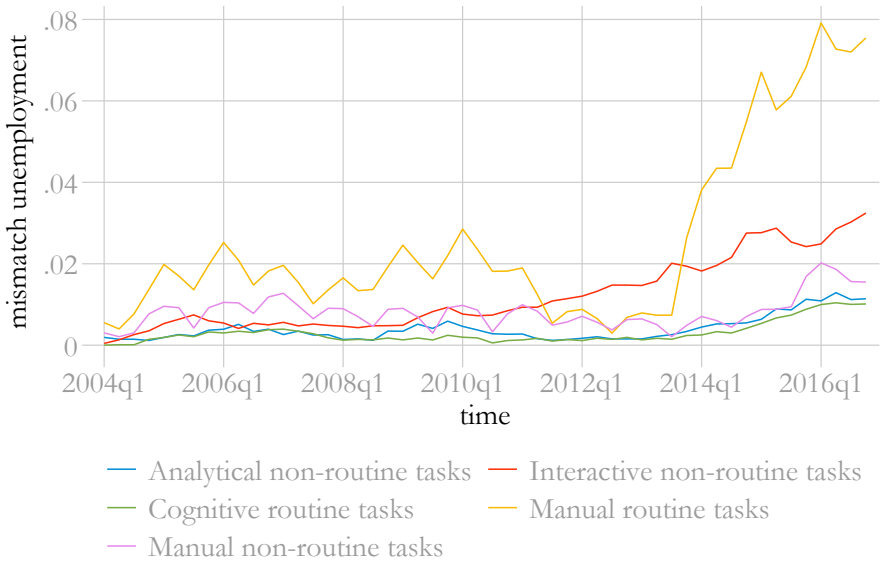
Labour markets differ in their supply of and in their demand for different skills. We see substantial regional differences in the unemployment rates and vacancy rates by skill category. Job finding rates may also differ substantially. Figure 15 highlights the development of the mismatch indicator over time by skill category. We see that the mismatch increased in particular for manual routine tasks and to some extent also for cognitive routine tasks and analytical non-routine tasks after 2014.

These differences correspond to shifts of the estimated Beveridge curves, where the shift is especially pronounced for manual routine tasks. Different skill categories have evolved differently over the recent years. In particular, we observe a substantial increase in the unemployment rate and a stable vacancy rate of manual routine tasks, where unemployment is typically higher than for other skill types.

This suggests increased labour market polarization which is caused by increased skill-mismatch for manual routine tasks. In contrast, we find stable unemployment rates, and a substantial increase of the vacancy rate, for cognitive routine tasks. We interpret this as evidence for a shortage of this specific skill type where few workers are available to fill vacancies.

We plot the resulting mismatch unemployment rates in Figure 8. Although mismatch unemployment for manual routine tasks was greater than for other skill categories before 2011, it increased substantially after 2014, from about 2 percent to almost 8 percent in 2016. While we observe an increase of mismatch unemployment after 2014 also for other skill categories, the increase for manual routine tasks is much more pronounced. It appears that the increase in mismatch unemployment for interactive non-routine tasks started already by 2010, after which it continually increased.

*Figure 8: Mismatch unemployment, by skill level.*




*Source: Own calculation based on data from Statistik Austria (2020) and AMS Österreich (2020).*

*Notes: Mismatch unemployment is defined as the difference between the unemployment rate under a stable matching productivity and the steady-state unemployment rate.*

## 4.4 Results by skill level and federal state

If we assume that each skill type has a distinct labour market in each region, we may repeat the analysis for the resulting 45 different labour markets. The interpretation of the results requires caution as, at least for neighboring regions or similar skill types, some markets are clearly connected. In addition, some of these labour markets are small, which leads to substantial uncertainty because of the sample size of the Labour Force Survey (LFS).

In Figure 18 we plot the Beveridge curves for analytical non-routine tasks for each of the nine regions. We do not find shifts of these Beveridge curves, with the exception of Upper Austria and Salzburg. We conclude from this evidence that the mismatch for analytical non-routine task is a minor problem in the Austrian labour market.

In contrast, the Beveridge curves for interactive non-routine tasks, plotted in Figure 19, exhibit considerable shifts in all federal states. It is striking that, with the exception of Vienna and Carinthia, the shifts are mainly caused by an increase in the vacancy rates. This suggests increased demand for interactive non-routine tasks, especially in Upper Austria, Salzburg and Vorarlberg.

The Beveridge curves for cognitive routine tasks, Figure 20, reveal shifts only in Styria, Upper Austria, and Salzburg. The shifts appear to be driven more by supply side factors as unemployment rates are relatively more stable than vacancy rates.

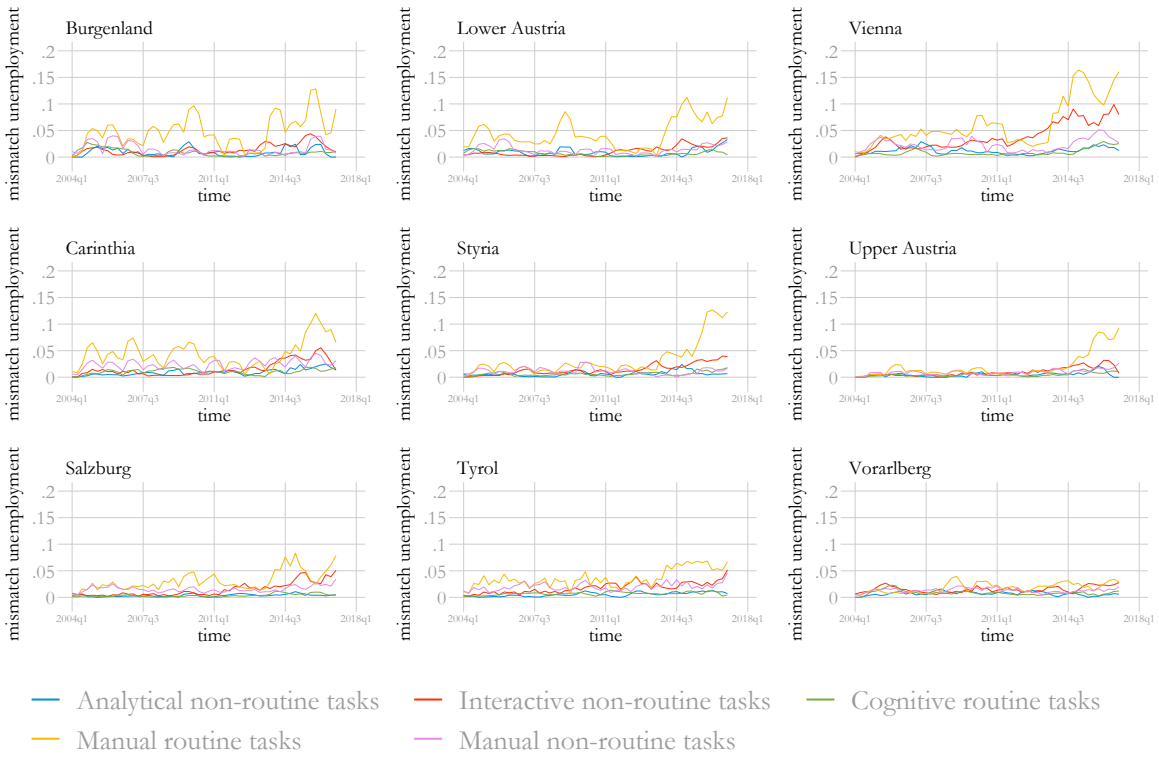
The Beveridge curves for manual routine tasks, Figure 21, shift outwards in almost all regions, with the exception of Upper Austria. These shifts, in contrast to the shifts for cognitive routine tasks, are caused by an increase in the unemployment rates rather than by greater vacancy rates. This suggests that the demand for manual routine tasks has been declining over time, with the implication that it will be difficult for unemployed workers with manual routine skills to find employment.

