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

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Abstract

During the last decade, the Austrian labour market experienced a substantial outward shift of the Beveridge curve. 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.

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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, Köppl-Turyna and Kucsera (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, Song, Topa and Violante (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, Katz and Kearney (2006), Goos and Manning (2007), Goos, Manning and Salomons (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, Levy and Murnane, 2003; Michaels, Natraj and Van Reenen, 2014). However, the literatur on the impact of overall employment effects of automation suggest a rather small impact. Acemoglu, Autor, Hazell and Restrepo (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 rather a changes in the task content of jobs rather than a strong reduction of employment[3].

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 unemploy-

[3]See, e.g., Klenert, Fernandez-Macias and Antón Pérez (2020), Dauth, Findeisen, Südekum and Woessner (2017) or Barbieri, Mussida, Piva and Vivarelli (2019).

ment. 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.

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

Workers move between three states, unemployment (U), employment (E), and inactivity (I). Hazard rates, λ_t^{IJ}, describe the transitions from labour market status I to labour market status J at time t. In other words, λ_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:

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

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

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

The steady state unemployment is given by:

$$u_t^{ss} = \frac{s_t}{s_t + f_t}, \quad (5)$$

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:

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

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 α of the matching function. We follow Barlevy (2011) and Veracierto (2011) and assume constant transition rates in the period before the Beveridge curve shift[4].

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 α parameter

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

(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 α and use these estimates to calculate the matching efficiency parameter A_t[5].

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).

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 A.6.

[5] For a general discussion on estimating matching efficiencies, see e.g., Crawley, Welch and Yung (2021).

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[6]. 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[7], following Bock-Schappelwein, Famira-Mühlberger and Leoni (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.

[6] See, e.g., Statistik Austria (2020) and Moser (2010).
[7] Table A.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.

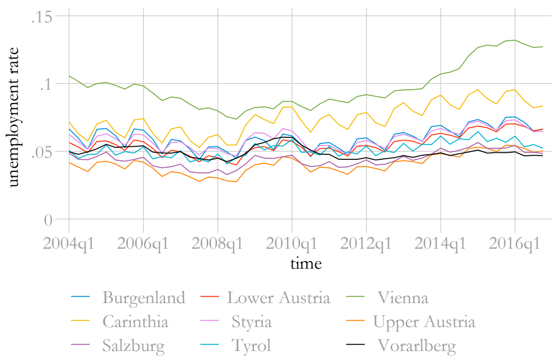
	Employment (%)	Unemployment (%)
Analytical non-routine tasks	15.4	7.3
Interactive non-routine tasks	21.6	13.4
Cognitive routine tasks	19.2	14.6
Manual routine tasks	13.3	31.7
Manual non-routine tasks	30.5	30.7

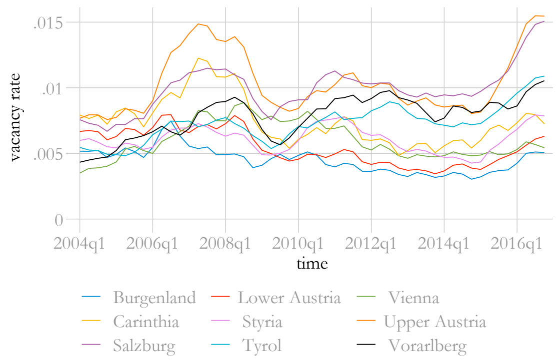
Source: Data on registered unemployed (PES) obtained from AMS Österreich (2020); data on employment obtained from Statistik Austria (2020).
Notes: Shares are calculated as a fraction of total values for Austria. Percentages are calculated on pooled data 2004:Q1 to 2016:Q4. ISCO-08 occupations are grouped as manual routine tasks, manual non-routine tasks, analytical non-routine tasks, interactive non-routine task, and cognitive routine tasks. See Table A.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.

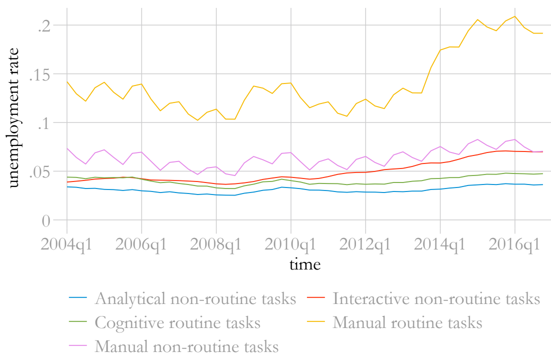


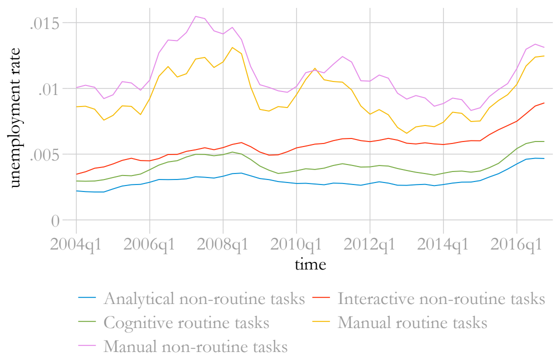


Source: Vacancies and unemployment obtained from AMS Österreich (2020); data on employment obtained from Statistik Austria (2020).

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.