The Beveridge curves for manual non-routine tasks, plotted in Figure 22, are fairly stable and there are only minor outward shifts in few regions. In contrast to manual routine tasks, we do not find substantial changes in the matching efficiency for manual non-routine tasks.

We plot the estimated mismatch unemployment by region and skill-type in Figure 9. The plots

reveal substantial differences by skill level and region. In particular, mismatch unemployment increased in all regions, with the expception of Vorarlberg. Mismatch unemployment increased most noticeably in Vienna, where we estimate an increase for manual routine tasks and interactive non-routine tasks. While the increase in mismatch unemployment is most pronounced in Vienna, we estimate increased mismatch unemployment for analytical non-routine tasks also in the other regions, however, at more moderate levels.

*Figure 9: Mismatch unemployment, by region and skill level.*




*Source: Own calculation based on data from Statistik Austria (2020) and AMS Österreich (2020).*

*Notes: Mismatch unemployment is defined as the difference between the unemployment rate under a stable matching productivity and the steady-state unemployment rate.*

The general increase in mismatch unemployment for interactive non-routine tasks we have seen before seems to be especially driven by the development in Vienna, where the increase is especially strong with almost 10 percent mismatch unemployment in 2016. For the rest of the skill levels, we do not see a strong increase in mismatch unemployment, even though there are smaller upward movements visible in manual non-routine tasks in Salzburg, Upper Austria, Lower Austria, and Tyrol at the end of our observation period.

## 5 Conclusion

We analyze the Austrain Beveridge curve shift that happened after 2014. We use detailed vacancy data, on both skill and regional level, from the Public Employment Office (AMS) and estimate labour market flows on disaggregate level using information from the Austrian LFS. Using these data, we disaggregate the labour market into several regional skill labour markets. Following the approach of Veracierto (2011), who uses a simplified version of the Mortensen and Pissarides (1994) model, we

estimate Beveridge curves for Austria and all corresponding disaggregated labour markets. Additionally, we calculate the mismatch unemployment corresponding to each of the disaggreagted levels. Our approach does not allow us to identify all potential causes of mismatch separately. However, following Şahin et al. (2014) we argue that analyzing different levels of disaggregation is informative, especially from a policy perspective.

First, we find a substantially increase in mismatch unemployment in Austria after 2014 from about 0.5 percent up to more than 2 percent. Second, we find an increase in most of the Austrian regions after 2014; the increase is especially strong in the region of Vienna, where mismatch unemployment rose from about 1 percent to more than 3 percent. Third, when we consider mismatch unemployment of different skill segments, we find an especially strong increase in mismatch unemployment for manual routine tasks. Mismatch unemployment increase from levels between 1 and 2 percent before 2014 to almost 8 percent after 2014.

While the reasons for the shift of the Beveridge curve have been debated substantially in the literature, our analysis confirms that a decrease in matching efficiency after 2014 led to a shift in the Beveridge curve. While so far the reasons for this shift only have been analyzed partially by Christl (2020), our analysis identifies detailed mismatch unemployment on regional and skill level. This is especially important from a policy point of view, since policies to tackle the mismatch problems on the labour market can be targeted especially on the identified labour markets.

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## List of Figures

*Figure 1.* Unemployment rates and vacancy rates, by region. . . . . 5
*Figure 2.* Unemployment rates and vacancy rates, by skill category. . . . . 5
*Figure 3.* Transition rates, aggregated data for Austria, 2004–2016. . . . . 6
*Figure 4.* Job finding rates, by region and skill category. . . . . 7
*Figure 5.* Mismatch Indicator and Beveridge Curves, aggregated data for Austria, 2004–2016. 8
*Figure 6.* Mismatch unemployment, aggregated data for Austria, 2004–2016. . . . . 9
*Figure 7.* Mismatch unemployment, by region. . . . . 10
*Figure 8.* Mismatch unemployment, by skill level. . . . . 11
*Figure 9.* Mismatch unemployment, by region and skill level. . . . . 12
*Figure 10.* Job findings rates, by estimation method. . . . . 21
*Figure 11.* Model prediction of the unemployment rate, Austria . . . . . 21
*Figure 12.* Mismatch indicators, by region, 2004–2016. . . . . 22
*Figure 13.* Beveridge curve, by region, 2004–2016. . . . . 22
*Figure 14.* Model prediction of the unemployment rate, by regions . . . . . 23
*Figure 15.* Mismatch indicator, by skill level, 2004–2016. . . . . 23
*Figure 16.* Beveridge curves, by skill level, 2004–2016. . . . . 24
*Figure 17.* Model prediction of the unemployment rate, by skill level . . . . . 24
*Figure 18.* Beveridge curves - analytical non-routine tasks . . . . . 25
*Figure 19.* Beveridge curves - interactive non-routine tasks . . . . . 25
*Figure 20.* Beveridge curves - cognitive routine tasks . . . . . 26
*Figure 21.* Beveridge curves - manual routine tasks . . . . . 26
*Figure 22.* Beveridge curves - manual non-routine tasks . . . . . 27

## List of Tables

*Table 1.* Employment and unemployment shares, by federal state. . . . . 4
*Table 2.* Employment and unemployment, by skill category. . . . . 4
*Table 3.* Summary statistics by region. . . . . 18
*Table 4.* Summary statistics by region (cont.) . . . . . 19
*Table 5.* Summary statistics by skill level. . . . . 20
*Table 6.* Classification of occupations . . . . . 28