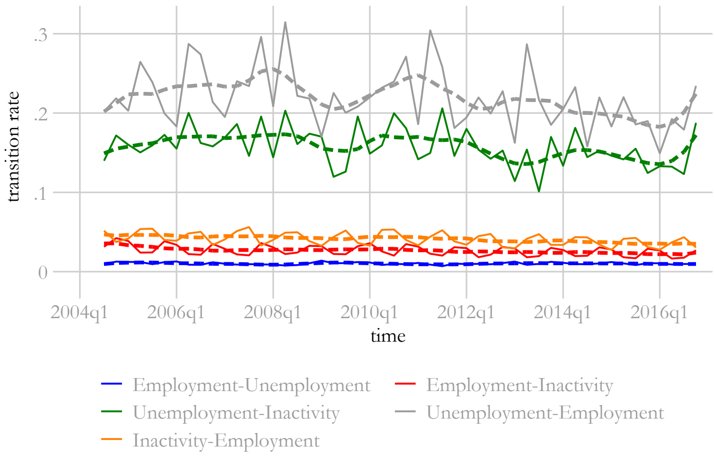
Source: Vacancies and unemployment obtained from AMS Österreich (2020); data on employment obtained from Statistik Austria (2020).
Notes: ISCO-08 occupations are grouped as manual routine tasks, manual non-routine tasks, analytical non-routine tasks, interactive non-routine task, and cognitive routine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

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

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).

and plot these by skill category and region in Figure 4.

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 A.4 and A.5.

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 A.6 for details.

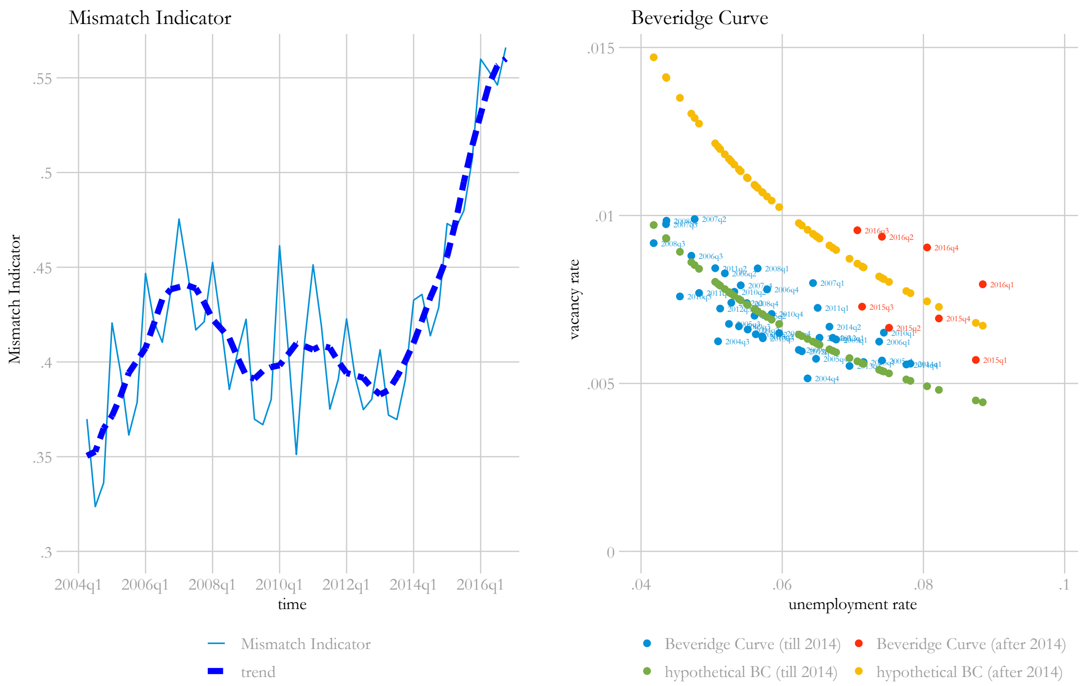
4. Results

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[8] (left) and the resulting Beveridge curves (right) based on aggregated quarterly data from 2004 until 2016.

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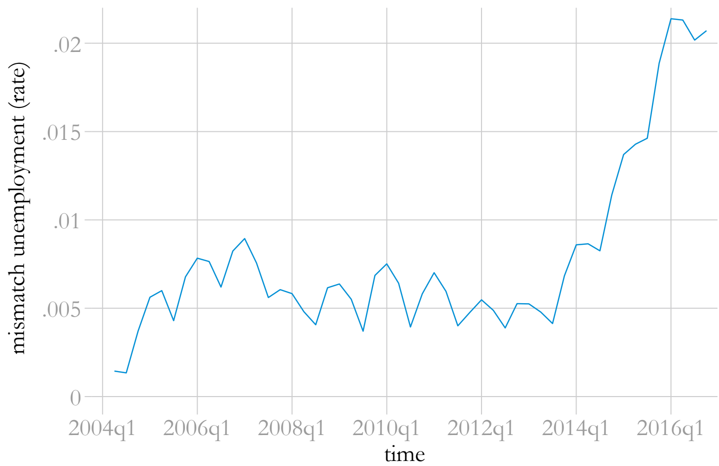
The mismatch indicator suggests a substantial increase in mismatch after 2014. To illustrate the effect of the increased mismatch, we split the sample into two periods, before 2014 and after 2014. We plot the Beveridge curves for the pre-2014 period (blue dots) and the quarters after 2014 (red dots).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

[8]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.

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[9]. 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.