## Annex

*Table 3: Summary statistics by region.*

| Variable | Mean | Std. Dev. | Min. | Max. | N |
|---|---|---|---|---|---|
| Burgenland | | | | | |
| unemployment rate | 0.06 | 0.016 | 0.039 | 0.091 | 52 |
| vacancy rate | 0.004 | 0.001 | 0.003 | 0.008 | 52 |
| job finding rate | 0.203 | 0.062 | 0.084 | 0.37 | 51 |
| separation rate | 0.012 | 0.025 | -0.035 | 0.055 | 51 |
| tightness | 14.758 | 6.491 | 5.279 | 30.332 | 52 |
| Lower Austria | | | | | |
| unemployment rate | 0.055 | 0.011 | 0.036 | 0.079 | 52 |
| vacancy rate | 0.005 | 0.002 | 0.003 | 0.009 | 52 |
| job finding rate | 0.2 | 0.056 | 0.094 | 0.363 | 51 |
| separation rate | 0.011 | 0.015 | -0.021 | 0.031 | 51 |
| tightness | 11.188 | 4.465 | 3.991 | 21.775 | 52 |
| Vienna | | | | | |
| unemployment rate | 0.098 | 0.017 | 0.071 | 0.138 | 52 |
| vacancy rate | 0.006 | 0.002 | 0.003 | 0.01 | 52 |
| job finding rate | 0.183 | 0.043 | 0.113 | 0.301 | 51 |
| separation rate | 0.02 | 0.011 | -0.001 | 0.041 | 51 |
| tightness | 17.891 | 6.81 | 7.138 | 34.947 | 52 |
| Carinthia | | | | | |
| unemployment rate | 0.074 | 0.019 | 0.042 | 0.11 | 52 |
| vacancy rate | 0.007 | 0.002 | 0.004 | 0.014 | 52 |
| job finding rate | 0.187 | 0.064 | 0.096 | 0.388 | 51 |
| separation rate | 0.015 | 0.027 | -0.035 | 0.064 | 51 |
| tightness | 11.297 | 5.309 | 3.267 | 23.017 | 52 |
| Styria | | | | | |
| unemployment rate | 0.059 | 0.012 | 0.041 | 0.084 | 52 |
| vacancy rate | 0.006 | 0.001 | 0.004 | 0.008 | 52 |
| job finding rate | 0.194 | 0.054 | 0.107 | 0.405 | 51 |
| separation rate | 0.012 | 0.018 | -0.023 | 0.038 | 51 |
| tightness | 10.344 | 3.58 | 5.333 | 19.761 | 52 |
| Upper Austria | | | | | |
| unemployment rate | 0.041 | 0.01 | 0.024 | 0.061 | 52 |
| vacancy rate | 0.01 | 0.003 | 0.007 | 0.016 | 52 |
| job finding rate | 0.28 | 0.086 | 0.1 | 0.497 | 51 |
| separation rate | 0.011 | 0.012 | -0.015 | 0.027 | 51 |
| tightness | 4.257 | 1.657 | 1.593 | 8.306 | 52 |
| Salzburg | | | | | |
| unemployment rate | 0.044 | 0.008 | 0.027 | 0.058 | 52 |
| vacancy rate | 0.01 | 0.002 | 0.007 | 0.015 | 52 |
| job finding rate | 0.249 | 0.069 | 0.124 | 0.436 | 51 |
| separation rate | 0.011 | 0.012 | -0.003 | 0.039 | 51 |
| tightness | 4.647 | 1.355 | 2.408 | 7.872 | 52 |

*Source: Own calculations, data on registered unemployed and vacancies obtained from AMS Österreich (2020); employment, job-finiding rate and seperation rate obtained from Statistik Austria (2020).*

*Table 4: Summary statistics by region (cont.)*

| Variable | Mean | Std. Dev. | Min. | Max. | N |
|---|---|---|---|---|---|
| Tyrol | | | | | |
| unemployment rate | 0.051 | 0.01 | 0.03 | 0.069 | 52 |
| vacancy rate | 0.007 | 0.002 | 0.005 | 0.012 | 52 |
| job finding rate | 0.21 | 0.071 | 0.089 | 0.424 | 51 |
| separation rate | 0.012 | 0.02 | -0.015 | 0.054 | 51 |
| tightness | 7.308 | 1.894 | 4.081 | 11.629 | 52 |
| Vorarlberg | | | | | |
| unemployment rate | 0.049 | 0.005 | 0.04 | 0.063 | 52 |
| vacancy rate | 0.008 | 0.002 | 0.004 | 0.011 | 52 |
| job finding rate | 0.234 | 0.053 | 0.101 | 0.353 | 51 |
| separation rate | 0.012 | 0.007 | 0.001 | 0.033 | 51 |
| tightness | 6.77 | 2.357 | 3.917 | 13.211 | 52 |

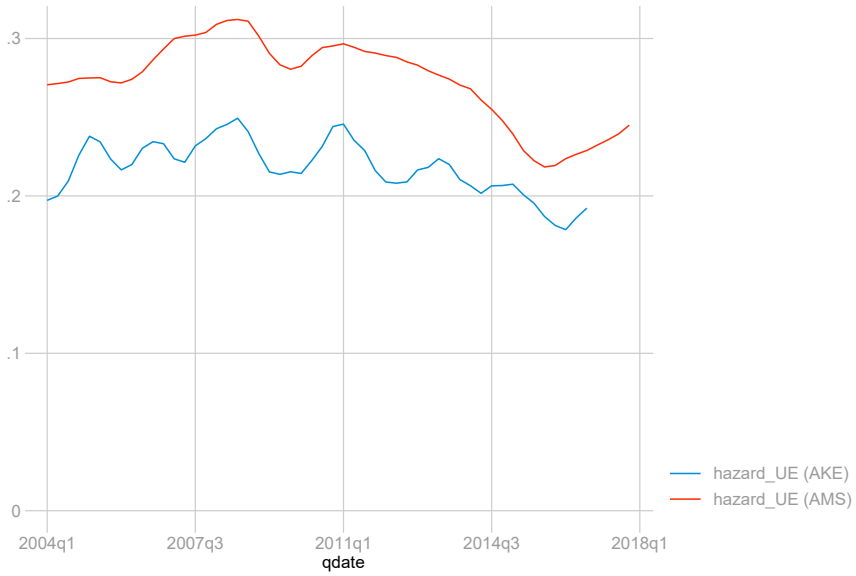
*Source: Own calculations, data on registered unemployed and vacancies obtained from AMS Österreich (2020); employment, job-finiding rate and seperation rate obtained from Statistik Austria (2020).*

*Table 5: Summary statistics by skill level.*

| Variable | Mean | Std. Dev. | Min. | Max. | N |
|---|---|---|---|---|---|
| analytical non-routine tasks | | | | | |
| unemployment rate | 0.031 | 0.004 | 0.024 | 0.038 | 52 |
| vacancy rate | 0.003 | 0.001 | 0.002 | 0.005 | 52 |
| job finding rate | 0.21 | 0.059 | 0.1 | 0.377 | 51 |
| separation rate | 0.007 | 0.003 | -0.003 | 0.013 | 51 |
| tightness | 10.652 | 2.28 | 6.428 | 17.064 | 52 |
| interactive non-routine tasks | | | | | |
| unemployment rate | 0.049 | 0.011 | 0.036 | 0.071 | 52 |
| vacancy rate | 0.006 | 0.001 | 0.003 | 0.009 | 52 |
| job finding rate | 0.279 | 0.065 | 0.174 | 0.422 | 51 |
| separation rate | 0.015 | 0.004 | 0.006 | 0.023 | 51 |
| tightness | 8.782 | 1.421 | 6.063 | 12.375 | 52 |
| cognitive routine tasks | | | | | |
| unemployment rate | 0.04 | 0.005 | 0.03 | 0.049 | 52 |
| vacancy rate | 0.004 | 0.001 | 0.003 | 0.006 | 52 |
| job finding rate | 0.224 | 0.05 | 0.14 | 0.325 | 51 |
| separation rate | 0.009 | 0.004 | -0.002 | 0.015 | 51 |
| tightness | 10.223 | 2.431 | 5.631 | 16.765 | 52 |
| manual routine tasks | | | | | |
| unemployment rate | 0.141 | 0.037 | 0.088 | 0.224 | 52 |
| vacancy rate | 0.009 | 0.002 | 0.006 | 0.015 | 52 |
| job finding rate | 0.131 | 0.034 | 0.074 | 0.211 | 51 |
| separation rate | 0.022 | 0.034 | -0.035 | 0.082 | 51 |
| tightness | 15.952 | 6.165 | 6.435 | 31.442 | 52 |
| manual non-routine tasks | | | | | |
| unemployment rate | 0.064 | 0.017 | 0.036 | 0.097 | 52 |
| vacancy rate | 0.011 | 0.002 | 0.008 | 0.017 | 52 |
| job finding rate | 0.219 | 0.056 | 0.127 | 0.368 | 51 |
| separation rate | 0.014 | 0.025 | -0.033 | 0.048 | 51 |
| tightness | 6.183 | 2.507 | 2.273 | 12.294 | 52 |