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



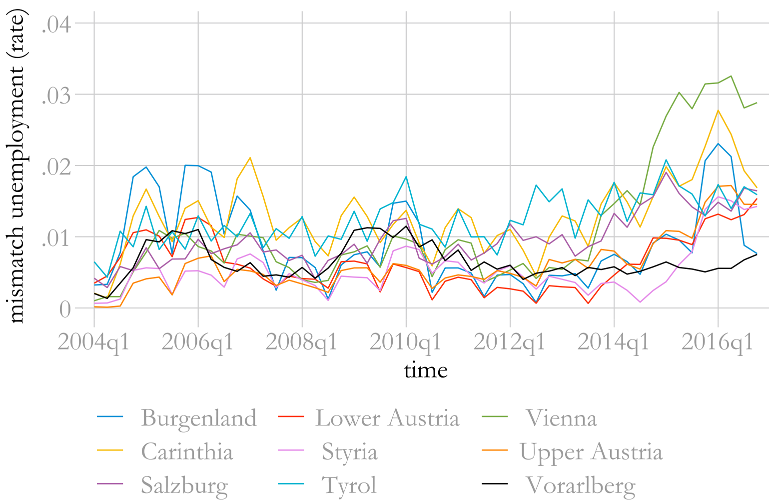
Source: Own calculation based on data from Statistik Austria (2020) and AMS Österreich (2020).
Notes: Mismatch unemployment is the difference between the unemployment rate under a stable matching productivity and the steady-state unemployment rate.

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

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 A.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 A.13 in the Annex. We note substantial shifts in the Beveridge curves after 2014, especially in Salzburg, Tyrol, Upper Austria, and Vienna.

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.

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.

4.3. Results by skill level

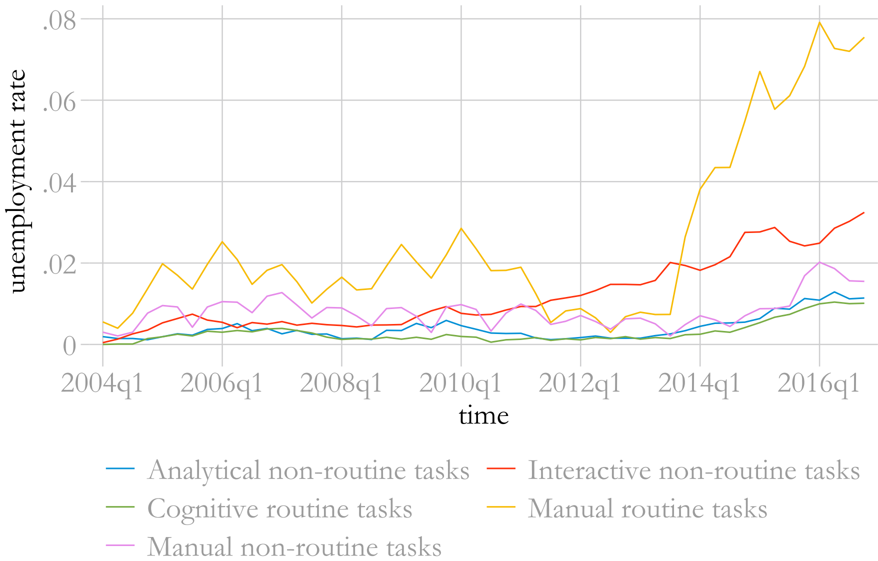
Labour markets differ in their supply of and in their demand for different skills. We see substantial regional differences in the unemployment rates and vacancy rates by skill category. Job finding rates may also differ substantially. Figure A.15 highlights the development of the mismatch indicator over 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 A.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 A.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.

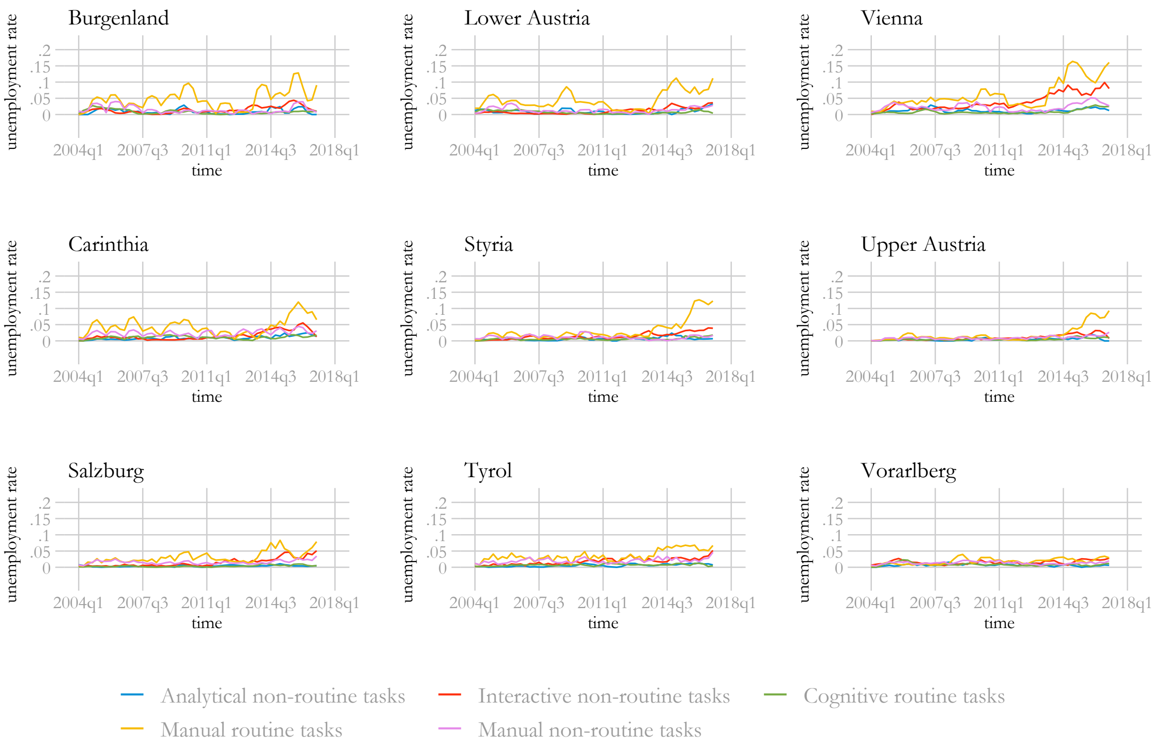
The Beveridge curves for cognitive routine tasks, Figure A.20, reveal shifts only in Styria, Upper Austria, and Salzburg. The shifts appear to be driven more by supply side factors as unemployment rates are relatively more stable than vacancy rates.

The Beveridge curves for manual routine tasks, Figure A.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 A.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 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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Appendix A. Additional Figures and Tables

Table A.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 A.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

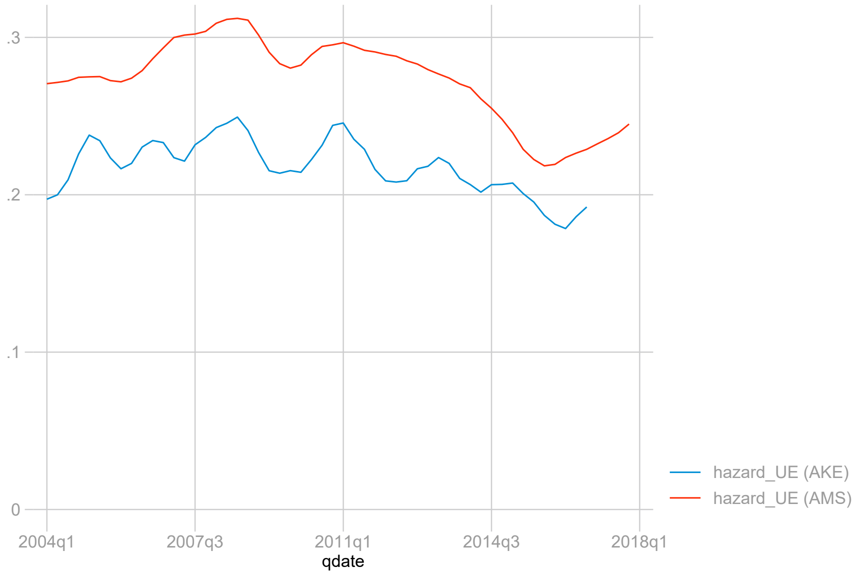
Source: Own calculations, data on registered unemployed and vacancies obtained from AMS Österreich (2020); employment, job-finiding rate and seperation rate obtained from Statistik Austria (2020).

Table A.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

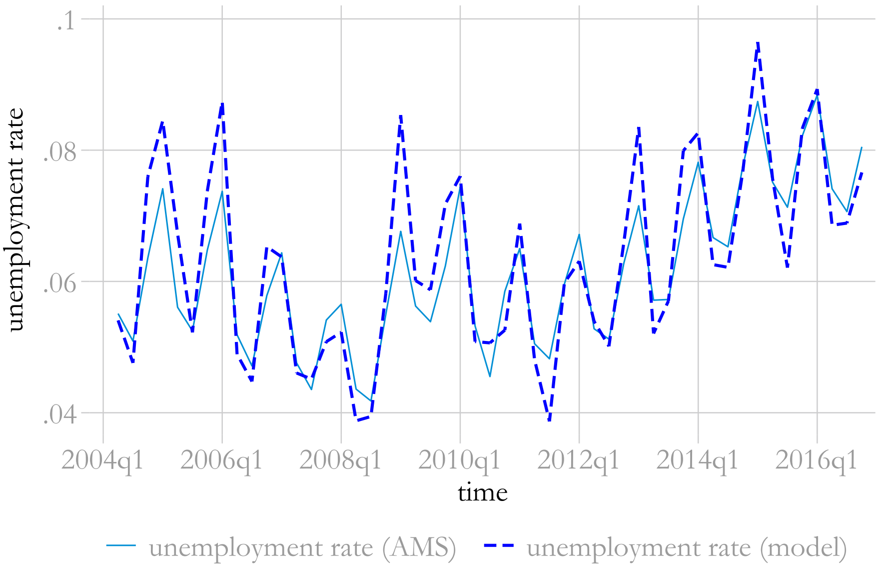
Source: Own calculations, data on registered unemployed and vacancies obtained from AMS Österreich (2020); employment, job-finiding rate and seperation rate obtained from Statistik Austria (2020).