*Source: Own calculations, data on registered unemployed and vacancies obtained from AMS Österreich (2020); employment, job-finiding rate and seperation rate obtained from Statistik Austria (2020).*

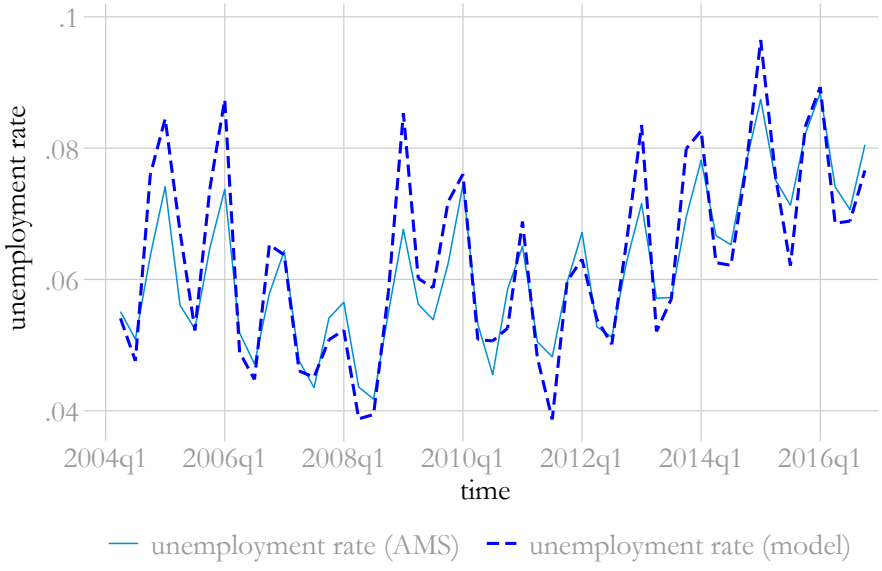
*Figure 10: Job findings rates, by estimation method.*




*Source: Own calculations, based on data from AMS Österreich (2020) and Statistik Austria (2020).*

*Notes: The graph plots the estimated job finding rates for the whole of Austria. The top line, AMS, is based on the approach by Shimer (2012), which we use here. The bottom line, AKE, is derived from an analysis of labour market flows (Christl, 2020).*

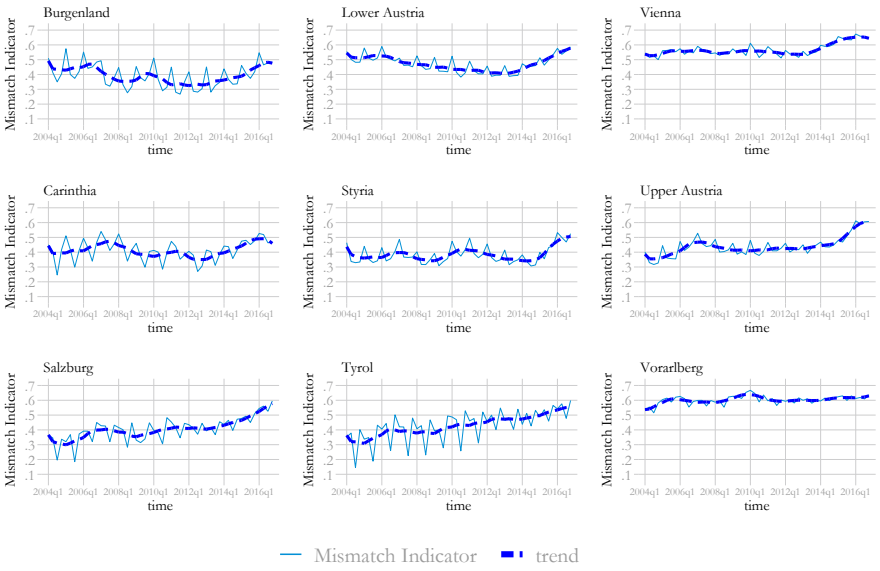
*Figure 11: Model prediction of the unemployment rate, Austria*




*Source: Own calculations, based on data from AMS Österreich (2020) and Statistik Austria (2020).*

*Notes: The graph plots the estimated unemployment rate for the whole of Austria and compares it with the unemployment rate observed in the data.*

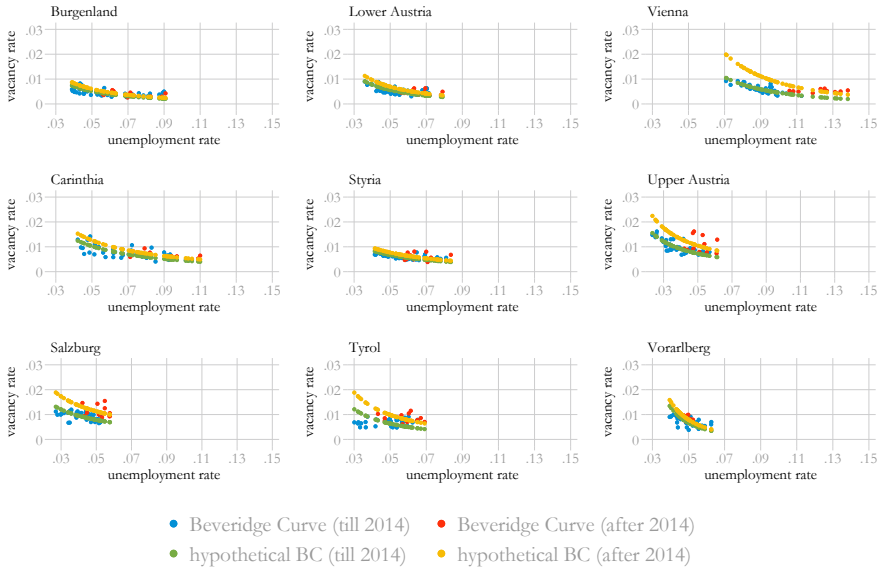
*Figure 12: Mismatch indicators, by region, 2004--2016.*