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



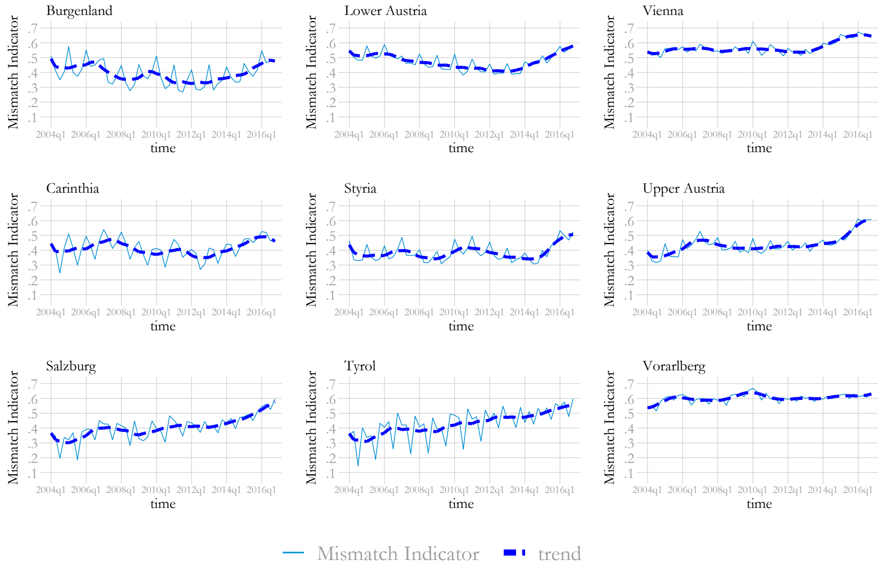
Source: Own calculations, based on data from AMS Österreich (2020) and Statistik Austria (2020).
Notes: The graph plots the estimated job finding rates for the whole of Austria. The top line, AMS, is based on the approach by Shimer (2012), which we use here. The bottom line, AKE, is derived from an analysis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

Figure A.11: Model prediction of the unemployment rate, Austria



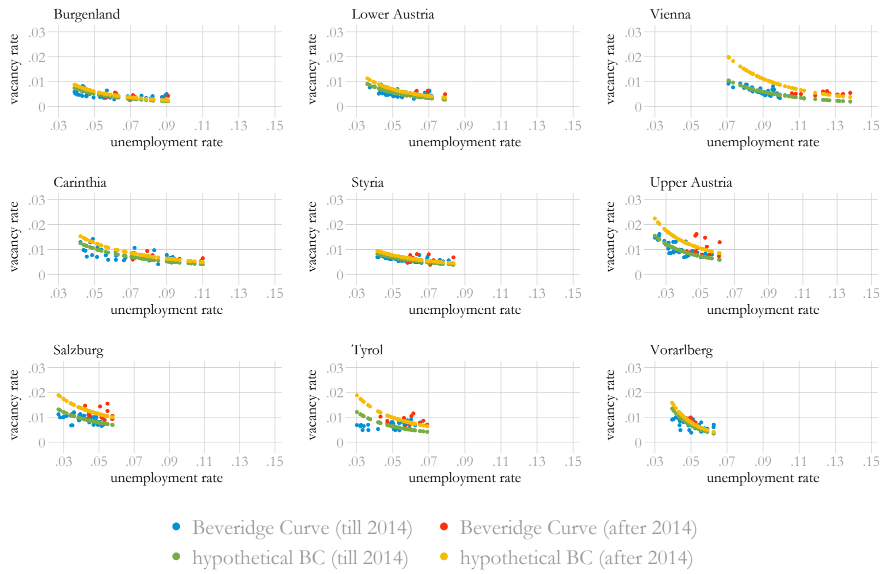
Source: Own calculations, based on data from AMS Österreich (2020) and Statistik Austria (2020).
Notes: The graph plots the estimated unemployment rate for the whole of Austria and compares it with the unemployment rate observed in the data.

Figure A.12: Mismatch indicators, by region, 2004–2016.



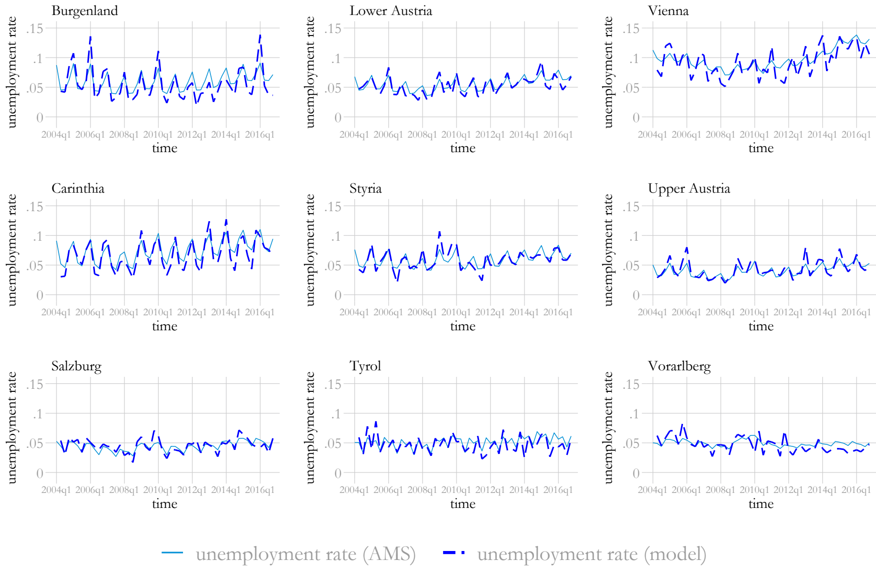
Source: Own calculations, based on data from AMS Österreich (2020) and Statistik Austria (2020).
Notes: The trend is derived by a locally weighted smoothing.

Figure A.13: Beveridge curve, by region, 2004–2016.



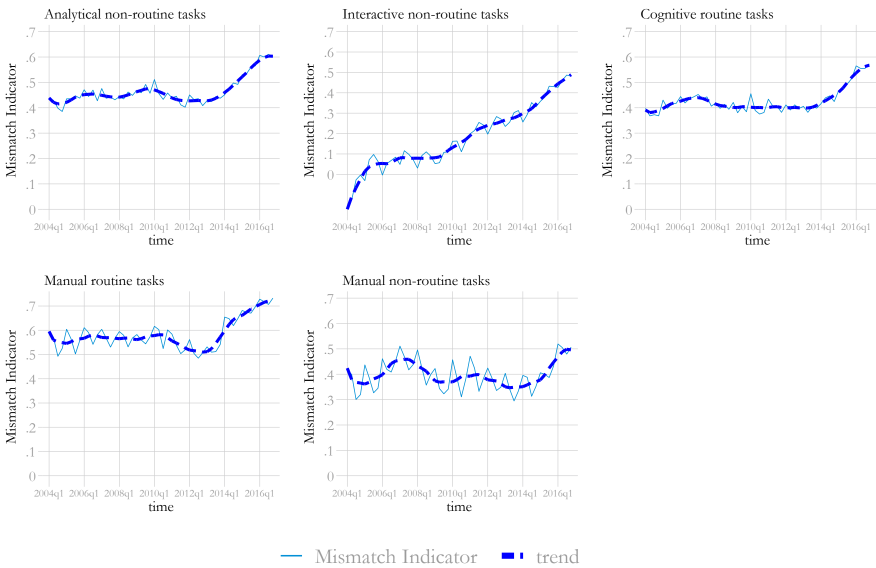
Source: Own calculations, based on data from AMS Österreich (2020) and Statistik Austria (2020).
Notes: The hypothetical Beveridge curves are estimated with the average matching efficiency before 2014 and after 2014.

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



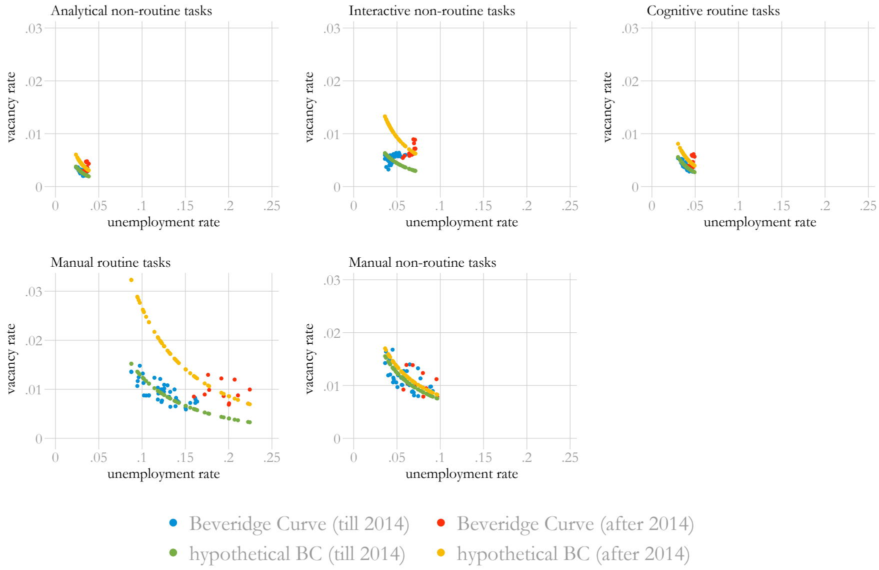
Source: Own calculations, based on data from AMS Österreich (2020) and Statistik Austria (2020).
Notes: The graph plots the estimated unemployment rate for the Austrian regions and compares it with the unemployment rate observed in the data.

Figure A.15: Mismatch indicator, by skill level, 2004–2016.



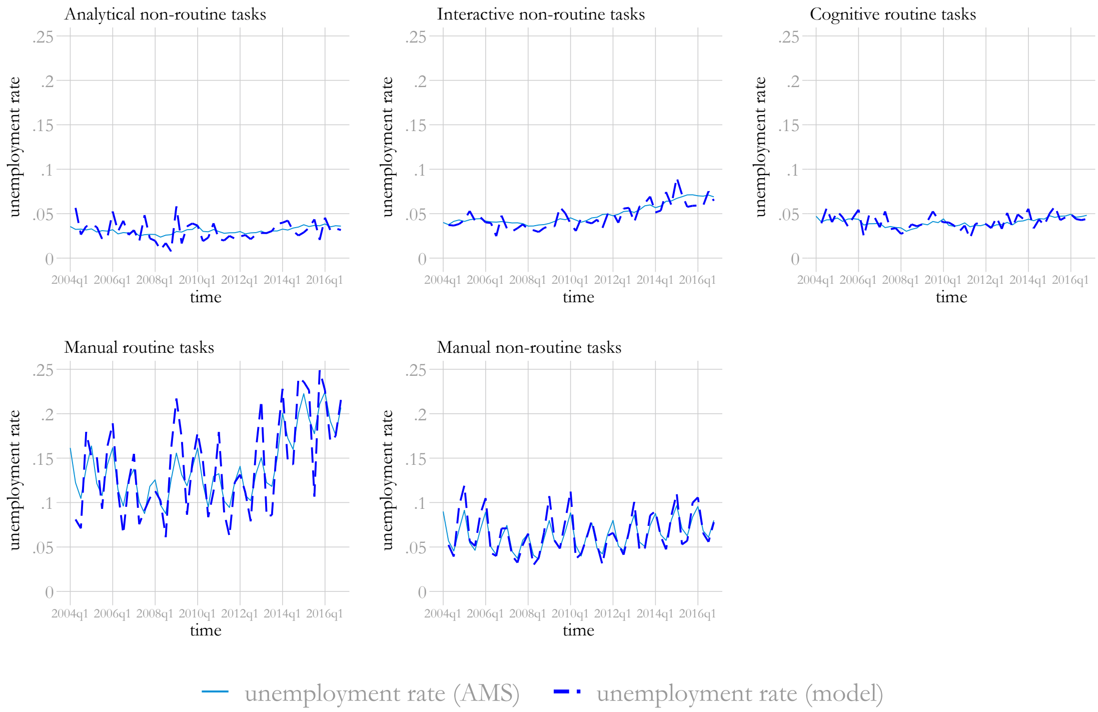
Source: Own calculations, based on data from AMS Österreich (2020) and Statistik Austria (2020).
Notes: The trend is derived by a locally weighted smoothing.