*Source: Own calculations, based on data from AMS Österreich (2020) and Statistik Austria (2020).*

*Notes: The trend is derived by a locally weighted smoothing.*

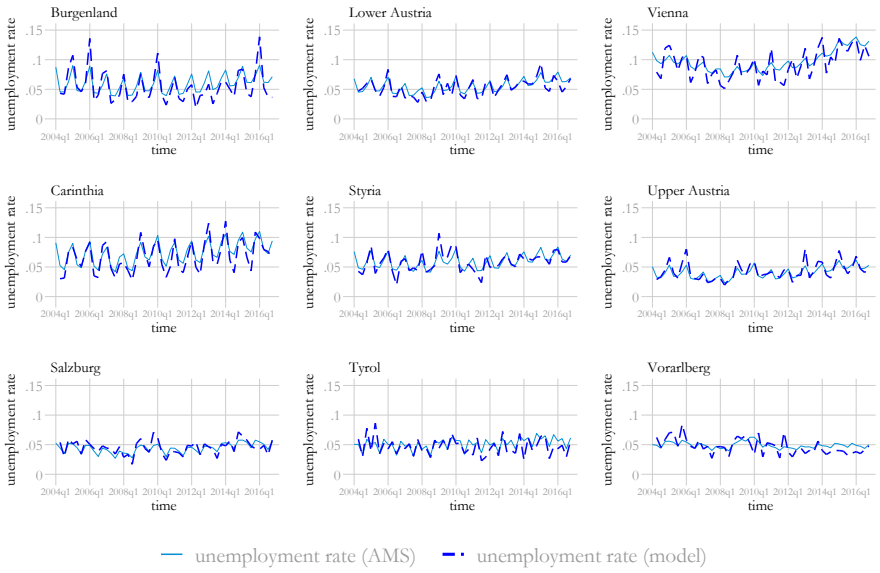
*Figure 13: Beveridge curve, by region, 2004--2016.*




*Source: Own calculations, based on data from AMS Österreich (2020) and Statistik Austria (2020).*

*Notes: The hypothetical Beveridge curves are estimated with the average matching efficiency before 2014 and after 2014.*

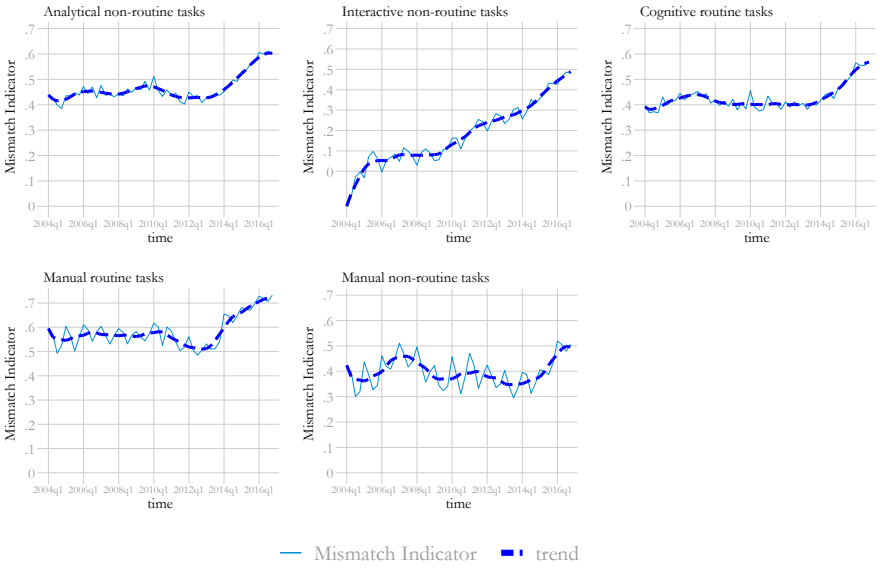
*Figure 14: Model prediction of the unemployment rate, by regions*




*Source: Own calculations, based on data from AMS Österreich (2020) and Statistik Austria (2020).*

*Notes: The graph plots the estimated unemployment rate for the Austrian regions and compares it with the unemployment rate observed in the data.*

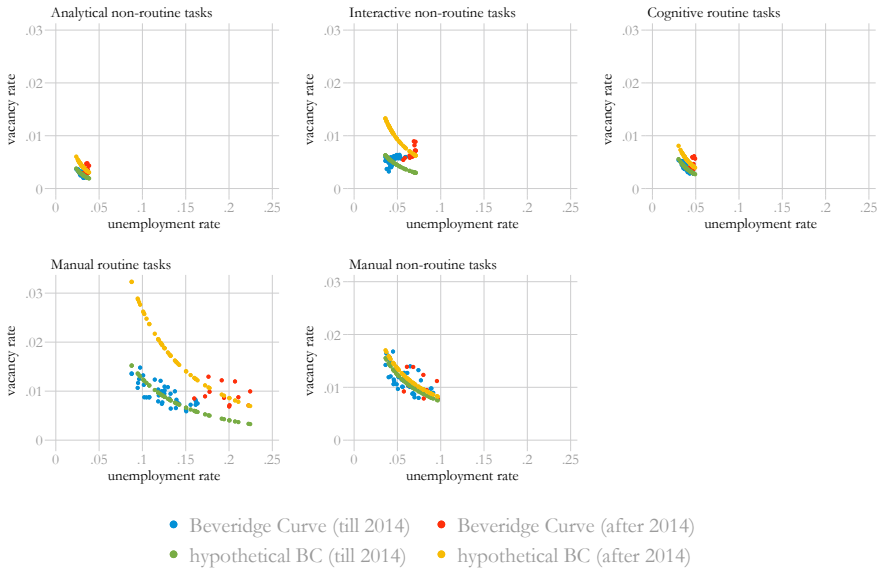
*Figure 15: Mismatch indicator, by skill level, 2004--2016.*




*Source: Own calculations, based on data from AMS Österreich (2020) and Statistik Austria (2020).*

*Notes: The trend is derived by a locally weighted smoothing.*

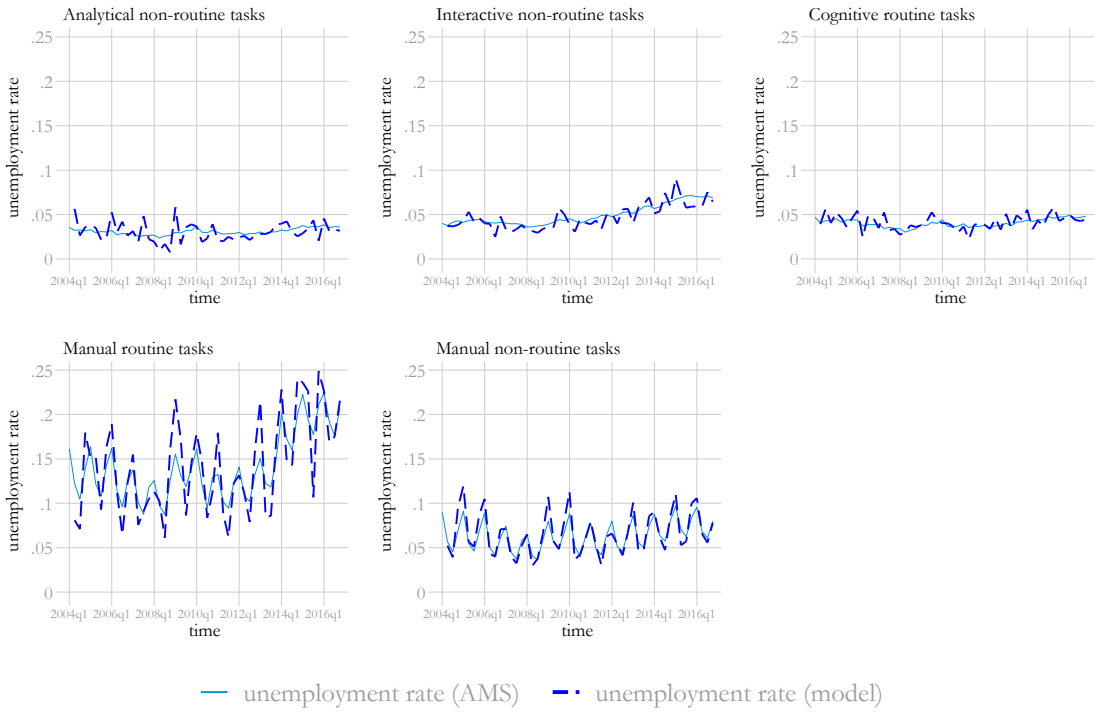
*Figure 16: Beveridge curves, by skill level, 2004--2016.*




*Source: Own calculations, based on data from AMS Österreich (2020) and Statistik Austria (2020).*

*Notes: The hypothetical Beveridge curves are estimated with the average matching efficiency before 2014 and after 2014.*

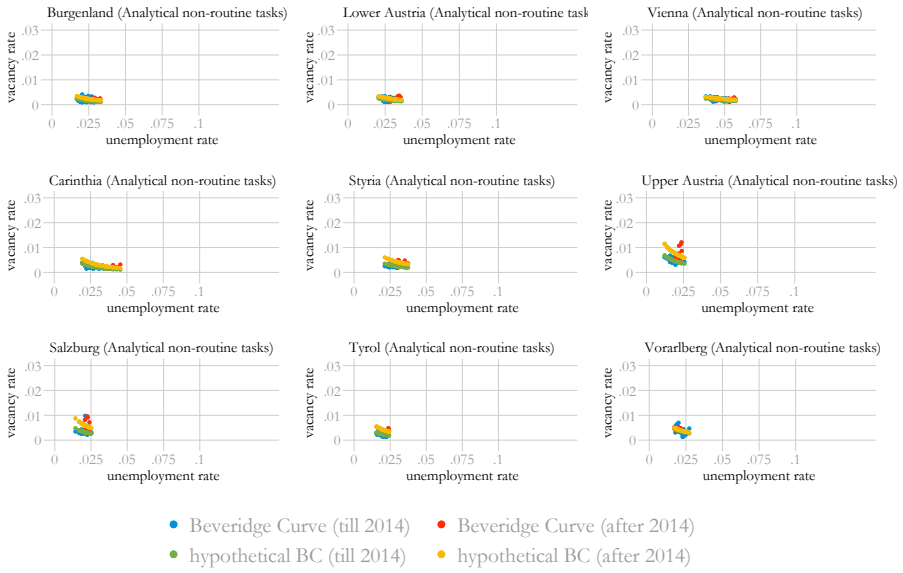
*Figure 17: Model prediction of the unemployment rate, by skill level*




*Source: Own calculations, based on data from AMS Österreich (2020) and Statistik Austria (2020).*

*Notes: The graph plots the estimated unemployment rate by skill level and compares it with the unemployment rate observed in the data.*

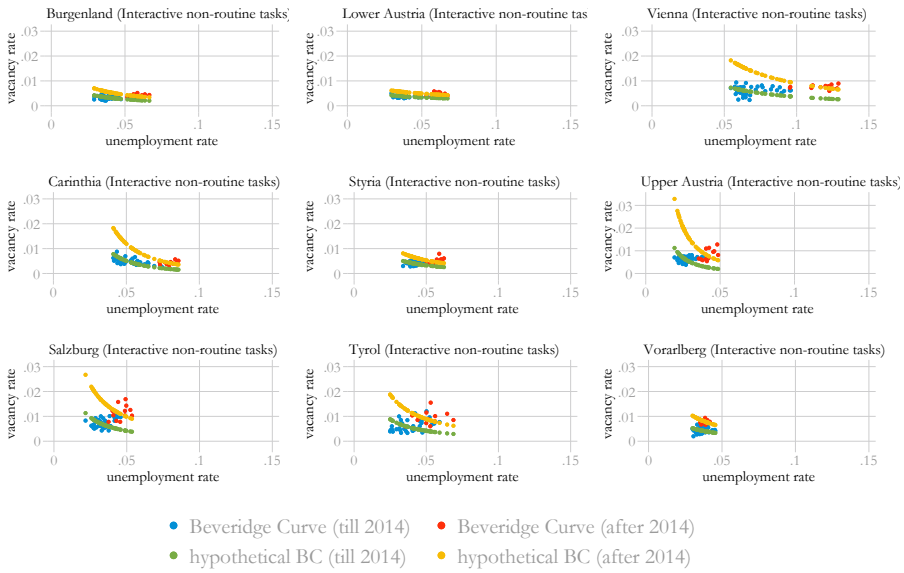
*Figure 18: Beveridge curves - analytical non-routine tasks*




*Source: Own calculations, based on data from AMS Österreich (2020) and Statistik Austria (2020).*

*Notes: The hypothetical Beveridge curves are estimated with the average matching efficiency before 2014 and after 2014.*

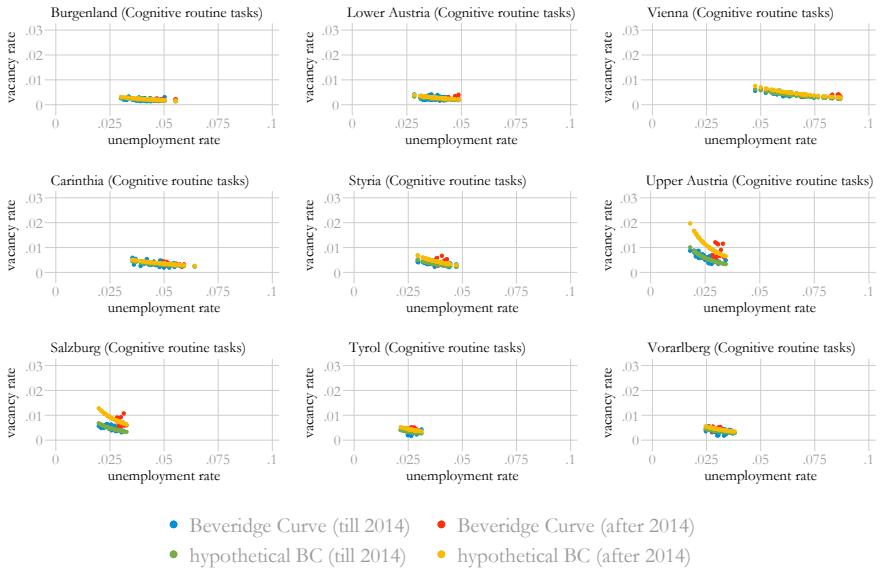
*Figure 19: Beveridge curves - interactive non-routine tasks*