Figure A.16: Beveridge curves, by skill level, 2004–2016.



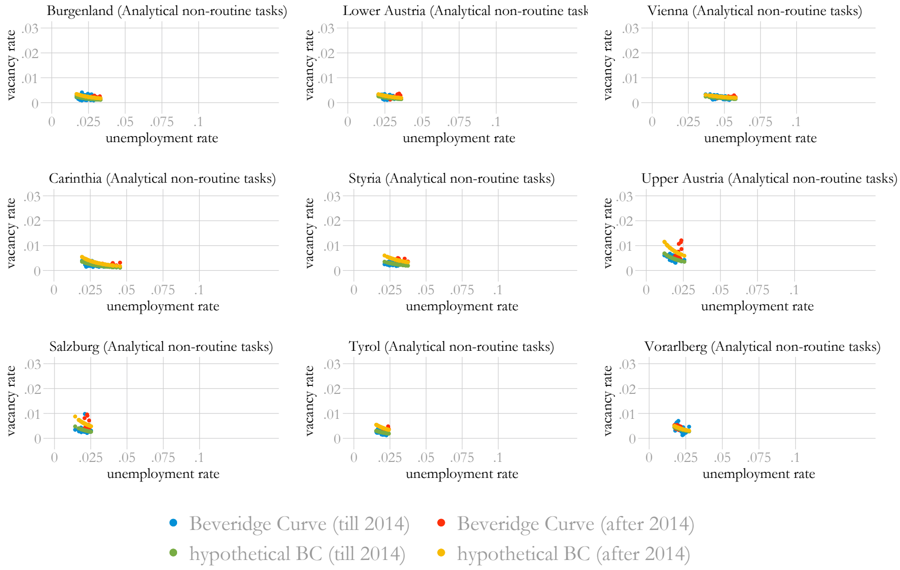
Source: Own calculations, based on data from AMS Österreich (2020) and Statistik Austria (2020).
Notes: The hypothetical Beveridge curves are estimated with the average matching efficiency before 2014 and after 2014.

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



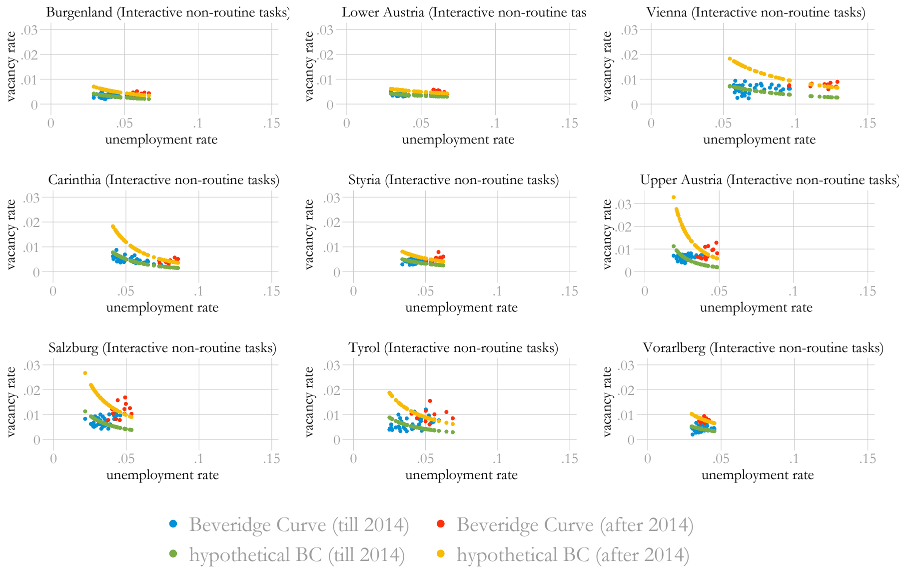
Source: Own calculations, based on data from AMS Österreich (2020) and Statistik Austria (2020).
Notes: The graph plots the estimated unemployment rate by skill level and compares it with the unemployment rate observed in the data.