*Source: Own calculations, based on data from AMS Österreich (2020) and Statistik Austria (2020).*

*Notes: The hypothetical Beveridge curves are estimated with the average matching efficiency before 2014 and after 2014.*

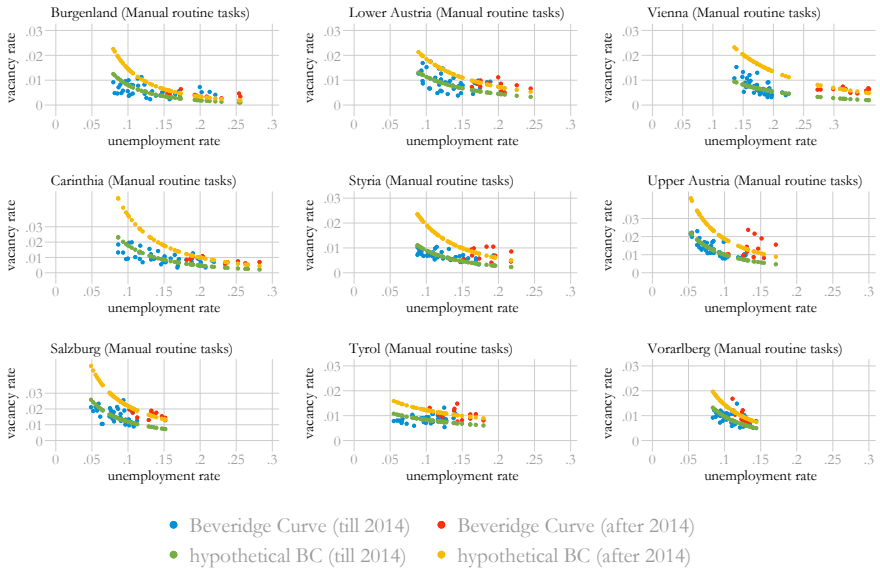
*Figure 20: Beveridge curves - cognitive routine tasks*




*Source: Own calculations, based on data from AMS Österreich (2020) and Statistik Austria (2020).*

*Notes: The hypothetical Beveridge curves are estimated with the average matching efficiency before 2014 and after 2014.*

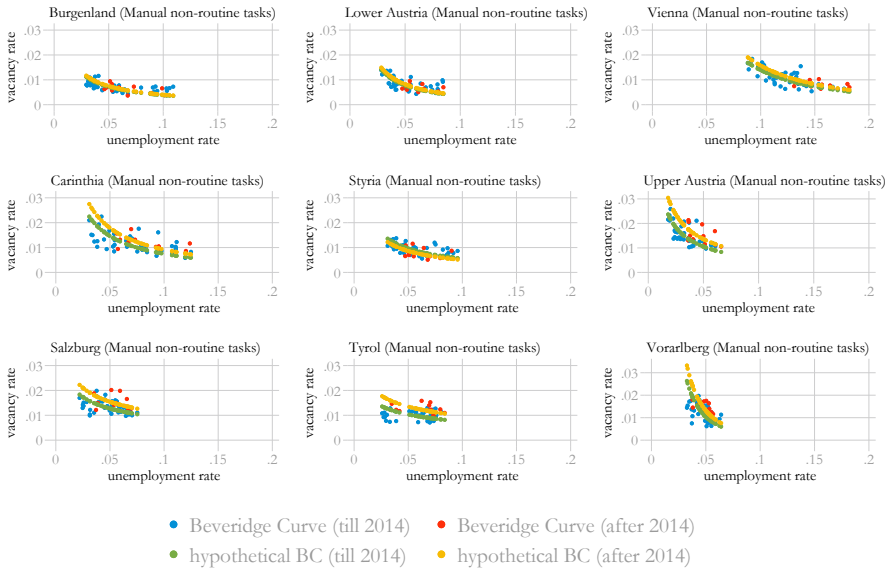
*Figure 21: Beveridge curves - manual routine tasks*




*Source: Own calculations, based on data from AMS Österreich (2020) and Statistik Austria (2020).*

*Notes: The hypothetical Beveridge curves are estimated with the average matching efficiency before 2014 and after 2014.*

*Figure 22: Beveridge curves - manual non-routine tasks*




*Source: Own calculations, based on data from AMS Österreich (2020) and Statistik Austria (2020).*

*Notes: The hypothetical Beveridge curves are estimated with the average matching efficiency before 2014 and after 2014.*

,

*Table 6: Classification of occupations*

| ISCO-08 | class | task category | description |
|---|---|---|---|
| 111 | 1 | manual routine tasks | Legislators and senior officials |
| 112 | 1 | manual routine tasks | Managing directors and chief executives |
| 121 | 1 | manual routine tasks | Business services and administration managers |
| 122 | 1 | manual routine tasks | Sales, marketing and development managers |
| 131 | 1 | manual routine tasks | Production managers in agriculture, forestry and fisheries |
| 132 | 1 | manual routine tasks | Manufacturing, mining, construction, and distribution managers |
| 133 | 1 | manual routine tasks | Information and communications technology service managers |
| 134 | 1 | manual routine tasks | Professional services managers |
| 141 | 1 | manual routine tasks | Hotel and restaurant managers |
| 143 | 1 | manual routine tasks | Other services managers |
| 211 | 1 | manual routine tasks | Physical and earth science professionals |
| 212 | 1 | manual routine tasks | Mathematicians, actuaries and statisticians |
| 213 | 1 | manual routine tasks | Life science professionals |
| 214 | 1 | manual routine tasks | Engineering professionals (excluding electrotechnology) |
| 215 | 1 | manual routine tasks | Electrotechnology engineers |
| 216 | 1 | manual routine tasks | Architects, planners, surveyors and designers |
| 221 | 1 | manual routine tasks | Medical doctors |
| 222 | 1 | manual routine tasks | Nursing and midwifery professionals |
| 225 | 1 | manual routine tasks | Veterinarians |
| 226 | 1 | manual routine tasks | Other health professionals |
| 231 | 1 | manual routine tasks | University and higher education teachers |
| 232 | 2 | interactive non-routine tasks | Vocational education teachers |
| 233 | 2 | interactive non-routine tasks | Secondary education teachers |
| 234 | 2 | interactive non-routine tasks | Primary school and early childhood teachers |
| 235 | 2 | interactive non-routine tasks | Other teaching professionals |
| 241 | 1 | manual routine tasks | Finance professionals |
| 242 | 1 | manual routine tasks | Administration professionals |
| 243 | 1 | manual routine tasks | Sales, marketing and public relations professionals |
| 251 | 1 | manual routine tasks | Software and applications developers and analysts |
| 252 | 1 | manual routine tasks | Database and network professionals |
| 261 | 1 | manual routine tasks | Legal professionals |
| 262 | 1 | manual routine tasks | Librarians, archivists and curators |
| 263 | 1 | manual routine tasks | Social and religious professionals |
| 264 | 1 | manual routine tasks | Authors, journalists and linguists |
| 265 | 1 | manual routine tasks | Creative and performing artists |
| 311 | 3 | cognitive routine tasks | Physical and engineering science technicians |
| 312 | 1 | manual routine tasks | Mining, manufacturing and construction supervisors |
| 313 | 3 | cognitive routine tasks | Process control technicians |
| 314 | 3 | cognitive routine tasks | Life science technicians and related associate professionals |
| 315 | 5 | manual non-routine tasks | Ship and aircraft controllers and technicians |
| 321 | 3 | cognitive routine tasks | Medical and pharmaceutical technicians |
| 322 | 3 | cognitive routine tasks | Nursing and midwifery associate professionals |
| 325 | 3 | cognitive routine tasks | Other health associate professionals |
| 331 | 3 | cognitive routine tasks | Financial and mathematical associate professionals |
| 332 | 2 | interactive non-routine tasks | Sales and purchasing agents and brokers |
| 333 | 3 | cognitive routine tasks | Business services agents |

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*Table 6 -- continued from previous page.*

| ISCO-08 | class | task category | description |
|---|---|---|---|
| 334 | 3 | cognitive routine tasks | Administrative and specialized secretaries |
| 335 | 3 | cognitive routine tasks | Regulatory government associate professionals |
| 341 | 2 | interactive non-routine tasks | Legal, social and religious associate professionals |
| 342 | 2 | interactive non-routine tasks | Sports and fitness workers |
| 343 | 2 | interactive non-routine tasks | Artistic, cultural and culinary associate professionals |
| 351 | 3 | cognitive routine tasks | Information and communications technology operations and user support technicians |
| 352 | 3 | cognitive routine tasks | Telecommunications and broadcasting technicians |
| 411 | 3 | cognitive routine tasks | General office clerks |
| 412 | 3 | cognitive routine tasks | Secretaries (general) |
| 413 | 3 | cognitive routine tasks | Keyboard operators |
| 421 | 2 | interactive non-routine tasks | Tellers, money collectors and related clerks |
| 422 | 2 | interactive non-routine tasks | Client information workers |
| 431 | 3 | cognitive routine tasks | Numerical clerks |
| 432 | 3 | cognitive routine tasks | Material-recording and transport clerks |
| 441 | 3 | cognitive routine tasks | Other clerical support workers |
| 511 | 5 | manual non-routine tasks | Travel attendants, conductors and guides |
| 512 | 5 | manual non-routine tasks | Cooks |
| 513 | 5 | manual non-routine tasks | Waiters and bartenders |
| 514 | 5 | manual non-routine tasks | Hairdressers, beauticians and related workers |
| 515 | 5 | manual non-routine tasks | Building and housekeeping supervisors |
| 516 | 5 | manual non-routine tasks | Other personal services workers |
| 521 | 2 | interactive non-routine tasks | Street and market salespersons |
| 522 | 2 | interactive non-routine tasks | Shop salespersons |
| 523 | 2 | interactive non-routine tasks | Cashiers and ticket clerks |
| 524 | 2 | interactive non-routine tasks | Other sales workers |
| 531 | 2 | interactive non-routine tasks | Child care workers and teachers' aides |
| 532 | 5 | manual non-routine tasks | Personal care workers in health services |
| 541 | 5 | manual non-routine tasks | Protective services workers |
| 611 | 5 | manual non-routine tasks | Market gardeners and crop growers |
| 612 | 5 | manual non-routine tasks | Animal producers |
| 613 | 5 | manual non-routine tasks | Mixed crop and animal producers |
| 621 | 5 | manual non-routine tasks | Forestry and related workers |
| 622 | 5 | manual non-routine tasks | Fishery workers, hunters and trappers |
| 711 | 5 | manual non-routine tasks | Building frame and related trades workers |
| 712 | 5 | manual non-routine tasks | Building finishers and related trades workers |
| 713 | 5 | manual non-routine tasks | Painters, building structure cleaners and related trades workers |
| 721 | 5 | manual non-routine tasks | Sheet and structural metal workers, molders and welders, and related workers |
| 722 | 5 | manual non-routine tasks | Blacksmiths, toolmakers and related trades workers |
| 723 | 5 | manual non-routine tasks | Machinery mechanics and repairers |
| 731 | 5 | manual non-routine tasks | Handicraft workers |
| 732 | 5 | manual non-routine tasks | Printing trades workers |
| 741 | 5 | manual non-routine tasks | Electrical equipment installers and repairers |
| 742 | 5 | manual non-routine tasks | Electronics and telecommunications installers and repairers |
| 751 | 5 | manual non-routine tasks | Food processing and related trades workers |
| 752 | 5 | manual non-routine tasks | Wood treaters, cabinet-makers and related trades workers |

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*Table 6 -- continued from previous page.*

| ISCO-08 | class | task category | description |
|---|---|---|---|
| 753 | 5 | manual non-routine tasks | Garment and related trades workers |
| 754 | 4 | analytical non-routine tasks | Other craft and related workers |
| 811 | 4 | analytical non-routine tasks | Mining and mineral processing plant operators |
| 812 | 4 | analytical non-routine tasks | Metal processing and finishing plant operators |
| 813 | 4 | analytical non-routine tasks | Chemical and photographic products plant and machine operators |
| 814 | 4 | analytical non-routine tasks | Rubber, plastic and paper products machine operators |
| 815 | 4 | analytical non-routine tasks | Textile, fur and leather products machine operators |
| 816 | 4 | analytical non-routine tasks | Food and related products machine operators |
| 817 | 4 | analytical non-routine tasks | Wood processing and papermaking plant operators |
| 818 | 4 | analytical non-routine tasks | Other stationary plant and machine operators |
| 821 | 4 | analytical non-routine tasks | Assemblers |
| 831 | 5 | manual non-routine tasks | Locomotive engine drivers and related workers |
| 832 | 5 | manual non-routine tasks | Car, van and motorcycle drivers |
| 833 | 5 | manual non-routine tasks | Heavy truck and bus drivers |
| 834 | 4 | analytical non-routine tasks | Mobile plant operators |
| 835 | 4 | analytical non-routine tasks | Ships' deck crews and related workers |
| 911 | 4 | analytical non-routine tasks | Domestic, hotel and office cleaners and helpers |
| 912 | 4 | analytical non-routine tasks | Vehicle, window, laundry and other hand cleaning workers |
| 921 | 4 | analytical non-routine tasks | Agricultural, forestry and fishery labourers |
| 931 | 4 | analytical non-routine tasks | Mining and construction labourers |
| 932 | 4 | analytical non-routine tasks | Manufacturing labourers |
| 933 | 4 | analytical non-routine tasks | Transport and storage labourers |
| 941 | 4 | analytical non-routine tasks | Food preparation assistants |
| 951 | 4 | analytical non-routine tasks | Street and related service workers |
| 961 | 4 | analytical non-routine tasks | Street vendors (excluding food) |
| 962 | 4 | analytical non-routine tasks | Other elementary workers |

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