Figure A.18: Beveridge curves - analytical non-routine tasks



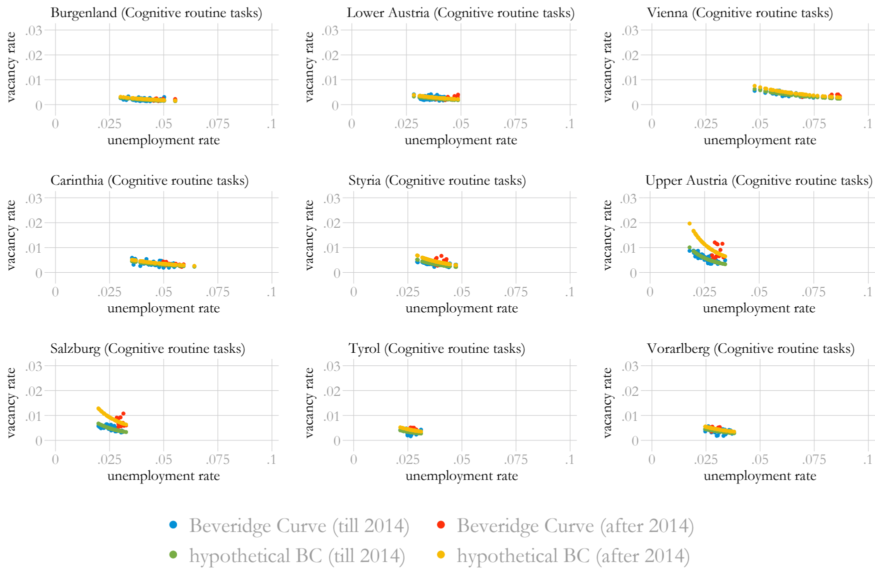
Source: Own calculations, based on data from AMS Österreich (2020) and Statistik Austria (2020).
Notes: The hypothetical Beveridge curves are estimated with the average matching efficiency before 2014 and after 2014.

Figure A.19: Beveridge curves - interactive non-routine tasks



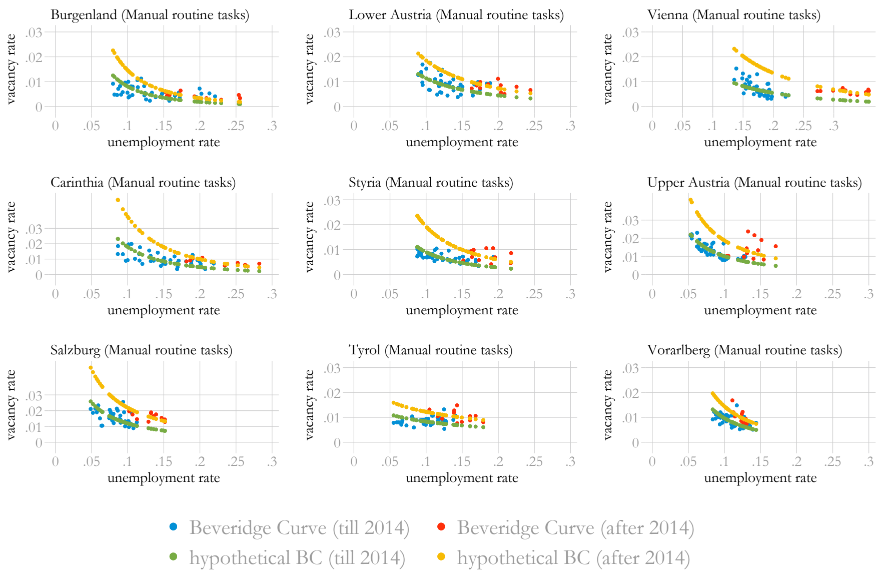
Source: Own calculations, based on data from AMS Österreich (2020) and Statistik Austria (2020).
Notes: The hypothetical Beveridge curves are estimated with the average matching efficiency before 2014 and after 2014.

Figure A.20: Beveridge curves - cognitive routine tasks



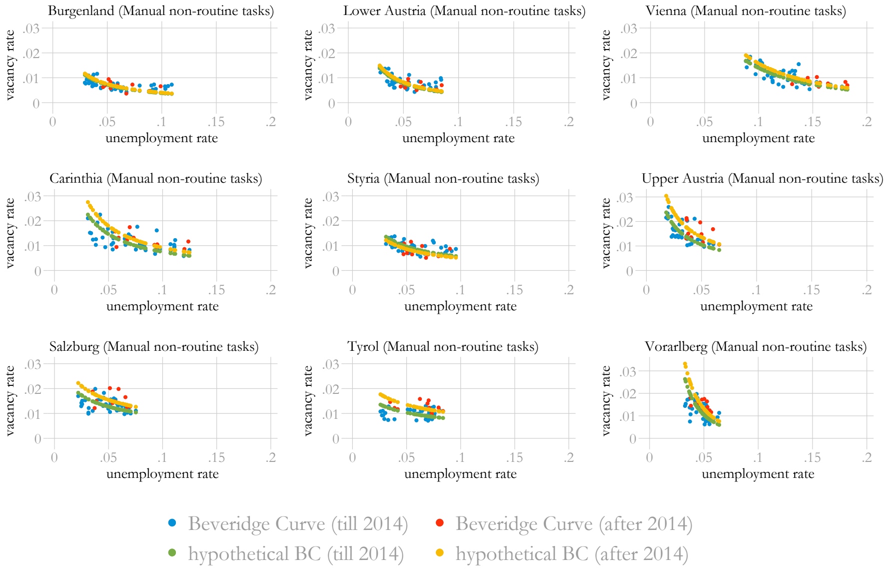
Source: Own calculations, based on data from AMS Österreich (2020) and Statistik Austria (2020).
Notes: The hypothetical Beveridge curves are estimated with the average matching efficiency before 2014 and after 2014.

Figure A.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 A.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.

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Table A.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
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

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Table A.6 – continued from previous page.

ISCO-08	class	task category	description
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
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